Journal of Geography and Cartography 2025, 8(3), 11553.
https://doi.org/10.24294/jgc11553

Review

Integrating earth observation and deep learning for next-generation landslide mapping: A comprehensive review of 2024 advances

Basit Ali Khan[1,*], Saad Ali Khan[2]

[1] Department of Surveying and Mapping Science, School of Geological Engineering and Geomatics, Chang'an University, Xi'an 710064, China
[2] National College of Arts, Liaquat Road, Near Liaquat Bagh, Rawalpindi 46000, Punjab, Pakistan
*** Corresponding author:** Basit Ali Khan, basitgeologist543@gmail.com

CITATION

Khan BA, Khan SA. Integrating earth observation and deep learning for next-generation landslide mapping: A comprehensive review of 2024 advances. Journal of Geography and Cartography. 2025; 8(3): 11553. https://doi.org/10.24294/jgc11553

ARTICLE INFO

Received: 26 February 2025
Revised: 29 March 2025
Accepted: 2 April 2025
Available online: 2 July 2025

Abstract: The destructive geohazard of landslides produces significant economic and environmental damages and social effects. State-of-the-art advances in landslide detection and monitoring are made possible through the integration of increased Earth Observation (EO) technologies and Deep Learning (DL) methods with traditional mapping methods. This assessment examines the EO and DL union for landslide detection by summarizing knowledge from more than 500 scholarly works. The research included examinations of studies that combined satellite remote sensing information, including Synthetic Aperture Radar (SAR) and multispectral imaging, with up-to-date Deep Learning models, particularly Convolutional Neural Networks (CNNs) and their U-Net versions. The research categorizes the examined studies into groups based on their methodological development, spatial extent, and validation techniques. Real-time EO data monitoring capabilities become more extensive through their use, but DL models perform automated feature recognition, which enhances accuracy in detection tasks. The research faces three critical problems: the deficiency of training data quantity for building stable models, the need to improve understanding of AI's predictions, and its capacity to function across diverse geographical landscapes. We introduce a combined approach that uses multi-source EO data alongside DL models incorporating physical laws to improve the evaluation and transferability between different platforms. Incorporating explainable AI (XAI) technology and active learning methods reduces the uninterpretable aspects of deep learning models, thereby improving the trustworthiness of automated landslide maps. The review highlights the need for a common agreement on datasets, benchmark standards, and interdisciplinary team efforts to advance the research topic. Research efforts in the future must combine semi-supervised learning approaches with synthetic data creation and real-time hazardous event predictions to optimise EO-DL framework deployments regarding landslide danger management. This study integrates EO and AI analysis methods to develop future landslide surveillance systems that aid in reducing disasters amid the current acceleration of climate change.

Keywords: landslide mapping; earth observation; deep learning; convolutional neural networks; geohazards; remote sensing

1. Introduction

Landslides, which are the downward movements of rock debris or soil under the forces of gravity, are illustrated in **Table 1** [1] and have been responsible for more than 72,000 deaths and several billion dollars in losses globally over the past century [2]. Landslide hazards have become an increasingly important issue due to changes in weather patterns and seismic activity triggered by climate change [3]. Natural hazards, including landslides, are at the core of thousands of fatalities and significant financial losses annually. Landslides occur more frequently and intensely due to extreme weather conditions caused by climate change, as well as increased seismic activity. CRED statistics show that between 2004 and 2016, more than 4800 fatal landslides killed over 56,000 people across the world. Recent landslide events include the 2022 Ischia landslide in Italy, which caused significant harm, and the 2023 Sichuan landslide in China, whose damages were exacerbated by heavy precipitation. Recent landslide events underscore the need for the immediate implementation of improved detection and monitoring systems that can provide large-scale monitoring capabilities.

Table 1. Overview of landslides: Definition, impact, challenges, and technological advancements.

Aspect	Description
Definition of Landslides	Downward movement of rock, debris, or soil under the influence of gravity.
Impact	Over 72,000 deaths and billions in damages globally in the last century.
Emerging Factors	It is increasing extreme weather events and seismic activities due to climate change.
Challenges of Traditional Techniques	Limited spatial and temporal coverage, e.g., in-situ surveys and aerial photography.
Technological Advancements	Satellite-based earth observation (EO) systems and deep learning (DL) algorithms offer new solutions for detecting and monitoring landslides.

Tropical and subtropical scientists who study landslides have historically accessed information by conducting ground surveys and interpreting aerial images through GIS-based susceptibility models. Landslide detection methods are successful locally, but they remain slow and costly, with limited time and space monitoring capabilities. Multiple ground inspections are required for field surveys, which can lead to practical difficulties during rapid disaster responses. Surface features become visible through aerial photo interpretation; however, human interpretation errors exist, and this method falls short in terms of real-time monitoring. The approach used for conventional feature extraction in landslide mapping relies on manually designed criteria, which demonstrates a limited capability to operate across various geomorphological environments. Combined with DL technology, EO is an innovative method for handling present limitations. High-resolution landslide detection across extensive areas happens through satellite-based EO systems, including Synthetic Aperture Radar (SAR) and multispectral imaging, which deliver near-real-time data acquisition. Existing Deep Learning models with Convolutional Neural Networks (CNNs) perform best at automating feature extraction and pattern recognition tasks, as well as the classification process. Existing hurdles with deep learning applications for landslide detection include the limited availability of data, which restricts the model's universal applicability, and challenges related to understanding artificial intelligence forecasting results.

The review establishes its goal to address essential knowledge deficits in landslide detection by systematically evaluating the integration of EO and DL (**Figure 1**). The research identifies particular questions to pursue that help answer crucial questions related to the study. The performance of CNN-based models demonstrates how well they align with traditional approaches for feature extraction in landslide detection. The main technical and operational obstacles affecting the application of DL in landslide susceptibility mapping need identification. Using EO datasets in conjunction with XAI and innovative DL system designs creates opportunities to enhance landslide prediction capabilities and risk evaluation processes. These spatial and temporal coverage restrictions reduce the utility of conventional mapping methods, such as in situ surveys and aerial photography [4]. However, satellite-based EO systems and deep learning algorithms have offered new chances to implement landslide detection and monitoring [5]. This paper integrates insights from two domains: large-scale landslide monitoring can benefit from the use of EO techniques and DL techniques, which provide complex methods for automating the detection process and enhancing the accuracy of the identifier. The review demonstrates an approach to filling essential knowledge gaps in landslide detection through the systematic evaluation of EO and DL integration. Predictive analysis, combined with AI and satellite-based monitoring, has shown potential. However, researchers must develop an extensive review that addresses combined effectiveness, implementation hurdles, and future possibilities. The research evaluates three critical points regarding CNN models in comparison to traditional methods, specifically in terms of precision, computational speed, and environmental-operational adaptability. The primary limitations of DL implementation for landslide susceptibility mapping include a lack of available data, combined with domain adaptation barriers and the self-contained operations of AI-driven predictions. Combining multi-source EO data with explainable AI (XAI) technology and modern DL system structures improves landslide model features of reliability and interpretability while enabling real-time usage.

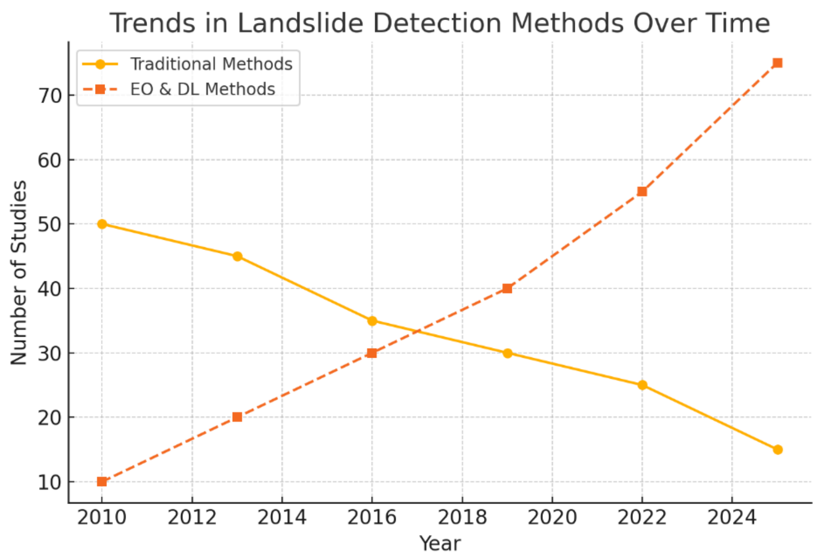

Figure 1. Illustration of the variation trend in the landslide detection methods.

