Geoenvironmental Disasters

REVIEW

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Conventional and advanced geospatial techniques for landslide detection and modeling: a comprehensive overview

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Abstract

Background Landslides represent a significant natural hazard, causing widespread human, infrastructure, and environmental losses. Geospatial technologies have become essential for monitoring, detection, and risk assessment of landslides. This review provides a comprehensive examination of the evolution and application of geospatial technologies in landslide research, addressing a significant gap in the current literature. First, we focus on landslide monitoring and detection, covering spaceborne and airborne Earth Observation (EO) technologies, ground-based remote sensing, mobile Geographic Information System (GIS) applications, and data processing methodologies, including traditional image and Artificial Intelligence (AI)-based approaches. Second, we examine landslide analysis, which includes susceptibility mapping, vulnerability and risk assessments.

Results Our bibliometric analysis reveals that landslide susceptibility is the most extensively studied category, followed by risk, while vulnerability remains significantly underexplored. China, India, South Korea, Iran, and the United States are the most active contributors across all three categories. China leads in susceptibility research due to high publication volume. A similar pattern is observed in risk studies, where China, Italy, India, and the United States have the most publications. However, the notable underrepresentation of vulnerability research suggests a gap in understanding the socio-economic and infrastructure impacts of landslides. These findings highlight the need for greater emphasis on vulnerability studies to improve landslide risk mitigation.

Conclusions Our results emphasize the need for increased focus on vulnerability studies to strengthen landslide risk mitigation strategies. In addition, we identify key challenges in landslide management and discuss emerging trends aimed at improving prediction, monitoring, and disaster response.

Keywords Landslide, Geospatial technology, Earth observation, Susceptibility, Early warning

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Introduction

Landslides represent a major geological hazard, posing substantial risks to human life, infrastructure, and the environment (Pradhan and Siddique 2019). Landslides, triggered by a combination of natural and anthropogenic factors, such as intense rainfall, seismic activity, deforestation, and land use changes, occur worldwide, resulting in significant socio-economic impacts (Schuster and Wieczorek 2018).

According to the Emergency Events Database (EM-DAT 2023), landslides accounted for nearly 72,000 deaths and caused over $11.5 billion in damages worldwide between 1900 and 2022. The impacts of landslides are often underreported, especially in low-income regions, suggesting that the actual figures may be even higher. Historical landslide data is systematically recorded and analyzed in several globally recognized databases, such as the Global Fatal Landslide Database (GFLD 2024), the Global Landslide Catalog (GLC) (Kirschbaum et al. 2010), EM-DAT (Lee et al. 2024), and DesInventar (Gómez et al. 2023), which collectively provide valuable insights into the spatial and temporal patterns of landslide occurrences.

Figure 1 provides a detailed illustration of fatal landslide occurrences worldwide from 2004 to 2017, based on data from the GFLD (Froude and Petley 2018). The figure highlights that approximately 75% of these fatal landslides occurred in Asia, a region characterized by complex topography, high population density, and frequent triggers such as monsoons, earthquakes, and deforestation. South America follows with 8% of the total incidents, where landslides are commonly triggered by intense rainfall in mountainous regions. Similarly, Central and North America and the Caribbean account for another 8% of global fatal landslides, often influenced by hurricanes and other severe weather events. Africa contributes to 5% of these occurrences, predominantly in countries with rapidly expanding urban areas prone to slope instability. Europe, although generally less affected, still accounts for 3% of the total, primarily in mountainous regions such as the Alps.

As an example, the 2008 Mw 7.9 Wenchuan earthquake in China resulted in the largest recorded landslide in history, with an estimated volume of 7.5 × 10^8 cubic meters. This massive event was characterized by a dramatic shift in the landscape, causing severe damage and creating a significant hazard for nearby communities (Huang et al. 2012). In comparison, the second-largest landslide occurred following the Mw 7.5 Papua New Guinea earthquake on February 25, 2018. This landslide covered an extensive area of approximately 145 km², highlighting the potential scale and impact of seismically induced landslides (Tanyaş et al. 2022). Landslides can vary greatly in their speed and impact. Some landslides happen suddenly and can be extremely destructive, such as the 2014 Oso landslide in Washington State, USA, which was triggered by heavy rainfall and caused 43 fatalities (Wartman et al. 2016). On the other hand, there

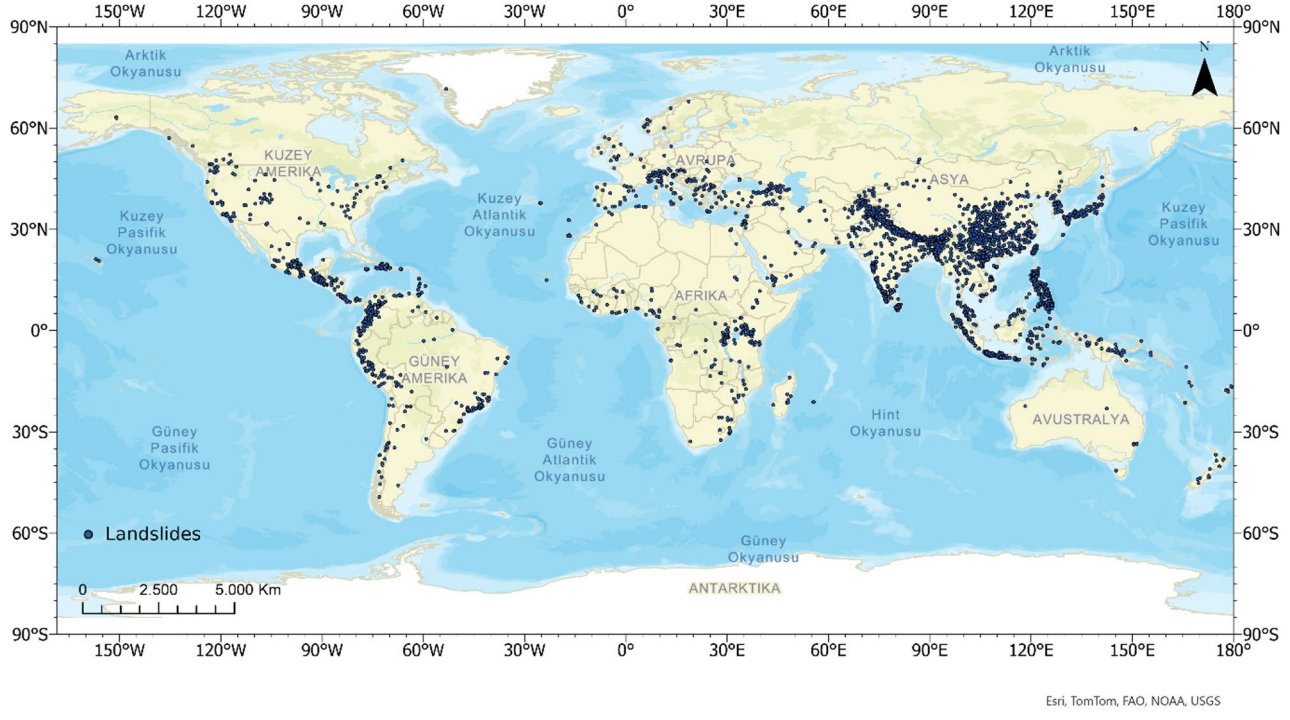


Fig. 1 Spatial distribution of fatal landslides reported in the global fatal landslide database (GFLD 2024)

are landslides that progress more slowly and can move at rates of less than 16 mm per year. For instance, the La Conchita landslide in California, which has been slowly moving since the 1995 and 2005 events, illustrates how long-term monitoring is crucial for managing ongoing risks (Aleotti 2004).

Understanding, monitoring, analyzing, and accurately predicting landslides is crucial for mitigating their adverse effects (Guo et al. 2025). Over the years, geospatial technologies have emerged as indispensable tools in landslide detection, mapping, and modeling, providing critical insights into landslide dynamics and risk assessment (Quesada-Román et al. 2019).

Conventional geospatial techniques, including traditional datasets, geographic information system (GIS), field surveys, expert-based methods, and slope stability have long been utilized to identify and analyze landslide-prone areas (Khasanov et al. 2021). These methods enable the collection and integration of topographical, geological, hydrological, and land use data, facilitating the creation of landslide susceptibility maps and hazard models. However, these traditional approaches often face limitations in terms of spatial resolution, temporal coverage, and processing efficiency, which can hinder the accuracy and reliability of landslide predictions (Strozzi et al. 2005).

Recent advancements in remote sensing technologies, such as Light Detection and Ranging (LiDAR), Synthetic Aperture Radar (SAR), Unmanned Aerial Vehicles (UAVs), and Machine Learning (ML) algorithms, have revolutionized landslide detection and modeling (Esposito et al. 2020; Jaboyedoff et al. 2018). These advanced techniques offer higher precision, improved data acquisition capabilities, and enhanced analytical methods that significantly outperform conventional approaches. Integrating these advanced tools with traditional geospatial methods provides a more comprehensive framework for landslide hazard assessment, allowing for real-time monitoring, detailed mapping, and robust modeling of landslide events (Jaboyedoff et al. 2018).

Many countries, either independently or through collaboration, are developing satellite systems tailored to specific applications, while spatial information processing and analysis tools are constantly evolving. These tools are becoming more user-friendly and incorporating new methods and techniques. In recent years, open-source software such as QGIS has emerged as a competitor to commercial platforms like ArcGIS, allowing researchers to create customized tools based on their specific needs (Guo et al. 2022). As a result, GIS, along with open-access satellite databases and other free spatial datasets, significantly reduces the cost and time required for analysis. These technologies also overcome obstacles inherent to field research, such as limited access to remote or dangerous areas and adverse weather conditions. Geospatial technologies provide essential data for various analyses, enabling the retrieval, mapping, tracking, simulation, and representation of disaster-related events with greater accuracy and speed, without requiring on-site visits.

Landslides can be analyzed through various lenses, each benefiting from advancements in geospatial technology. While there are review papers that address certain aspects of landslide research, these studies often concentrate on narrow topics rather than providing a comprehensive overview of all geospatial applications in this field. For instance, some reviews may focus solely on remote sensing techniques or GIS-based models, leaving other important technologies and their historical development unaddressed.

To our knowledge, no recent review comprehensively examines the evolution and application of geospatial technologies in landslide research. Therefore, our paper aims to bridge that gap by offering an in-depth exploration of both traditional and current geospatial applications used in landslide analysis. We will discuss a range of technologies, including satellite imagery, GIS, and real-time monitoring tools, highlighting their contributions and limitations. Additionally, this review will address ongoing challenges such as data integration issues, the need for more accurate predictive models, and the difficulties in real-time monitoring of landslide-prone areas. By identifying these challenges and weaknesses, the review will propose areas for future research and technological improvement, ultimately aiming to enhance landslide management and response efforts. Figure 2 provides an overview of the structure of this review, outlining the key sections and topics that will be covered.

