Review article: Deep Learning for Potential Landslide Identification: Data, Models, Applications, Challenges, and Opportunities

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Abstract.

As global climate change and human activities escalate, the frequency and severity of landslide hazards have been increasing. Early identification, as an important prerequisite for monitoring, evaluation, and prevention, has become increasingly critical. Deep learning, as a powerful tool for data interpretation, has demonstrated remarkable potential in advancing landslide identification, particularly through the automated analysis of remote sensing, geological, and topographic data. This review provides an overview of recent advancements in the utilization of deep learning for potential landslide identification. First, the sources and characteristics of landslide-related data are summarized, including satellite observation data, airborne remote sensing data, and ground-based observation data. Next, commonly used deep learning models are classified based on their roles in potential landslide identification, such as image analysis and time series analysis. Then, the role of deep learning in identifying rainfall-induced landslides, earthquake-induced landslides, human activity-induced landslides, and multi-factor-induced landslides is summarized. Although deep learning has achieved considerable success in landslide identification, it still faces several challenges, including data imbalance, limited model generalization, and the inherent complexity of landslide mechanisms. Finally, future research directions in this field are discussed. It is suggested that integrating knowledge-driven and data-driven approaches for potential landslide identification will further enhance the applicability of deep learning, offering broad prospects for future research and practice.

1 Introduction

Landslides are complex geological hazards triggered by both natural processes and human activities, involving intricate interactions among geological, hydrological, topographic, and meteorological factors (Fidan et al., 2024). Globally, landslides cause significant loss of life and property each year, particularly in mountainous areas with intense rainfall, seismic activity, and fragile geological conditions (Askarinejad et al., 2018; Ehsan et al., 2025; Marín-Rodríguez et al., 2024). According to United Nations Office for Disaster Risk Reduction (2023), more than 1,000 landslide-related disasters occur annually, resulting in thousands of fatalities and substantial economic damage. With the intensification of climate change, extreme weather events are becoming more frequent, further increasing global landslide risks (Wang et al., 2023c).

Faced with these escalating threats, the focus of landslide risk management should shift from post-disaster response toward proactive identification and prevention. Potential landslides refer to slopes that exhibit early signs of instability and may evolve into landslides under external triggers such as rainfall or earthquakes. They represent the precursor stage of landslide development (Lin et al., 2024; Yang et al., 2020a). Timely identification and monitoring of such slopes are crucial for disaster prevention and risk mitigation (Strzabala et al., 2024).

However, the inherent uncertainty and dynamic nature of potential landslides make their identification challenging. On the one hand, it is not possible to determine that a landslide will definitely occur just because there are signs of deformation on the slope (Peres and Cancelliere, 2014; Zhang et al., 2019). Multiple factors need to be comprehensively considered to assess the possibility of its instability. On the other hand, the uncertainty of external factors increases the difficulty of judgment. Sudden events such as heavy rainfall and earthquakes may instantly change the stress state of the slope and trigger signs of deformation (Yang et al., 2024c). Given the dynamic characteristics of potential landslides, it is also essential to conduct long-term monitoring of the landslides with potential hazards after identification (Lakhote et al., 2025).

Conventional approaches to potential landslide identification, including field surveys, geological analysis, and interferometric radar techniques, have contributed substantially to hazard assessment but remain costly, time-consuming, and limited in spatial coverage (Akosah et al., 2024; Zhao and Lu, 2018). Machine learning has partially improved efficiency but still depends heavily on manual feature engineering, requiring expert knowledge to design relevant predictors (Sheng et al., 2023). These limitations restrict the scalability and adaptability of conventional approaches in complex geospatial environments.

In contrast, deep learning provides an effective data-driven alternative for landslide research. As a subfield of machine learning, deep learning performs hierarchical feature extraction through multiple nonlinear transformations (Janiesch et al., 2021; Nava et al., 2023). By leveraging large-scale, multi-source data, deep learning models can automatically extract representative features, capture nonlinear dependencies, and conduct pattern recognition in high-dimensional datasets (Aslam et al., 2021; Wang et al., 2023a; Zhou et al., 2023). These capabilities make deep learning particularly suitable for identifying and characterizing potential landslides across diverse spatial and temporal scales (Nava et al., 2021; Yang et al., 2024d).

Within this research context, potential landslide identification can be broadly categorized into two main types. The first focuses on post-event regional assessments, which are conducted after major rainfall or earthquakes but prior to large-scale slope failures, using remote sensing data to detect deformation, topographic changes, or vegetation anomalies. The second involves retrospective analyses of historical landslides to establish relationships between triggering factors and failure characteristics, thereby identifying other slopes that exhibit similar instability patterns. Despite their differing temporal focuses, both types share common methodological foundations and depend on the integration of multi-source environmental data for reliable assessment.

Building on these foundations, this review aims to provide a comprehensive synthesis of deep learning applications in the field of potential landslide identification. Specifically,

(1) we categorize commonly used heterogeneous data into three major types to support research on potential landslide identification. These data sources form the foundation for applying deep learning in this field.

(2) we introduce the roles and mechanisms of widely used deep learning models in potential landslide identification, and conduct a comparative analysis of their respective advantages and limitations.

(3) we examine the performance of these models across different application scenarios through representative case studies, highlighting their adaptability and effectiveness in potential landslide detection.

(4) we summarize the key challenges currently faced in applying deep learning to potential landslide identification and outline emerging opportunities and promising future directions for further advancement.

Through our analysis, we identified several key trends in the application of deep learning to potential landslide identification. First, researchers are increasingly adopting multi-source data fusion approaches, integrating information from diverse sources to construct a more comprehensive representation of the geological environment (Guo et al., 2025; Liu et al., 2020b; Wang et al., 2024d). Second, deep learning models have been successfully applied across multiple scales, ranging from large-scale landslide susceptibility mapping with Convolutional Neural Networks (CNNs) to real-time slope deformation monitoring with Recurrent Neural Networks (RNNs) (Azarafza et al., 2021; Soni et al., 2025; Xie et al., 2024; Zhao et al., 2024f). Despite these advances, the field continues to face critical challenges that will shape its future trajectory. Addressing these challenges requires a paradigm shift, future research is expected to place greater emphasis on integrating physical knowledge with data-driven approaches, thereby advancing the field from conventional, reactive post-disaster responses toward intelligent, proactive pre-disaster risk management.

2 Deep Learning for Potential Landslide Identification: Data Source

Accurate identification of potential landslides is the primary step in effectively preventing and mitigating the impacts of landslide hazards. Data sources are the cornerstone of achieving this objective. Different types of data provide indispensable information for potential landslide identification from various perspectives, and drive ongoing advancements in related research and practices.

In potential landslide identification, the richness and reliability of data sources directly determine the accuracy and effectiveness of research. Data sources not only provide fundamental information to outline the landslide environments, but also enable dynamic monitoring and precise analysis. This section will comprehensively review the critical roles played by three main types of data sources: satellite observation data, airborne remote sensing data, and ground-based observation data (see Fig. 1).

2.1 Satellite Observation Data

Since the launch of Landsat-1, the first Earth observation satellite dedicated to surface research and monitoring, on July 23, 1972, satellite data have become widely accessible. Their applications have long extended beyond single-purpose analysis or results (Wulder et al., 2022). With the continuous development of satellite observation, its immense potential for application in landslide research has become evident (Liu et al., 2021d). At present, satellite observation data mainly include space-borne

Synthetic Aperture Radar (SAR) and optical remote sensing data, both of which are widely used as inputs for deep learning models in landslide identification.

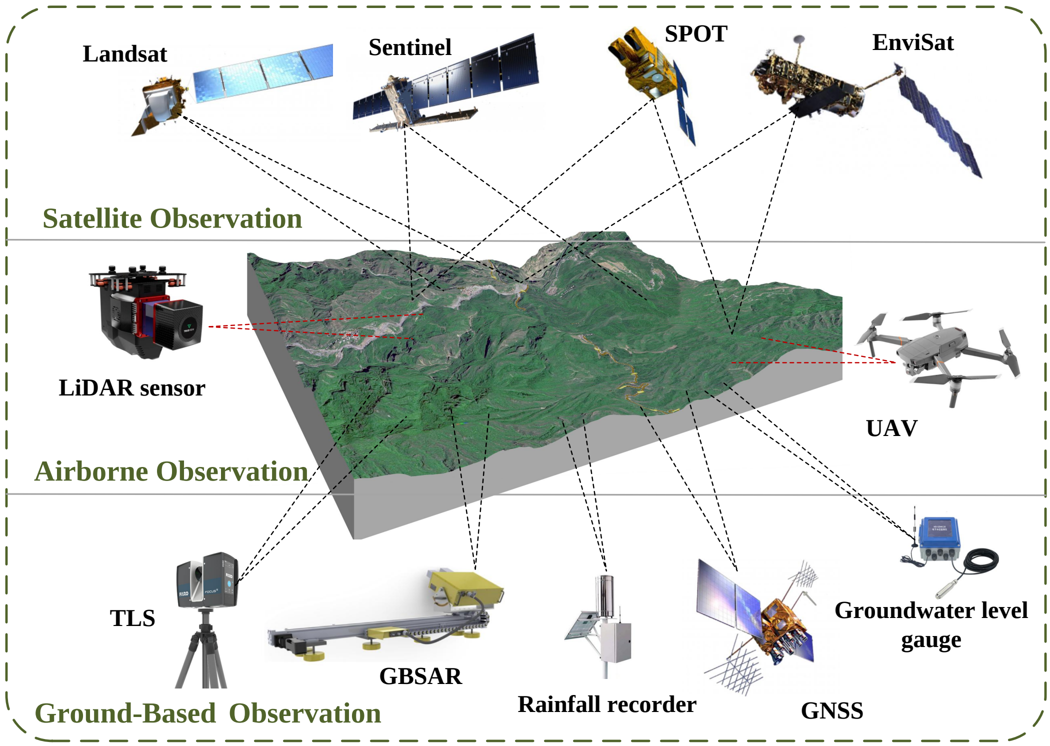

Figure 1. Data sources for potential landslide identification. Satellite observations (e.g., Landsat, Sentinel, SPOT, and Envisat) provide optical and radar imagery with varying spatial resolutions for detecting and mapping landslides. Airborne observations (LiDAR, UAV) deliver high-resolution topographic and photographic data, while ground-based observations (TLS, GBSAR, GNSS, rainfall and groundwater sensors) offer continuous in-situ monitoring of slope dynamics.

2.1.1 Space-borne SAR

SAR is an active microwave remote sensing system (Franceschetti and Lanari, 2018). It is not only capable of acquiring data on demand by actively emitting microwave signals but also facilitates partial penetration of vegetation cover through its longer wavelength bands (such as the L-band), thereby allowing the retrieval of surface deformation information beneath vegetated areas.

A critical operational advantage of SAR lies in its capacity to image regardless of illumination (day or night) and weather conditions (Koukiou, 2024). The continuous, unimpeded time series data this provides is essential for serving as input to deep learning models, allowing these models to be trained to identify long-term patterns of terrain change. For this reason, SAR is widely employed for the crucial task of continuous monitoring in high-risk environments, where cloud cover and the timing of a disaster are unpredictable.

Notably, the NASA–ISRO SAR Mission (NISAR), jointly developed by the National Aeronautics and Space Administration (NASA) and the Indian Space Research Organisation (ISRO), was successfully launched in 2025 (Indian Space Research Organisation, 2025; NASA, 2025). The satellite carries both L-band and S-band SAR systems, enabling more precise and frequent measurements of surface deformation. With a revisit period of approximately 12 days, it delivers globally consistent coverage with a balanced spatial and temporal resolution. This capability provides researchers with abundant and continuous observations, supporting large-scale, high spatiotemporal resolution landslide early detection and dynamic monitoring.

Interferometric SAR (InSAR) has been developed based on the principle of measuring phase differences between two or more SAR images of the same area (Dai et al., 2022; Ma et al., 2023b; Zeng et al., 2024). By coherently processing these images, InSAR obtains high-precision surface elevation information and can be further applied to detect ground deformation.

In contrast, SAR mainly provide backscatter information of ground objects. Although some features of ground objects can be identified according to the scattering characteristics, their ability to obtain topographic elevation information is relatively weak. InSAR, on the other hand, can directly generate topographic elevation data, which is of great significance for analyzing the topography and geomorphology in the identification of potential landslides, and determining key elements such as the topographic undulation and slope of potential landslide areas.

When screening for potential landslides over a large area, InSAR has higher efficiency (Dun et al., 2021; Tang et al., 2025; Zhang et al., 2021). When monitoring large potential landslide areas such as mountainous regions, InSAR can quickly obtain topographic deformation information over a large area, promptly detect potential areas with potential landslides, and reduce the workload and blind spots of manual inspections.

Recent studies have integrated InSAR-derived deformation velocity fields with deep learning models to automatically detect slow-moving or latent landslides. For example, Liu et al. (2022d) employed an InSAR-CNN framework to map active landslides in the Eastern Tibet Plateau area, achieving a detection accuracy of over 90%. Similarly, Zhang et al. (2022d) proposed a two-stage detection deep learning network (InSARNet) for detecting anomalous deformation areas in Maoxian County, Sichuan Province, with a recognition accuracy of 93.88%. Targeting the complex deformation mechanisms of multi-type landslides in Zigui County, Three Gorges Reservoir Area, Hu et al. (2025b) used InSAR time-series displacement as the core data, develop a deep learning architecture based on the integrated framework of EMD and GRU, break through the limitations of conventional models such as single-type, single-target, and low-accuracy, and achieve dual-accurate prediction of displacement and failure time for multi-type landslides.

Differential InSAR (D-InSAR) is an advancement of InSAR that eliminates topographic phase through differential processing, focusing specifically on deformation information extraction (Shen et al., 2022). The emergence of D-InSAR not only enables the transition from mixed deformation-topography signals to pure deformation signal extraction but also extends its applicability from detecting discrete deformation events to identifying slow-moving landslide processes, significantly enhancing the reliability of landslide monitoring (Zhong et al., 2024).

2.1.2 Optical Remote Sensing

Optical remote sensing refers to the acquisition of surface information through sensors that measure reflected solar radiation. Its application in geological hazard investigations dates back to the 1970s (Fu et al., 2024; Liu and Wu, 2016).

Optical remote sensing offers high resolution, currently capable of achieving spatial resolutions as fine as 0.3 meters or better. For example, Maxar's WorldView-3 delivers 0.31 m panchromatic imagery (Hu et al., 2016; Longbotham et al., 2014), while India's Cartosat-3 satellite achieves panchromatic imagery with a resolution of up to 0.25 m (Gupta et al., 2024). In potential landslide identification, it not only facilitates the retrieval of detailed surface textures and color characteristics using rich spectral data but also enables the direct identification of morphological features and object contours via visual interpretation of imagery (Cheng and Han, 2016; Li et al., 2022; Ma and Wang, 2025).

Landslide formation typically follows a progressive process from deformation to failure, accompanied by precursor indicators such as tensile cracks, stepped scarps, and localized collapses. These indicators exhibit distinct spectral signatures in optical imagery compared to their surroundings, enabling both manual interpretation and automated detection. In deep learning applications, multispectral optical images have been widely used to train CNN-based models for potential landslide identification. Lu et al. (2023a) developed a method for achieving accurate landslide mapping using medium-resolution remote sensing images and DEM data, which has the potential for deployment in large-scale landslide detection. Jiang et al. (2022a) proposed a TL-Mask R-CNN for identifying a small number of old landslide samples in the area along the Sichuan-Tibet Transportation Corridor. The results show that the pixel accuracy of segmentation for new landslides and old landslides can reach 87.71% and 75.86% respectively.

In vegetated mountainous regions, surface vegetation often undergoes detectable changes before a landslide event. Optical remote sensing leverages multispectral data, particularly red and near-infrared bands, to monitor vegetation health and identify potential landslide zones (Coluzzi et al., 2025; Fiorucci et al., 2018). Furthermore, the calculation of the Normalized Difference Vegetation Index (NDVI) facilitates the evaluation of vegetation health in potential landslide regions, providing critical insights into potential landslide precursors (Verrelst et al., 2015).