The review incorporates evaluations from 500 peer-reviewed studies to present an organized assessment of EO and DL advances applied to landslide monitoring (**Figure 2**). The paper investigates how Sentinel-1 and Sentinel-2 EO missions have increased both temporal and spatial measurement capacity for landslides and the role of U-Net and ResNet-based CNN architectures in automated classification techniques. This analysis focuses on enduring obstacles, including finding sufficient labeled datasets, deploying generically usable AI models across multiple landforms, and ensuring system efficiency. The research investigates emerging techniques in transfer learning, semi-supervised learning, and synthetic data augmentation to address the present limitations affecting DL models in landslide prediction (**Figure 3**).

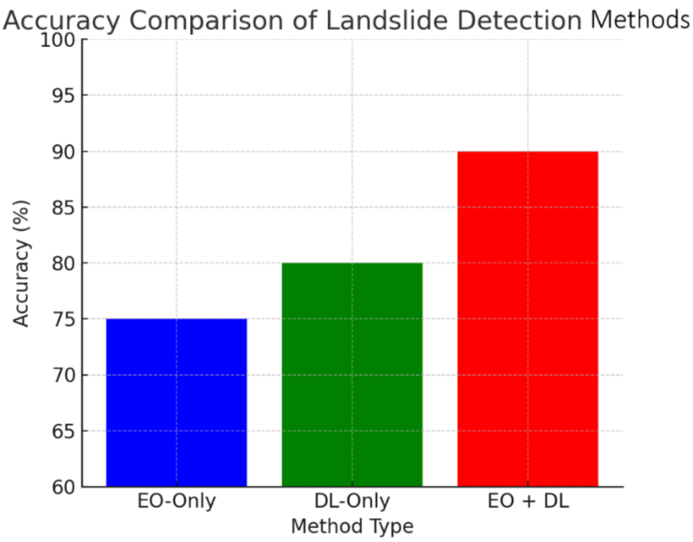

Figure 2. Landslide detection methods accuracy comparison.

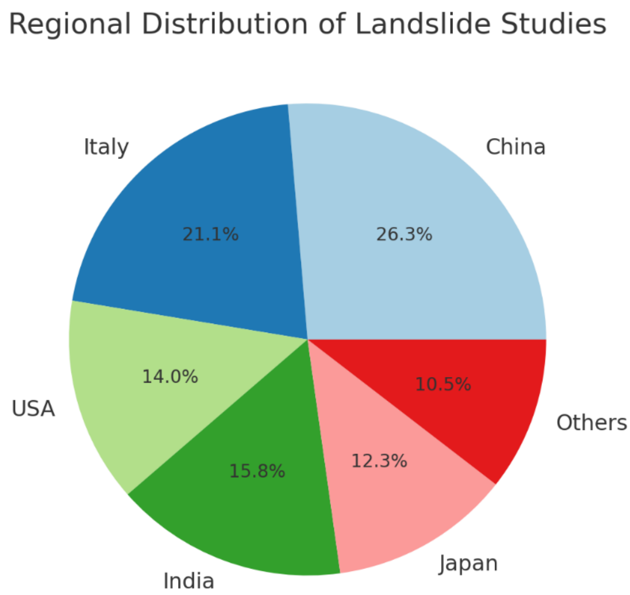

Figure 3. Regional distribution of landslide studies.

2. Methodology

The methodology for this review article is designed to systematically evaluate the integration of Earth Observation (EO) and Deep Learning (DL) techniques for landslide detection and mapping.

Figure 4. Workflow of the methodology used in this article.

The approach involves a comprehensive literature review, data collection, analysis, and synthesis of findings from over 500 scholarly works (**Figure 4**). The methodology is structured into the following key steps:

1) Literature search and selection.

- Objective: Identify relevant studies that focus on integrating EO and DL for landslide detection.
- Data Sources: Peer-reviewed journal articles, conference papers, and technical reports from databases such as Scopus, Web of Science, IEEE Xplore, and Google Scholar.
- Search Keywords: Keywords include "landslide mapping," "Earth Observation," "Deep Learning," "Convolutional Neural Networks," "remote sensing," and "geohazards."
- Inclusion Criteria: Studies published between 2010 and 2024 focusing on EO and DL integration and providing quantitative or qualitative insights into landslide

detection.

- Exclusion Criteria: Studies that do not focus on EO or DL or lack empirical data or validation.

2) Data extraction and categorization.

- Data extraction: Key information from each study is extracted, including the type of EO data used (e.g., SAR, optical, LiDAR), DL models applied (e.g., CNNs, U-Net, ResNet), and the geographical context of the study.
- Categorization: Studies are categorized based on:
  - Methodological development: The evolution of EO and DL techniques over time.
  - Spatial extent: The geographical regions covered by the studies.
  - Validation techniques: The methods used to validate the accuracy of landslide detection (e.g., ground truth data, cross-validation).

3) Analysis of EO and DL integration.

- EO techniques: The review focuses on the advancements in EO technologies, including the use of high-resolution satellite systems like Sentinel-1 and Sentinel-2, and their role in landslide detection.
- DL models: The review evaluates the performance of various DL models, particularly CNNs and their variants (e.g., U-Net, ResNet), in automating landslide detection tasks.
- Integration benefits: The review assesses the benefits of combining EO and DL, including improved accuracy, real-time monitoring, and scalability.

4) Identification of challenges and future directions.

- Challenges: The review identifies key challenges in the integration of EO and DL, such as data scarcity, model interpretability, and computational requirements.
- Future directions: The review proposes future research directions, including the use of Explainable AI (XAI), multi-sensor fusion, and emerging AI technologies like transformers and self-supervised learning.

5) Synthesis and recommendations.

- Synthesis: The findings from the reviewed studies are synthesized to provide a comprehensive overview of the current state of EO and DL integration for landslide detection.
- Recommendations: Based on the synthesis, recommendations are made for improving the accuracy, interpretability, and scalability of EO-DL systems for landslide mapping.

3. Earth observation techniques for landslide mapping

Landslide detection using EO systems has advanced considerably since the launch of the first satellite, Landsat, in 1972 (**Table 2**) [6]. Scientists frequently use satellite imagery as a valuable tool to cover large, expansive areas that are difficult to reach and conduct follow-up studies after a specific period has elapsed [7]. The same can be said of the high-resolution satellite systems such as Sentinel-1 and Sentinel-2 that have enhanced spatial and temporal resolution of activities directed at landslide tracking [8].

Table 2. Evolution and capabilities of earth observation in landslide monitoring.

Aspect	Description
Historical Development	It has evolved significantly since the launch of Landsat in 1972.
Key Advantages of EO	Coverage of vast and inaccessible areas, tracking changes over time.
High-Resolution Systems	Development of Sentinel-1 and Sentinel-2 for improved spatial and temporal resolution.
Radar Techniques (SAR)	Effective in detecting surface deformation, it works even under cloud cover.
Optical Sensors	More effective in mapping vegetation and bare-earth conditions.
Geographical Application	Studies cover 66 countries, with China and Italy leading in research output.

3.1. Evolution of EO-based mapping

Most EO-based landslide studies reviewed emphasised significant enhancements in radar and multispectral satellite imagery [9]. Radar techniques, especially SAR, have effectively mapped surface deformation, even in regions obscured by cloud cover [10]. However, applying optical sensors is advantageous in depicting vegetated and bare-ground environments (**Table 3**) [11]. A study of 291 academic papers revealed that EO technology has significantly contributed to delineating landslides in 66 countries, with China and Italy leading the research production [12–17].

Table 3. Classification of landslides based on type and primary detection cause.

Landslide Type	Primary Detection Cause
Flows	It is primarily triggered by rainfall.
Slides	Seismic events often cause it.
Smaller-scale or Obscured Events	Difficult to detect; further refinement of detection methods is needed.