Methodology

Bibliometric data for this study were obtained from the SCOPUS database (a comprehensive scientific abstract and citation source) and included all document types, such as research and review articles, conference papers, book chapters, and books. The search covered publications from 2000 to July 2025. We divided our study into three categories: (1) landslides susceptibility; (2) landslides vulnerability; and (3) landslides risk (refer to Tables S1–S5 for the search queries and the resulting number of retrieved documents). The final dataset comprised 1,580 susceptibility-related, 202 vulnerability-related, and 932 risk-related publications. Refined documents were then exported into VOSviewer software using CSV format, where data analysis was performed Fig. 3

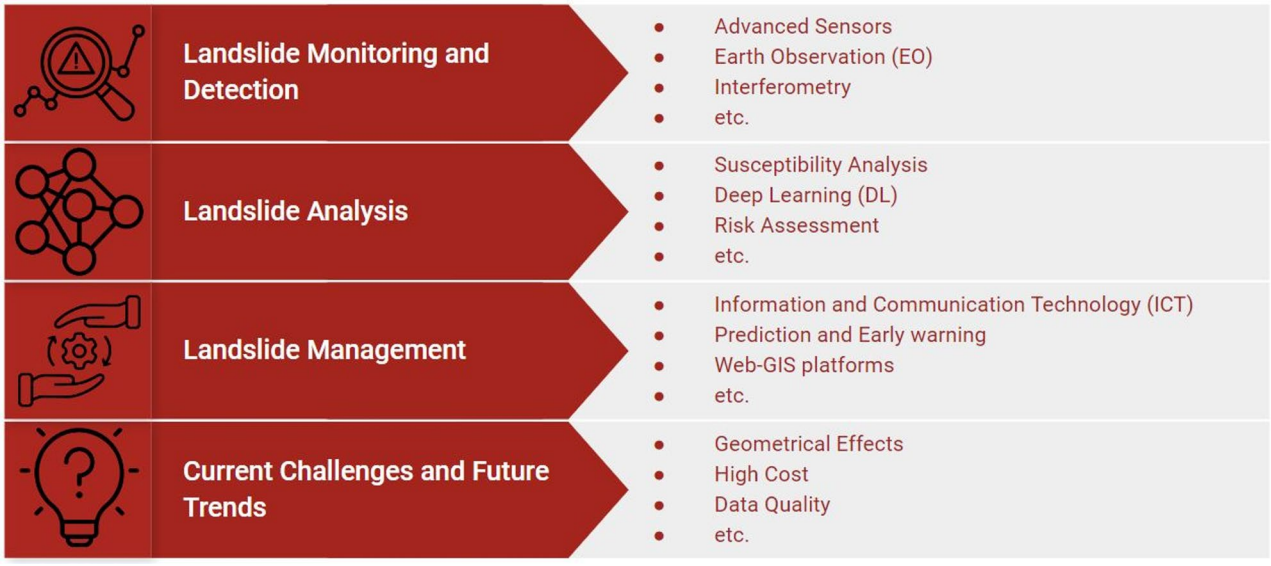


Fig. 2 Overview of the review structure, outlining the key sections and topics covered, including landslide monitoring and detection, landslide analysis, landslide management, and emerging challenges and future research directions

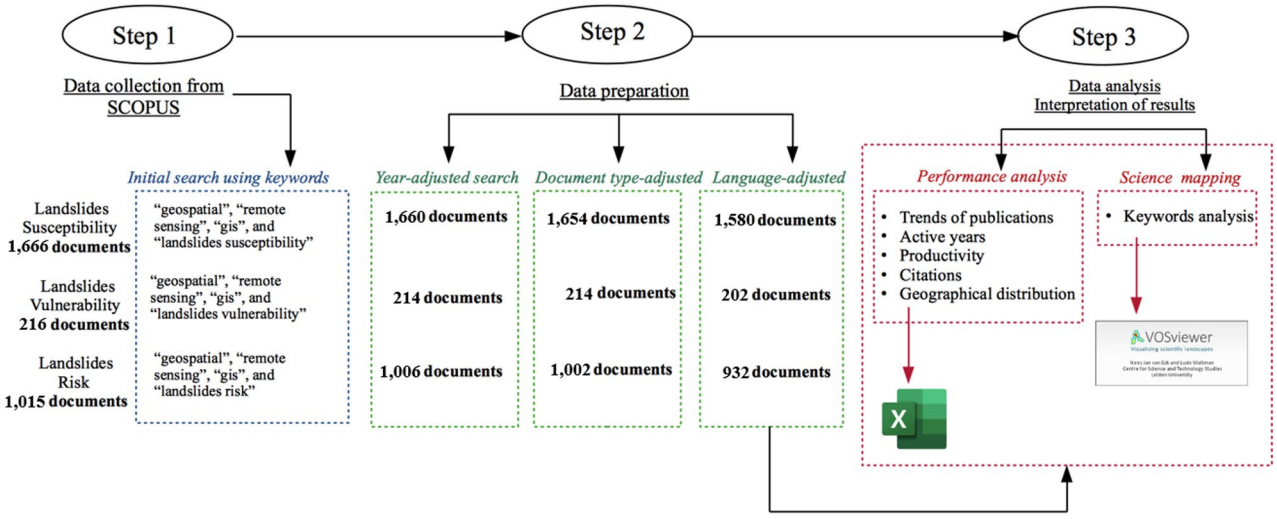


Fig. 3 Overview of the research methodology, illustrating the three-step process: (1) Data collection (2) Data preparation; and (3) Data analysis

Landslide monitoring and detection

Effective landslide monitoring and detection are crucial for managing and mitigating the impacts of landslides on communities and infrastructure (Sultana and Tan 2021). This process involves systematically tracking and documenting landslide activity through various methods and technologies. By utilizing tools such as landslide inventory maps, remote sensing, and advanced data analysis techniques, researchers and authorities can identify potential landslide-prone areas, assess changes over time, and enhance prediction capabilities.

Landslide inventory maps are crucial tools that systematically document where landslides have occurred in a given area (Guzzetti et al. 2012). These maps help identify potential landslide-prone areas, which is important for understanding risks and impacts. Major events like earthquakes or heavy rains can trigger numerous landslides, and mapping these events provides valuable data on their locations and distribution (Emberson et al. 2022; Yunus et al. 2023). However, accurate landslide detection requires extensive spatial coverage and frequent data collection to monitor changes over time. Traditional field measurements can be challenging due to their limitations in scale, cost, and access. In contrast, geospatial technologies offer a broad and cost-effective way to observe large areas, including remote or inaccessible regions, without requiring physical presence. Therefore, monitoring landslides effectively relies on remote sensing data, which

provides continuous and detailed information about both past and current landslide activity. Remote sensing can be conducted through various methods, including satellite and airborne systems, as well as ground-based approaches (Casagli et al. 2023; Xu et al. 2023). Each method has its strengths and limitations, depending on factors like the size of the study area, the type of landslide, and the specific monitoring needs.

Recently, Artificial Intelligence (AI) and ML have become increasingly important in Earth observation. These technologies enhance landslide monitoring by improving image analysis, such as classifying images, detecting and removing clouds, and increasing the spatial resolution of satellite images (Yordanov et al. 2021). The following sections will explore these advancements in more detail.

Earth observation (Space-borne and air-borne)

Traditionally, landslides have been detected through field surveys, aerial photography, and visual interpretation of orthophotographs. While these methods have historical significance, they are often unreliable, requiring significant expertise, training, and predefined interpretation criteria (Guzzetti et al. 2012). A notable advancement in visual analysis was the stereoscopic technique, which uses old stereo pairs of aerial photographs – some dating back to the 1950s – to detect past landslides (Mihalić Arbanas and Arbanas 2014). Although stereoscopic analysis has contributed to landslide detection, the advent of Earth Observation (EO) technologies has revolutionized landslide detection, shifting from localized, field-based methods to automated, multi-temporal, and global-scale analysis. EO platforms provide continuous monitoring, large-scale coverage, and high temporal resolution, allowing researchers to track terrain changes, assess risk factors, and develop predictive models. Since the launch of Landsat-1 in 1972 (Wulder et al. 2022), EO techniques have been recognized as powerful tools for landslide studies (Mantovani et al. 1996). Early EO applications relied on Landsat and SPOT imagery for landslide detection (Pohl and Van Genderen 1998). Today, a wide range of satellites, equipped with optical multispectral, SAR, and thermal sensors, offer complementary capabilities for landslide analysis. EO satellites operate in two primary orbits: polar and geostationary. Polar-orbiting satellites, operating at low altitudes (less than 1,000 km from the Earth's surface), offer high spatial resolution but lower temporal resolution. In contrast, geostationary satellites, positioned at approximately 36,000 km above Earth, provide high temporal resolution – capturing images at intervals of just a few minutes – albeit with lower spatial accuracy (Petropoulos et al. 2012). Many satellite platforms are equipped with multispectral and SAR sensors, which collect data across the visible, infrared, thermal, and microwave regions of the electromagnetic spectrum.

Key considerations in remote sensing for landslide detection include spatial resolution and revisit time. For instance, monitoring slow-moving landslides demands high accuracy, as small cumulative displacements over several months might otherwise go undetected. The integration of multiple EO sensors, such as optical and SAR, enhances landslide detection capabilities by combining surface change analysis, ground displacement monitoring, and environmental factor assessments.

Among satellite sensors, very-high-resolution (VHR) multispectral and SAR systems have become indispensable. VHR satellites can capture spatial resolutions between 0.3 and 1 m in panchromatic mode and 2.5 to 4 m in multispectral mode. For instance, the commercial satellite IKONOS provides a spatial resolution as fine as 0.75 m. Other examples include the WorldView series (Singla and Trivedi 2024), GeoEye, QuickBird-2 (launched in 2001), IKONOS-2 (launched in 1999), SPOT-5 (launched in 2002), and the Pléiades series. Temporal resolution also varies: IKONOS-2 collects data every three days, QuickBird-2 every 2–12 days, and SPOT-5 every 26 days. For example, Đurić et al. (2017) used Pléiades, WorldView-2, and SPOT-6 to detect landslides in Serbia. Combining sensors, such as Sentinel-2 A and 2B with Landsat-8 and 9, further reduces revisit intervals to 2–3 days (Li and Chen 2020), enhancing observation frequency (Refer to Table 1).

SAR pixels capture both the amplitude and phase of the backscattered signal from the Earth's surface. This principle forms the basis for Interferometric Synthetic Aperture Radar (InSAR). The data acquisition mode and sensor type used affect the spatial resolution of SAR images (Di Baldassarre et al. 2011). InSAR offers several advantages, including temporal repetitiveness (up to 6 days with Sentinel-1 images), the ability to operate in all weather and lighting conditions, coverage of inaccessible areas, and the possibility of analyzing phenomena dating back to 1992, when the C-band ERS 1 satellite first began data collection. These capabilities make InSAR a highly promising technology. Its application in studying natural phenomena began in the 1970s, with the first landslide detected using InSAR in 1999 (Solari et al. 2020).

Yang et al. (2024) developed an integrated framework that combines InSAR, clustering methods, and deep learning (Temporal Fusion Transformer - TFT) to enhance the accuracy and interpretability of landslide displacement prediction in Badui region in eastern Tibet. The proposed method was more successful compared to traditional methods. However, some environmental conditions, such as dense vegetation or steep terrain, reduced the accuracy of the measurements.

Table 1 Overview of key Earth observation satellites used in landslide studies.