However, the broad spectral bands of multispectral sensors limit their ability to detect more subtle, diagnostically specific precursory signals. The advancement beyond broad-band multispectral imaging to hyperspectral imaging has opened new avenues for landslide precursor detection (Kilgore and Restrepo, 2025; Ye et al., 2019). Hyperspectral sensors capture hundreds of contiguous spectral bands, enabling the identification of specific mineralogies (e.g., expansive clays like smectite that influence slope stability) and subtle geochemical alterations on slope surfaces. For instance, the shifting absorption features in the short-wave infrared region can signal changes in soil water content and mineral composition that often precede failure (Thimsen et al., 2017). The integration of these rich spectral datasets with deep learning architectures has significantly advanced automated landslide analysis (Huang et al., 2022c; Shahabi et al., 2021). These models excel at learning complex patterns from high-dimensional spectral-spatial information, enabling highly accurate detection of landslide scars and even precursory features like cracks and seepage zones that are otherwise challenging to identify.

While both space-borne SAR and optical remote sensing are pivotal for large-area landslide screening, they offer complementary capabilities and have distinct limitations. Optical remote sensing provides intuitive visual interpretation of geomorphological features but is rendered useless by cloud cover and darkness. In contrast, space-borne SAR, with its all-weather, day-and-night imaging capability, excels in detecting millimeter-to-centimeter-scale surface deformation through InSAR techniques, which is a direct precursor to landslide failure. However, InSAR performance can be degraded in heavily vegetated areas due to temporal decorrelation and in steep terrain due to geometric distortions (Lin et al., 2022; Yan et al., 2024), areas where optical stereo imaging for DEM generation might be less affected. Therefore, the integration of SAR-derived deformation maps and optical-based geomorphological maps is considered a best practice for regional-scale landslide inventory mapping and preliminary hazard assessment (Xun et al., 2022).

2.2 Airborne Remote Sensing Data

Airborne remote sensing data, typically acquired by manned aircrafts, provide high-resolution imagery of localized areas. Advanced airborne platforms equipped with oblique photogrammetry and, more recently, close-range photogrammetry technologies enable millimeter-level accuracy in 3D photogrammetry, facilitating the observation of subtle surface deformations, rock mass structures, and the construction of highly detailed 3D models of terrain and above-ground infrastructure (Macciotta and Hendry, 2021; Xu et al., 2023). Among these technologies, airborne photogrammetry and airborne radar are the most commonly used.

2.2.1 Airborne Light Detection and Ranging (LiDAR)

LiDAR has been used for landslide and other geological hazard investigations in many regions since the late 1990s. As an active remote sensing system, LiDAR can laterally scan a range of 60° and capture 400,000 points per second, enabling large-scale 3D scanning of terrain, structures, and vegetation within a short period (Mallet and Bretar, 2009). It offers centimeter-level accuracy in both horizontal and vertical dimensions.

Airborne LiDAR is irreplaceable in capturing 3D details and penetrating vegetation, particularly in densely vegetated areas where conventional aerial photography faces significant limitations. Airborne LiDAR not only acquires high-resolution Digital Surface Models (DSMs) from laser point cloud data but also generates high-accuracy DEMs by removing vegetation contributions (Fang et al., 2022; Jaboyedoff et al., 2012; Yan et al., 2023), thereby revealing concealed hazard features such as mountain fractures, loose deposits, and landslide masses under vegetation cover.

Point cloud data obtained from airborne LiDAR can monitor dynamic changes in mountainous terrain by detecting deformations such as subsidence, displacement, and uplift, while also facilitating the construction of 3D landslide models to simulate sliding directions and impact areas. Through intuitive visualization of slope morphology and structure from multiple perspectives, LiDAR enables researchers to conduct a comprehensive assessment of slope conditions and identify subtle hazard features that may not be easily discernible in 2D imagery.

These high-precision DEMs and point clouds serve as critical inputs for deep learning models. For instance,Wei et al. (2023) proposed the Dynamic Attentive Graph Network (DAG-Net) model to construct dynamic edge features for enhancing point cloud representations, achieving the highest mean Intersection over Union (mIoU) of 0.743 and an F1-score of 0.786. Based on the advanced PointNet and PointNet++ architectures, Farmakis et al. (2022) developed deep neural networks for 3D point cloud learning. The best-performing model achieved accuracies of approximately 89% and 84% during the final and shortest monitoring campaigns, respectively. These examples demonstrate that airborne LiDAR data are not only suitable but have been effectively applied in deep learning-based landslide analysis.

2.2.2 Unmanned Aerial Vehicle (UAV)

UAV aerial photogrammetry provides outstanding maneuverability and high-precision measurements. Traversing over steep slopes and valleys, UAVs are able to monitor areas that are often inaccessible to satellites and manned aerial platforms (Niethammer et al., 2012), thus addressing critical observational limitations.

In large-scale and topographically complex regions, UAVs can perform efficient aerial inspections, overcoming the limitations of ground-based inspections in inaccessible or visually obstructed regions. By rapidly scanning mountain slopes, embankments, and gullies, UAVs provide a comprehensive understanding of the geological conditions and enable timely identification of macro-scale geomorphic anomalies. However, given cost-effectiveness constraints, UAVs are currently more commonly used for periodic and continuous monitoring in localized areas. They are particularly well-suited for rapid and dynamic monitoring of landslides in high-priority zones.

With the rapid advancement of UAVs, centimeter-level vertical and oblique aerial photogrammetry is now achievable (Fan et al., 2020). The high-definition cameras mounted on UAVs are able to capture the subtle cracks on the surface of the mountain.These cracks may be early signs of a landslide (Sun et al., 2024a). By conducting a comparative analysis of the images taken at different times, the development and changes of the cracks can be monitored, including the increase in the length, width and depth of the cracks, as well as the changes in the crack orientation.

In some mountainous areas or valleys, there may be a large number of loose accumulations. These accumulations may trigger landslides under specific conditions. Aerial photography by UAVs can clearly identify information such as the distribution range, accumulation quantity and accumulation shape of these loose accumulations, and assess their potential threats to the surrounding environment. This capability is leveraged in deep learning applications, where time-series UAV imagery is processed using RNNs or 3D CNNs to monitor the spatiotemporal evolution of these cracks, providing a data-driven approach for early warning (Xu et al., 2025; Sandric et al., 2024).

Airborne platforms bridge the gap between satellite and ground-based observations. LiDAR is unparalleled in generating high-precision DEM, revealing concealed paleo-landslides and subtle topographic features critical for hazard mapping. However, its deployment is costly and logistically complex. UAVs, as a flexible and cost-effective alternative, have democratized high-resolution data acquisition. They can be equipped with various sensors (e.g., optical, multispectral, and even lightweight LiDAR) to conduct rapid response surveys following triggering events such as earthquakes or heavy rainfall (Han et al., 2023). While UAV-derived models have ultra-high resolution, their coverage is limited per sortie compared to airborne campaigns. The choice between them often involves a trade-off between coverage, cost, operational flexibility, and the specific requirement for vegetation penetration.

By equipping UAVs with LiDAR sensors to effectively remove vegetation from the data, this integrated approach combines the strengths of photogrammetry and LiDAR (Mandlburger et al., 2020; Wallace et al., 2012). It allows researchers to reveal landslide boundaries, crack patterns, and other deformation features hidden beneath vegetation cover, enabling rapid deployment and targeted area monitoring while mitigating vegetation-related challenges in landslide assessment.

2.3 Ground-based Observation Data

Satellite observation and airborne remote sensing are mainly employed for identifying potential landslides based on surface morphology. However, these approaches are often affected by vegetation cover, viewing geometry, and atmospheric noise, which may lead to misclassification or omission (Almalki et al., 2022; Dubovik et al., 2021). Therefore, ground-based observation techniques play a critical complementary role, offering higher temporal resolution, accuracy, and localized verification for potential landslide identification. In recent years, data collected from ground-based monitoring instruments have not only been used for field validation but also increasingly incorporated into deep learning frameworks to improve temporal continuity and physical interpretability in landslide detection and forecasting.

2.3.1 Ground-based Synthetic Aperture Radar (GB-SAR)

GB-SAR is an active ground-based microwave remote sensing system that has been developed over the past decade, effectively integrating the principles of SAR imaging with electromagnetic wave interferometry. By leveraging precise measurements of sensor system parameters, attitude parameters, and geometric relationships between orbits, GB-SAR quantifies spatial positions and subtle changes at specific surface points, allowing for the measurement of surface deformations with millimeter or even sub-millimeter precision.

Compared with spaceborne SAR, GB-SAR can adjust the incidence and azimuth angles of radar waves, thereby avoiding phase decorrelation caused by terrain-induced occlusion in spaceborne observations. Consequently, they are particularly suitable for monitoring steep slopes, canyons, and other areas with limited line-of-sight coverage from satellites (Noferini et al., 2007).

During landslide movement, the ground experiences noticeable subsidence, displacement, or cracking. GB-SAR can be configured for high-resolution, continuous observation to capture instantaneous deformations during the landslide creep phase and generate corresponding displacement maps (Liu et al., 2021a; Xiao et al., 2021a). For example,Long et al. (2018) proposed a GBSAR persistent scatterer point selection method based on the mean coherence coefficient, amplitude dispersion index, estimated signal-to-noise ratio, and displacement accuracy index. Han et al. (2022) proposed an LSTM-based approach for processing GB-InSAR time series data. **?** employed two deep learning methods to investigate the potential and advantages of processing raw GBSAR data for automatic radar classification.

For small-scale regional monitoring, GB-SAR can establish customized geometric configurations specifically designed for target areas. Utilizing mobile rail systems or multi-antenna setups, GB-SAR reconstructs 3D deformation vector fields of landslide masses (Shi et al., 2025), identifying sliding directions and potential failure surfaces.

2.3.2 Terrestrial Laser Scanning (TLS)

TLS emerged in the mid-1990s. It plays a unique role in local refined monitoring by emitting laser pulses and measuring their reflection time (Stumvoll et al., 2021; Teza et al., 2007).

The landslide often manifests as a sharp change in the ground surface. TLS can provide data with sufficient accuracy, assisting researchers in identifying the features of these landslides (Abellán et al., 2009; Teng et al., 2022).

By quickly and massively collecting spatial point position information, TLS can automatically splice and rapidly obtain the appearance of the measured object. It can be used to construct high-precision surface models and appearance models of buildings and structures. The 3D model can display the shape and structure of the mountain and the detailed features of the ground surface from different angles and in all directions (Zhou et al., 2024a), enabling geological experts and engineers to have a more intuitive understanding of the overall situation of the landslide area. For example, the cracks in the mountain, the loose accumulations, and the degree of weathering of the rocks can be clearly seen, providing richer information for the identification of potential landslide hazards.

In the context of deep learning, TLS-derived 3D point clouds have become critical inputs for morphological feature extraction and automatic landslide identification. For example, Senogles et al. (2022) integrated TLS point cloud data to assess surface displacements induced by landslide movements. Wang et al. (2025) provided a practical and adaptable solution for landslide monitoring by integrating TLS point clouds with embedded RGB imagery.

These examples confirm that TLS data are not only suitable but already actively used in deep learning-based landslide recognition, providing precise geometric constraints for multi-source fusion frameworks that combine DEM, optical, and InSAR information.

Ground-based techniques provide the highest precision for monitoring a specific slope of interest. GB-SAR and TLS are both non-contact remote sensing methods, but they operate on different principles. GB-SAR offers continuous, all-weather, mm-level deformation monitoring over a large area (several km^2) from a single station, making it ideal for early warning. Its drawback is the need for a stable, opposing installation point with a clear line-of-sight (Monserrat et al., 2013). TLS, on the other hand, provides mm-to-cm-level 3D point clouds of the slope surface, excellent for quantifying volume changes and detailed geometric changes. However, it is typically used for periodic surveys rather than continuous monitoring and has occlusion shadows (Huang et al., 2019).

2.3.3 Ground-based Sensor Devices

Compared to the aforementioned data sources, ground-based sensors offer key advantages, including high precision, real-time capabilities, and multi-parameter fusion (Dai et al., 2023). They can address the limitations of remote sensing and provide critical ground-based dynamic information for potential landslide identification.

Ground-based sensing devices are highly diverse, and the data they acquire directly reflect the state of landslide masses. These datasets provide foundational inputs for deep learning models, enabling multi-dimensional analysis and interpretation of potential landslide conditions. For example, ground sensors (e.g., GNSS receivers and crack meters) can collect parameters like displacement and tilt angle at frequencies ranging from minutes to seconds, capturing transient, anomalous signals just prior to landslide events, thereby filling the temporal resolution gap in remote sensing (see Fig. 1). These data are often used as input sources for RNN models and their variants (Bai et al., 2022; Wang et al., 2021a). By integrating time series data with SAR imagery, deep learning models can be trained to uncover correlation patterns between surface deformations and subsurface parameters (Jiang et al., 2022b). Instruments such as piezometers and soil pressure gauges can directly monitor key parameters like pore water pressure and soil stress on the sliding surface. By combining the obtained subsurface data with geomechanical equations, the position of the sliding surface or geotechnical strength parameters can be inferred.

Therefore, GB-SAR, TLS, and ground-based sensors are not only auxiliary observation techniques but are increasingly serving as key data sources for deep learning-driven landslide identification. Their integration into CNN, LSTM, and Generative Adversarial Network (GAN) frameworks enables high-resolution spatial-temporal modeling of slope behavior, bridging the gap between field-scale monitoring and large-scale hazard prediction.

2.4 Summary of Data Source for Potential Landslide Identification

In summary, no single data source is sufficient for a comprehensive potential landslide identification framework. Regional-scale satellite data, particularly InSAR, is optimal for the early detection of pre-landslide deformations over vast areas. Airborne platforms, such as UAVs, then provide high-resolution optical and LiDAR data to characterize the precise geometry and activity of identified potential landslides. Finally, ground-based and in-situ sensors enable site-specific, real-time monitoring of high-risk slopes, validating remote sensing findings and supporting early warning systems. The strategic integration of these multi-platform data is crucial for transitioning from regional screening to mechanistic understanding and risk mitigation.

Beyond these general data modalities, recent years have also witnessed the emergence of benchmark datasets that serve as standardized testbeds for developing and evaluating deep learning methods in landslide identification. Such datasets are essential for ensuring reproducibility, enabling fair comparison across models, and accelerating methodological advances. Representative examples include the CAS Landslide Dataset, a large-scale, multi-sensor dataset explicitly designed for deep-learning-based landslide mapping (Xu et al., 2024); the Landslide4Sense (L4S) benchmark, developed within an international competition, which provides multisource satellite image patches (Ghorbanzadeh et al., 2022b); and the Diverse Mountainous Landslide Dataset (DMLD), which emphasizes high-resolution instances from complex mountainous terrains (Chen et al., 2024b). In addition, slope-unit-based benchmark datasets have been constructed to support susceptibility mapping and regional-scale comparisons (Martinello et al., 2021).

These datasets serve as valuable resources for pixel-level segmentation and slope-unit-based susceptibility modeling. However, in practice, the compilation of landslide inventories faces considerable challenges, making it difficult to obtain comprehensive and accurate records (Kong et al., 2025; Lee et al., 2018). Consequently, data scarcity remains a common issue in landslide hazard identification, particularly in remote regions or areas with limited accessibility. Therefore, it is necessary to further expand their geographical coverage and establish standardized evaluation protocols.

3 Deep Learning for Potential Landslide Identification: Models

The effectiveness of deep learning in potential landslide identification largely depends on selecting an appropriate model architecture suited to the data type and specific task. While all deep learning models excel at automated feature extraction, their internal architectures predispose them to excel in different aspects of the overall workflow. Therefore, this section does not merely list models, but organizes them based on their primary function in the potential landslide identification pipeline. We analyze several commonly used deep learning models by categorizing them into five functional roles: image analysis and processing, time series analysis, data generation, anomaly detection, and data fusion.

3.1 Models for Image Analysis and Processing in Potential Landslide Identification

Image data plays a critical role in potential landslide identification, especially through remote sensing, satellite, and UAV imagery. These images enable the acquisition of large-scale terrain data, encompassing complex geographical features, vegetation coverage, and ground fissures, which often serve as potential precursors to landslide occurrences. The adoption of deep learning has facilitated a shift from conventional manual visual interpretation to automated high-precision segmentation.

As illustrated in Fig. 2, a CNN is mainly composed of convolutional, pooling, and fully connected layers, each responsible for distinct operations on the input data (Kattenborn et al., 2021; LeCun et al., 1998; Liu et al., 2022b).