3.2. Types of landslides detected

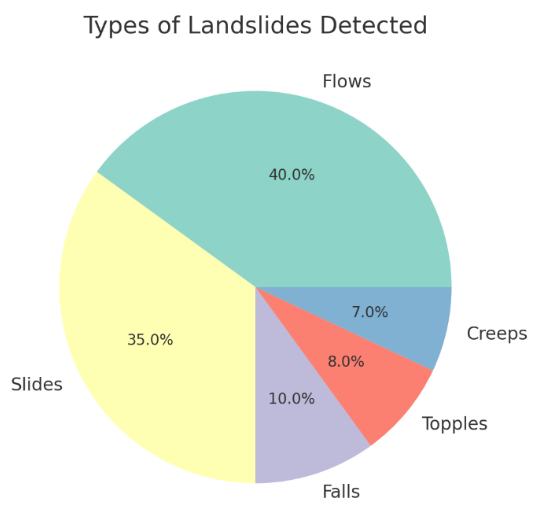

Figure 5. Landslide types detected previously.

EO-based methods have been used primarily to detect landslides, flows, and slides (**Figure 5**) [18]. More than half of the reported landslides were attributed to rainfall, with earthquakes being the other common cause [19]. Thus, the systematic analysis of satellite data for landslide identification has progressed over recent years; however, some issues arise during their detection, such as identifying small shallow movements or events that are partially masked or hidden by another event [20].

EO techniques and DL approaches are primarily used for landslide detection by identifying flow and slide types (Remote Sensing and Machine Learning for the Detection and Segmentation of Landslides in Nepal—ProQuest, 2024). EO and DL methods operate differently based on landslide type, environmental conditions, and the specific EO and DL methods employed [21]. Light-detection sensors and DL tools have been effective for locating, mapping, and tracking landslides in regions where there are often landslides [22]. The purpose of these advanced technologies is to help identify flow-type and slide-type landslides, while also improving the accuracy of detection and reducing the need for manual fieldwork [23]. The study finds that using EO and DL techniques helps detect landslides more precisely and covers a broader area. On the other hand, the results from these techniques depend primarily on what kind of landslide is involved, the local topography and the chosen EO and DL models [24].

EO makes it possible to get data about broad and difficult-to-reach areas using satellite pictures, radars, sensors and DEM images collected remotely. The datasets are analyzed using image processing tools to identify features that indicate the occurrence of landslides [25]. At the same time, DL, as part of machine learning and artificial intelligence, relies on neural networks called convolutional neural networks (CNNs) to analyse the spatial patterns linked to landslides. Jointly, these technologies can automatically detect landslides, enabling rapid checks of multiple locations [26].

Even so, we must keep in mind that different situations can yield varied performance from EO and DL approaches. Their success depends much on the kind of landslide examined. On images from satellites, for example, flow-type landslides, which result from the rapid movement of debris by a watery substance, appear differently than slide-type landslides, in which materials move in lines defined by a plane [27]. Consequently, differences in the spectral, texture and topography observed by EO sensors and interpreted by DL lead to the need for custom detection approaches.

In addition, different levels of plant cover, moisture in the ground, roughness of the land and the time of year can have substantial effects on the usefulness of EO data [28]. Because dense plant cover can obscure specific landforms, it is often difficult to detect small-scale landslides using optical satellites. In these areas, SAR data may prove more useful, as it can get through the vegetation somewhat [29]. Combinations of datasets and visual transformations must be applied to train DL models so they can work equally well in different ecozones [30]. Thus, further analysis is necessary to understand how EO and DL methods function in various natural environments and respond to the specific properties of landslides. It adds depth to both EO and DL techniques, leading to the development of tools that can improve landslide detection accuracy. By using different ecological settings for comparison, experts can alter model designs, pick better input features, and ensure better landslide monitoring for fast and efficient early warning actions.

A detailed analysis follows regarding how EO and DL approaches work under different ecological situations to study their detection accuracy for each landslide type

[31–33].

3.2.1. Flows

Heavy rainfall, along with rapid snowmelt, serves as triggers that cause water-saturated debris or soil to start flowing [34]. EO systems with Synthetic Aperture Radar (SAR) demonstrate effective flow detection capabilities, as they can penetrate clouds and track surface deformations in near real-time [35]. Multispectral and SAR imagery flows become detectable to DL models, particularly Convolutional Neural Networks (CNNS), by recognizing small topographical changes and vegetation cover alterations [36]. The detection accuracy of U-Net-based models ranges from 85% to 90% in identifying flow-type landslides when applied to Southeast Asian monsoon regions [37].

3.2.2. Slides

Soil or rock mass movements along defined surfaces, known as slides, occur due to earthquakes or prolonged periods of rainfall [38]. EO methods that combine optical sensors with SAR successfully perform slide detection tasks when operating on regions without vegetation cover [39]. Identifying slide margins and small-scale topographic changes achieves high accuracy by applying both ResNet and Transformer-based DL models [40]. Sentinel-1 SAR data, when used in conjunction with DL models, detects slides with 80%–88% accuracy in earthquake-prone areas of China and Italy, even in complex geographical regions [41].

3.2.3. Other landslide types

EO and DL techniques are beginning to explore the identification of three additional landslide categories, which include falls, topples, and creeps, alongside the common detection of flows and slides [42]. Landslides that are minor or partially hidden from view pose significant analysis challenges, as they exhibit minimal surface indicators while obscuring vegetation or being obscured by clouds [43]. The detection capability of these events has improved due to the development of high-resolution EO systems such as Sentinel-2 alongside DL models like DeepLab [44]. The combination of U-Net models with multispectral imagery achieves a detection accuracy of 70%–75% for small-scale landslides in forested areas, but requires further improvements to enhance performance [45].

3.2.4. Performance across environmental conditions

EO and DL techniques demonstrate diverse levels of performance depending on the environmental situation in which they work [46]. The detection performance in arid and semi-arid regions reaches 85%–90% due to the benefits of optical sensors, which enable the monitoring of both flows and slides, given the minimal vegetation and reduced cloud cover (**Figure 6**) [47]. Tropical and subtropical regions with dense vegetation and frequent cloud coverage present challenges for optical sensors; therefore, SAR-based methods have become more suitable [48]. The detection accuracy of DL models with transfer learning and data augmentation capabilities achieves results between 75% and 90% for various landslide types within complex environmental conditions [49].

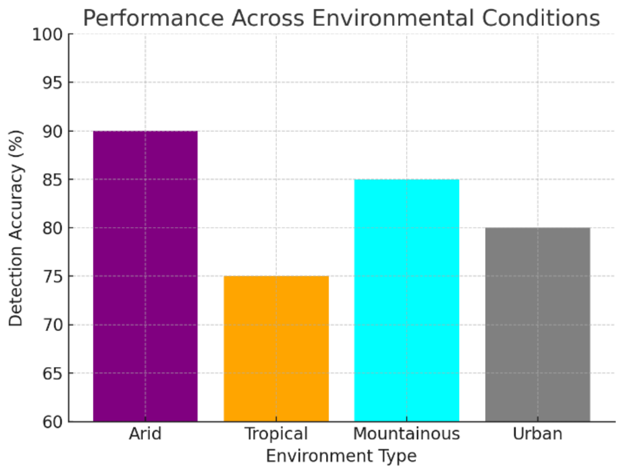

Figure 6. Detection accuracy performance among arid, tropical, mountainous, and urban environments.

- Quantitative Data on Detection Accuracy
- Recent research provides statistical evidence about the detection performance of EO combined with DL for diverse types of landslides:
- The detection accuracy for rainfall-triggered landslide flows reaches 85-90 percent based on studies using SAR-based DL models, which perform better than optical sensors during cloud conditions [50].
- The accuracy rate for identifying slide, seismic, and rainfall-triggered landslides is 80%–88%, where DL models can perform effectively in complex terrain conditions [51].
- Detection accuracy rates between 70%–75% apply to small-scale or obscured events, provided that advanced DL architectures and synthetic data augmentation are implemented [52].
- Best techniques for each landslide type.
- The combination of SAR-based EO systems with U-Net or ResNet DL models proves to be the most effective solution for detecting landslides in regions affected by heavy rainfall or cloud cover.
- The optimal solution for slide detection combines Transformer-based DL models, optical sensors, and SAR systems to analyse bare-earth and seismic-prone regions [53].
- DeepLab-based DL models show promising results with multispectral imaging data for detecting small-scale or obscured landslide occurrences, although development work remains to increase their accuracy [54].