Satellite	Sensor type	Spatial resolution	Repeat cycle	Example study
Landsat-8	Optical – multispectral (OLI) + thermal (TIRS)	15 m (Panchromatic) 30 m (Multispectral)	16 Days	(Chen et al. 2018, 2020; Mwaniki et al. 2017; Verdonen et al. 2020; Wen and Teo 2022)
SPOT-5	Optical – high-resolution imaging (HRG instrument)	< 3 (Panchromatic) 10 m (Multispectral)	26 Days	(Borghuis et al. 2007; Delacourt et al. 2009; Le Bivic et al. 2017; Verdonen et al. 2020)
Sentinel-2	Optical – multispectral (MSI)	10 m(Multispectral)	5 Days	(Bacha et al. 2022; Ghorbanzadeh et al. 2021; Shahabi et al. 2021)
WorldView 2&3	Optical – very high-resolution (PAN + MS)	WorldVeiw-3: 0.31 m (Panchromatic) 30 m (in the CAVIS bands) WorldVeiw-2: 0.41 m (Panchromatic) 1.64 m (Multispectral)	1 Day	(Bera et al. 2021; König et al. 2019; Kropáček et al. 2015; Verdonen et al. 2020)
IKONOS-2	Optical – high-resolution (PAN + MS)	1 m (Panchromatic) 4 m (Multispectral)	14 Days	(Deroin et al. 2017; Kouli et al. 2010; Kropáček et al. 2015)
Geo-Eye	Optical – high-resolution (PAN + MS)	0.41 m (Panchromatic) 1.64 m (Multispectral)	1.7 Days at 1-metre GSD resolution4.6 days at 25° off-nadir (0.59 m GSD)	(Bera et al. 2021; Deroin et al. 2017; Murillo-García et al. 2014)
QuickBird-2	Optical – high-resolution (PAN + MS)	0.61 m (Panchromatic) 2.44 m (Multispectral)	2.8 Days at 1-metre GSD resolution 1.5 days at 1.5-metre GSD resolution	(Verdonen et al. 2020)
Pléiades	Optical – very high-resolution (twin satellites)	0.5 (Panchromatic) 2 m (Multispectral)	26 Days	(Desrues et al. 2019; Lacroix et al. 2015; Stumpf et al. 2014)
ALOS-2	Radar – L-band SAR (PALSAR-2)	10 m	14 Days	(Adriano et al. 2020; Ge et al. 2019; Pour and Hashim 2017)
Sentinel-1	Radar – C-band SAR	5_40m	6–12 Days	(Mondini et al. 2019; Solari et al. 2018; Tzouvaras et al. 2020)
TerraSAR-X	Radar – X-band SAR	Up to 1 m	11 Days	(Bianchini et al. 2012; Haghshenas Haghighi and Motagh 2016; Motagh et al. 2013; Solari et al. 2018; Zhao et al. 2018)
RADARSAT-2	Radar – C-band SAR	3–100 m	24 Days	(Luo et al. 2016; Solari et al. 2018)

All satellite specifications (sensor type, Spatial resolution, and repeat cycle) were obtained from the European space agency's official website (https://www.esa.int/) as accessed on 12 March 2025. The listed references are a selection of studies demonstrating the application of these satellites in landslide research

The development of Differential InSAR (D-InSAR) techniques, which analyze pairs of radar images acquired by SAR sensors, has been a key advancement. D-InSAR can detect deformations ranging from millimeters to centimeters, making it ideal for monitoring slow-moving landslides over large areas (Fárová et al. 2019). However, D-InSAR faces challenges such as phase decorrelation, phase unwrapping errors, and atmospheric phase disturbances, which can compromise data quality (Fornaro et al. 2015). To address these issues, Multi-Temporal Interferometric SAR (MTInSAR) approaches have been developed (Niraj et al. 2022). By using data from multiple time periods within the same baseline, MTInSAR reduces atmospheric disturbances and unwrapping errors compared to traditional D-InSAR methods. This makes it highly valuable for landslide studies, providing millimeter-level accuracy along with medium-to-high temporal and spatial resolution (Delacourt et al. 2007). Each individual SAR acquisition can measure displacement with an accuracy of 1 to 3 mm. When phase decorrelation or loss of coherence complicates InSAR data, amplitude-based methods, which examine changes in speckle patterns between pre- and post-landslide events, can serve as effective alternatives. Combining phase and amplitude data offers a powerful approach for landslide investigation over broad areas.

In addition to radar data, optical sensors have also been successfully combined with radar data for landslide detection through techniques like image fusion and multi-sensor classification. Another pivotal technology is LiDAR, or laser scanning. Since the early 2000s, LiDAR has been invaluable for producing detailed topographic maps with high spatial resolution and accuracy (Carter et al. 2001). LiDAR allows for the acquisition of 3D terrain information with high accuracy and spatial resolution (Jaboyedoff et al. 2012). LiDAR sensors can collect more than 10,000 data points per second, from either fixed or mobile platforms. Depending on the sensor's position,

LiDAR can be airborne or ground-based. For example, Görüm (2019) used airborne LiDAR to detect landslides in a mixed forest environment in Ulus, Turkey. The study highlighted how even small, frequent landslides could be easily identified from vegetation-free LiDAR data, proving its utility in dense forested regions like Turkey's Black Sea areas. LiDAR's effectiveness is further enhanced when integrated with other technologies like SAR. Cai et al. (2022) demonstrated this by combining LiDAR and SAR data to detect slow-moving landslides in the Jiuzhaigou earthquake-affected area. By leveraging these advanced tools together, researchers can achieve greater accuracy and insight into landslide dynamics, ensuring more reliable detection and monitoring.

As an essential component of space-based remote sensing, Unmanned Aerial Vehicles (UAVs) have become increasingly valuable for landslide monitoring due to their high-resolution imaging capabilities and operational flexibility. UAVs can fly at low altitudes, collect high-resolution data, and operate under cloud cover, making them highly efficient. Ullo et al. (2021) introduced a comprehensive dataset for UAV-based landslide detection. Lu et al. (2020) demonstrated the utility of UAVs in detecting landslides in Sichuan Province, China. UAVs provide rapid, localized assessments and complement satellite-based monitoring. Technological advancements have also led to the development of pansharpening algorithms that enhance the spatial resolution of multispectral images by integrating higher-resolution panchromatic images (Choi et al. 2019). However, care must be taken as such integration can sometimes alter image characteristics. Furthermore, UAVs' performance can be adversely affected by extreme weather conditions following an earthquake, limiting their observational efficiency and coverage (Chen et al. 2024).

Ground-based remote sensing

In addition to satellites, ground-based geospatial techniques such as ground-based interferometry, Doppler radar, and LiDAR have proven highly effective for monitoring and detecting landslides. These methods are particularly well-suited for focusing on specific slopes over both short and long periods. One notable technique is Ground-Based SAR (GBSAR), a terrestrial radar imaging system that allows for real-time monitoring of landslide-prone areas. GBSAR interferometry, developed later, had its first application in landslide monitoring in 2003 (Pieraccini and Miccinesi 2019). Operating in the "Ku" frequency band, GBSAR is highly sensitive to even the smallest deformations, detecting movements ranging from sub-millimeter to millimeter scale (Karunathilake et al. 2019). With the ability to capture data at intervals as short as 10 s, GBSAR provides an excellent tool for real-time landslide monitoring and early warning systems. For instance, Karunathilake et al. (2019) used GBSAR to continuously monitor mountainous terrain at a road reconstruction site in Minami-Aso, Kumamoto, Japan. The method was designed to be comprehensible to both experts and non-experts, making it accessible and affordable for a variety of scientific and industrial applications. However, the study also highlighted areas for improvement, such as challenges in estimating landslide movement direction due to the slope's aspect angle and inaccuracies in displacement measurements in forested areas, caused by interference from tree canopies.

In Austria, a GBSAR system was deployed to monitor landslide-induced deformations with high spatial and temporal resolution, successfully identifying a slowly deforming upper scarp and a rapidly evolving debris accumulation zone (Leva et al. 2003). This study demonstrated GBSAR's capability in tracking progressive slope failures and emphasized its cost-effectiveness as a complementary technique to spaceborne SAR and traditional geodetic instruments, particularly in inaccessible regions.

Traditional GBSAR methods face challenges in real-time processing of high-frequency, continuous deformation data. To address this, Xiang et al. (2023) developed a novel real-time processing method utilizing a dynamic Kalman filter based on the Permanent Scatterer (PS) network. This approach enables instantaneous radar image processing, ensuring high accuracy in deformation monitoring. Another key limitation of GBSAR is that it is used for monitoring landslide deformations in small areas, such as localized mountainous regions and mining sites. Consequently, for large-scale assessments of Earthquake-Triggered Landslides (ETLs) as secondary hazards of seismic events, the use of spaceborne SAR imagery becomes essential (Chen et al. 2024).

Similarly, Doppler radar offers real-time, long-range, wide-area detection of rockfalls and related slope hazards. Carlà et al. (2024) emphasized the effectiveness of Doppler radar for tracking slope instability. For example, Schneider et al. (2023) used Doppler radar to monitor rockfalls from an active landslide complex in Brienz/Brinzauls, Swiss Alps, from January 2018 to October 2022. The system not only proved reliable for real-time monitoring but also functioned as an automatic traffic control mechanism, closing a major road in response to 166 recorded rockfall incidents during the study period.

Ground-based LiDAR is another indispensable tool in landslide detection. Ju et al. (2023) employed LiDAR to analyze 1,326 small-scale shallow landslides in Hong Kong by comparing high-resolution LiDAR datasets collected before and after the events. The study demonstrated LiDAR's capacity for detailed terrain analysis and landslide detection. Jaboyedoff et al. (2018) provide a comprehensive review of LiDAR systems, detailing their applications and advantages.

When selecting a remote sensing technique, there is no single method that is universally better than others. The most suitable approach depends on factors specific to each landslide scenario, such as the type of landslide, the size of the area being monitored, the distance involved, and the geomechanical properties of the region. Key considerations also include spatial resolution, data acquisition frequency, accuracy, and the velocity of detectable movements. Many remote sensing datasets can be accessed through platforms like Google Earth Engine (GEE), the United States Geological Survey (USGS) Earth Explorer, and Copernicus, providing valuable resources for landslide monitoring and analysis.

Mobile GIS

Significant advancements in digital mapping and mobile GIS have revolutionized landslide hazard and risk data acquisition, particularly with the increasing availability of open-source geospatial technologies (Olyazadeh et al. 2017). These innovations have enabled more efficient, accurate, and flexible data collection and analysis in the field of natural hazard management, including landslide monitoring and risk assessment. One prominent example of this progress is the British Geological Survey's (BGS) digital field mapping system, BGS-SIGMA mobile, launched in 2013 (Bricker et al. 2022). This system integrates a customized version of ArcMap 10, a leading GIS software, with Microsoft Access 2007, to create a robust platform for both mobile and desktop use. The BGS-SIGMA system is tailored specifically to meet the needs of geologists and field scientists, offering a seamless workflow between data collection in the field and subsequent data analysis and interpretation.

The system is equipped with two customized toolbars: one designed for mobile data collection and the other for desktop-based data processing. The mobile toolbar is optimized for use with tablet PCs that are equipped with GPS functionality, allowing field scientists to gather geospatial data efficiently in real-time. This capability is particularly useful in remote or hazardous areas where landslides are more likely to occur, as it enables the collection of high-precision location data and field observations that are critical for accurate hazard assessment (Bricker et al. 2022).

The desktop toolbar, on the other hand, is designed for post-fieldwork analysis. It facilitates data interpretation, quality assurance, and the creation of finalized datasets for integration into larger geospatial databases. This allows for the generation of high-quality maps and reports that can be used for hazard modeling, risk assessment, and decision-making processes.