Convolutional layers, the core of CNNs, use kernels of various sizes to extract multi-scale features from geospatial imagery, which is crucial for landslide identification Hussain et al. (2019); Shi et al. (2020); Yao et al. (2021). Small kernels are effective in detecting fine-grained precursors such as ground fissures and localized soil texture changes. For instance, Hamaguchi et al. (2018) proposed a Local Feature Extraction (LFE) module to enhance the capability of CNNs in identifying small object instances in remote sensing imagery. Wang et al. (2024a) demonstrated the exceptional capability of convolutional layers in extracting extremely small and subtle features by identifying cracks as narrow as 0.05 m width using a U-Net–based model. In contrast, larger kernels help in recognizing the overall morphology and boundaries of landslide bodies. From the perspective of general visual tasks, Ding et al. (2022) demonstrated that larger convolution kernels substantially improve the shape bias of CNNs, facilitating the recognition of large-scale structures and overall morphological patterns compared with using small kernels alone. Li et al. (2025) employed multiple large convolution kernels (kernel sizes = 5, 7, and 9) within the deep learning-based feature fusion with scale-adaptive kernel attention module to fuse multi-scale features, thereby enhancing the global perception of landslide boundaries and morphology as well as the capture of contextual background information.

Pooling layers downsample feature maps, improving computational efficiency and model robustness. In landslide mapping, this translation invariance is particularly beneficial, as it allows the model to consistently identify landslide features regardless of their slight positional variations across different image patches (Mao et al., 2024).

The final fully connected layer flattens the pooled feature maps and performs classification, outputting results that distinguish potential landslide areas from non-landslide areas or enable further analysis of landslide types (Wu et al., 2024b).

The layers of a CNN can be combined in various ways, forming distinct CNN architectures. These architectures are primarily determined by task requirements, which may include image classification, multi-class segmentation, or object localization within a scene.

Conventional CNNs typically consist of multiple stacked convolutional layers, pooling layers, and fully connected layers. However, increasing network depth introduces challenges such as vanishing gradients and degradation arise, resulting in model performance deterioration.

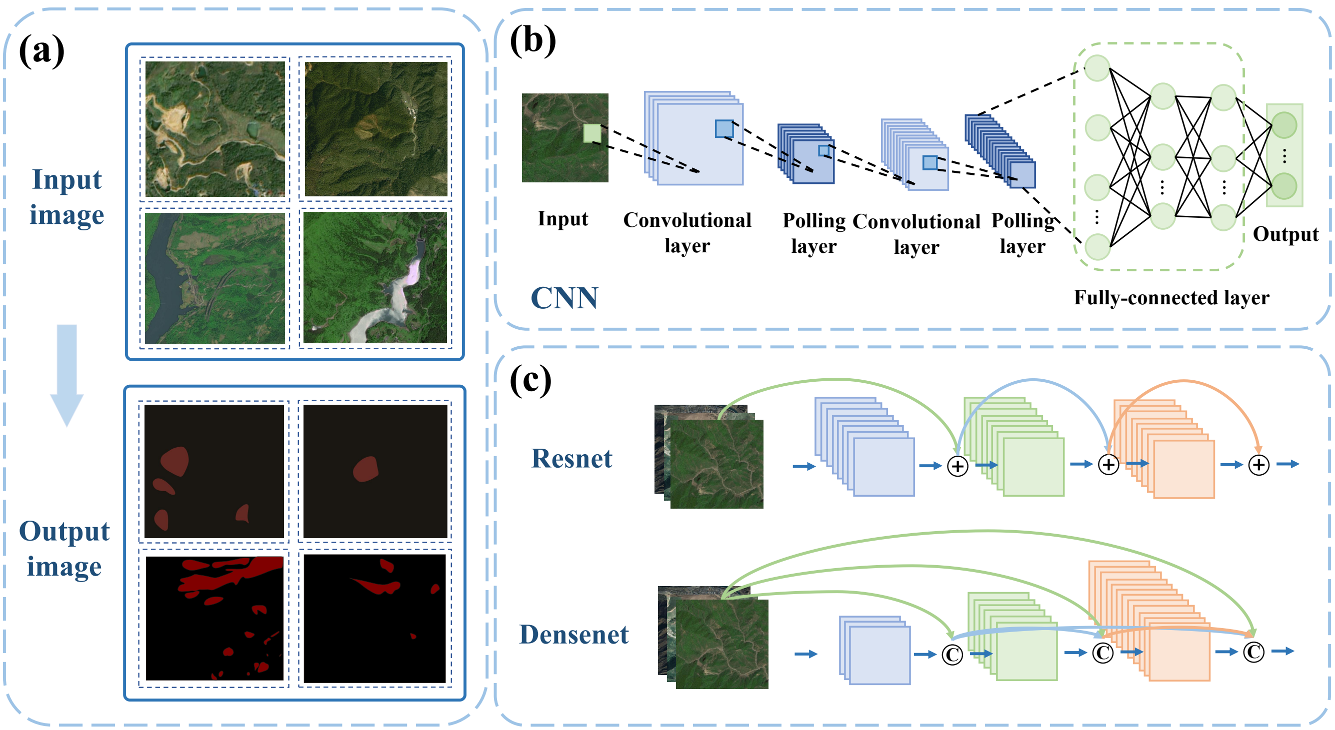

Figure 2. The role of deep learning models in image analysis and processing. (a) Comparison of landslide images before and after identification. (b) Schematic of a basic CNN architecture. A conventional CNN typically comprises stacked convolutional layers, pooling layers, and fully connected layers. (c) Comparative schematic of ResNet and DenseNet architectures. In contrast to ResNet, which combines features through summation before passing them to subsequent layers, DenseNet integrates features via channel-wise concatenation.

ResNet mitigates the vanishing gradient problem in very deep networks through residual connections (Qi et al., 2020; Yang et al., 2022). This architectural advancement has been successfully applied to landslide detection in complex terrains, such as the work by Ullo et al. (2021), who demonstrated that a ResNet-based classifier could achieve high accuracy in distinguishing landslide scars from surrounding vegetation and bare soil in satellite imagery by effectively learning hierarchical features.

Models with higher parameter counts generally exhibit greater representational capacity but are prone to overfitting, while demanding higher computational resources and temporal costs for both training and inference (Ebrahimi and Abadi, 2021).

For instance, (He et al., 2016) introduced ResNet-152 and other deep residual network architectures, demonstrating that deeper structure achieve superior performance compared with shallower counterparts. Hasanah et al. (2023) explicitly highlighted the differences in layer depth and parameter count among various ResNet versions (ResNet-50, 101, and 152), noting that the increased number of parameters in deeper networks inevitably leads to longer training times.

DenseNet is a further innovation of ResNet (Huang et al., 2017). Both of these neural networks are based on a similar idea, which is to establish a "shortcut" between different layers. However, the structure of DenseNet is simpler and more effective, with fewer parameters. The structural differences between ResNet and DenseNet are illustrated in Fig. 2. In ResNet, each layer is only connected to the previous layer, while in DenseNet, each layer is directly connected to all previous layers, and each layer can obtain gradients from the loss function. This can optimize the information flow and gradients of the entire network, making it easier to train and performing better on small datasets. The structure of DenseNet enables more effective reuse of features, meaning that each layer can directly access and build upon the feature maps generated by all preceding layers instead of re-learning similar representations. This dense connectivity not only strengthens information and gradient flow across the network but also reduces redundancy and the total number of parameters. Moreover, the layers of DenseNet are narrower than those of other deep learning networks (Liu et al., 2021c), making it reduce redundancy by learning with fewer feature maps. This architecture is suitable for the extraction of multi-scale landslide features under complex terrains, even with limited landslide training samples (Cai et al., 2021; Li et al., 2021; Ullo et al., 2021).

With the rapid expansion of deep learning methods based on CNNs, semantic segmentation models have increasingly become the standard in landslide detection (Lu et al., 2023b; Zhou et al., 2024b). As a fundamental task in computer vision, semantic segmentation assigns a specific class label (e.g., "landslide" or "non-landslide") to each pixel in an image, thereby enabling dense pixel-level classification (Guo et al., 2018).

Numerous advanced semantic segmentation networks have been proposed and validated for automatic landslide detection, significantly enhancing the efficiency and accuracy of large-scale detection.

U-Net is a typical example, which features a U-shaped architecture (Ronneberger et al., 2015). U-Net’s encoder-decoder structure with skip connections has become a benchmark for landslide segmentation (Chandra et al., 2023; Chen et al., 2022b; Meena et al., 2022). For example, Nava et al. (2022) applied the attention U-Net to Sentinel-1 SAR data for rapid mapping of earthquake-induced landslides, demonstrating the effectiveness of U-Net variants in pixel-level segmentation of landslide bodies under cloud-covered or topographically complex conditions.

When dealing with complex features in landslide-prone areas, DeepLab is a more suitable choice than U-Net (Sandric et al., 2024). While U-Net excels at preserving fine-grained spatial details through its skip-connections, its ability to capture long-range contextual information is limited by its relatively small receptive field. DeepLab, built upon deep CNNs, addresses this critical limitation by employing dilated convolutions to exponentially expand the receptive field without sacrificing resolution or increasing parameters substantially.

More importantly, DeepLab integrates an Atrous Spatial Pyramid Pooling (ASPP) module, which is key to its superior performance on multi-scale objects like landslides (Chen et al., 2017; Huang et al., 2024a). The ASPP module operates in parallel on the same feature map using multiple convolutional branches with different dilation rates (e.g., rates = 6, 12, 18).

Each branch effectively captures contextual information at a different scale, from fine details to broad, image-level contexts (Niu et al., 2018). All these multi-scale features are then concatenated and fused. This allows the network to simultaneously leverage both local textual cues and global contextual cues, thereby significantly improving recognition accuracy and reducing false positives in geologically complex environments.

After achieving semantic segmentation to obtain the accurate extent of a landslide and the classification of ground objects, change detection is employed to monitor the changes in the landslide area over time. By comparing the segmentation results of multiple temporal phases or directly analyzing the feature differences, the dynamic evolution of potential hazards can be quantified (Amankwah et al., 2022).

Wang (2023) demonstrates that 3D CNNs can directly process these 3D tensors. These models capture both spatial and temporal dependencies through 3D convolutional kernels, enabling the direct processing of multi-temporal image sequences. The outputs typically take two complementary forms: (1) change hotspot maps, which highlight regions of significant spatial change across time, and (2) temporal variation curves, which illustrate the evolution of pixel- or region-based feature values throughout the temporal sequence. Together, these representations provide intuitive and complementary tools for characterizing dynamic processes in landslide-prone areas, such as the initiation, progression, and spatial distribution of slope failures.

Some studies even have integrated attention mechanisms into conventional CNN architectures to enhance the analysis of multi-temporal remote sensing imagery, thereby enabling the identification of landslide hazard evolution over time. For example, Meng et al. (2024) proposed a framework based on CNN and optimized Bidirectional Gated Recurrent Unit (BiGRU) with an attention mechanism, designed to forecast landslide displacement with a step-like curve. Dong et al. (2022) proposed L-Unet which combines multi-scale feature fusion with attention modules to improve landslide segmentation performance, particularly at boundaries.

3.2 Models for Time Series Analysis in Potential Landslide Identification

The occurrence of a landslide is a gradual accumulation process, usually influenced by a variety of factors. We refer to data that reflect the changing states of a landslide body over time as time series data. Time series data analysis aims to excavate the information hidden in the time series data to help identify potential landslides.

Different from conventional statistical or physical models, deep learning models can automatically reveal dynamic change trends and periodic patterns in the data, providing more accurate information for landslide prediction and early warning. Recently, deep learning–based temporal models have become key tools for extracting nonlinear dependencies and temporal evolution patterns in landslide-related time series. The structural characteristics and differences among these models are illustrated in Fig. 3.

RNNs are a class of deep learning models specialized in processing sequential data, capable of capturing temporal dependencies within input sequences (Elman, 1990). Unlike conventional feedforward neural networks, in an RNN, each neuron not only receives the current input but also the output of the previous time step as additional input. This structure endows the RNN with a memory mechanism (Ngo et al., 2021; Zaremba et al., 2014).

In landslide prediction, RNNs have been employed to model displacement time series under rainfall or groundwater fluctuations, revealing short-term deformation patterns preceding slope failure (Chen et al., 2015; Zhang et al., 2022c).

To overcome the vanishing gradient problem inherent in RNNs, LSTM introduces memory cells and gating mechanisms that selectively retain relevant temporal information (Graves, 2012; Landi et al., 2021; Sherstinsky, 2020; Smagulova and James, 2019; Staudemeyer and Morris, 2019; Yu et al., 2019). As shown in Fig. 3, LSTM networks extend the basic RNN structure by incorporating gating units that control information flow, enabling them to better capture cumulative and delayed slope responses to environmental triggers. This capability allows them to model the cumulative and delayed responses of slopes to prolonged rainfall or reservoir water level fluctuations.

LSTM models have been widely applied in landslide displacement prediction and early warning. Yang et al. (2019) analyzed the relationships among landslide deformation, rainfall, and reservoir water levels, and found that compared with static models, the LSTM approach more accurately captured the dynamic characteristics of landslides and effectively leveraged historical information. Xu and Niu (2018) used a LSTM model to predict the displacement evolution of the Baijiabao landslide using rainfall and hydrological level data, achieving a higher correlation compared with traditional regression models. In another study focused on shallow landslides, Xiao et al. (2022) used a week-ahead LSTM model, which exhibited stable performance and improved prediction accuracy in short-term prediction scenarios. Additionally, Gidon et al. (2023) constructed a Bi-LSTM model and achieved a detection accuracy of 93% in the Mawiongrim area. This effectively addresses the limitations of traditional methods and can provide a reliable technical solution for disaster early warning in this area as well as other similar landslide-prone areas.

The GRU is a simplified variant of the LSTM that achieves similar accuracy with fewer parameters and reduced computational costs (Cho et al., 2014), making it well-suited for real-time landslide monitoring systems (Chung et al., 2014; Rawat and Barthwal, 2024; Zhang et al., 2022e).

Furthermore, GRU models effectively identify precursory displacement acceleration, allowing early detection of slope instability triggered by rainfall or seismic shaking (Chang et al., 2025; Yang et al., 2025).

Transformer, first introduced by Vaswani et al. (2017), was originally designed for natural language processing but has since become a cornerstone architecture in modern machine learning, achieving state-of-the-art performance across diverse domains such as computer vision and multimodal learning.

Unlike conventional recurrent or convolutional models, the Transformer is built upon stacked encoder–decoder layers and relies on a key innovation: the self-attention mechanism (see Fig. 5). This mechanism enables the model to automatically compute a weight vector (i.e., an attention distribution) for each element in the sequence based on its relevance to all other elements. By evaluating all positions simultaneously (Esser et al., 2021; Huang and Chen, 2023), the Transformer efficiently captures global dependencies across long sequences in parallel, making it more effective than RNNs or CNNs at modeling long-range relationships.

When applied to landslide-related time series data, the Transformer can adaptively learn latent temporal features and patterns, automatically adjusting parameters to accommodate diverse landslide scenarios (Wang et al., 2024b; Zerveas et al., 2021).

However, a key drawback of the standard Transformer is its quadratic computational complexity with respect to sequence length, which becomes prohibitive for very long sequences (Zhuang et al., 2023). This also complicates the interpretation of how the model extracts features and makes decisions from large amounts of landslide data, posing challenges for practical deployment. It is worth noting that mitigating this quadratic complexity is an active research area, with many efficient Transformer variants being developed. For example, Zhao et al. (2024f) combined the strengths of CNN and Transformer architectures, selecting and analyzing nine landslide-conditioning factors to successfully achieve accurate landslide localization and detailed feature capture. Ge et al. (2024) proposed the LiteTransNet model based on the Transformer framework, effectively capturing and interpreting the varying importance of historical information during the prediction process. Therefore, while powerful, the vanilla Transformer may not be the optimal choice for all practitioners, and its computational demands should be carefully considered.

In contrast, RNN-based models exhibit a relatively simple architecture and are conceptually intuitive (Li et al., 2021; Wang et al., 2020b), making them more interpretable. Transformers, however, are structurally more complex with numerous parameters, requiring substantial computational resources during training and being susceptible to overfitting on small datasets.