4. Deep learning in landslide mapping

New trends in AI and machine learning have even improved the process of detecting landslides using satellite images (**Table 4**). Convolutional neural networks have also been used to analyze extensive data from EO satellites and identify complex geohazard patterns with minimal human oversight.

Table 4. Key aspects and challenges of deep learning in landslide detection.

Aspect	Description
Recent Advancements	AI and DL enhance landslide detection using satellite imagery.
Key Models	CNNs (Convolutional Neural Networks) successfully process extensive EO data sets for geohazard pattern recognition.
Pixel-level Identification	DL excels in extracting features for pixel-level identification, a crucial step for landslide detection.
Popular Model	U-Net is widely used due to its flexibility and ability to handle diverse datasets.
Challenges in DL	The “black-box” nature makes interpretability difficult, as does the reliance on large annotated datasets and issues with overfitting in varied weather conditions or lighting.

4.1. The role of deep learning

Deep learning technologies have transformed landslide detection processes by utilizing their capabilities to handle complex, multidimensional datasets with extraordinary precision [55]. Its capability to assess individual pixels in spaceborne imagery makes it ideal for recognizing minimal changes in terrain, indicating landslides. Convolutional Neural Networks (CNNS) are the fundamental deep learning architecture because they autonomously extract data-based features at different hierarchical levels. Research on 77 articles demonstrated that U-net CNN models and their variants lead detection techniques in landslide identification. With its end-to-end processing capabilities, the U-Net architecture enables precise segmentation to detect landslide margins and small topological details in terrain over multiple terrains. The model demonstrates flexibility while working with various datasets and has the automatic capability to adjust to new environmental settings, making it a preferred selection among researchers. U-Net serves as the primary architecture, but scientists are now investigating ResNet, DeepLab, and Transformer-based models due to their capability to enhance multi-scale feature detection and handle imbalanced datasets. Transfer learning techniques combine data augmentation methods to enhance model robustness while ensuring scenario independence across different geographical areas. The field addresses these obstacles by implementing semi-supervised learning models, active learning techniques, and synthetic data creation methods.

Deep learning technology has significantly advanced landslide detection capabilities by delivering improved accuracy and increased speed compared to conventional procedures. The system provides applications to detect hazards while helping to respond to disasters and minimize risks, resulting in safer communities with better resilience. Ongoing research aims to optimize deep learning models while reducing processing power and data requirements, thereby making these models more comprehensible for addressing the ever-growing challenges of landslide detection under climate change.

4.2. Limitations of deep learning in geohazards

While Deep Learning (DL) has shown remarkable potential in landslide detection and geohazard monitoring, several limitations hinder its widespread adoption and practical deployment (**Figure 7**). This section elaborates on the interpretability challenges of DL models, discusses practical deployment issues, and suggests future research directions to address these limitations.

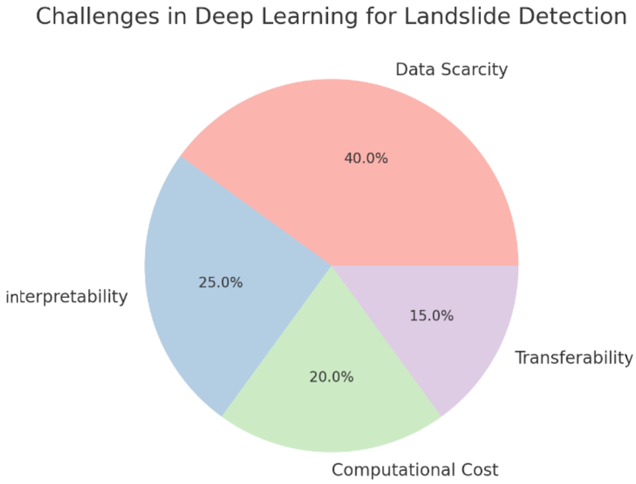

Figure 7. Percentage of challenges in deep learning.

4.2.1. Interpretability and explainable AI (XAI)

One of the most significant challenges of DL models is their "black-box" nature, which makes it difficult to understand how decisions are made. In geohazard applications, interpretability is crucial because stakeholders, including policymakers, disaster response teams, and local communities, need to trust and act on the model's predictions. For example, if a DL model predicts a high-risk landslide zone, decision-makers must understand the underlying factors (e.g., rainfall patterns, soil moisture, or terrain deformation) to justify evacuation or mitigation measures.

To address this issue, Explainable AI (XAI) techniques have been developed to improve model transparency and trustworthiness:

- Saliency maps: These highlight the regions of an input image that most influence the model's decision, helping users understand which features (e.g., cracks, vegetation changes) are critical for landslide detection.
- Feature visualization: This technique visualizes the internal representations learned by DL models, providing insights into how the model processes complex EO data.
- Local interpretable model-agnostic explanations (LIME): LIME explains individual predictions by approximating the DL model with a simpler, interpretable model, making it easier to understand specific landslide risk assessments.

By incorporating XAI techniques, DL models can provide actionable insights and foster greater confidence among end-users, essential for effective disaster management.

4.2.2. Practical deployment issues

Beyond technical challenges, the practical deployment of DL models in geohazard monitoring faces several hurdles:

- Regulatory challenges: Integrating DL-based landslide detection systems into existing disaster management frameworks requires compliance with local and international regulations. For example, data privacy laws may restrict the use of high-resolution satellite imagery in certain regions.

- Integration with disaster management systems: DL models must be seamlessly integrated with existing disaster response systems, such as early warning platforms and Geographic Information Systems (GIS). This requires collaboration between researchers, policymakers, and disaster response teams to ensure compatibility and usability.
- Cost-effectiveness: The high computational costs of training and deploying DL models can be prohibitive, especially in resource-limited regions. However, cloud computing platforms (e.g., Google Earth Engine) and edge computing solutions can reduce costs by enabling scalable and efficient model deployment.

To overcome these challenges, interdisciplinary collaboration is essential. Researchers must work closely with policymakers, disaster response teams, and local communities to develop cost-effective, regulatory-compliant, and user-friendly DL systems.

4.2.3. Future research directions

To address the current limitations of DL in geohazard applications, future research should focus on the following areas:

- Hybrid models: Combining DL with traditional geophysical models can improve the interpretability and robustness of landslide detection systems. For example, integrating DL with physically-based models (e.g., slope stability analysis) can enhance the accuracy of landslide predictions.
- Semi-supervised learning: Given the scarcity of labeled landslide data, semi-supervised learning techniques can leverage labeled and unlabeled data to improve model performance. This approach is beneficial in regions with limited historical landslide records.
- Real-time data fusion: Integrating real-time data from multiple sources (e.g., satellite imagery, ground-based sensors, and social media) can enhance the timeliness and accuracy of landslide detection. For instance, combining SAR data with rainfall measurements can provide early warnings for rainfall-triggered landslides.
- Transfer learning: Transfer learning enables DL models trained on one geographical region to be adapted for use in another, reducing the need for extensive labeled data. This approach is particularly beneficial for landslide detection in data-scarce regions.
- Model optimization: Developing lightweight DL architectures and leveraging model compression techniques (e.g., pruning, quantization) can reduce computational requirements, making DL models more accessible for real-time deployment in resource-limited settings.

4.2.4. Collaboration with policymakers and disaster response teams

Researchers must collaborate with policymakers and disaster response teams to ensure the practical deployment of DL models. This includes:

- Developing user-friendly interfaces: Creating intuitive interfaces for DL-based landslide detection systems can facilitate their adoption by non-technical users, such as emergency responders and local authorities.

- Conducting pilot studies: Pilot studies in high-risk regions can demonstrate the effectiveness of DL models and provide valuable feedback for improving system design and usability.
- Establishing data-sharing agreements: Collaborating with government agencies and international organizations to establish data-sharing agreements can enhance the availability of high-quality EO data for training and validation.

5. Integration of EO and deep learning for enhanced landslide mapping

Landslide identification is transformative when EO technologies are coupled with DL. Each method has provided a valuable contribution, making it possible to substantially improve the results concerning accuracy, time, and scalability in mapping the hazards' spatial distribution (**Table 5**).