The integration of ArcMap and Microsoft Access in the BGS-SIGMA system enhances data management capabilities, ensuring that data collected in the field can be easily organized, stored, and retrieved for future analysis. Furthermore, by supporting both field-based data collection and desktop analysis, BGS-SIGMA mobile provides a comprehensive solution that bridges the gap between on-site observations and the analytical needs of researchers and policymakers (Jordan and Napier 2016).

This system exemplifies the growing trend towards digital and mobile GIS solutions in geosciences, contributing to more effective and responsive hazard monitoring. By leveraging open-source and customizable tools, BGS-SIGMA mobile allows for greater adaptability to the specific needs of different geological surveys, making it a valuable asset in landslide hazard management.

Beyond proprietary systems like BGS-SIGMA, open-source mobile GIS platforms such as QField for QGIS have become increasingly valuable in landslide monitoring and geohazard assessment. These tools enable efficient field data collection, real-time geospatial visualization, and seamless integration with desktop GIS environments. For example, in a recent study, Acosta-Quesada and Quesada-Román (2024) employed QField alongside QGIS to facilitate real-time access to geospatial layers during fieldwork in Santa Ana, Costa Rica. This integration allowed researchers to cross-reference landslide and flood hazard zones with morphogenetic data, enhancing the accuracy of hazard mapping. QField not only improves the reliability of hazard assessments but also strengthens risk management efforts by supporting more informed land-use and mitigation strategies.

While mobile GIS platforms improve field-based hazard assessment, advanced remote sensing techniques, particularly LiDAR processing software, further enhance landslide detection and terrain analysis. Applications such as LAStools, CloudCompare, and QGIS-PDAL enable field scientists to process LiDAR-derived point clouds efficiently, assess slope stability, detect topographic changes, and refine hazard maps on-site. Sestras et al. (2025) developed a novel approach for landslide monitoring by integrating UAV photogrammetry and LiDAR data using specialized LiDAR software, point cloud analysis (CloudCompare), and GIS tools. Their methodology enhances the accuracy and reliability of terrain deformation analysis by optimizing the mapping strengths of both photogrammetry and LiDAR technologies.

Data processing

Traditional image processing approaches

After capturing and collecting raw data from various sources, pre-processing steps such as reducing speckle noise, orthoimaging, image mosaicking, image composition, and cloud removal are often required (Konishi and Suga 2018). Once pre-processed, the data becomes suitable for landslide extraction. Satellite data analysis

techniques for image processing can be grouped into the following categories: change detection, pixel-based indexing, object-based segmentation, displacement measurement, and AI-based methods (Novellino et al. 2024).

Change detection (CD) This technique, which compares pre- and post-event images, was commonly used in the 2000s and 2010s. While effective in identifying landscape alterations, this method is time-consuming and dependent on the availability of high-resolution pre-event imagery, which is often lacking in many regions(Li et al. 2016a, b). Landslides often involve a mix of materials (e.g., weathered volcanic rock, soil, grass), making their boundaries difficult to detect.
To overcome these challenges, Li et al. (2016a, b) proposed a Change Detection based Markov Random Field (CDMRF) method, which improves detection but still faces issues such as over- and under-detection, highlighting the limitations of relying solely on CD techniques.

Indexing (Pixel-Based) Traditionally, classification was achieved using pixel-based methods like the Maximum Likelihood Classifier (MLC). These techniques include both manual and automatic thresholding methods, and are sensitive to user-defined parameters. Borghuis et al. (2007) compared supervised and unsupervised classifications of SPOT-5 imagery with manual delineation and found that automated methods tended to overestimate landslide areas due to spectral similarities with surrounding features. Unsupervised classification showed better agreement with manual mapping, but the approach remains prone to inaccuracies.

Segmentation (Object-Based) Segmentation techniques are an alternative to pixel-based methods, using image objects rather than individual pixels as the basic analysis units. With the rise of high-resolution imagery, object-based algorithms have improved landslide mapping by integrating spectral, spatial, and contextual features (Keyport et al. 2018). Studies by Saba et al. (2023) and Hölbling et al. (2012) demonstrated that Object-Based Image Analysis (OBIA) provides greater spatial consistency than traditional pixel-based approaches. Multi-resolution segmentation has proven to be a successful approach in various applications (Duan et al. 2020; Ghorbanzadeh et al. 2023; Lu et al. 2024). However, its effectiveness can be limited by site-specific characteristics and manual thresholding.
Li et al. (2015) demonstrated that OBIA outperformed pixel-based methods by producing more contiguous terrain segments, reducing computational time, and better representing real-world landslide features.

Similarly, Moosavi et al. (2014) that the object-oriented approach significantly surpassed pixel-based classification, primarily due to its ability to integrate both spectral and geometric attributes, thereby reducing spectral variance and enhancing accuracy. **Displacement Measurements**: Techniques such as InSAR and Pixel Offset Tracking (POT) offer wide-area coverage and precise measurement capabilities, providing detailed information on ground surface deformations (Wasowski and Bovenga 2014). However, both techniques face challenges in capturing full 3D displacements, particularly for complex landslides—InSAR being less sensitive to north-south motion, and POT limited in detecting non-rigid deformations (Hu et al. 2018; Weinzaepfel et al. 2013).

To address these limitations; Chen et al. (2025) proposed an integrated framework combining SAR and optical data via the Flight Path Management and Digital Flight (FPM-DF) method, enabling improved 3D displacement mapping and offering a more complete understanding of landslide kinematics.

AI-Based approaches

Recent developments in AI have significantly improved landslide detection accuracy and efficiency. The integration of AI technologies, remote sensing and geospatial datasets, has facilitated more accurate and automated approaches to landslide detection and susceptibility assessment (Li et al. 2024). AI techniques for landslide mapping involve training data-driven models on a wide range of parameters. Among AI methodologies, ML and Deep learning (DL) are the most widely used AI methods for landslide extraction. Mohan et al. (2021) reviewed the role of ML and DL in landslide detection from remote sensing data. Traditional ML methods like Support Vector Machine (SVM) and Decision Trees struggle with the spatial complexity and uncertainty of landslides (Lei et al. 2019). DL, a subset of ML, offers improved performance in image classification, object detection, and change detection, with multiple layers of data abstraction from lower to higher levels (Längkvist et al. 2016).

Ghorbanzadeh et al. (2019) conducted a comparative study of ML and Convolutional Neural Network (CNN) methods for landslide detection in Nepal's Rasuwa district. Their findings revealed that DL approaches, such as CNNs, require less human supervision than traditional methods, making them highly adaptable to various regions when retrained with new data. This advantage highlights the growing importance of DL in the field of landslide detection, particularly in regions with diverse environmental conditions. Similarly, Ye et al. (2019) demonstrated the effectiveness of a DL framework for detecting landslides in hyperspectral images, achieving superior accuracy compared to conventional classification techniques. These studies underscore the potential of DL in enhancing the precision and efficiency of landslide detection, particularly in remote sensing applications.

Several innovative DL models have been proposed to address specific challenges in landslide detection. Lei et al. (2019), for instance, introduced a Fully Convolutional Network with Pyramid Pooling (FCN-PP), which efficiently balances a wide receptive field with contextual information, overcoming the limitations of global pooling in CNN, FCN, and U-Net models. In another advancement, Liu et al. (2020) developed an improved U-Net model, which outperformed the standard U-Net by 13.8% in terms of accuracy for post-earthquake landslide detection in China. Similarly, Niu et al. (2022) introduced the Reg-SA-UNet++model, an enhanced version of UNet++, while Zhang et al. (2023) proposed the Re-Net model, which integrates multi-scale information through a multi-branch structure. These innovations mark significant progress in the application of DL for landslide detection, with each model contributing to improved accuracy and contextual understanding. Semantic segmentation models, particularly U-Net, have been among the most widely used DL approaches for landslide detection, especially between 2019 and 2023 (Chandra and Vaidya 2024).

Recently, Chen et al. (2024) developed the BisDeNet framework, a DL model that stands out for its strong feature extraction capabilities, low parameter requirements, and low model complexity. This development highlights the ongoing efforts to streamline DL architectures for landslide detection without compromising performance. Additionally, Ma et al. (2019) demonstrated the effectiveness of combining CNNs with Sparse Autoencoders (SAE) for preprocessing remote sensing images and image fusion, further expanding the toolkit for landslide detection. To address the inefficiencies of traditional manual landslide detection in large-scale InSAR datasets, Ma et al. (2025) introduced InSAR-YOLOv8, an enhanced deep-learning object detection algorithm specifically designed for automatic landslide identification from wide-area InSAR measurements. Their results demonstrated that InSAR-YOLOv8 outperforms existing methods, including Faster R-CNN, RTMDet, Double-Head-Faster-RCNN, YOLOv3, Nas-FCOS, and YOLOvX, by achieving higher accuracy, improved efficiency, and reduced computational complexity. Notably, the model excels in detecting small-scale landslides while maintaining robust performance with fewer computational resources.

Unlike traditional change detection methods, many of these advanced techniques are capable of operating solely with post-event data, eliminating the need for pre-event imagery. This flexibility makes them particularly useful in regions where pre-event data may be limited or unavailable. These advancements in deep learning form the foundation for further analysis in landslide susceptibility modeling, risk assessment, and the development of early warning systems, which will be discussed in the following sections.

Landslide analysis

Landslide analysis is critical for understanding and mitigating the impacts of landslide hazards, which are influenced by a range of geological, hydrological, and anthropogenic factors (Galve et al. 2016). This analysis typically focuses on three main aspects: susceptibility, vulnerability, and risk (Zhou et al. 2024). Susceptibility analysis identifies areas prone to landslides by assessing the influence of terrain factors such as slope, soil type, and land cover. Vulnerability analysis evaluates the potential impacts on communities, infrastructure, and the environment, considering factors like physical exposure, socioeconomic conditions, and resilience capacities. Risk analysis integrates susceptibility and vulnerability to estimate the potential losses and damages that could result from landslide events (Fig. 4 illustrates the key factors influencing each component).

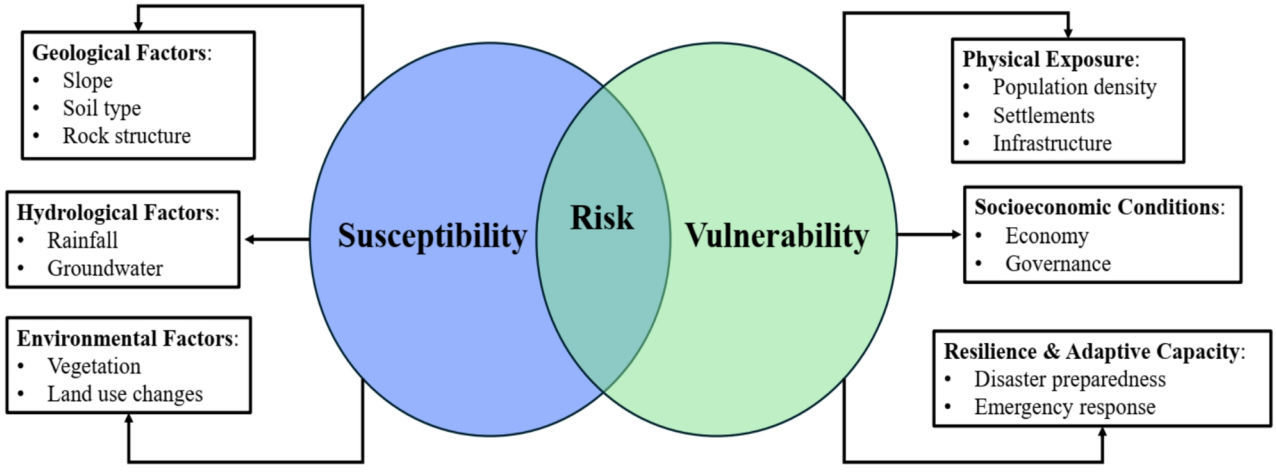


Fig. 4 Conceptual framework illustrates the relationship between landslide susceptibility, vulnerability, and risk

Landslide Susceptibility refers to the likelihood of an area experiencing landslides. Susceptibility maps, especially when combined with predictive models, are crucial for assessing hazard potential and forecasting future events. These tools are essential in supporting early warning systems (Yordanov et al. 2021).