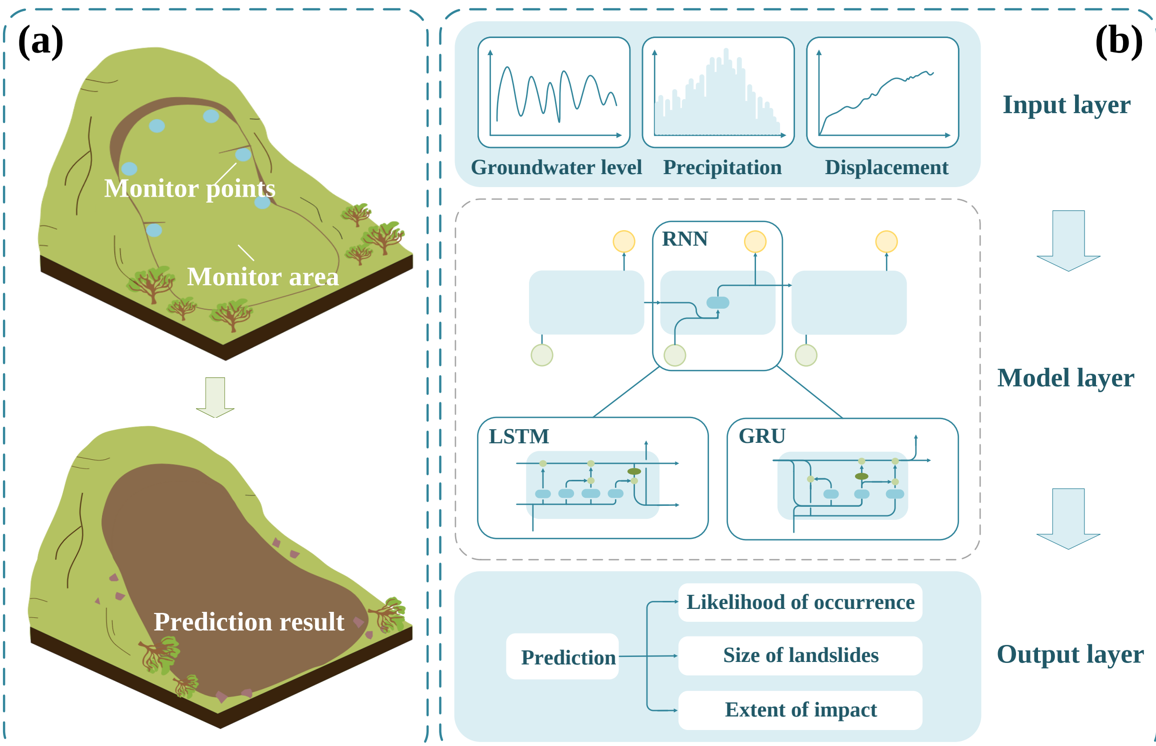

Figure 3. The role of deep learning models in time series analysis. (a) In potential landslide identification, time series data can be obtained through monitoring. (b) RNNs, LSTMs, and GRUs provide more accurate information for landslide prediction by processing time series data.

3.3 Models for Data Generation in Potential Landslide Identification

Data generation refers to modeling the underlying data distribution to generate entirely new samples independent of the original dataset (Kingma et al., 2014; Moreno-Barea et al., 2020; Shorten and Khoshgoftaar, 2019), thereby enriching the dataset. In potential landslide identification, data generation mitigates challenges of data scarcity and imbalanced class distributions, thereby enhancing the generalization capability of predictive models.

Deep generative models are the leading deep learning approach for synthetic data generation (Alam et al., 2018; Karras et al., 2020; Ma et al., 2024; Xu et al., 2015). They utilize deep neural networks to learn latent representations of data and optimize the learning process through specific objective functions. A key characteristic of deep generative models lies in their probabilistic nature. They not only classify or reconstruct data but also capture the underlying distribution of geospatial features, thereby enabling the generation of new landslide samples that are statistically consistent with observed patterns. Commonly used deep generative models include GANs, Variational Autoencoders (VAEs), and diffusion models (see Fig. 4).

GANs consist of a generator and a discriminator that compete in an adversarial process (Goodfellow et al., 2014). The generator synthesizes data resembling real samples, while the discriminator attempts to distinguish between generated and real data. The workflow of adversarial training for GAN-based data generation is schematically depicted in Fig. 4. Through iterative adversarial training, the generator learns to produce high-quality synthetic data that closely matches the distribution of real data (Gui et al., 2021; Saxena and Cao, 2021).

In the context of landslide studies, GANs have demonstrated strong capabilities in data augmentation and remote sensing image enhancement. For example, Feng et al. (2024) achieved the first implementation of using a GAN to generate synthetic high-quality landslide images, aiming to address the data scarcity issue that undermines the performance of landslide segmentation models. Al-Najjar and Pradhan (2021b) proposed a novel approach that employs a GAN to generate synthetic inventory data. The results indicate that additional samples produced by the proposed GAN model can enhance the predictive performance of Decision Trees (DT), Random Forest (RF), Artificial Neural Network (ANN), and Bagging ensemble models.

Despite their advantages, GANs may suffer from mode collapse, leading to limited diversity in the generated data, especially when certain landslide types are underrepresented (Fang et al., 2020a). Moreover, their unstable training process requires careful hyperparameter tuning and substantial computational resources, which may constrain their application in real-time hazard scenarios. Nevertheless, with improved architectures such as Conditional GAN (CGAN) (Kim and Lee, 2020; Loey et al., 2020; Mirza and Osindero, 2014), image-to-image translation with GAN (Pix2Pix) (Isola et al., 2017; Qu et al., 2019), and Wasserstein GAN (WGAN) (Arjovsky et al., 2017; Wang et al., 2019), GANs are becoming increasingly viable tools for high-resolution landslide mapping and synthetic data generation in remote sensing-based susceptibility analysis.

As a probabilistic variant of AEs, VAEs introduce latent-space regularization through variational inference (Hinton and Salakhutdinov, 2006; Kingma and Welling, 2013). The encoder compresses input data into a latent representation characterized by a mean and a standard deviation, while the decoder reconstructs the data by sampling from this distribution. This enables the model to generate new data with inherent randomness and diversity (Islam et al., 2021; Oliveira et al., 2022).

In landslide research, VAEs have been successfully applied to learn and reconstruct geomorphological patterns of slope instability. For instance, Cai et al. (2024) proposed and demonstrated the superior capability of the VAE-GRU model in generating narrow predictive intervals while maintaining high coverage probabilities, representing a substantial improvement over the state-of-the-art methods for probabilistic landslide prediction.

Compared with GANs, VAEs produce more diverse but slightly less detailed samples, due to their structured latent space constraints. This characteristic is particularly beneficial for exploring a wide range of potential landslide morphologies and for augmenting training datasets used in susceptibility prediction. However, VAEs may still struggle with highly imbalanced datasets, as their probabilistic reconstruction tends to favor majority classes. Integrating VAEs with stratified sampling or cost-sensitive learning could help overcome this limitation and further enhance landslide prediction performance.

When computational resources and training time permit, diffusion models provide a powerful alternative for generating high-quality, diverse, and stable data (Croitoru et al., 2023; Ho et al., 2020; Yang et al., 2023a; Zhu et al., 2023a). These models learn the data distribution by gradually adding noise to real samples (forward diffusion) and then reconstructing clean data through a reverse denoising process (see Fig. 4). The resulting models can sample new, realistic data points that reflect complex terrain and geophysical variability. For example, Lo and Peters (2024) proposed a Terrain-Feature-Guided Diffusion Model (TFDM) to fill gaps in DEM data. Similarly, Zhao et al. (2024b) employed a Denoising Diffusion Probabilistic Model (DDPM) conditioned on incomplete DEMs, which serves as a transitional kernel during diffusion reversal to progressively reconstruct sharp and accurate DEMs.

Despite their successful applications in image synthesis, denoising, and remote-sensing image enhancement (Leher et al., 2025; Sui et al., 2024; Xiao et al., 2023; Zou et al., 2024), diffusion models have not yet been widely applied directly to the identification of potential landslides and remain in the exploratory stage. Nonetheless, our optimism for their application is grounded in their potential to address key challenges such as limited labeled data through generative augmentation and, more importantly, to provide uncertainty quantification in predictions, which is vital for risk assessment.

In conclusion, deep generative models provide a transformative solution for overcoming the challenges of limited and imbalanced landslide datasets. By synthesizing realistic, diverse, and statistically consistent samples, these models can improve the robustness and generalization of landslide prediction frameworks. Among them, GANs are effective for generating visually realistic imagery and data augmentation; VAEs capture probabilistic geomorphic transitions; and diffusion models ensure stability and fidelity in high-resolution terrain synthesis.

3.4 Models for Anomaly detection in Potential Landslide Identification

Anomaly detection plays a critical role in potential landslide identification, as it enables the distinction between normal environmental variations and genuine precursors of slope instability (Deijns et al., 2020; Jiang et al., 2020). In landslide monitoring, the goal of anomaly detection is to identify subtle yet significant deviations. Examples include abnormal surface displacements, changes in surface coherence, or irregularities in sensor signals. Such deviations may occur prior to landslide events. With the advancement of deep learning, data filtering has evolved from rule-based threshold detection to automated feature learning, al-

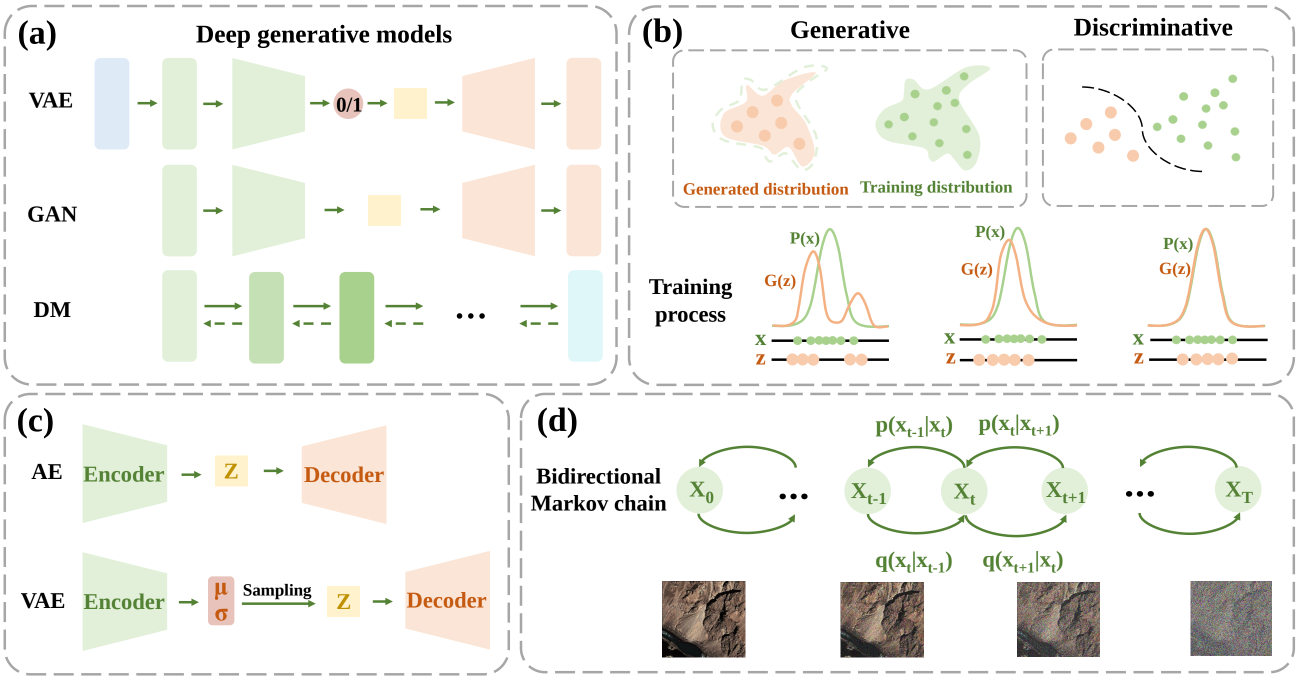

Figure 4. The role of deep learning models in data generation. (a) Comparative schematic of three commonly used deep generative model architectures. GAN: adversarial training. VAE: maximize variational lower bound. Diffusion models: gradually add Gaussian noise and then reverse. (b) Schematic of the adversarial training workflow for GAN-based data generation. (c) Comparative architecture of AE and its variational counterpart, VAE. (d) Schematic of a diffusion model applied to denoise potential landslide data.

lowing models to capture complex spatiotemporal dependencies and identify anomalies within high-dimensional, multi-source datasets.

AEs are widely used for unsupervised anomaly detection due to their ability to reconstruct input data and highlight deviations from learned normal patterns (Sakurada and Yairi, 2014; Zhou and Paffenroth, 2017). An AE consists of an encoder that compresses data into a low-dimensional latent representation and a decoder that reconstructs it.

During training, the AE learns the intrinsic features of normal landslide data, such as sensor-based displacement time series or radar backscatter from stable slopes. When abnormal data are input, such as sudden displacement spikes or incoherent radar signals, the reconstruction error increases significantly, serving as an indicator of potential instability. For instance, Shakeel et al. (2022) developed an InSAR deformation anomaly detector based on an AE–LSTM architecture. Experimental analyses using synthetic deformation test scenarios achieved an overall performance accuracy of 91.25%.

By defining a reconstruction error threshold, anomalies can be quantitatively detected. When the reconstruction error of new sensor data exceeds this threshold, it may signal slope movement acceleration or surface disturbance associated with potential landslides. Thus, AEs provide a data-driven method to detect early-warning signs without requiring manually labeled failure data.

As previously introduced, VAE is a probabilistic extension of AEs (Nawaz et al., 2024). VAEs introduce stochastic latent variables characterized by mean and variance, allowing them to model data uncertainty (see Fig. 4). During training, VAEs learn the latent distribution of normal samples and reconstruct inputs accordingly. When new observation data deviate significantly from the learned distribution, the reconstruction error increases accordingly, and this phenomenon can be used as an indicator of potential anomalies (Kingma and Welling, 2013; Li et al., 2020; Park et al., 2018).

In landslide applications, VAEs have been shown to outperform conventional AEs in handling complex, multivariate datasets that integrate topographic, meteorological, and geotechnical factors. For example, Han et al. (2025) proposed an unsupervised failure mode recognition algorithm based on a deep convolutional autoencoder, which integrates surface displacement, vertical displacement, and rainfall monitoring data from slopes to accurately identify the developmental stages of slope failure, achieving a recognition accuracy of 99.30%.

Compared to AEs, VAEs are particularly advantageous for capturing uncertainty and latent correlations between environmental variables, making them ideal for anomaly detection in integrated landslide early-warning systems (Kumar et al., 2024; Pol et al., 2019). However, they require larger datasets for stable training, and their probabilistic outputs may demand post-processing for operational thresholding.

GANs can also be adapted for anomaly detection by exploiting their discriminator network's ability to distinguish between real and generated data (Kang et al., 2024; Xia et al., 2022). In landslide monitoring, GAN-based anomaly detection models learn the distribution of stable slope features, and deviations from this distribution can indicate abnormal conditions (Radoi, 2022).

AnoGAN extends conventional GANs by directly incorporating anomaly detection as one of its primary objectives (Lin et al., 2023; Thomine et al., 2023). It introduces an additional encoder during training, which maps input data to the latent space. The difference between this latent vector and the latent vector of normal samples generated by the generator serves as the basis for anomaly detection.

RNNs and their variants are particularly effective for time series–based anomaly detection, learning temporal dependencies and predicting future trends (Zamanzadeh Darban et al., 2024; Zhang et al., 2022a). In landslide monitoring, these models can process continuous displacement or rainfall time series to identify deviations from expected temporal behavior. These temporal models complement image-based approaches by providing continuous surveillance and early detection capabilities (Wu et al., 2024a).

When combined with AEs or GANs, RNN-type architectures can form hybrid frameworks capable of both spatial and temporal anomaly detection, enabling multi-source consistency checking in landslide early-warning systems. Geiger et al. (2020) demonstrated a growing trend of utilizing LSTM networks as both the generator and discriminator within GAN frameworks for time-series anomaly detection. Similarly, Whitaker (2023) illustrated the application of LSTM–GAN architectures in identifying temporal anomalies.

3.5 Models for Data Fusion in Potential Landslide Identification

In practical applications, the identification of potential landslide hazards is a complex task that influences by multiple factors (Zhang et al., 2018). These factors are often reflected through different data sources. We can roughly divide heterogeneous data into four categories: image data, time series data, structured data, and textual data. Given this heterogeneity, data fusion is essential for the accurate identification of potential landslides.

Since heterogeneous data differ in feature scale, spatial resolution, and data modality, deep learning models are increasingly utilized to automatically extract nonlinear and high-order feature interactions across data sources, offering significant advantages over conventional statistical fusion techniques. In landslide applications, deep learning-based data fusion can integrate multi-modal inputs such as Sentinel-1 InSAR deformation, rainfall time series, and terrain derivatives for regional-scale susceptibility mapping or real-time early warning.

Due to the non-Euclidean and topologically complex nature of landslide-related terrain, conventional CNN-based models are limited in representing irregular spatial dependencies. Graph Neural Networks (GNNs) have emerged as powerful architectures to model such relationships by representing spatial entities (e.g., slope units, grid cells, or sensor nodes) as graph nodes and their geospatial or topological interactions as edges (Scarselli et al., 2008; Ying et al., 2018; Zeng et al., 2022).