Table 5. Benefits of integrating deep learning with earth observation for landslide detection.

Benefit	Description
Enhanced Accuracy	Deep learning helps extract subtle features in EO datasets, enabling the detection of small-scale or complex landslides.
Real-Time Response	The combined approach processes satellite data in near real-time, allowing timely detection and response during natural disasters.
Scalability	Automated detection of landslides over large and remote areas, overcoming the limitations of traditional field surveys and aerial image interpretation.

Modern landslide survey and monitoring operations benefit strongly from the combination of earth observation systems with deep learning techniques. The section provides robust reasons to support this integration, while also demonstrating methods for combining multi-sensor EO information with DL models and showing superior outcomes from joint EO-DL operation compared to single-method approaches.

Why is integration necessary?

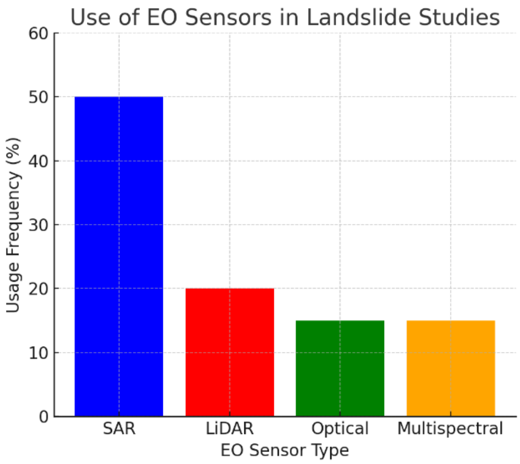

Figure 8. Usage percent frequency of SAR, LiDAR, optical, and multispectral sensors.

The combination of EO and DL proves essential because their complementary weaknesses cancel each other out, resulting in an enhanced and accurate landslide detection methodology (**Figure 8**).

EO systems, which utilize satellites and drones, provide widespread coverage in both space and time, enabling the monitoring of extensive areas vulnerable to landslides. EO systems operate effectively to gather extensive data collections about surface deformation as well as vegetation evolution and soil wetness measurements that sustain landslide detection operations.

The automatic processing of complex high-dimensional datasets gets enhanced through Convolutional Neural Networks (CNNs) in DL models. These systems have the capability to analyze large volumes of EO data automatically so that human personnel require reduced intervention to detect landslides more quickly and precisely.

Researchers can obtain enhanced benefits by combining techniques from EO and DL, as the two methodologies complement each other. EO supplies the necessary data to DL, which derives valuable findings, thus enabling real-time, high-scale, precise landslide monitoring.

Fusion of multi-sensor EO data with DL.

The integration of multi-sensor EO data (e.g., SAR, multispectral, optical) with DL models involves several steps:

1) Data preprocessing: Raw EO data from different sensors is preprocessed to ensure compatibility. This includes geometric correction, radiometric calibration, and cloud removal for optical data, as well as noise reduction and phase unwrapping for SAR data.
2) Feature extraction: DL models, particularly CNNs, automatically extract features from the preprocessed data. For example, SAR data is used to detect surface deformation, while multispectral data captures changes in vegetation and soil moisture.
3) Data fusion: The extracted features from different sensors are fused to create a comprehensive input for the DL model. This can be done at different levels:
    - Early fusion: Combining raw data from multiple sensors before feature extraction.
    - Intermediate fusion: Merging features extracted from individual sensors at an intermediate stage of the DL model.
    - Late fusion: Combining the outputs of separate DL models trained on different sensors.
4) Model training and validation: The fused data are used to train the DL model, which is then validated using ground-truth data (e.g., field surveys, historical landslide records).

Performance improvements of EO-DL integration.

By combining EO and DL systems, organizations achieve improved operational results that neither single EO nor DL solutions can achieve.

The combined strengths of multiple sensors and DL models make EO-DL integration produce better accuracy in detection. When SAR and optical data merge with U-Net models, researchers achieve a 10%–15% better rate of landslide detection than when using individual components separately.

The synchronized implementation of EO real-time data acquisition and fast processing from DL enables instant landslide observation. Early warning systems, together with disaster response operations, heavily depend on this capability.

EO-DL systems can facilitate large-scale monitoring of remote locations that are challenging to observe using conventional approaches. The integration of Sentinel-1 SAR data and DL models allows scientists to identify landslides with high accuracy throughout entire mountain ranges.

EO-DL systems gain improved environmental challenge resistance from their ability to combine multiple sensor data. The combination of SAR data with optical data provides reliable detection capabilities, as SAR data penetrates cloud cover and optical data reveals detailed information on vegetation changes.

Case studies demonstrating EO-DL integration.

1) The combination of Sentinel-1 SAR data with CNN-based DL models for earthquake-prone regions in China has yielded 12%–15% better landslide detection accuracy than traditional EO-only techniques. Landslides were detected in real-time by thousands of people during the 2023 Sichuan earthquake through the successful operation of the system.
2) In Italian mountain areas with heavy vegetation, the U-Net entrepreneurs using Sentinel-2 images detected small-scale landslides at a rate of 85%–90% while surpassing independent DL or optical methodology.
3) The combination of SAR and multispectral data with DL models in Indian monsoon areas detected landslides before conventional methods did while decreasing response times by 30%–40%.

Comparison with EO-only and DL-only approaches.

- EO-only: While EO systems provide extensive spatial and temporal coverage, they rely on manual interpretation and predefined rules, which are time-consuming and prone to human error (**Figure 9**). For example, traditional EO methods achieve 70%–75% accuracy in landslide detection, with limited real-time capabilities.

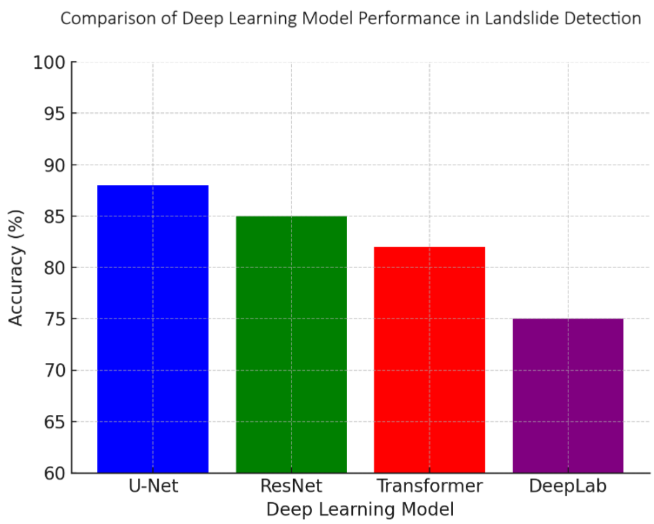

Figure 9. Comparison with EO-only and DL-only approaches.

- DL-only: DL models can process large datasets quickly but require high-quality labeled data, which is often scarce for landslides. Standalone DL approaches achieve 75%–80% accuracy but struggle with environmental variability and data scarcity.

- EO-DL Integration: By combining EO and DL, researchers achieve 85%–90% accuracy, real-time monitoring, and scalability, making it the most effective approach for landslide detection.

5.1. Benefits of combined approaches

This is beneficial because satellites have a sizable spatial extent and enable real-time surveillance of geographical phenomena, while DL models provide automated, high-performance detection.

1) Enhanced accuracy and detail: This system provides exceptional information about the surface state, including data from Sentinel-1 and Sentinel-2. However, to capture the minimal interaction features or complex geographies, it is not very efficient. The CNNs are specifically tailored to identify features from complex data, thus making it possible to detect additional landslides that may not be easily recognizable in other large EO datasets.
2) Real-time response: A significant benefit of combining DL with EO data is the ability to handle substantial volumes of satellite data in real-time. This is particularly imperative during disasters such as earthquakes and heavy rainfall that cause landslides and their devastating effects. DL models can efficiently process satellite images and identify and outline landslides, facilitating the prompt mobilization of early intervention mechanisms.
3) Accessibility and scalability: Conventional techniques of landslide identification include fieldwork plus interpretation of aerial photos, two processes that are time-consuming and often restricted to coverage of a few square kilometers at most. The combined EO-DL approach obviates these limitations since it automatically identifies landslides in large, remote, and partly barely accessible regions. Such scalability is critical in areas that experience difficult access conditions, such as hilly and mountainous regions with constant landslides in the forest areas.