Vulnerability is a critical component of risk assessment and helps in predicting the potential consequences of landslides. The United Nations Office for Disaster Risk Reduction (UNISDR) defines vulnerability as "the degree to which someone or something can be affected by a particular hazard, depending on various factors and processes" including physical exposure, economic and social characteristics, and personal well-being (UNISDR, 2016). Estimating vulnerability is fundamental for accurately predicting the impacts of landslides (Singh et al. 2017).

Risk, as defined by the UNISDR, is "the probability of harmful consequences or expected losses (such as deaths, injuries, property damage, disrupted livelihoods, economic activities, or environmental damage) resulting from the interaction between natural or human-induced hazards and vulnerable populations" (UNDRR 2010). Risk combines three main components: hazard, exposure of elements at risk, and vulnerability, as outlined by (Varnes 1984).

These three aspects – susceptibility, vulnerability, and risk are interrelated and form the foundation for assessing landslide hazards and developing strategies for mitigation and management. The relationship among these components can be mathematically expressed as:

$R = H \times E \times V$ (Eq. 1).

where R represents Risk, H is Hazard, E denotes Elements at risk, and V is Vulnerability, as shown in Eq. (1).

Landslide susceptibility mapping

Landslide susceptibility mapping has evolved significantly since early foundational studies by Brabb et al. (1972) in California and Carrara et al. (1977) in Italy. These pioneering works provided key insights into identifying landslide-prone areas and laid the groundwork for modern approaches. Over time, susceptibility mapping has advanced through the integration of diverse data sources and technological innovations, enabling more accurate and scalable assessments.

Qualitative methods evaluate the potential for landslides using expert judgment and heuristic knowledge (Sarkar and Anbalagan 2008). They often involve assessing historical landslide occurrences, field observations, and understanding of terrain features to subjectively identify susceptible areas. These approaches are straightforward but may lack reproducibility and objectivity due to their reliance on expert opinions (Dahl et al. 2010).

In contrast to qualitative approaches, quantitative methods are data-driven and apply statistical or mathematical models to assess relationships between landslide occurrences and conditioning factors such as slope, geology, rainfall, and land use(Gómez and Kavzoglu 2005). These methods include Logistic Regression (LR), machine learning (ML) algorithms, and probabilistic frameworks, offering greater objectivity and predictive accuracy, particularly when combined with high-resolution geospatial data and advanced computational tools. The most widely used quantitative approaches, statistical, heuristic, and geotechnical models, are illustrated in Fig. 5 (Den Eeckhaut et al. 2010). Statistical models are generally preferred over heuristic ones for their consistency and replicability(Guzzetti et al. 1999),. Quantitative approaches are often categorized into multivariate and bivariate methods. Common multivariate methods include (Ayalew and Yamagishi 2005; Budimir et al. 2015) and principal component analysis (PCA) (Ahmed and Dewan 2017). On the other hand, bivariate methods such as the Frequency Ratio (FR), Evidential Belief Functions (EBF) (Althuwaynee et al. 2012), and Weights-of-Evidence (WoE) are also frequently employed for landslide susceptibility mapping. These statistical techniques help quantify the correlation between different factors (e.g., slope, soil type) and landslide occurrences, making them robust tools for generating reliable susceptibility maps.

Over the past 20 years, simple ML algorithms have been increasingly applied to landslide susceptibility modeling (Yordanov et al. 2021). Initially prominent in domains like computer vision and natural language processing, ML has more recently been adopted in geoscience applications(Reichstein et al. 2019). ML methods analyze complex data relationships to generate accurate, repeatable predictions. Commonly applied algorithms include Artificial Neural Networks (ANN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), Naive Bayes (NB), and Multilayer Perceptron (MLP), with SVM, DT, and RF achieving prediction accuracies exceeding 90% (Merghadi et al. 2020). Additionally, studies have shown that DT and RF models offer high accuracy and stability in landslide susceptibility predictions, which is vital for effective hazard management (Daud et al. 2025; Dou et al. 2019). spite their strength, basic ML models face limitations; for example, NB and Bayesian networks showed differing results in Korea due to independence assumptions (Lee et al. 2020) Other techniques, such as Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA), have also been employed(Pham and Prakash 2017; Wang et al. 2020),, although they too have modeling constraints. As research progresses, there has been a notable shift toward more sophisticated models, including DL and ensemble learning methods. DL, a subdiscipline of ML, enhances traditional (ANNs by employing multilayer deep neural networks that progressively extract features from raw

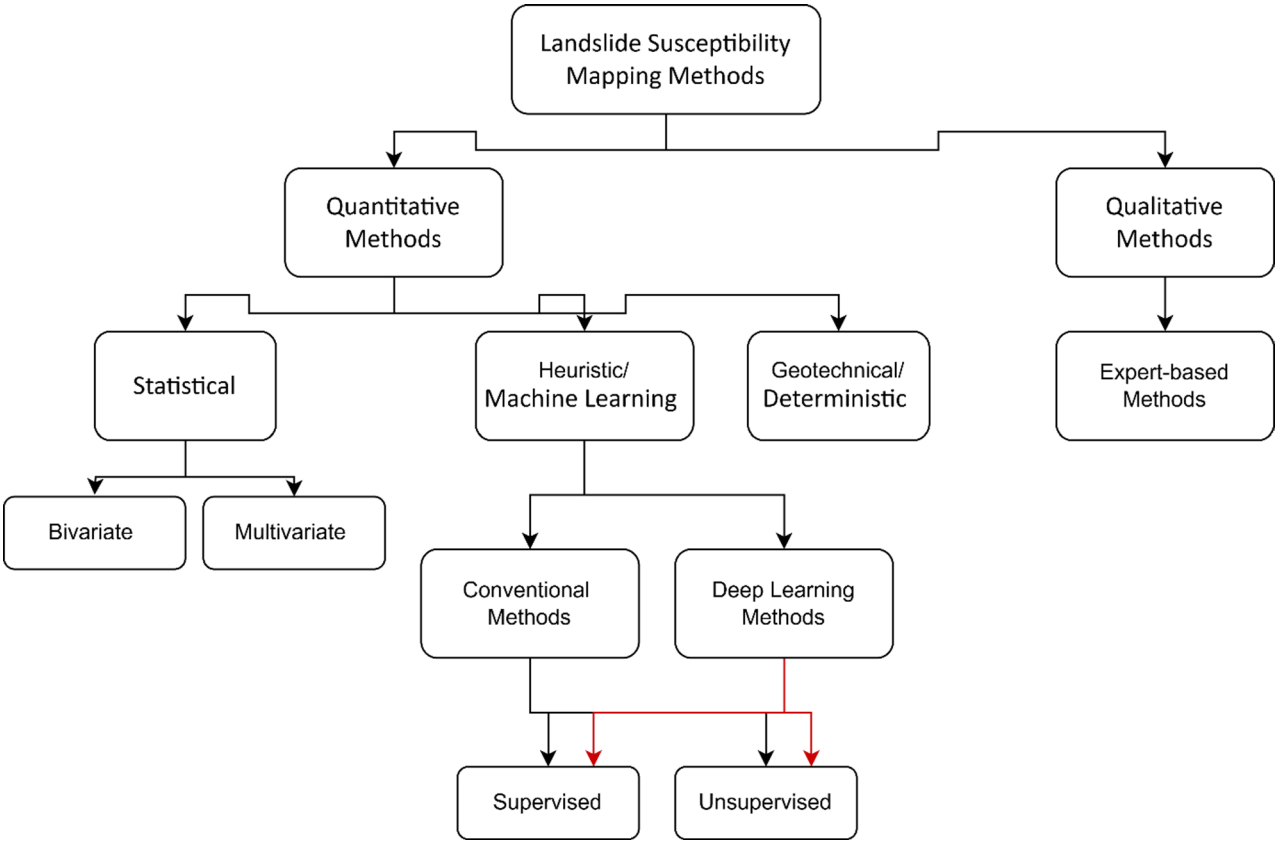


Fig. 5 Classification of landslide susceptibility mapping methods, broadly categorized into qualitative and quantitative approaches

input data. Unlike traditional ANNs, DL models operate on a larger scale and complexity, with architectures such as CNNs (e.g., VGGNet, ResNet, Inception, DenseNet), being prominent in supervised learning tasks. In contrast, unsupervised DL techniques train each layer independently using outputs from previously trained layers.

Recent advancements highlight the application of deep learning methods in landslide susceptibility mapping (Dou et al. 2021). For example, Azarafza et al. (2021) developed a CNN-DNN model in Isfahan, Iran, while RNNs have shown even higher performance in similar applications across the country. These advancements reflect the growing trend of adopting DL to improve prediction accuracy and capture intricate spatial patterns. Recent studies also highlight that deep learning models, particularly DNNs, maintain high predictive accuracy regardless of the landslide sampling strategy used (Dou et al. 2020).

In addition to traditional and advanced ML methods, Web-GIS-based approaches offer valuable tools for mapping susceptible zones. For example, Acharya et al. (2015) introduced a conceptual framework for a GIS-based Web Landslide Susceptibility Information System (WebLSIS) tailored for Nepal's hilly regions. This system featured a client-facing website that enabled users to input landslide data and visualize hazard levels. On the server side, it integrated a GIS system and database for processing data and publishing maps, providing an interactive platform for landslide risk assessment.

A critical aspect of susceptibility mapping is the selection of conditioning factors, which lacks standardized global guidelines (Shahabi et al. 2012). The choice of variables depends on the study area's scale, terrain, landslide type, and failure mechanisms (Yordanov et al. 2021). This variability contributes to the absence of global standards in landslide susceptibility mapping. To address this, Reichenbach et al. (2018) categorized landslide conditioning factors into five thematic groups: morphological, land cover, geological, hydrological, and others (e.g., precipitation). Additionally,. van Westen et al. (2008) provided a comprehensive schematic of the essential datasets required for landslide susceptibility, hazard, and risk assessments.

Data preparation remains a cornerstone of landslide modeling, with geospatial technologies playing a central role. Digital Elevation Models (DEMs) derived from sources such as SRTM, ASTER, ALOS, and LiDAR are essential for analyzing terrain influences. Microwave remote sensing supports moisture estimation through land surface emissivity, using sensors like AMSR-E,

ASCAT, RADARSAT, and WindSAT (Mohanty et al. 2017).

Vegetation indices, particularly NDVI, derived from multispectral sensors, are also widely used. High-resolution platforms such as WorldView-3, LiDAR, and IKONOS offer detailed inputs for improving susceptibility assessments (Chen et al. 2022).