In landslide identification, GNNs enable explicit modeling of spatial connectivity and geological adjacency, allowing the propagation of geomorphic and hydrological information across neighboring units. For example, Kuang et al. (2022) proposed an innovative landslide forecasting model based on GNNs, in which graph convolutions are employed to aggregate spatial correlations among different monitoring sites. Ren et al. (2025) introduced a novel GNN framework with conformal prediction (GNN-CF) for landslide deformation interval forecasting, addressing the limitations of conventional models in handling predictive uncertainty.

According to the differences in message passing and aggregation methods, GNNs have derived various variants. For example, Graph Convolutional Network (GCN) is generated by generalizing the convolutional operation to graph-structured data (Kipf and Welling, 2016; Sharma et al., 2022; Wang et al., 2020a), and Graph Attention Network (GAT) dynamically weights the importance of neighboring nodes by introducing the attention mechanism (Veličković et al., 2017; Yuan et al., 2022; Zhou and Li, 2021). The emergence of these new architectures makes GNN variants more targeted than conventional GNNs and suitable for modeling heterogeneous relationships. Currently, they are often used for weighted analysis of the impacts of different geographical factors on landslides (Kuang et al., 2022; Li et al., 2025; Zhang et al., 2024e).

As highlighted in Section 3.2, the Transformer's self-attention mechanism and modular architecture make it a universal framework for processing sequential data and enabling multimodal fusion (see Fig. 5).

In this context, the core advantage of the Transformer lies in its ability to integrate diverse input data (e.g., satellite imagery, GPS time series, and geological maps). It achieves this by employing independent embedding layers to convert each modality into a unified vector representation, which is then fused through the self-attention mechanism. This mechanism computes the interactions and correlations among all elements across different modalities, thereby enabling the model to capture cross-modal dependencies and extract joint feature representations within a unified framework. This capability makes the Transformer particularly suitable for landslide studies (Li et al., 2025). For example, Piran et al. (2024) enhanced short-term precipitation forecasting by applying transfer learning with a pre-trained Transformer model. Zhang et al. (2024e) incorporated Transformer modules to build a graph-Transformer model that integrates global contextual information for the generation and analysis of Landslide Susceptibility Maps (LSMs).

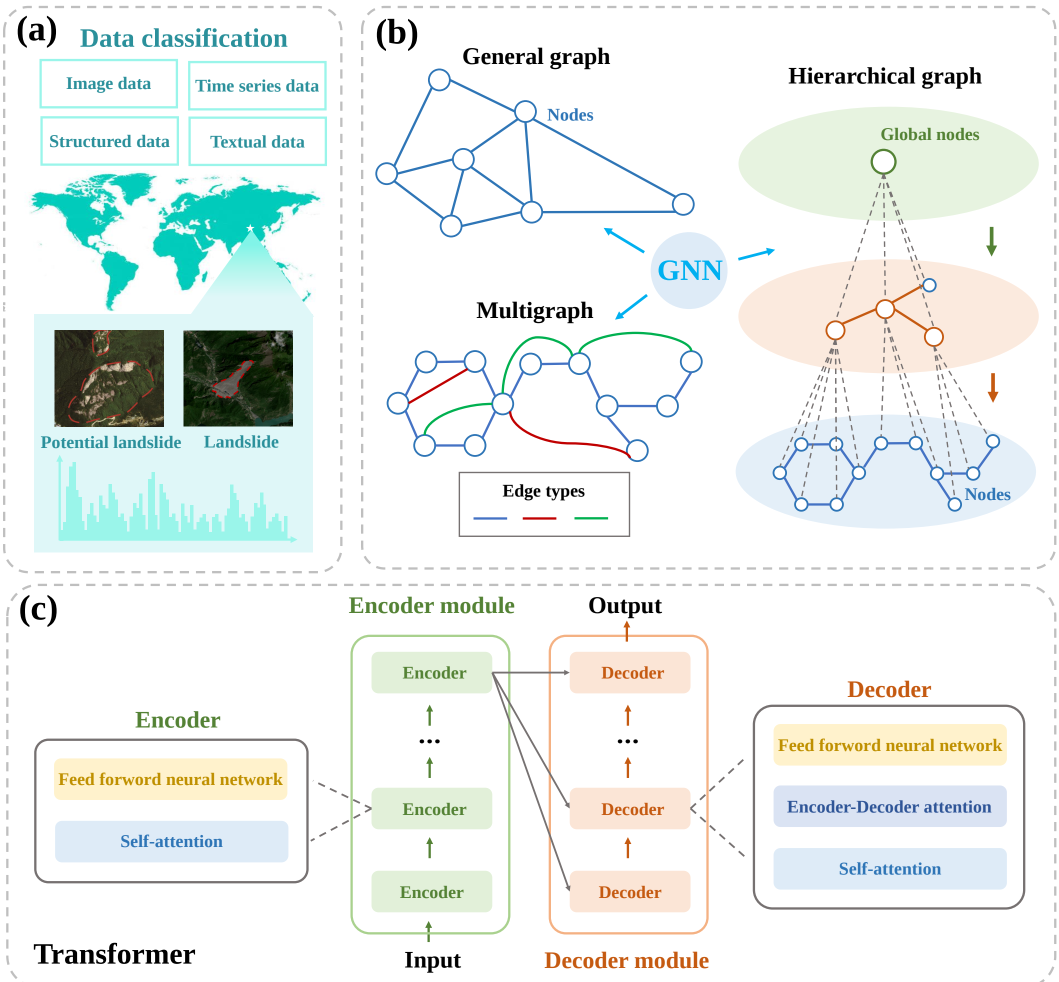

Figure 5. The role of deep learning models in data fusion. (a) Classification of heterogeneous data for potential landslide identification. (b) Schematic of general graph and more complex graphs. (c) Schematic of the fundamental Transformer architecture.

4 Deep Learning for Potential Landslide Identification: Applications

The preceding sections have laid the groundwork by discussing the data prerequisites and model architectures fundamental to deep learning in potential landslide research. Building upon that foundation, this section turns to the practical applications of deep learning for identifying potential landslides across diverse real-world scenarios.

Given that landslides are triggered by different dominant factors, the mechanisms, data characteristics, and monitoring strategies vary substantially among different types. To provide a systematic and targeted analysis, thissection organizes the applications according to four major triggering categories: rainfall-induced landslides, earthquake-induced landslides, human activity-induced landslides, and multi-factor-induced landslides (see Fig. 6). For each category, we briefly outline its geological characteristics, summarize representative deep learning applications, and discuss model adaptability and monitoring considerations. This structure allows for a comprehensive understanding of how deep learning frameworks can be tailored to the unique challenges posed by different landslide-inducing mechanisms.

4.1 Application of Deep Learning in the Identification of Rainfall-induced Landslides

Rainfall stands as the predominant global trigger for landslides. Intense and short-duration rainfall events (lasting from a few hours to several days) often induce shallow landslides (Ma and Wang, 2024), whereas prolonged rainfall (lasting from several weeks to months) can lead to deeper and larger landslides, with depths ranging from 5 to 20 meters (Casagli et al., 2023). Consequently, rainfall intensity, cumulative precipitation, and rainfall duration constitute critical triggering parameters for rainfall-induced landslides (Mondini et al., 2023).

Sustained or intense rainfall elevates slope unit weight and moisture content, alters pore water pressure regimes, and reduces shear strength via the principle of effective stress, thereby initiating surface instability. This hydro-mechanical coupling establishes a pronounced positive correlation between rainfall patterns and slope deformation (Li et al., 2022).

Temporally, landslides exhibit both abrupt failure and delayed responses to rainfall. Pre-existing fractures act as preferential pathways for rainwater infiltration, yet the time required for percolation to reach slip zones introduces a hysteresis effect in slope deformation relative to precipitation events (Jiang et al., 2023; Liu et al., 2022c). During wet seasons, intense rainfall elevates groundwater tables, inducing fully saturated conditions in slope materials. This saturation amplifies shear strain rates, triggering rapid acceleration of landslide movement. Post-rainfall, groundwater levels remain elevated for extended periods (weeks to months), resulting in sustained but decelerated sliding velocities rather than complete stabilization. Consequently, despite concentrated rainfall during wet seasons, numerous landslides occur in subsequent dry periods (Ren et al., 2023), highlighting the delayed destabilization governed by lingering pore pressure dynamics. The hysteresis phase reflects progressive energy accumulation toward critical thresholds, while abrupt failure signifies rapid energy release during instability. This transition is typically characterized by a near-instantaneous shift from stable to unstable states when pore water pressures or soil moisture content exceed critical thresholds, with minimal intermediate deformation phases.

The spatial clustering of rainfall-induced landslides fundamentally arises from the coupling of moisture transport efficiency and geotechnical strength degradation within specific geomorphic units (Wicki et al., 2020; Yu et al., 2021). Spatially, such landslides are concentrated in high-rainfall zones and permeable lithologies, where hydro-mechanical feedback dominates slope destabilization. High-rainfall zones, characterized by frequent and intense precipitation, impose dual hydrological stresses on slopes: surface runoff erodes toe regions, while infiltration elevates pore pressures, collectively acting as external drivers of failure. Highly permeable strata, characterized by high porosity or interconnected fractures, accelerate water migration. Combined with high permeability, these properties regulate water retention time within the slope and control the efficiency of pressure transmission, forming an internal transport network that facilitates landslide progression. The superposition of these mechanisms drives slope stability beyond critical thresholds over short timescales, culminating in abrupt failure.

What determines the critical threshold for rainfall-induced landslides? First, it is essential to define the critical threshold as the minimum amount of rainfall required to trigger a landslide under specific geological and topographic conditions (Naidu et al., 2018; Segoni et al., 2018b). This threshold is typically classified into two types: empirical thresholds, which are derived from statistical relationships between historical landslide events and rainfall data, and physically based thresholds, which incorporate hydromechanical models. Both approaches assume rainfall as the primary destabilizing driver. To operationalize these thresholds for landslide prediction, monitoring systems integrate rain gauge and remote sensing to assess proximity to critical saturation levels (Li et al., 2023; Piciullo et al., 2018). Moreover, the relationship between rainfall and landslides is often nonlinear and influenced by multiple factors. Deep learning models enable data-driven determination of context-specific critical rainfall values across diverse geological and topographical settings (Sala et al., 2021; Segoni et al., 2018a). For example, Badakhshan et al. (2025) incorporated the role of soil strength. Soares et al. (2022) utilized the U-Net model, reveals that the inclusion of a normalized vegetation index layer enhances model balance and significantly improves segmentation accuracy.

Following the development of rainfall threshold models, real-time monitoring of historically rainfall-induced landslides is imperative. First, continuous surveillance enables early detection of subtle deformations and precursory anomalies (Guzzetti et al., 2020; Zhu et al., 2023b), facilitating timely reactivation warnings to mitigate secondary hazards to lives and infrastructure. Second, by continuously monitoring rainfall, soil moisture, and groundwater levels, we can support dynamic recalibration of threshold parameters. This data assimilation enhances model adaptability to evolving hydrogeological conditions, ensuring operational relevance across heterogeneous terrains.

While the physical mechanisms governing rainfall-induced slope failures have been well studied (Arnone et al., 2011; Xiong et al., 2024), recent advances in deep learning have significantly improved our ability to automatically identify and predict such events using heterogeneous data.

In the context of rainfall-induced landslides, spatiotemporal data (e.g., rainfall intensity, cumulative precipitation, soil moisture, and slope displacement time series) are the primary inputs. Deep learning models are selected according to data characteristics and task objectives. For instance, CNNs are commonly used to extract spatial rainfall–topography features and delineate susceptible zones from remote sensing images (Peng and Wu, 2024; Xu et al., 2022a; Zhang et al., 2022b). The encoder–decoder architecture, such as U-Net, enables pixel-level segmentation of rainfall-triggered landslides (Bhatta et al., 2025), with the inclusion of vegetation or soil moisture layers improving feature discrimination.

When temporal evolution is essential, RNNs and LSTMs effectively model sequential dependencies between rainfall and slope deformation (Biniyaz et al., 2022; Liu et al., 2025). These models are capable of learning hysteretic responses and time lags between precipitation events and ground displacement, enabling early warning through time-series forecasting.

Deep learning also facilitates data-driven rainfall threshold estimation. Instead of relying solely on empirical or physically based thresholds, models such as Fully Connected Neural Networks (FNNs) and attention-based transformers can derive adaptive rainfall thresholds from multi-year rainfall–landslide records, capturing regional nonlinearities (Wu et al., 2023).

4.2 Application of Deep Learning in the Identification of Earthquake-induced Landslides

Earthquakes not only trigger landslides during the seismic phase but also increase the susceptibility of post-earthquake landslides by weakening slope materials or forming co-seismic landslide deposits (Zhang et al., 2024a; Zhao et al., 2024a). On the one hand, the seismic vibrations can loosen the structure of the rock and soil mass on the slope, reducing the cementation between particles. The originally intact rock mass may develop cracks, and the density of the soil decreases, thus reducing the overall stability of the slope and making it more prone to landslides after the earthquake. On the other hand, the landslides that have occurred during the earthquake process will generate a large amount of deposits. These co-seismic landslide deposits are usually accumulated at positions such as the lower part of the slope or in valleys. They are in a relatively unstable state themselves, providing a material basis for subsequent re-sliding (Fan et al., 2019; Yao et al., 2024).

So, what is the temporal relationship between earthquake-induced landslides and seismic events? When an earthquake occurs, landslides may be triggered instantaneously by seismic ground motion, typically within seconds to minutes after the earthquake. Such landslides are mainly triggered by the Peak Ground Acceleration (PGA) or Peak Ground Velocity (PGV) of the seismic ground motion (Kargel et al., 2016; Zhao et al., 2023). When these values reach a certain level, they are sufficient to enable the rock and soil masses on the slope to overcome the frictional force and shear strength, thus leading to the occurrence of landslides.

Earthquake-induced landslides are typically concentrated in areas of high seismic intensity, particularly on steep slopes or within loose accumulations (Li et al., 2024). A fault is a place where the rocks in the earth's crust break and undergo relative displacement. Its existence destroys the continuity and integrity of the rock mass, making it more prone to deformation and damage under the action of seismic forces. On the hanging wall of a reverse fault, the compressive force usually causes the rock blocks to break, and mountain landslides are likely to occur during seismic events. In contrast, on the footwall of a normal fault, the tensile force may cause the rock blocks to fracture and loosen, thus increasing the risk of mountain landslides.

The Newmark model is a commonly used basic model in the research of earthquake-induced landslides (Jibson, 2007; Newmark, 1965). Based on a simplified assumption, it regards the rock and soil masses on the slope as rigid blocks. When these rigid blocks are affected by seismic vibrations, they slide on the slope surface. By calculating the cumulative downhill displacement of the rigid blocks caused by the continuous increase of seismic vibrations, the stability of the slope under the action of an earthquake is measured. In other words, the greater the cumulative downslope displacement, the more unstable the slope is during the earthquake, and the higher the likelihood of a landslide occurring. However, Newmark's model exhibits critical limitations: (1) dependence on oversimplified soil or rock strength assumptions, and (2) inadequate integration of high-resolution seismic motion data. Deep learning models address these gaps by processing massive real-time datasets, filtering noise from obscured remote sensing imagery (Wang et al., 2024e), and fusing seismic parameters with multispectral satellite data through cross-modal architectures (Dahal et al., 2024).

Within hours to days post-main shock, aftershocks can further destabilize already loosened slope structures, triggering secondary landslides clustered near co-seismic failure zones or aftershock epicenters (Sun et al., 2024b; Zhang et al., 2024c). These landslides are often concentrated around the mainshock-induced landslide bodies or the epicentral region of aftershocks, potentially forming disaster chains (e.g., landslides blocking rivers, leading to the formation and subsequent failure of landslide dams, which may trigger flooding). Even years post-earthquake, relic landslide deposits may reactivate through gradual creep or extreme climatic forcing, necessitating long-term spatiotemporal monitoring and dynamic risk reassessment (Jones et al., 2021; Li et al., 2021). Moreover, earthquake-induced landslides are often associated with complex 3D topographic changes, which are difficult to capture using conventional 2D analyses. Deep learning frameworks enable precise reconstruction of landslide geometries by processing LiDAR-derived or UAV-derived 3D point clouds, capturing volumetric deformation patterns critical for mechanistic modeling.