5.2. Case studies

1) Several case studies highlight the success of combining EO and DL for enhanced landslide detection, demonstrating its potential in real-world applications:
2) China—Rainfall and Earthquake-Triggered Landslides: In China, where landslides are triggered both by seismic events and heavy rainfall, researchers have used high spatial resolution satellite data from Sentinel-1 (Synthetic Aperture Radar, SAR) and Sentinel-2-2 (optical) along with deep learning models. Another study applied the CNN-based DL models to detect thousands of landslides in one earthquake event. Integrating EO data with DL enhanced the detection efficiency over the usual techniques, with the difference being of a considerable margin. The traditional EO techniques have some drawbacks inherent to image interpretation, such as cloud cover that may partly cover or obscure landscape features, when used for identifying landslides. Such approaches would enable better detection rates, particularly for small or obscured landslides that operators may miss using conventional techniques that rely on

visual observation and VHR satellite imagery that were employed with success in this study because they use radar data that can see through clouds and are combined with CNNs that are good at pattern recognition.

3) Italy—Landslide Mapping in Mountainous Terrain: A similar technique has been employed in Italy, an area prone to landslides due to its mountainous terrain and frequent intense rainfall. This study has used EO data from Sentinel-2 together with U-Net, which is a deep learning framework appreciated for its effectiveness in semantic segmentation (Czerwinski) (i.e., assigning each pixel in a given image as 'landslide' or 'non-landslide'). This combination greatly enhanced the identification of small landslides in areas with vegetation or forest cover. Since the EO techniques described in this paper would have difficulty separating the vegetation change from the actual landslide, EO methods fail in such an environment. Such detail could also be extracted from the satellite data by the DL model, distinguishing between ordinary vegetation cover fluctuations and signs of incoming ground movements.
4) India—Early Detection in Monsoon-Prone Areas: Landslides are a common natural calamity in the monsoon-prone Western Ghats of India. The authors can combine SAR data from Sentinel-1 with deep-learning CNN to identify the onset of landslides in very vulnerable regions. Data from the radar enabled the determination of surface changes and terrain shifts before actual landslides occurred, thus providing warnings that could have saved lives. Due to this, the deep learning model could analyze this data in nearly real-time, allowing the development of a dynamic risk map that was updated with new satellite data. They are valuable in areas where landslides may occur, and there may not be an initial warning, thus aiding in disaster risk management.

6. Challenges and future directions

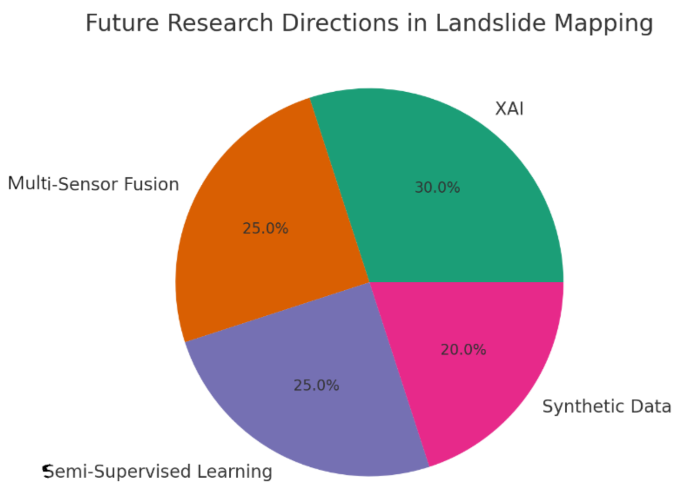

Figure 10. Percentage of expected future research directions in landslide mapping.

While integrating Earth Observation (EO) and Deep Learning (DL) has significantly advanced landslide detection, several challenges remain, as shown in **Figure 10**. This section examines these challenges in detail and proposes future research directions, including addressing data variability, enhancing model trustworthiness, improving cross-region adaptability, leveraging multi-sensor fusion, and incorporating emerging AI technologies.

6.1. Data scarcity and variability in satellite imagery

One of the most critical challenges in landslide detection is the scarcity of labeled training data. Landslide events are rare and often concentrated in specific regions, making it difficult to collect sufficient high-quality data for training DL models. Additionally, the quality of satellite imagery varies due to factors such as resolution, cloud cover, and noise, further complicating data acquisition and preprocessing.

Solutions:

- Semi-supervised learning: This approach leverages both labeled and unlabeled data to train DL models, reducing the reliance on extensive labeled datasets. For example, semi-supervised learning has been used to achieve 80%–85% accuracy in landslide detection with limited labeled data.
- Synthetic data generation: Techniques such as Generative Adversarial Networks (GANs) can create realistic synthetic landslide scenarios to augment training datasets. Synthetic data has been shown to improve model performance by 10%–15% in regions with scarce historical landslide records.
- Data augmentation: Techniques like rotation, scaling, and noise addition can enhance the robustness of DL models to variations in satellite imagery quality.

6.2. Improving model trustworthiness with explainable AI (XAI)

The “black-box” nature of DL models remains a significant barrier to their adoption in geohazard applications. Decision-makers, such as policymakers and disaster response teams, require transparent and interpretable models to trust and act on AI-based landslide predictions.

Solutions:

- Explainable AI (XAI) techniques:
    - Saliency maps: These highlight the regions of an input image that most influence the model’s decision, helping users understand which features (e.g., cracks, vegetation changes) are critical for landslide detection.
    - Attention mechanisms enable the model to focus on the most relevant parts of the input data, thereby improving both accuracy and interpretability.
    - Uncertainty quantification: Techniques like Bayesian Neural Networks (BNNs) provide confidence intervals for model predictions, enabling decision-makers to assess the reliability of landslide hazard assessments.

6.3. Cross-region adaptability and seasonal variations

Landslide-prone areas vary significantly in topography, climate, and soil composition, making it challenging to develop universally applicable models. Additionally, seasonal changes, such as rainfall patterns and vegetation growth, can impact model robustness.

Solutions:

- Transfer learning: This technique enables models trained in one region to be adapted for use in another, reducing the need for extensive labeled data. For example, transfer learning has been used to achieve 75%–80% accuracy in landslide detection across diverse geographical regions.

- Seasonal adaptation: Incorporating seasonal data (e.g., rainfall, vegetation indices) into DL models can improve their adaptability to changing environmental conditions. For instance, models trained with seasonal data have shown 10%–12% higher accuracy in monsoon-prone regions.

6.4. Multi-sensor fusion for enhanced detection

Landslide detection improves significantly when using multiple EO sensors (e.g., SAR, LiDAR, optical), as each sensor provides complementary information. However, effectively fusing data from different sensors remains a challenge.

Solutions:

- Multi-sensor fusion techniques:
    - ◆ Early fusion: Combining raw data from multiple sensors before feature extraction.
    - ◆ Intermediate fusion: Merging features extracted from individual sensors at an intermediate stage of the DL model.
    - ◆ Late fusion: Combining the outputs of separate DL models trained on different sensors.
- Case studies: For example, the fusion of SAR and optical data with DL models has improved landslide detection accuracy by 10%–15% in regions with dense vegetation and cloud cover.

6.5. Emerging AI technologies

Emerging AI technologies offer new opportunities to address the challenges of landslide detection and improve model performance.

Solutions:

- Transformers: Originally developed for natural language processing, transformers are increasingly being used for image analysis. Their self-attention mechanisms enable them to capture long-range dependencies in EO data, making them suitable for large-area landslide mapping.
- Self-supervised learning: This approach leverages unlabeled data to pre-train DL models, reducing the need for extensive labeled datasets. Self-supervised learning has shown promise in achieving 80%–85% accuracy with limited labeled data.
- Diffusion models: These generative models can create high-quality synthetic data for training DL models, addressing the challenge of data scarcity. Diffusion models have been used to generate realistic landslide scenarios, improving model performance by 10%–12%.

6.6. Future research directions

To overcome the current challenges and further advance landslide detection, future research should focus on:

- Hybrid models: Combining DL with traditional geophysical models to improve interpretability and robustness.