Landslide vulnerability and risk mapping

Implementing techniques to reduce geological risks and natural vulnerabilities is crucial for developing disaster prevention and mitigation strategies across various scales. One area where geospatial technologies have proven particularly effective is in landslide vulnerability assessment, a process that begins with comprehensive data collection and preparation (Kannan et al. 2013). The role of geospatial technology is most prominent in creating spatial thematic layers, which are essential for vulnerability and risk analysis, using image processing and GIS tools.

For instance, Malaysia's landslide statistics highlight the urgency of such efforts. Between 2007 and March 2016, Malaysia recorded 171 landslides, placing it 10th globally for landslide frequency (Nor Diana et al. 2021). In a study, socioeconomic vulnerability factors were reviewed to identify the key elements critical for vulnerability analysis. These factors – ranging from population demographics to physical environmental conditions – serve as essential inputs for determining the vulnerability of landslide-prone areas. Variables such as population density, age, gender, income, and building height, as well as physical factors like slope, proximity to rivers, and land use, provide a robust framework for assessing vulnerability.

Each of these vulnerability factors possesses distinct spatial, temporal, and thematic characteristics, all of which need to be accounted for during the assessment process. For instance, proximity to rivers is a key factor in landslide vulnerability and can be determined using DEMs and GIS tools like Euclidean distance analysis (Saleem et al. 2019). Similarly, land use/land cover data can be extracted from various geospatial resources, such as aerial photographs or satellite imagery, including IRS-1 C LISS III (Kannan et al. 2013), SPOT (Balcik and Kuzucu 2016), Landsat (Alam et al. 2020), and more advanced platforms like Sentinel (Karra et al. 2021). Other geospatial tools, such as LiDAR, can be used to generate building height data, while runoff maps can be developed using information on soil, slope, rainfall, and land use (Chan et al. 2018).

As previously mentioned, risk assessment follows once the hazard and vulnerability levels have been established. Early reviews on GIS applications for risk assessment conducted by Wadge et al. (1993) and Coppock (1995), highlighted the importance of using these technologies to process and analyze complex datasets. The advancement of geospatial science has revolutionized quantitative landslide risk assessment, making it possible to handle the large volumes of multidisciplinary data required. Today, these capabilities allow the effective communication of risk information to a broad audience, supporting planning and decision-making at multiple levels. Furthermore, tools like the Geo-Information Tools for Landslide Risk Assessment (Van Westen 2004) have become integral in this field, facilitating more precise and comprehensive risk evaluations.

The integration of geospatial technologies in landslide vulnerability and risk assessment has significantly improved our ability to manage natural hazards. By leveraging multidisciplinary data, GIS tools enable more precise, data-driven strategies that can be implemented to reduce landslide risk and enhance disaster preparedness.

Empirical dimension

Experimental methods have been widely used in numerous aspects of landslide studies, especially in predicting their occurrence. In particular, the likelihood of a landslide can be determined by three methods, including theoretical (Wan and Xue 2023), empirical (Qiu et al. 2018), and computer simulations (Zhao et al. 2020). Theoretical methods rely on such parameters as coefficient of friction and velocity values, which are usually hard to calculate accurately, and therefore incomplete data leads to unreliable prediction outputs (Hungr et al. 2005). In contrast, computer simulations are generally very sensitive to input variables, especially if the dataset is big, and therefore it can influence the predictive capabilities of the model (McDougall and Hungr 2005). Because of these limitations, both methods require simplifying the assumptions, especially when field measurements are not accurate. Regarding the empirical methods, these are considered to be more reliable, as they do not include complex input data and allow for estimating landslide travel distance straightforwardly. For example, in the study of Guo et al. (2014), such an empirical model was developed for landslide travel distance estimation based on a prediction algorithm. It was done using real data from the Wenchuan earthquake region. The results showed that, unlike previously developed theoretical models, this one was capable of producing substantially better outcomes.

Another example of using the empirical-statistical methods was shown in the study of (Hungr 2010) on the landslide dam formation. Fan et al. (2014) also suggested the same methodological approach to calculate the landslide dam formation using Digital Elevation Models (DEMs) caused directly by the seismic event. This model is based on the principle of using the past landslides as a base to predict the future possible events by assuming that the main features of landslides are constant

and remain unchanged. However, this assumption was opposed by another study. Thus, according to Corominas and Moya (2008), such parameters as slope and factors such as earthquake triggering mechanisms both lead to dynamical changes in rocks; moreover, climatic factors as well as land use changes can also lead to dynamic shifts and therefore must be considered in the model.

Empirical methods are also widely used to estimate specific parameters or features that support the prediction of landslide occurrence instead of direct estimation of its events. For example, Huang et al. (2015) utilized both empirical and probabilistic methods to determine the landslide extremes for a particular region – the Huangshan region of Anhui Province in China. The results proved that one of the benefits of such an approach is that it can easily handle limited precipitation datasets, such as accumulated or hourly rainfall values, that are very typical in field measurements. As a result, four different emergency levels were estimated, including zero level, outlook level, attention level, and warning level, using threshold values from probability functions. Therefore, it was proved that empirical models can significantly improve the existing early warning systems in an easier and more reliable way, allowing for risk mitigation, especially in mountainous regions.

Several studies have focused on ensemble empirical methods to improve the performance of existing experimental models (Du et al. 2020). For example, Peruzzetto et al. (2020) used the combination of computer and empirical models to detect landslide occurrence in Martinique, France. The combination of these two methods allowed us to decrease the uncertainty and prediction errors by more than 50% compared to empirical models used alone. The only limitation generally noticed is that these models do not account for such factors as further earthquakes or intensive rain (Sidle and Ochiai 2007). However, these limitations have been addressed by Goetz et al. (2011), in their study they proposed to merge the empirical models with physical models to account for such parameters as slope stability and other topographical features.

Dou et al. (2025) demonstrated the effectiveness of integrating D-InSAR, UAV imagery, and airborne LiDAR for assessing co-seismic surface deformation caused by the 2025 Xigaze earthquake. This multi-sensor fusion approach successfully delineated co-seismic displacement patterns and enhanced the mapping of surface ruptures. The study underscores the potential of combined remote sensing techniques for improving post-earthquake hazard assessment, forecasting secondary disasters, and guiding reconstruction planning.

Empirical models have been proven to be useful, especially when there is a lack of input data (Safaei et al. 2011). Their simplicity (Sarfraz et al. 2022) and low cost (Segoni et al. 2022), however, allow for the production of rapid hazard maps despite the limitations, like triggering effects or dynamic landslide monitoring. Instead, they are usually suitable to catch the location of landslides rather than the period when they may occur (Goetz et al. 2011; Ye et al. 2025).

Spatiotemporal and bibliometric analysis of landslide studies

Figure 6 shows the percentage of susceptibly, vulnerability and risk publications over 2000–2025 according to subject area. Earth and Planetary Sciences contributed the highest percentage of publications in all three categories, with approximately 36% for susceptibility, 35.3% for risk, and 28.5% for vulnerability. This is followed by Environmental Science (22.2%, 18.3%, and 26%, respectively) and Social Sciences, which also showed notable contributions, particularly in the vulnerability domain (10%). Other fields such as Computer Science, Engineering, and Agricultural and Biological Sciences also had moderate percentages, highlighting the interdisciplinary nature of landslide research.

Figures 7 and 8 present the number of publications and citations related to landslide susceptibility, vulnerability, and risk from 2000 to 2025. The data indicate that research on landslide susceptibility has the highest number of publications and citations, with a sharp peak in 2024 (145 publications), followed by high outputs in 2023 (116) and 2022 (122). This increase can be attributed to advancements in remote sensing, GIS, and ML techniques, which have enabled more precise landslide susceptibility and risk assessments. Risk-related publications also increased steadily, peaking at 92 in 2023, while vulnerability-related studies remain significantly lower, never exceeding 23 publications (2016). The lower number of vulnerability studies highlights a research gap in assessing the social, economic, and infrastructure impacts of landslides. However, a notable increase in publications on landslide vulnerability is evident in 2016.

In Fig. 9, maps were constructed using bibliometric software named VOSviewer. Each circle corresponds to the particular keyword and the size of a circle shows its frequency. For example, in "Keywords occurrence sustainability": we made search in Scopus regarding the landslides sustainability, subsequently downloaded all the keywords from all articles we found on this topic. From analysis, it is seen that the most frequently used keyword is "GIS", so we can stay that susceptibility was mostly done using GIS techniques.

According to Fig. 10, the spatial distribution of landslide susceptibility studies highlights a strong research focus in China, with 356 studies ($n = 356$). India follows with ($n = 222$) publications, while Italy ($n = 86$) and South Korea ($n = 77$) have also made substantial contributions.

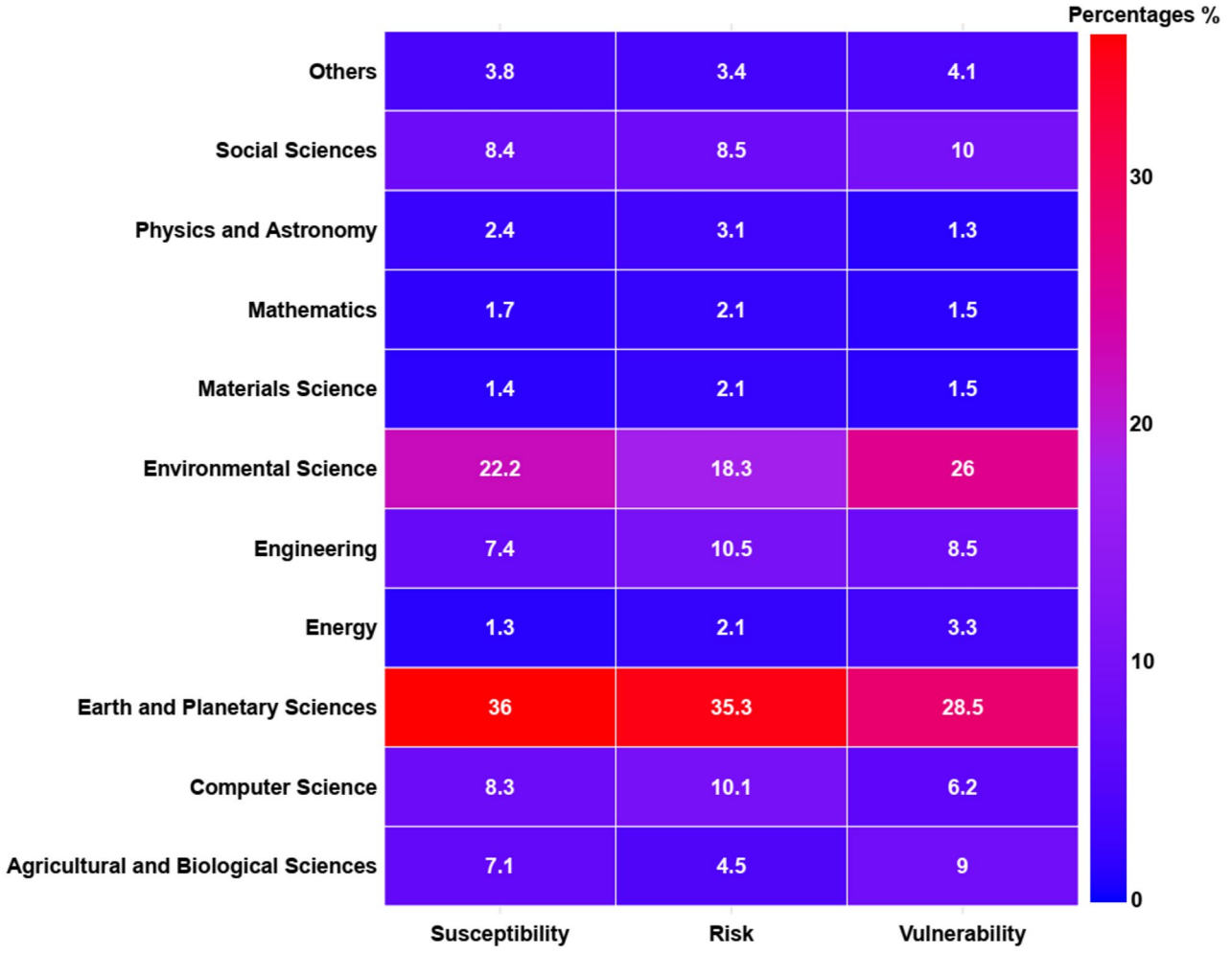


Fig. 6 Heatmap representation of the percentage of publications related to landslide susceptibility, vulnerability, and risk across different subject areas between 2000 and 2025