Current applications of deep learning in earthquake-induced landslides primarily focus on semantic segmentation and change detection (Chowdhuri et al., 2022; Huang et al., 2023b; Liu et al., 2020a; Yang et al., 2024b). Liu et al. (2021b) employed Graph Isomorphism Networks (GIN) to model long-range dependencies among high-level features extracted by ResNet-50. Zi et al. (2021) utilized a hybrid architecture combining GATs and channel self-attention mechanisms enhances the modeling of feature interdependencies from ResNet-50. Yang et al. (2023b) incorporated a spatial attention module to capture contextual dependencies and extract rich non-local spatial features, proposing a novel semantic segmentation network, EGCN, to enhance landslide recognition accuracy.

Both physics-based and data-driven model calibration rely on earthquake-induced landslides inventories (Bhuyan et al., 2023; Tanyaş et al., 2017). Despite increased inventory availability, persistent issues of representativeness and completeness limit model generalizability and mechanistic fidelity.

4.3 Application of Deep Learning in the Identification of Human Activity-induced Landslides

Human activity-induced landslides typically arise unintentionally during construction activities, where initial slope equilibrium is disrupted by slope toe excavation or water infiltration into exposed fractures (Zhao et al., 2022). Compared to natural landslides, human activity-induced failures are often more controllable, underscoring the critical importance of pre-disaster identification for risk mitigation. These landslides are characterized by localized micro-deformation and subsurface disturbances, necessitating integrated monitoring systems that combine high-resolution remote sensing data with ground-based sensors for early anomaly detection.

Current predominant anthropogenic triggers include mining and loading (Ma et al., 2023a; Xu et al., 2022b). These activities induce severe surficial damage, with stratigraphic movement and surface deformation leading to the formation of ground fissures. Such fissures compromise surface ecosystems and vegetation, while also penetrating subsurface mining cavities, posing grave risks to operational safety. Consequently, deep learning models are essential for automated ground fracture extraction to enable real-time hazard mapping and preventive interventions (Huangfu et al., 2024).

Moreover, the triggers of human activity-induced landslides are not only related to natural conditions but also closely associated with dynamic human activities. Consequently, their analysis necessitates the integration of multimodal and cross-scale data to capture coupled environmental and behavioral drivers (see Fig. 6). In engineering operations such as mining or road construction, factors including proximity to potential landslide zones, excavation depth, and slope angles must be rigorously evaluated through geohazard risk assessments. During excavation phases, geotechnical investigations are imperative to identify weak lithological strata or fracture-dense zones predisposed to instability. Continuous slope stability monitoring requires deploying IoT-enabled sensors to track temporal variations in surface fissure dimensions and subsurface displacement vectors. Monitoring data from these sensors can be integrated into deep learning models for multimodal analytics, enabling dynamic risk prediction and adaptive mitigation planning.

For spatial mapping and fissure extraction, CNNs and U-Net-based segmentation models have demonstrated strong capability in identifying artificial slope features from optical or SAR imagery. CNN-based models can capture high-level semantic information on excavation scars, road cuts, and spoil heaps that indicate anthropogenic disturbance. Tao et al. (2024) employed the DRs-UNet model to investigate the use of deep learning for UAV-based crack identification, the developmental patterns of fissures, and the feedback interactions between underground mining progress and corresponding surface conditions. Wu et al. (2021) proposed the PUNet model for detecting and mapping localized rapid subsidence induced by mining activities. Meng et al. (2025) introduced the GF-Former model to achieve precise segmentation of ground fissures in remote sensing imagery.

When surface deformation time series or micro-displacement data from GB-InSAR, InSAR, or IoT sensors are available, RNN-based models are applied to model the temporal evolution of slope deformation (Han et al., 2022; Li et al., 2025). These models are particularly effective in detecting precursory motion trends caused by progressive excavation or loading activities.

To mitigate misclassification between anthropogenic signatures and natural terrain, integrating multispectral data with topographic elevation data enhances discriminative capacity (Meng et al., 2021; Selamat et al., 2023). For instance, in mountainous regions, DEMs revealing artificially excavated steep slopes combined with fractured geological strata from structural maps provide preliminary evidence of human influence on landslide susceptibility (Lian et al., 2024).

In fact, landslides triggered solely by human activities are relatively rare. Single human activities are typically insufficient to independently trigger landslides, with natural factors often acting in conjunction with human activities. Furthermore, the prohibitive cost of acquiring subsurface disturbance data results in sparse historical landslide samples for specific engineering scenarios, limiting data-driven model training.

4.4 Application of Deep Learning in the Identification of Multi-factor-induced Landslides

Multi-factor-induced landslides result from the synergistic interaction of multiple natural and anthropogenic factors (Hao et al., 2023). Their triggering mechanisms involve the dynamic spatiotemporal coupling of these factors, driving progressive destabilization of geomaterials through cumulative strength degradation. The formation of such landslides may involve various types of movements, including collapse, creep, and flow phenomena. They often exhibit characteristics such as complexity, nonlinearity, and suddenness. Therefore, their identification is markedly more complex compared to landslides triggered by singular factors.

Unlike simpler landslide types, identifying composite landslides necessitates multimodal data fusion to holistically assess predisposing conditions (Li, 2025; Yin et al., 2023). It further requires disentangling the nonlinear superposition effects of multiple factors and quantifying their relative contributions to failure initiation.

In multi-factor-induced landslides, earthquakes and rainfall often interact with other factors (Dou et al., 2019). During heavy rainfall, the rate of landslide formation after an earthquake may be higher, possibly driven by the removal of excessively steep slopes, changes in vegetation and groundwater, and alterations in the mechanical properties of the bedrock and weathered layers in the earthquake-induced landslides canopy. This necessitates systematic investigation of multi-hazard coupling effects to quantify emergent risks.

In addition to constructing physics-based models that account for multiple factors and quantify their interactions through the solution of governing equations, GNNs can also be employed (Lei et al., 2025). These models are capable of capturing the spatiotemporal dependencies and nonlinear couplings among various triggering factors. For example, Ren et al. (2025) employed a GNN to capture and model the complex spatiotemporal dependencies among multiple monitoring locations during landslide deformation. Zeng et al. (2022) used the graphical representation capability of the GNN model to analyze environmental relationships within a study region, where nodes were defined as geographic units delineated by terrain surface approximations, and edges captured the interactions between node pairs. Zhang et al. (2024d) constructed a geographically constrained relational graph based on node features representing environmental similarity and employed a cosine similarity approach to associate landslides with their surrounding geographic environments.

Cross-attention mechanisms can also be integrated into the model to capture spatiotemporal dependencies among contributing factors. For instance, Hu et al. (2025a) integrated global landslide feature vectors with local feature maps through a cross-attention mechanism to enhance the discriminative capability between landslides and background geomorphology. Another noteworthy fusion strategy is the gated fusion unit. Inspired by the gating structures in recurrent neural networks (Arevalo et al., 2017; Kumar and Vepa, 2020; Tsai et al., 2019), this mechanism learns dynamic weights (typically implemented through gating functions such as Sigmoid) to adaptively regulate the information flow of features from different modalities, thereby emphasizing salient features and suppressing noise. Compared with cross-attention, the gated fusion mechanism is generally more lightweight and provides an alternative approach for multimodal feature fusion (Yang et al., 2024a). For instance, Liu et al. (2022a) proposed a gated fusion unit module for multimodal remote sensing image semantic classification, enabling early fusion of heterogeneous modality features.

With the accumulation of new data and the dynamic variations in multi-factor-induced landslides, regular model updates are critical to ensuring identification accuracy and adaptability. Existing studies predominantly apply deep learning methods based on comprehensive historical landslide datasets. However, when new data becomes available, a naive approach is to retrain the model from scratch, which is computationally inefficient and fails to capture the connections between new observations and historical knowledge. A common strategy from the machine learning literature to address this is fine-tuning, where a model

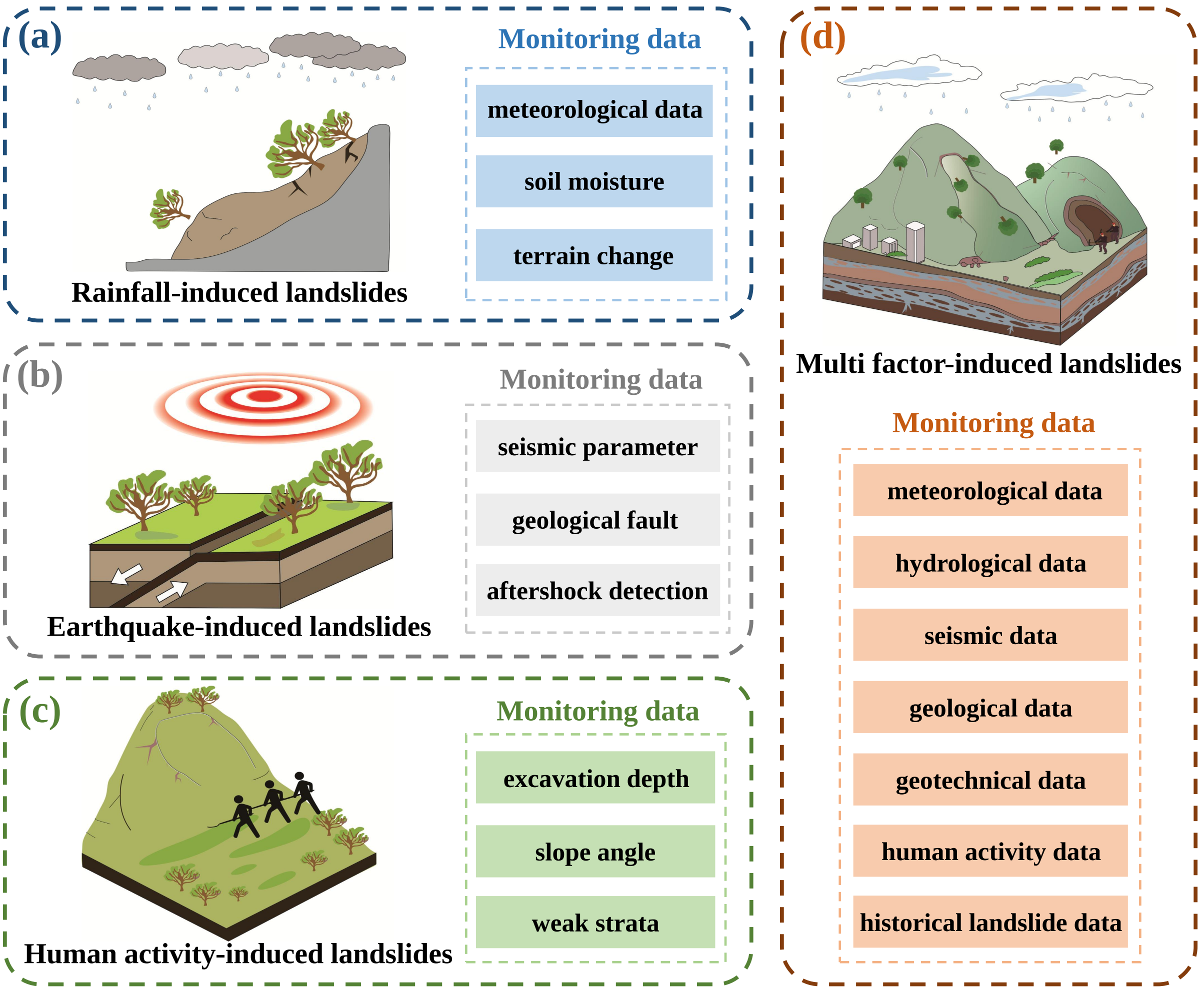

Figure 6. Selection of monitoring data for different types of landslides (a) Rain-induced landslides. (b) Earthquake-induced landslides. (c) Human activity-induced landslides. (d) Multi-factor-induced landslides.

pre-trained on a historical dataset is further trained on new data (Süalp and Rezaei, 2025). While this avoids full retraining, standard fine-tuning can still lead to catastrophic forgetting of previously learned patterns.

To better accommodate the dynamic nature of landslides, incremental learning methods offer a more advanced and promising solution (Huang et al., 2022a; Wang et al., 2024c). These methods enable the model to continuously learn from new data streams, gradually optimizing parameters while striving to preserve knowledge from previous tasks. Compared to models that require retraining or basic fine-tuning (Zhao et al., 2024c), models integrated with incremental learning can more effectively leverage historical data and adaptively incorporate new information, thereby enhancing long-term adaptability (Zhen et al., 2025).

4.5 Summary on the Applications of Deep Learning for Potential Landslide Identification

In general, the process of the applications of deep learning for potential landslide identification involves data collection, preprocessing, model construction, training, and validation, followed by deploying the trained model to identify potential landslides. Variations arise in data sources, trigger mechanisms, and model handling approaches specific to each landslide type. For rainfall-induced landslides, the model prioritizes rainfall-related data, with particular emphasis on simulating rainfall infiltration effects. Earthquake-induced landslides require prioritization of seismic data, including earthquake magnitude and post-seismic geological alterations. Human activity-induced landslides demand focused analysis of the relationship between engineering activities and geological changes. In contrast, multi-factor-induced landslides necessitate models that integrate multiple triggering mechanisms and perform a comprehensive assessment of the cumulative effects of diverse contributing factors.

Whether landslides are triggered by rainfall or earthquakes, gravity remains the dominant driving force (She et al., 2024). The primary role of triggering factors lies in reducing slope stability or amplifying gravitational effects. Before and during landslide occurrence, deformation of slope geomaterials constitutes the most observable phenomenon (Zhou et al., 2025). This deformation often manifests as the formation and expansion of cracks.

Since landslide deformation is a dynamic process, ranging from initial minor changes to eventual large-scale sliding, each stage exhibits distinct characteristics. Therefore, landslides can be classified into distinct stages based on their deformation characteristics, enabling more accurate identification of impending disaster warning signals (Zhang et al., 2024b). Here, we categorize landslide evolution into three phases: (1) creep deformation stage, (2) intermediate development stage, and (3) progressive failure stage (see Fig. 7).

In the creep deformation stage, the slope gradually deforms under the influence of various factors, though surface manifestations may not be readily observable. Small, discontinuous cracks with limited width may emerge on the slope surface or crest. High-precision measuring instruments can detect localized minor displacements or deformations (Zhan et al., 2024). Vegetation on the slope may exhibit tilting or leaning patterns, with tree orientations potentially aligning in consistent directions. In the intermediate development stage, slope deformation progresses at a relatively stable rate. Initially observed surface cracks gradually widen and elongate, eventually interconnecting to form larger fracture networks. Crack widths may expand from a few centimeters to tens of centimeters or more, accompanied by displacement between soil or rock blocks. Monitoring systems can record slope displacements at a relatively constant rate. Slope deformation disrupts pre-existing groundwater flow paths, resulting in alterations to groundwater levels, volume, or quality within the landslide mass and surrounding areas. The progressive collapse stage predominantly reflects pre-sliding slope deformation characteristics and is critical for identifying imminent landslides (Cascini et al., 2022; Chen et al., 2024a). In progressive landslides, the potential sliding surface gradually evolves into a continuous failure plane. In sudden landslides, due to their abrupt evolutionary process, no distinct sliding surface is evident, making it necessary to rely on other indicators for identification. Physical phenomena such as crack widening and deepening, formation of enclosed boundaries by cracks and drainage holes, increased displacement at the rear edge of the

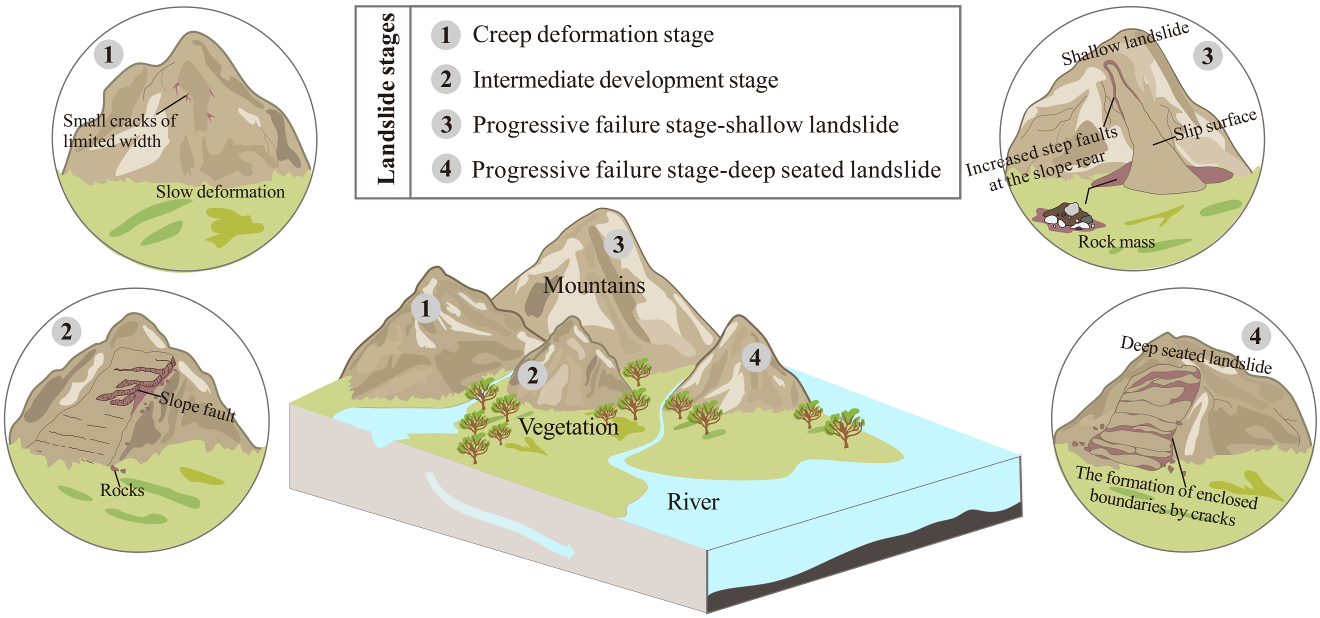

Figure 7. The development of landslides is divided into three stages with distinctive identification markers.

slope, bulging at the slope's toe, increased seepage at the slope foot, an increase in slope angle, and reverse tilting of the slope collectively aid in identifying potential landslides.