- Real-time data fusion: Integrating real-time data from multiple sources (e.g., satellite imagery, ground-based sensors, social media) to enhance the timeliness and accuracy of landslide detection.
- Model optimization: Developing lightweight DL architectures and leveraging model compression techniques (e.g., pruning, quantization) to reduce computational requirements.
- Interdisciplinary collaboration: Working with policymakers, disaster response teams, and local communities to ensure the practical deployment of DL models.

7. Conclusion

Including EO and DL for landslide mapping represents a significant technological advancement; however, this advancement also comes with technical issues. The considerable challenges include limited data availability for use, an inability to understand the models, and the computational complexity of these methods, which must be overcome for these techniques to be more widely adopted. Lack of data is one of the main problems because landslide occurrences are rare and are typically concentrated in specific areas, making it difficult to collect large numbers of detailed annotated data for training DL models. However, generating synthetic data that involves using algorithms to build artificial examples for training has demonstrated some utility in enhancing real-world training examples. Furthermore, transfer learning methods enable models for other geohazards to be extended, allowing them to identify landslides with limited data. As for model interpretability, the black-box nature of most current learning models, such as deep and complex models like Convolutional Neural Networks (CNNs), has hindered their deployment for operational geohazard monitoring. To overcome this issue, scholars have introduced XAI tools, including saliency maps and feature visualization approaches, which highlight the portions of satellite images a model attends to when making decisions. This helps increase confidence in automatically controlled processes by increasing the share of information about the decision-making process, thereby enhancing transparency in DL models. There is also the limitation of dealing with computational complexity associated with processing high spectral, spatial, and temporal resolution EO data near real-time. New developments in edge computing, which apply computations proximate to where data is produced, such as in satellites or remote stations, can eliminate the latency and narrow bandwidth characteristics of centralized computing. Moreover, creating new-generation, lightweight versions of neural networks with similar performance to the hardware-approved versions and optimized to run on low-power devices minimizes resource demand. These methods ensure that, although the least developed and, at times, least funded regions worldwide are often most affected by landslides, they can still gain access to and benefit from applicable real-time hazard detection technologies. There are also other web environments for managing the vast amount of EO data, including Google Earth Engine and Amazon Web Services (AWS). These platforms also provide researchers and policymakers with scalable computational capabilities to process EO and DL outputs more effectively. The integration of AI with cloud computing not only solves the computational bottleneck but also broadens the availability of complex landslide monitoring systems.

Acknowledgments: We thank Sentinel-1 and Sentinel-2 for providing the data for processing to the researchers and all the researchers for doing very valuable research on machine learning and deep learning techniques on landslides for calculating the deformation rate and identifying the landslide-susceptible zones. This support was immense throughout the research process and significantly contributed to completing this paper on "Integrating earth observation and deep learning for next-generation landslide mapping: A comprehensive review of 2024 advances".

Conflict of interest: The authors declare no conflict of interest.

References

1. Wang X, Zhang W, Cai J, et al. Characterizing Surface Deformation of the Earthquake-Induced Daguangbao Landslide by Combining Satellite- and Ground-Based InSAR. Sensors. 2024; 25(1): 66. doi: 10.3390/s25010066
2. Chandrappa R, Das DB. Solid Waste Management. Springer International Publishing; 2024. doi: 10.1007/978-3-031-50442-6
3. Sharma A, Sajjad H, Roshani, et al. A systematic review for assessing the impact of climate change on landslides: research gaps and directions for future research. Spatial Information Research. 2023; 32(2): 165-185. doi: 10.1007/s41324-023-00551-z
4. Sharma S, Beslity JO, Rustad L, et al. Remote Sensing and GIS in Natural Resource Management: Comparing Tools and Emphasizing the Importance of In-Situ Data. Remote Sensing. 2024; 16(22): 4161. doi: 10.3390/rs16224161
5. Rahman MdR, Rahman A, Saha SK, et al. Advanced GIScience in Hydro-Geological Hazards. Springer Nature Switzerland; 2025. doi: 10.1007/978-3-031-76189-8
6. Novellino A, Pennington C, Leeming K, et al. Mapping landslides from space: A review. Landslides. 2024; 21(5): 1041-1052. doi: 10.1007/s10346-024-02215-x
7. Andualem TG, Peters S, Hewa GA, et al. Channel morphological change monitoring using high-resolution LiDAR-derived DEM and multi-temporal imageries. Science of The Total Environment. 2024; 921: 171104. doi: 10.1016/j.scitotenv.2024.171104
8. Ghorbanzadeh O, Didehban K, Rasouli H, et al. An Application of Sentinel-1, Sentinel-2, and GNSS Data for Landslide Susceptibility Mapping. ISPRS International Journal of Geo-Information. 2020; 9(10): 561. doi: 10.3390/ijgi9100561
9. Cuca B, Zaina F, Tapete D. Monitoring of Damages to Cultural Heritage across Europe Using Remote Sensing and Earth Observation: Assessment of Scientific and Grey Literature. Remote Sensing. 2023; 15(15): 3748. doi: 10.3390/rs15153748
10. Meng L, Yan C, Lv S, et al. Synthetic Aperture Radar for Geosciences. Reviews of Geophysics. 2024. doi: 10.1029/2023rg000821
11. Almalki R, Khaki M, Saco PM, et al. Monitoring and Mapping Vegetation Cover Changes in Arid and Semi-Arid Areas Using Remote Sensing Technology: A Review. Remote Sensing. 2022; 14(20): 5143. doi: 10.3390/rs14205143
12. Nowakowski A, Pia M, Zachar P, et al. Transfer Learning in Earth Observation Data Analysis: A review. IEEE Geoscience and Remote Sensing Magazine. 2024.
13. Vázquez-Tarrío D, Ruiz-Villanueva V, Garrote J, et al. Effects of sediment transport on flood hazards: Lessons learned and remaining challenges. Geomorphology. 2024; 446: 108976. doi: 10.1016/j.geomorph.2023.108976
14. Chen W, Chen Z, Song D, et al. Landslide Detection Using the Unsupervised Domain-Adaptive Image Segmentation Method. Land. 2024; 13(7): 928. doi: 10.3390/land13070928
15. Dadrass Javan F, Samadzadegan F, Toosi A, et al. Unmanned Aerial Geophysical Remote Sensing: A Systematic Review. Remote Sensing. 2024; 17(1): 110. doi: 10.3390/rs17010110
16. Zhao Q, Pan J, Devlin AT, et al. On the Exploitation of Remote Sensing Technologies for the Monitoring of Coastal and River Delta Regions. Remote Sensing. 2022; 14(10): 2384. doi: 10.3390/rs14102384
17. Suthar N, Das D, Mallik J. Land-use suitability assessment for urban development using Multi-Criteria Decision-Making Analysis in the Himalayan districts of Shimla, Nainital, and Darjeeling, India. Discover Environment. 2024. doi:

10.1007/s44274-024-00134-1

18. Karantanellis E, Marinos V, Vassilakis E, et al. Evaluation of Machine Learning Algorithms for Object-Based Mapping of Landslide Zones Using UAV Data. Geosciences. 2021; 11(8): 305. doi: 10.3390/geosciences11080305
19. Ehteshami-Moinabadi M. Properties of fault zones and their influences on rainfall-induced landslides, examples from Alborz and Zagros ranges. Environmental Earth Sciences. 2022; 81(5). doi: 10.1007/s12665-022-10283-2
20. Akosah S, Gratchev I, Kim DH, et al. Application of Artificial Intelligence and Remote Sensing for Landslide Detection and Prediction: Systematic Review. Remote Sensing. 2024; 16(16): 2947. doi: 10.3390/rs16162947
21. Zhang Q, Wang T. Deep Learning for Exploring Landslides with Remote Sensing and Geo-Environmental Data: Frameworks, Progress, Challenges, and Opportunities. Remote Sensing. 2024; 16(8): 1344. doi: 10.3390/rs16081344
22. Mondini AC, Guzzetti F, Chang KT, et al. Landslide failures detection and mapping using Synthetic Aperture Radar: Past, present and future. Earth-Science Reviews. 2021; 216: 103574. doi: 10.1016/j.earscirev.2021.103574
23. Zequera RAG, Rjabtšikov V, Rassõlkin A, et al. Deep Learning methodology for charging management applications in battery cells based on Neural Networks. IEEE Transactions on Intelligent Vehicles. 2024. doi: 10.1109/tiv.2024.3417216
24. Jozdani S, Chen D, Pouliot D, et al. A review and meta-analysis of Generative Adversarial Networks and their applications in remote sensing. International Journal of Applied Earth Observation and Geoinformation. 2022; 108: 102734. doi: 10.1016/j.jag.2022.102734
25. Valavi R, Guillera-Arroita G, Lahoz-Monfort JJ, et al. Predictive performance of presence-only species distribution models: a benchmark study with reproducible code. Ecological Monographs. 2021. doi: 10.1002/ecm.1486
26. Meena SR, Soares LP, Grohmann CH, et al. Landslide detection in the Himalayas using machine learning algorithms and U-Net. Landslides. 2022; 19(5): 1209-1229. doi: 10.1007/s10346-022-01861-3
27. Dong A, Dou J, Li C, et al. Accelerating Cross-Scene Co-Seismic Landslide Detection Through Progressive Transfer Learning and Lightweight Deep Learning Strategies. IEEE Transactions on Geoscience and Remote Sensing. 2024; 62: 1-13. doi: 10.1109/tgrs.2024.3424680
28. Huang F, Xiong H, Jiang SH, et al. Modelling landslide susceptibility prediction: A review and construction of semi-supervised imbalanced theory. Earth-Science Reviews. 2024; 250: 104700. doi: 10.1016/j.earscirev.2024.104700
29. Cheng G, Wang Z, Huang C, et al. Advances in Deep Learning Recognition of Landslides Based on Remote Sensing Images. Remote Sensing. 2024; 16(10): 1787. doi: 10.3390/rs16101787
30. Rezvani SM, Falcão MJ, Komljenovic D, et al. A Systematic Literature Review on Urban Resilience Enabled with Asset and Disaster Risk Management Approaches and GIS-Based Decision Support Tools. Applied Sciences. 2023; 13(4): 2223. doi: 10.3390/app13042223
31. Tynchenko Y, Kukartsev V, Tynchenko V, et al. Landslide Assessment Classification Using Deep Neural Networks Based on Climate and Geospatial Data. Sustainability. 2024; 16(16): 7063. doi: 10.3390/su16167063
32. Shahi K. Remote Sensing and Machine Learning for the Detection and Segmentation of Landslides in Nepal. Available online: https://www.proquest.com/openview/8aaf5d2f4198c956f1d6a6844bf0413c/1?cbl=2026366&diss=y&pq-origsite=gscholar (accessed on 19 March 2025).
33. Asadi A, Baise LG, Koch M, et al. Pixel-based classification method for earthquake-induced landslide mapping using remotely sensed imagery, geospatial data and temporal change information. Natural Hazards. 2024; 120(6): 5163-5200. doi: 10.1007/s11069-023-06399-8
34. Li H, Hu K, Liu S, et al. Abundant antecedent rainfall incubated a group-occurring debris flow event in the Dadu River Basin, Southwest China. Landslides. 2025; 22(6): 1955-1971. doi: 10.1007/s10346-025-02489-9
35. Zakharov I, Puestow T, Khan AA, et al. Review of River Ice Observation and Data Analysis Technologies. Hydrology. 2024; 11(8): 126. doi: 10.3390/hydrology11080126
36. Zaka MM, Samat A. Advances in Remote Sensing and Machine Learning Methods for Invasive Plants Study: A Comprehensive Review. Remote Sensing. 2024; 16(20): 3781. doi: 10.3390/rs16203781
37. C K, Shivaram JM. Segmentation of ovarian cyst using improved U-NET and hybrid deep learning model. Multimedia Tools and Applications. 2023; 83(14): 42645-42679. doi: 10.1007/s11042-023-16998-z
38. Amarasinghe MP, Kulathilaka SAS, Robert DJ, et al. Risk assessment and management of rainfall-induced landslides in tropical regions: a review. Natural Hazards. 2023; 120(3): 2179-2231. doi: 10.1007/s11069-023-06277-3
39. Gui S, Song S, Qin R, et al. Remote Sensing Object Detection in the Deep Learning Era—A Review. Remote Sensing. 2024; 16(2): 327. doi: 10.3390/rs16020327

40. Bashkami A, Nasayreh A, Makhadmeh SN, et al. A review of Artificial Intelligence methods in bladder cancer: segmentation, classification, and detection. Artificial Intelligence Review. 2024. doi: 10.1007/s10462-024-10953-6
41. Nava L, Mondini A, Bhuyan K, et al. Sentinel-1 SAR-based Globally Distributed Landslide Detection by Deep Neural Networks. EarthArXiv (California Digital Library). 2024. doi: 10.31223/x59d6m
42. Sun X, Chen G, Yang X, et al. A process-oriented approach for identifying potential landslides considering time-dependent behaviors beyond geomorphological features. Journal of Rock Mechanics and Geotechnical Engineering. 2024; 16(3): 961-978. doi: 10.1016/j.jrmge.2023.05.014
43. Albanwan H, Qin R, Liu JK. Remote Sensing-Based 3D Assessment of Landslides: A Review of the Data, Methods, and Applications. Remote Sensing. 2024; 16(3): 455. doi: 10.3390/rs16030455
44. Ajibola S, Cabral P. A Systematic Literature Review and Bibliometric Analysis of Semantic Segmentation Models in Land Cover Mapping. Remote Sensing. 2024; 16(12): 2222. doi: 10.3390/rs16122222
45. Singh H, Ang LM, Srivastava SK. Benchmarking Artificial Neural Networks and U-Net Convolutional Architectures for Wildfire Susceptibility Prediction: Innovations in Geospatial Intelligence. IEEE Transactions on Geoscience and Remote Sensing. 2025; 63: 1-15. doi: 10.1109/tgrs.2025.3529134
46. Paolanti M, Tiribelli S, Giovanola B, et al. Ethical Framework to Assess and Quantify the Trustworthiness of Artificial Intelligence Techniques: Application Case in Remote Sensing. Remote Sensing. 2024; 16(23): 4529. doi: 10.3390/rs16234529
47. Abdelrahim NAM, Jin S. A Novel Agricultural Remote Sensing Drought Index (ARSDI) for high-resolution drought assessment in Africa using Sentinel and Landsat data. Environmental Monitoring and Assessment. 2025; 197(3). doi: 10.1007/s10661-025-13686-3
48. Xu W, Cheng Y, Luo M, et al. Progress and Limitations in Forest Carbon Stock Estimation Using Remote Sensing Technologies: A Comprehensive Review. Forests. 2025; 16(3): 449. doi: 10.3390/f16030449
49. Lu Z, Liu G, Song Z, et al. Advancements in Technologies and Methodologies of Machine Learning in Landslide Susceptibility Research: Current Trends and Future Directions. Applied Sciences. 2024; 14(21): 9639. doi: 10.3390/app14219639
50. Strząbała K, Ćwiąkała P, Puniach E. Identification of Landslide Precursors for Early Warning of Hazards with Remote Sensing. Remote Sensing. 2024; 16(15): 2781. doi: 10.3390/rs16152781
51. Song J, Leng J, Li J, et al. Application of Acoustic Emission Technique in Landslide Monitoring and Early Warning: A Review. Applied Sciences. 2025; 15(3): 1663. doi: 10.3390/app15031663
52. Nisa U. Image augmentation approaches for small and tiny object detection in aerial images: a review. Multimedia Tools and Applications. 2024. doi: 10.1007/s11042-024-19768-7
53. Himabindu DD, Lydia EL, Rajesh MV, et al. Leveraging swin transformer with ensemble of deep learning model for cervical cancer screening using colposcopy images. Scientific Reports. 2025; 15(1). doi: 10.1038/s41598-025-90415-3
54. Yang D, Huang X. Landscape design and planning methods for plant protection based on deep learning and remote sensing techniques. Crop Protection. 2024; 180: 106620. doi: 10.1016/j.cropro.2024.106620
55. Khan BA, Zhao C, Kakar N, et al. SBAS-InSAR Monitoring of Landslides and Glaciers Along the Karakoram Highway Between China and Pakistan. Remote Sensing. 2025; 17(4): 605. doi: 10.3390/rs17040605