Other countries with moderate research output include Turkey ($n = 72$), Iran ($n = 69$), the United States ($n = 61$), and Malaysia ($n = 51$).Landslide vulnerability research remains significantly underrepresented compared to susceptibility studies, with the highest number of publications originating from India ($n = 46$), China ($n = 20$), and Italy ($n = 17$). The overall volume of research on vulnerability assessment is relatively low, with most nations producing fewer than 10 studies over the 24-year period. The distribution of landslide risk studies follows a pattern similar to susceptibility and research, with China ($n = 218$), Italy ($n = 132$), India ($n = 95$), and the United States ($n = 41$) leading in publication output. Other countries such as Malaysia ($n = 32$), and Turkey ($n = 30$), also contribute moderately. However, risk assessments remain less prevalent compared to susceptibility studies, with the majority of countries reporting fewer than 20 studies.

Landslide management

Landslide management encompasses several key stages, including prediction and early warning, prevention, mitigation, preparedness, response and rescue, relief and recovery, and damage assessment. In recent years, the need for ICT-based strategies and tools to assist decision-makers in disaster preparedness and response has been increasingly recognized (Albano and Sole 2018). Furthermore, the growing demand for flexible and adaptive solutions has highlighted the importance of fostering collaboration among public agencies, private organizations, nonprofits, and communities (Mitsova 2019).

Geospatial technology plays a critical role in all phases of disaster management, from early-warning planning to resource distribution during recovery, developing preparedness solutions, and prioritizing response efforts. A key element in landslide management is the communication network, with space technology applications offering significant support. By integrating remote sensing with communication satellites, effective emergency

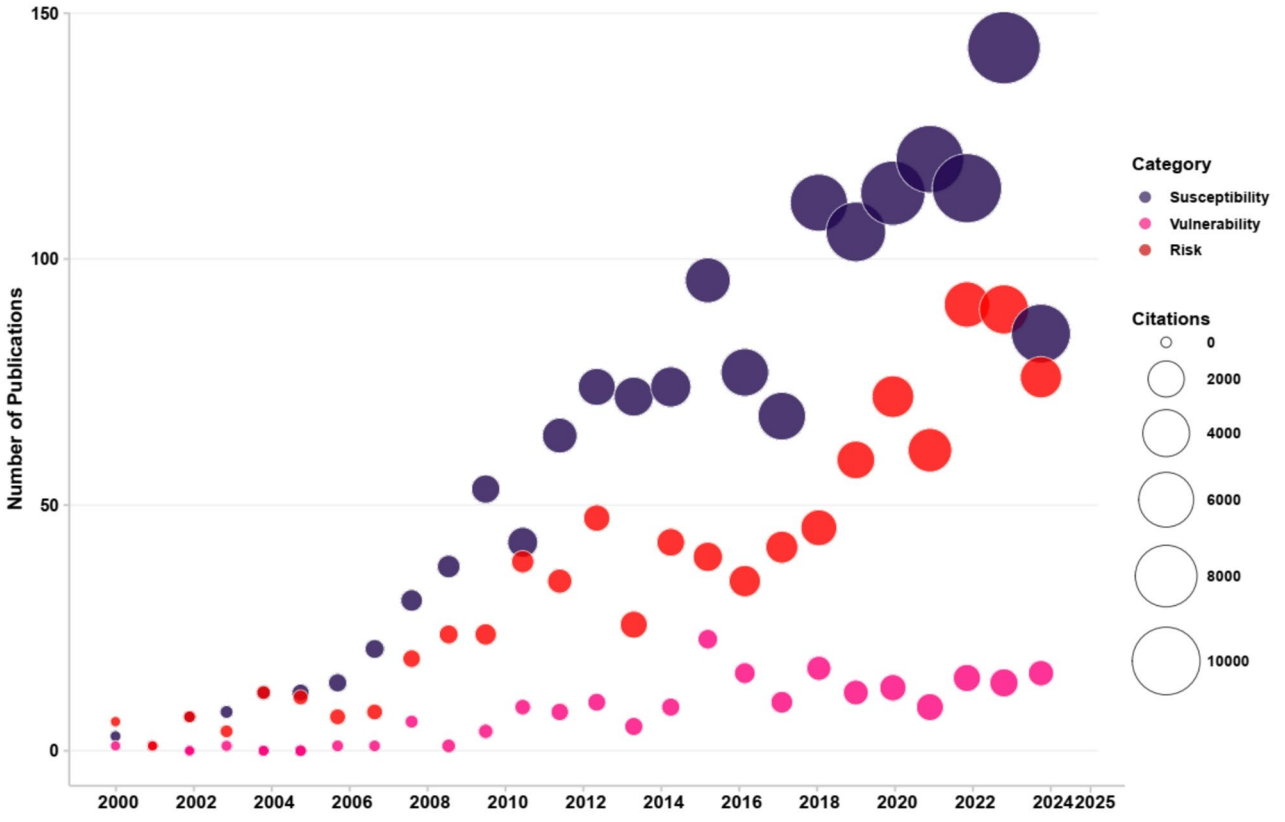


Fig. 7 Temporal trends in landslide susceptibility, vulnerability, and risk publications from 2000 to 2025, with bubble size representing the number of citations

communication frameworks can be developed, providing essential geospatial data for disaster management.

The rapid development of technology has also enabled the collection of vast amounts of data from various sensors, including smartphones, satellites, social media, IoT devices, LoRA (long-range) radio communication, LiDAR, HAM radio, GNSS, and other tracking systems (Ghosh 2023). This geospatial data is crucial at every stage of landslide management, as it enhances decision-making through the use of big data and AI-powered ML tools. These advanced tools have been widely adopted by decision-makers globally, showcasing the potential of data-driven solutions in disaster management.

Prevention Preventing landslides remains a complex challenge due to the intricate geodynamic and micro-physical processes involved. One promising approach is the use of Wireless Sensor Networks (WSN), which offers mobile deployment, reduced wiring costs, temporary connectivity, expanded coverage, and suitability for harsh environments where traditional wiring is impractical. For example, Romdhane et al. (2017) demonstrated the effectiveness of WSNs in landslide prevention in Papua, New Guinea, using low-power, long-range communication. Kumar et al. (2020) employed WSNs for multi-site remote monitoring of landslide-prone areas in South India, achieving highly accurate time synchronization across the network.

Prediction and early warning Predicting landslides is based on the principle that past and present conditions are crucial for forecasting future events (Ma et al. 2021). By analyzing historical and current data, researchers can estimate future landslide behaviors, frequencies, extents, and impacts. Early warning systems focus on assessing the likelihood of landslides by considering susceptibility and triggering factors like rainfall, groundwater levels, and earthquakes. In recent years, ML-based early warning systems have emerged as valuable tools. For example, Krkač et al. (2017) used RF models to predict landslide motion in Zagreb, Croatia, based on GNSS data, rainfall, and groundwater levels. Guzzetti et al. (2020) reviewed several early warning systems implemented at local, national, and global levels. Additionally, Web-GIS platforms are increasingly used for the early warning and prediction of geological disasters, offering valuable insights for emergency monitoring systems.

There are a number of early warning systems that were developed, tested, improved, and widely implemented for landslide detection over the last several decades

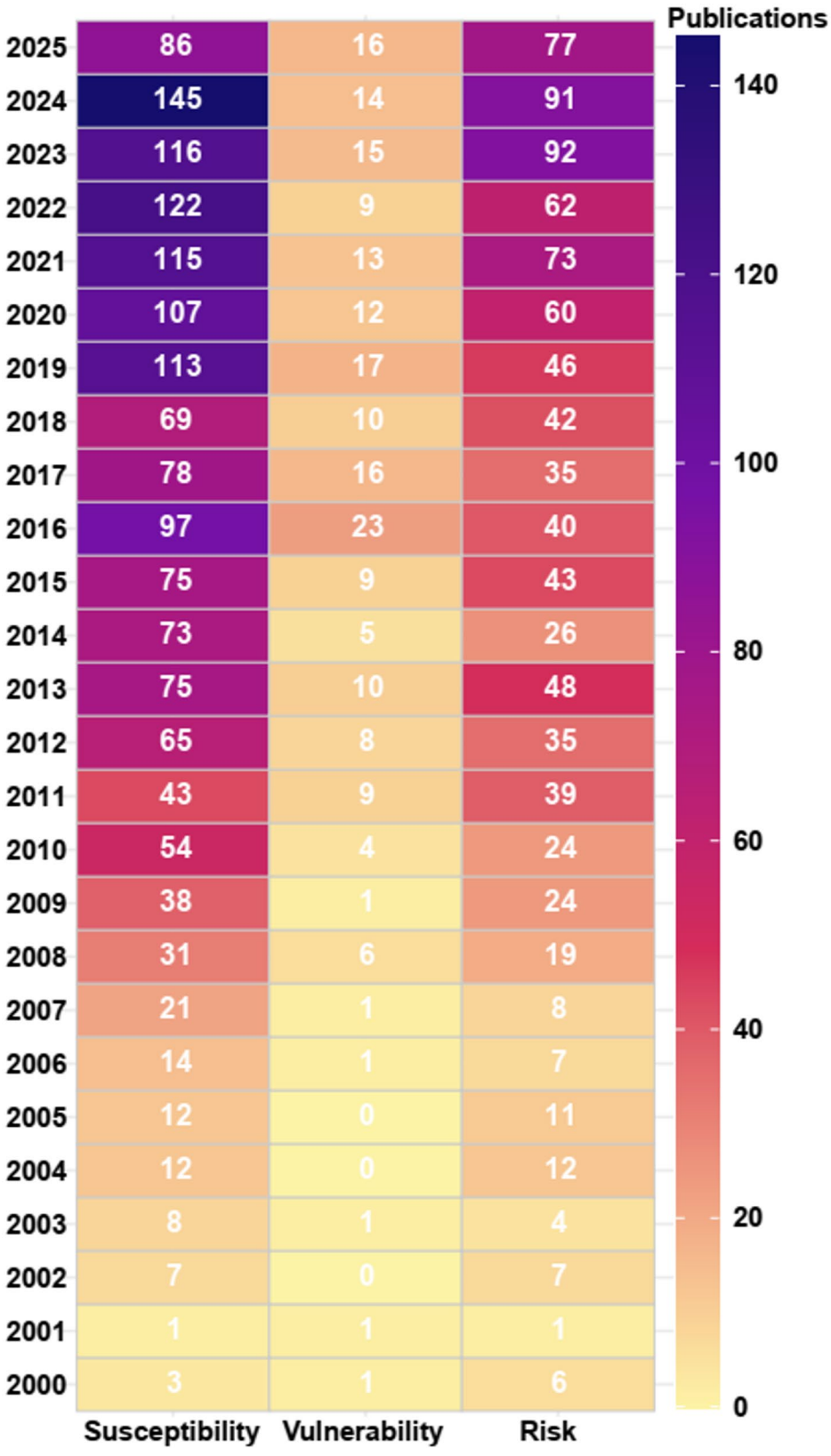


Fig. 8 Annual distribution of publications on landslide susceptibility, vulnerability, and risk from 2000 to 2025. The color gradient reflects the number of publications