Theoretically, the unique identification markers of each stage can serve as input features for deep learning models, enabling direct classification of landslides into distinct stages. This facilitates the implementation of more targeted mitigation measures for each stage. Since slope changes ultimately result from displacement variations, we propose that a landslide identification method based on deformation characteristics as indicative factors holds great potential.

After classifying landslide stages based on deformation characteristics, different mitigation strategies should be applied to each phase. In the creep deformation stage, the focus should be placed on landslide triggering factors, with risk reduction measures such as drainage systems and slope cutting. In the intermediate development stage, monitoring should be intensified alongside temporary reinforcement measures. In the progressive collapse stage, emergency evacuation and stabilization of the potential landslide mass must be prioritized.

5 Deep Learning for Potential Landslide Identification: Challenges

5.1 Data Quality and Availability

In potential landslide identification, the performance of deep learning models is critically dependent on both data quality and availability (Alzubaidi et al., 2023; Gaidzik and Ramírez-Herrera, 2021; Whang et al., 2023). Low-quality or unreliable data directly impair the models' feature extraction capabilities, while insufficient data availability constrains their generalization capacity and real-time monitoring efficacy (Azarafza et al., 2021; Xiao and Zhang, 2023).

In the natural environment, non-landslide states are the norm, while the landslide state is relatively rare (see Fig. 8). This leads to the data collected mainly consisting of normal geological conditions, with much less data representing potential landslides. Such a severe skewness in the class distribution results in a serious imbalance in the data, that is, there is a huge difference in quantity between the minority class (landslide samples) and the majority class (non-landslide samples) (Jiang et al., 2024). Gupta and Shukla (2023) demonstrated that this data imbalance can cause learning algorithms to be biased towards the majority class, perform poorly on the minority class. This bias impedes the predictive ability of the learning algorithms, and ultimately lead to the final model's poor performance in identifying and predicting the minority class of landslide samples.

Even if some landslide inventory data have been collected, it is often difficult for these data to represent the real landslide situations within the study area. There may be issues such as omissions and biases, which greatly reduce the credibility of the results derived from these data (Woodard and Mirus, 2025; Zêzere et al., 2017).

The presence of irrelevant input dimensions within the data necessitates larger training datasets for deep learning models to achieve satisfactory generalization performance. This can be attributed to the models' tendency to overfit to noise or spurious patterns within extraneous features, thereby failing to capture task-relevant characteristics. Such overfitting diminishes adaptability to unseen data, reduces prediction accuracy, and ultimately degrades data efficiency (D'Amario et al., 2022). As a result, deep learning models may exhibit inaccurate recognition or even failure when confronted with novel, complex scenarios outside the training distribution.

Different types of features vary in terms of data format, dimensions, and semantics, posing a key challenge in achieving high-level feature fusion for complementary and synergistic information integration (Liu et al., 2023b). For example, different sensor data exhibit significant differences in physical meaning and data structure (Ghorbanzadeh et al., 2022a). Optical imagery (RGB matrices) reflects surface coverage but is susceptible to cloud interference. SAR data (complex phase) can capture deformation information but contains speckle noise. LiDAR point clouds (3D coordinates) provide high-precision terrain data but have limited coverage. Ground sensors (temporal scalars) enable real-time monitoring of subsurface parameters but are spatially sparse. Direct fusion of such multi-modal data induces feature space incompatibility, hindering cross-modal correlation extraction (Cai et al., 2021; Jin et al., 2022). Zhang et al. (2023) highlights that even remote sensing data exhibits high heterogeneity in imaging mechanisms, illumination conditions, and spectral characteristics.

Furthermore, multiple types of heterogeneous data will increase model complexity, potentially leading to prolonged training times, excessive computational demands, and overfitting risks. Simple combination of low-level detail features with high-level semantic features may introduce contextual noise, compromising feature robustness and semantic coherence (Ji et al., 2020). When designing densely connected convolutional networks, a balance must be struck between model complexity and generalization capacity to mitigate overfitting on training data and ensure robust performance on unseen scenarios (see Fig. 8).

5.2 Limitations of Deep Learning Models

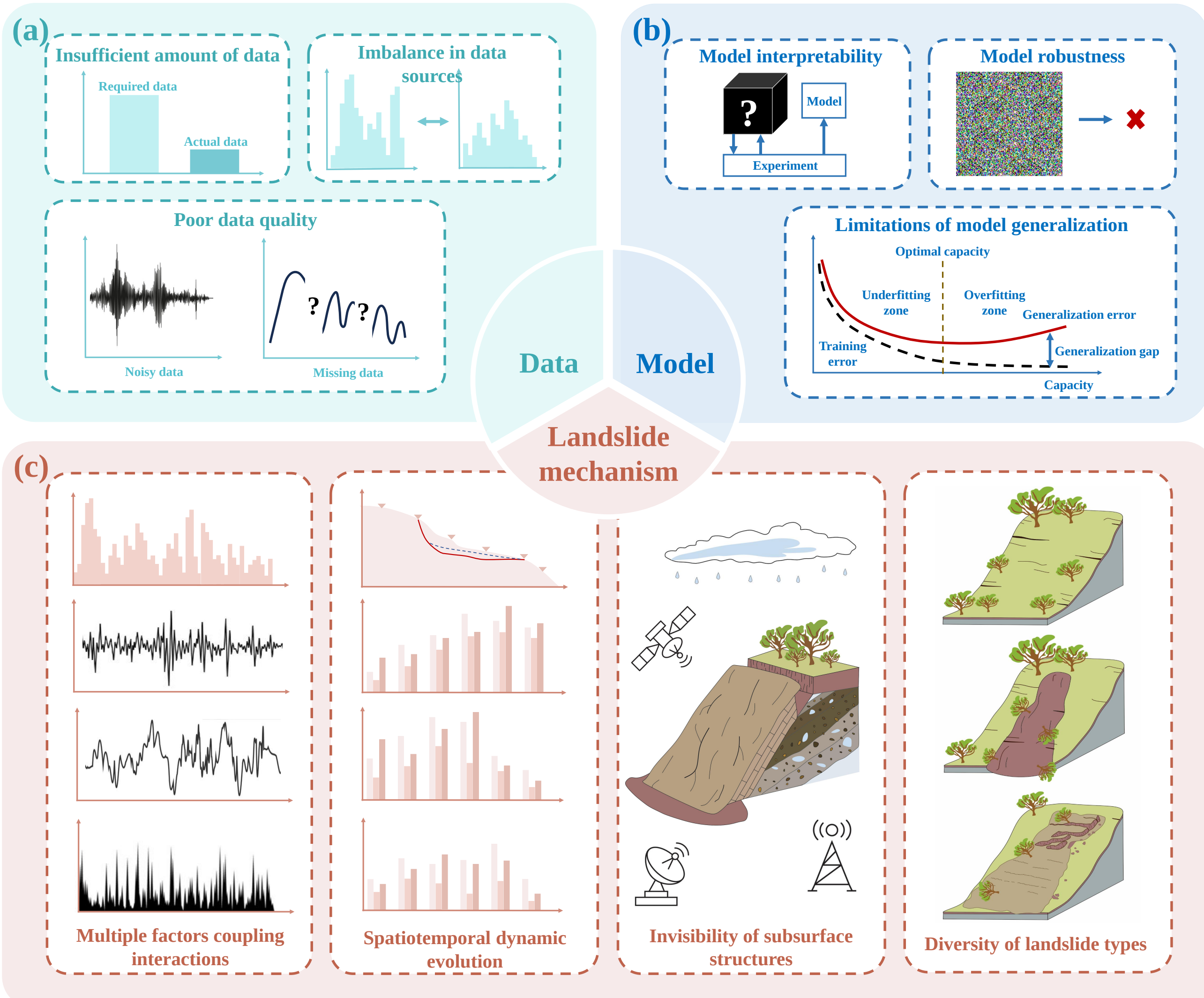

Figure 8. Challenges of deep learning in potential landslide identification. (a) Data quality and availability. (b) Limitations of deep learning models. (c) Complexity of landslide mechanisms.

Although deep learning models have achieved success in landslide identification (Meena et al., 2022; Su et al., 2021; Yi and Zhang, 2020), they are plagued by several inherent limitations. Among these, the most critical challenge is their lack of interpretability (Li et al., 2025), which refers to the difficulty in explaining the internal decision-making processes behind their predictions.

Deep learning architectures typically contain a large number of parameters and layers, making it challenging to intuitively interpret their internal weights and feature representations. It is often unclear whether the model's predictions are based on key geological features (e.g., slope gradient, lithological structure, fracture distribution) or influenced by irrelevant factors such as vegetation color or image noise. In potential landslide identification, a common issue is that models may mistakenly classify shadows or cloud cover as potential landslides, yet the underlying causes of such misclassifications remain opaque. When multimodal data are integrated for landslide detection, it is also challenging to clarify how the model weights different data sources.

The abstract features extracted by these models also lack a clear correspondence to interpretable geological indicators (see Fig. 8). Even when the model successfully identifies potential landslides based on texture patterns in remote sensing imagery, it remains unclear whether these patterns correspond to actual geomechanical parameters or physical processes.

Moreover, the probability values output by the models often lack physical meaning and therefore cannot effectively represent geological uncertainty. In practice, high-risk areas predicted by the model may conflate "uncertainty caused by data absence" with "risk of the geological conditions themselves" (Achu et al., 2023; Feng et al., 2022). Even experienced geologists may struggle to validate the geological plausibility of such features, thereby constraining the adoption of deep learning results in practical engineering applications.

Compounding these issues, there also exists an inherent inconsistency between data-driven feature learning and the complexity of real-world geological processes. Deep learning models tend to capture superficial statistical patterns rather than the governing physical mechanisms that are generalizable across different regions and environmental conditions. Consequently, in potential landslide identification, substantial manual annotation efforts are often required when transferring models across regions or sensors.

Despite the availability of diverse datasets, the lack of standardized, high-quality annotated benchmarks has severely hindered the development and fair comparison of deep learning models (Fang et al., 2024). Current models are often trained and validated on independent, task-specific datasets, thereby preventing an objective assessment of state-of-the-art performance and limiting our ability to evaluate their true generalization capacity across varying geological settings and triggering factors.

5.3 Complexity of Landslide Mechanisms

5.3.1 Multiple Factors Coupling Interactions

The formation of landslides involves the dynamic coupling of multiple factors such as geological structures, geotechnical mechanics, hydrological conditions, topography, meteorological factors, vegetation coverage, and human activities (Scheingross et al., 2020; Yi et al., 2022). Therefore, the triggering mechanisms are inherently multiscale, ranging from microscopic interparticle friction to macroscopic slope instability, and encompassing both transient dynamic responses and long-term temporal evolution (see Fig. 8).

For example, geotechnical materials and structural features of the geological setting influence soil stability, while hydrological factors such as rainfall infiltration and groundwater fluctuations alter soil mass properties, critically weakening shear strength due to pore pressure variations. Extreme meteorological events can alter slope stress regimes, while topographic parameters define geomorphic susceptibility thresholds. Human activities further influence slope stability. The interactions among these factors are highly nonlinear and temporally variable, making them difficult to characterize through simple mathematical formulations.

This implies that variations in individual factors may induce cascading effects rather than linear responses. For example, rainfall-induced landslides exhibit threshold-dependent behavior governed by coupled hydro-mechanical processes. When rainfall intensity or duration supasses critical thresholds, the rapid rise of the groundwater table increases pore water pressure, thereby reducing effective stress and weakening shear strength according to the principle of effective stress. Such hydro-mechanical feedback often culminates in abrupt slope failure.

5.3.2 Spatiotemporal Dynamic Evolution

The inducing factors of landslides are not only extremely complex in spatial distribution but also highly dynamic in terms of time (Gao et al., 2023). This variability makes the research process of the landslide mechanism more difficult.

From the perspective of temporal dynamics, landslide formation is not instantaneous but evolves through prolonged stages, each governed by distinct mechanisms (see Fig. 7). This dynamic progression across different timescales creates a fundamental modeling challenge: since the numerical simulation of long-term creep requires a long time step, while the dynamic process of short-term abrupt changes requires a time resolution in the microsecond level, it is difficult to establish a unified model for these two situations. This will further intensify the conflict of time scales.

In terms of spatial heterogeneity, the influence scope of landslides usually involves geological structures ranging from the microscopic structure of geotechnical particles to the regional scale. Moreover, there are differences in the stratum structure, slope morphology, vegetation coverage, water content, which makes the effects of the same inducing factor vary in different regions. For example, in loose soil layers, heavy rainfall may lead to shallow landslides, while on rocky slopes with well-developed joints, earthquakes or water level fluctuations may trigger deep-seated landslides.

Through the interaction of factors at different temporal and spatial scales, positive or negative feedback affects the evolutionary trend of landslides, making the triggering, evolution and reactivation of landslides more complex and increasing the uncertainty of prediction (Huang et al., 2022b; Li et al., 2023).

5.3.3 Invisibility of Subsurface Structures

Landslide occurrence is intrinsically linked to subsurface structures. However, due to their invisibility, obtaining comprehensive geological information directly is challenging, adding significant complexity to the study of landslide mechanisms (Li et al., 2021; **?**).

The occurrence of landslides is not merely linked to surficial phenomena but more critically governed by subsurface geological structures and hydrogeological characteristics. Subterranean features such as faults and folds directly influence the mechanical properties and stability of rock and soil masses. However, the inherent opacity of subsurface systems limits the accuracy of delineating these structures' spatial distribution, scale, and orientation through surface surveys or sparse borehole sampling, often yielding fragmented insights. Groundwater dynamics play a critical role in modulating slope stability. Fluctuations in the water table alter pore water pressure and effective stress within geomaterials, leading to a reduction in shear strength according to the principle of effective stress. Yet, direct monitoring of hydraulic head variations is inherently challenging, particularly in heterogeneous subsurface environments where localized aquifers exhibit divergent responses to hydrological forcing. Despite advancements in geophysical imaging and hydrological monitoring, the structural anisotropy and permeability heterogeneity of subsurface formations perpetuate ambiguities in mechanistic interpretations, risking oversights in landslide hazard assessments.

The invisibility of subsurface structures makes it difficult to monitor the specific processes and critical points of these dynamic changes in real time. Consequently, researchers can only infer these processes based on surface manifestations or limited monitoring data. This results in ambiguity and uncertainty in the analysis and interpretation of acquired indirect data. Even when model outputs exhibit qualitative agreement with field observations, the validity of underlying assumptions and parameterizations cannot be definitively verified.

5.3.4 Diversity of Landslide Types

Landslides exhibit considerable typological variation, with distinct instability mechanisms and evolutionary pathways governed by geological settings, triggering factors, and kinematic behaviors. Based on material composition, landslides can be classified into rock landslides, soil landslides, debris flow landslides, and composite landslides, each exhibiting distinct variations in physical properties as well as failure modes (McColl and Cook, 2024; Yu et al., 2024). For instance, rock landslides dominated by brittle fracture differ fundamentally from soil landslides governed by plastic shear. Kinematic categorization further distinguishes translational sliding, toppling, creep, and flow-like movements, each involving divergent mechanical processes and triggering thresholds (Shu et al., 2021).

Due to the diversity of landslide types, with each type having different characteristics and influencing factors, it is very difficult to establish a universal research model for the mechanism of landslides. For different types of landslides, corresponding models need to be established according to their specific characteristics and main influencing factors (Milledge et al., 2022). This not only requires a large amount of on-site observation data and experimental research to determine the model parameters, but also requires consideration of the applicability and limitations of the models.

Furthermore, cross-typological interactions among landslides amplify predictive challenges. For example, collapsed debris may transition into debris flows, a process that is governed by hydromechanical coupling and granular-fluid dynamics. Such multi-typological and multi-process couplings resist comprehensive characterization via single-theory frameworks. Instead, they necessitate multi-scale numerical simulations to accurately reproduce the entire process. Consequently, the diversity of landslide phenomena requires interdisciplinary integration across solid mechanics, fluid dynamics, and multi-physics couplings. This task substantially increases the dimensionality and complexity of mechanistic studies, demanding hybrid modeling frameworks and cross-domain validation protocols.

6 Deep Learning for Potential Landslide Identification: Opportunities

6.1 Multi-source Data Fusion

Different methods specialize in identifying specific types of landslides, and no single method can address all potential landslide types. Therefore, research on potential landslide identification should gradually shift from using single-source data toward multi-temporal, multi-source integrated analysis (Chen et al., 2023b; Ge et al., 2022; Xu et al., 2021b).

Multi-source data can comprehensively represent complex influencing factors by integrating various datasets, thereby enhancing information completeness. For instance, topographic and geological data reveal slope stability, remote sensing captures surface deformations, meteorological and hydrological data describe triggering conditions, and ground monitoring provides high-precision dynamic information. Integrating these data enables the construction of a complete feature system covering landslide-causing factors, prone environments, and inducing conditions, while avoiding the one-sidedness inherent to single-source observations.

In the identification of potential landslides, multi-source data fusion specifically refers to the integration of raw data from different sources before feature extraction. Each data source has unique strengths in resolution, coverage, and observation scale, and their fusion achieves complementarity and cross-verification (Liu et al., 2020b; Wang et al., 2021a). For example, combining satellite and UAV data allows both large-scale screening and detailed crack detection (Xia et al., 2021), while merging geological surveys with InSAR time-series deformation distinguishes stable slopes from creeping zones. This cross-validation effectively reduces noise and misjudgment caused by data uncertainty.

Integrating multi-source data fusion with deep learning enables the coupling of data and model advantages (Chen et al., 2023; Zheng et al., 2021). The fusion reduces uncertainty through comprehensive data representation, while deep learning extracts nonlinear features and captures hidden correlations. Together, they improve the accuracy of potential landslide identification and promote a shift from experience-driven to intelligence-driven hazard monitoring. In the future, the development of cross-modal pre-trained models and edge intelligence will further enhance real-time early warning and hazard simulation, forming the backbone of an integrated "aerial-space-ground-subsurface" monitoring framework.

To advance this paradigm, we advocate for a community-driven benchmark that embodies the multi-modal philosophy. Such a benchmark should include co-registered data from optical, SAR, LiDAR, DEM, and ground-based sensors, reflecting the integrated monitoring reality. Establishing this benchmark is a crucial step toward translating data fusion capabilities into reliable and reproducible AI solutions for global landslide risk reduction.

6.2 Model Ensemble

Model performance depends significantly on the nature of tasks, data characteristics, and specific requirements. Despite its ability to capture specific feature dimensions, a single deep learning model is susceptible to limited generalization, model bias, and overfitting when confronted with data noise and scene heterogeneity (Kavzoglu et al., 2021; Lv et al., 2022). Given these differences, model ensemble provides an effective approach to optimization and generalization.

In the identification of potential landslides, model ensemble essentially achieves a synergistic effect through the aggregation of diversity. While avoiding the limitations and vulnerabilities of individual models, it also unleashes the complementary potential of multiple models through designed mechanisms (Zhou et al., 2022).

This approach can be implemented through several pathways. Feature-level integration involves processing different data features with specialized models and fusing the results. A more common tactic is heterogeneous model combination, which refers to combining various types of models to improve the accuracy of potential landslide identification. Each model can exert its advantages in different feature spaces (Fang et al., 2021), thus forming a powerful predictive combination. A prominent example is the CNN-LSTM hybrid, which capitalizes on CNNs' spatial feature extraction and LSTMs' temporal dependency modeling, making it particularly suited for rainfall-terrain coupled landslide prediction (Gao et al., 2024). Furthermore, advanced architectures like stacking enable deeper model coupling. For instance, Guo et al. (2024) employed a stacked framework integrating 1D-CNN, RNN, and LSTM to form a CRNN-LSTM ensemble, achieving significant performance gains.

Therefore, model ensemble is not a mere technical aggregation but a systematic solution to core challenges like poor generalization, feature bias, and learning from small samples. It transforms the local advantages of multiple models into a global optimum at the system level, achieving comprehensive breakthroughs in identification accuracy and engineering applicability. It is important to note, however, that these performance gains come with increased computational cost and complexity, a necessary trade-off in practice.

6.3 Knowledge-data Dually Driven Paradigm for Potential Landslide Identification

Conventional knowledge-driven methods, grounded in physical mechanics, rely on precise prior knowledge of geological structures and hydrological conditions. However, landslides are influenced by complex, coupled multi-factor interactions, characterized by high parameter uncertainty, making it challenging to comprehensively address such scenarios (Roy and Saha, 2019). Purely data-driven approaches, though capable of extracting patterns from massive datasets, lack physical interpretability, are susceptible to noise interference, and struggle to establish causal relationships in prediction outcomes (Qi et al., 2024). A critical challenge and opportunity, therefore, lies in bridging the gap between data-driven predictive capabilities and a physically interpretable understanding of landslide processes.

To bridge this critical gap, a fundamental shift towards a knowledge-data dually driven paradigm is imperative. This paradigm moves beyond simple combination to a deep integration, where physical principles actively constrain and inform the deep learning architecture. Future research should focus on developing novel frameworks capable of explicitly incorporating landslide typologies and physical laws. For instance, Physics-Informed Neural Networks (PINNs) can embed governing equations directly into the model's loss function, while knowledge graphs can structurally represent the complex relationships between predisposing factors and failure mechanisms.

This synergy, aligned with future concepts like "digital twin" and "smart Earth," establishes a closed-loop "theory-practice" verification mechanism (Chen et al., 2024c; Das et al., 2024; Huang et al., 2023a; Riahi et al., 2022; Sukor et al., 2019; Zhao et al., 2024e). The ultimate goal is to advance landslide identification from mere pattern recognition towards physically interpretable, causally-aware forecasting, thereby transforming geological hazard mitigation from passive response to proactive prevention.

The overall workflow of this knowledge-data dually driven paradigm for potential landslide identification is conceptually summarized in Fig. 9.

In the first stage, multi-source data are systematically collected, organized, and integrated into a comprehensive dataset through feature extraction and spatiotemporal alignment.

In potential landslide identification, data sources are highly diverse. Thus, the initial step involves systematically collecting heterogeneous data and centralizing their management. This approach mitigates the limitations of single-source data, facilitating a more comprehensive and robust characterization of potential landslides. These data include high-dimensional feature information essential for data-driven models, as well as key parameters necessary for knowledge-based analytical frameworks. Furthermore, since multi-source data may differ in acquisition time and spatial coverage, spatiotemporal alignment is required to ensure interoperability and facilitate synergistic analysis. The collected data should be preprocessed, including cleaning (removal of errors and outliers), standardization (unit homogenization), and classification (based on data type or region). These steps ensure that the data retain inherent physical significance and maintain consistent scales before being input into models, thereby establishing a reliable foundation for subsequent knowledge-data integration.

If the objective extends beyond identifying landslide locations to distinguishing their types and scales, the dataset must encompass information that captures these characteristics. During dataset construction, feature extraction and annotation methods should be chosen to emphasize these distinctions. For instance, combining texture analysis of remote sensing imagery with slope and aspect analysis of terrain data enables the extraction of features correlated with landslide types and magnitudes. Explicit annotations indicating each sample's landslide type and scale are incorporated during labeling.

In the second stage, mechanistic constraints are integrated into the data-driven model to achieve knowledge-data dually driven fusion.

Prior knowledge can be derived from external sources, including domain expertise, historical records, and physical principles, or mechanistic models can be employed to preprocess raw monitoring data. These outputs serve as a foundation for initializing parameters in data-driven models, which is crucial because the choice of initial values substantially affects both training efficiency and final performance (Cui et al., 2024; Liu et al., 2023a; Ma and Mei, 2025).

Beyond initialization, knowledge embedding involves translating landslide physics into model constraints to guide learning and optimization (Dahal and Lombardo, 2025; Liu et al., 2024). At the architectural level, physical equations can be structurally encoded as differentiable network layers, enabling gradient-based optimization. At the loss function level, physical constraints can be directly incorporated into the training objective, ensuring that predictions remain consistent with established principles. A representative example of this paradigm is the PINN framework (Raissi et al., 2019). PINNs embed governing equations (such as partial differential equations describing slope hydrology or stress-strain processes) into the neural network training objective, thereby constraining the learning process with domain knowledge. This approach not only reduces dependence on large annotated datasets but also enhances interpretability and cross-regional transferability (Karniadakis et al., 2021).

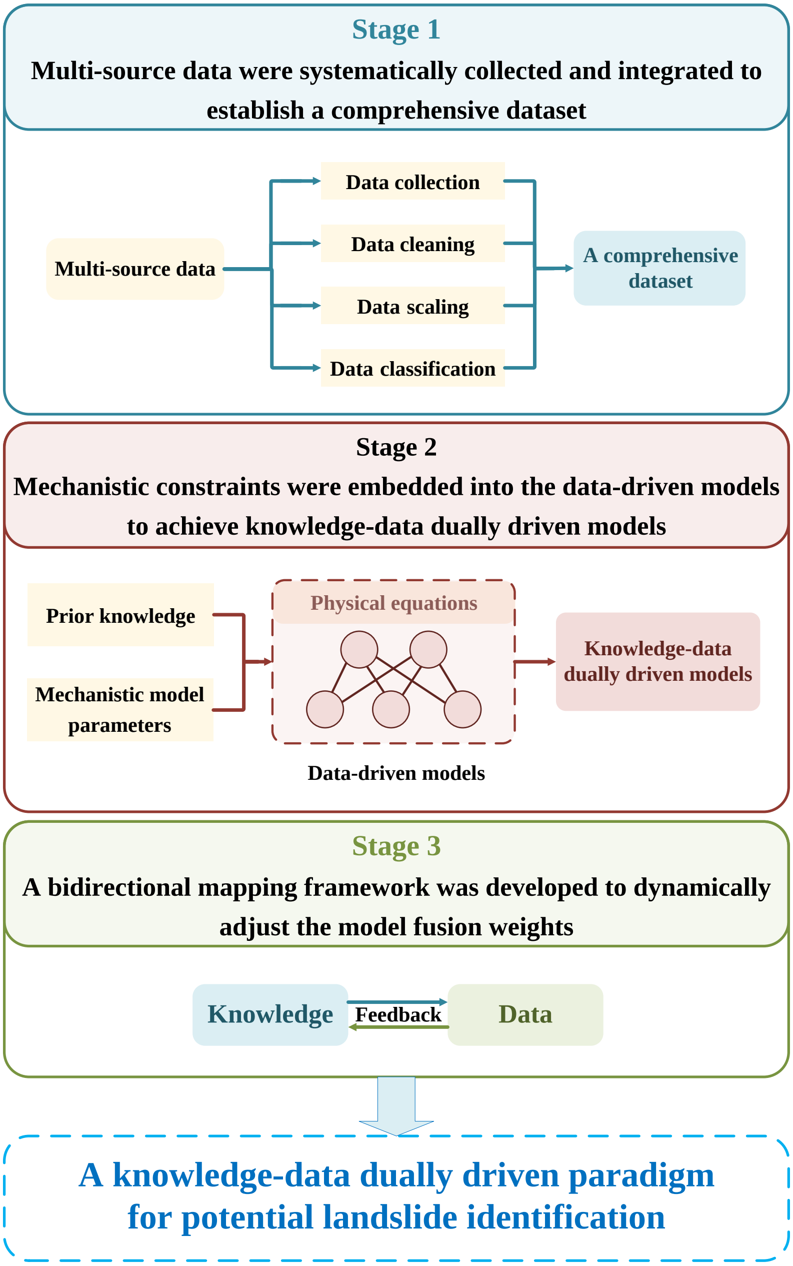

Figure 9. Flowchart of knowledge-data dually driven paradigm for potential landslide identification.

Although applications of PINNs in landslide research remain limited (Moeineddin et al., 2023), they provide a promising
1130 avenue for bridging purely data-driven approaches with physically grounded mechanisms (Wu et al., 2022).

In the third phase, a bidirectional mapping framework for knowledge-data dually driven is established to facilitate dynamic collaborative optimization.

The model's performance is periodically evaluated using real-time monitoring data, enabling the reverse calibration of knowledge analysis parameters to achieve bidirectional feedback. Through this feedback mechanism, knowledge-data dually driven models undergo mutual verification and iterative refinement.

In practical applications, model validation can be performed using historical or field monitoring data to evaluate predictive accuracy. While optimizing model parameters for region-specific geological conditions, fusion weights are dynamically adjusted based on different stages of landslide evolution. During the initial phase of a landslide, knowledge analysis is more effective in identifying underlying factors and developmental trends, justifying a higher fusion weight for knowledge components. Conversely, during the acceleration or sliding phases, real-time monitoring data becomes crucial, and data-driven models excel at capturing dynamic changes, requiring a higher weight for data-driven components. This dynamic weight adjustment knowledge maximizes the integration of mechanistic and data-driven approaches, enhancing the model's ability to identify landslide risks across different evolutionary stages.

The knowledge-data dually driven paradigm, operating through an iterative "theory-guided data assimilation and data-informed theoretical refinement" mechanism, has advanced potential landslide identification from empirical reliance to scientifically quantifiable methodologies.

Furthermore, the spatial analysis capabilities of Geographic Information System (GIS) were integrated into the practical identification workflow, enabling the study area to be partitioned into distinct landslide risk categories.This risk stratification considers the combined influence of region-specific factors, ensuring scientifically robust and practically viable classifications.

In high-risk areas, detailed investigations can be carried out using spatial remote sensing technologies, including high-resolution optical satellite image change detection and InSAR deformation analysis. Multi-temporal high-resolution optical satellite imagery is analyzed using image change detection algorithms to identify anomalous surface alterations. SAR enables precise measurement of millimeter-scale surface displacements, facilitating early detection of slope deformation precursors. Then, UAVs and airborne LiDAR can then be employed for further identification of high-risk areas. High-resolution imagery can be acquired through UAV-mounted sensors. Image interpretation and analysis facilitate the identification of potential landslide indicators, including irregular slope geometries, soil loosening patterns, and anomalous vegetation growth. LiDAR enables the rapid acquisition of high-precision 3D point cloud data, which accurately captures topographic changes and penetrates vegetation canopies to reveal concealed ground surfaces, aiding in the detection of vegetation-obscured landslide precursors. Ground-based observations are subsequently integrated to validate findings and acquire real-time dynamic information of landslide bodies. A comprehensive assessment, combining expert knowledge with field-derived practical experience, is conducted to finalize the screening and confirmation of potential landslides. Critical parameters including location, scale, hazard level, and potential sliding direction are determined, providing an empirical foundation for subsequent landslide mitigation strategies.

7 Conclusions

In this review, we summarized the latest advancements in the applications of deep learning for potential landslide identification, as well as the challenges and opportunities for the future. First, we examined seven major heterogeneous data sources available for potential landslide identification. Next, we introduced the five common roles of deep learning models in potential landslide identification. Then, we reviewed the applications of deep learning in the analysis of four typical landslides and discussed the common-used monitoring methods. Finally, we analyzed the current challenges and future research directions.

Several key conclusions are drawn. (1) Single data source often fail to ensure the accuracy of identification, whereas multi-source data fusion can address this issue to some extent. (2) Deep learning models have been widely applied in potential landslide identification, but they still face challenges in terms of interpretability and complexity. Future research should focus on further enhancing the structure and algorithms of deep learning models. (3) Knowledge-data dually driven paradigm for potential landslide identification can improve its accuracy on both theoretical and practical levels.

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