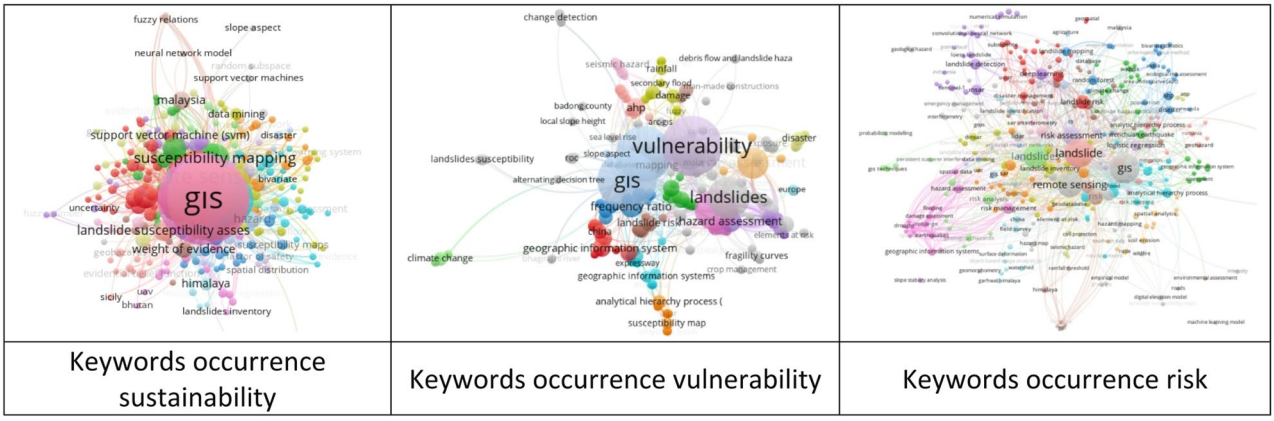


Fig. 9 Keyword co-occurrence networks for sustainability, vulnerability, and risk in landslide research, generated using VOSviewer

(Abraham et al. 2021; Strząbała et al. 2024). According to the United Nations Inter-Agency Secretariat of the International Strategy for Disaster Reduction (UN ISDR) (2005) and United Nations Inter-Agency Secretariat of the International Strategy for Disaster Reduction (UN ISDR) (2006), these systems play a key role in reducing landslide risk and are crucial for supporting sustainable development and the well-being of communities. Early warning systems help populations respond quickly and take adequate measures to avoid injuries and save lives, reduce infrastructure damages, and minimize negative impact on environments (Chae et al. 2017). Primary steps in developing an early warning system are to recognize landslide risk and recognize high-risk areas, while secondary steps include methods of potential landslide detection, developing response measures, and managing rapid response (Segoni et al. 2018).

Nowadays, many countries use landslide early warning systems. For example, in 2005 Japan proposed a countrywide level of landslide early warning system, which became operational in 2007 (Osanai et al. 2010). This system allows the detection of the probability and risk of landslide occurrence using precipitation rate data such as 60-minute cumulative rainfall level and hydrological indexes like water content in soil. These indicators are usually calculated for 5-km grids across the country. Kitazawa and Hale (2021) have studied public perception of landslide early warning systems. It was found that despite emergency notifications drawing the public's attention, they do not necessitate such emergency actions like evacuation.

Due to topographic features and intense precipitations preserved in the central uplands of Sri Lanka, these regions are highly sensitive to landslide occurrence, the same as frequently observed in Japan due to the same environmental conditions. According to Fujita (2022), an earlier developed landslide early warning system in Japan was introduced and adopted in Sri Lanka. This system was specifically tested in areas like Aranayake. Based on this, Sri Lanka has initiated a 5-year program, "Development of early warning technology of rain-induced rapid and long-travelling landslides" (Konagai et al. 2023). Despite successful implementation of this research, particular limitations remain, especially in public awareness and trust of the early warning system. Another country that successfully established an early landslide warning system is China (Yang et al. 2020). Their system integrates not only precipitation and soil data but also accounts for slope inclination combined with hydro-mechanical models that allow for prediction of landslides. The last approach was also tested and validated on real field data during several landslide events, and evacuation warnings were successfully issued in the areas of heavy debris flows (Xu et al. 2020).

In India, many of the Himalayan regions, especially those located at the Northern and Western Ghats, are the most sensitive to landslide occurrence due to active seismic activity and further earth movement seams (Martha et al. 2021). These regions have been installed with an early warning system that uses a Deep Earth Probes (DEPs) network for monitoring various geophysical parameters and their dynamic changes over time (Ramesh et al. 2023). In the United States, the U.S. Geological Survey (USGS), together with the National Oceanic and Atmospheric Administration (NOAA), also developed a system for early landslide warning. Unlike previously adopted systems, this one integrates precipitation levels and ground-motion data with satellite data to predict the likelihood of landslides Baum and Godt (2010). As also mentioned by Baum and Godt (2010), the efficient implementation of early warning systems highly depends on several critical elements, including landslide susceptibility, warning thresholds inherent to specific areas, impenetrable networks for meteorological and geotechnical data measurements, and robust computational methods to easily handle all required data.

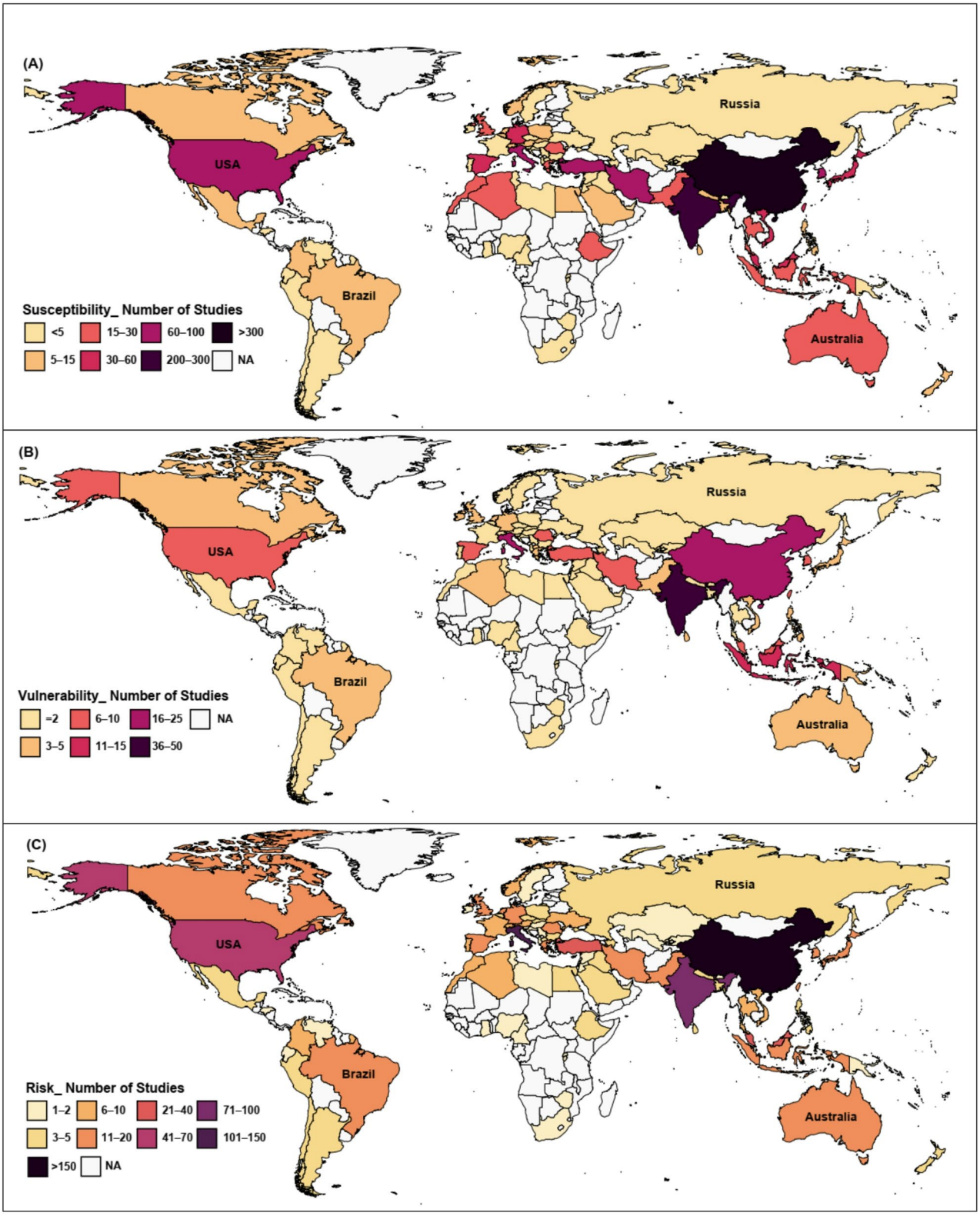


Fig. 10 Spatiotemporal distribution of landslide-related publications (2000–2025) by country. (A) Number of landslide susceptibility studies, (B) Number of landslide vulnerability studies, and (C) Number of landslide risk studies. Darker shades indicate a higher number of publications, with China, and India showing the high research contributions across all three categories

Moreover, installing special rain gauge instruments and soil moisture monitoring networks with extended weather radar coverage is of key importance in risk-prone areas, especially in regions with repeated debris flows.

Pecoraro et al. (2019) has made an in-depth review concerning the major components of landslide early warning systems used around the world. The results are summarized in Fig. 11, showing the main parameters, applied instruments, monitoring systems, and methodology used. According to their result, rainfall and ground displacement were identified as the most frequently monitored parameters (represented by the blue bars in Fig. 11), with rain gauges, GPS, weather stations, and inclinometers serving as the primary monitoring instruments. However, when considering only the parameters and instruments directly utilized for issuing warnings (represented by the orange bars in Fig. 11), ground displacement and velocity emerged as the key indicators. In these cases, GPS, embedded extensometers, total stations, and inclinometers were the most commonly utilized monitoring tools.

In addition, Fig. 12 (regenerated from Pecoraro et al. 2019) presents the operational periods for some of the landslide early warning systems implemented worldwide (Abraham et al. 2022; Gamperl et al. 2021; Hidayat et al. 2019; Lee et al. 2025; Marin and Marin-Sanchez 2024; Pecoraro et al. 2019; Segoni et al. 2018).

Preparedness and response Landslide risk maps are essential for disaster prevention and control, enabling

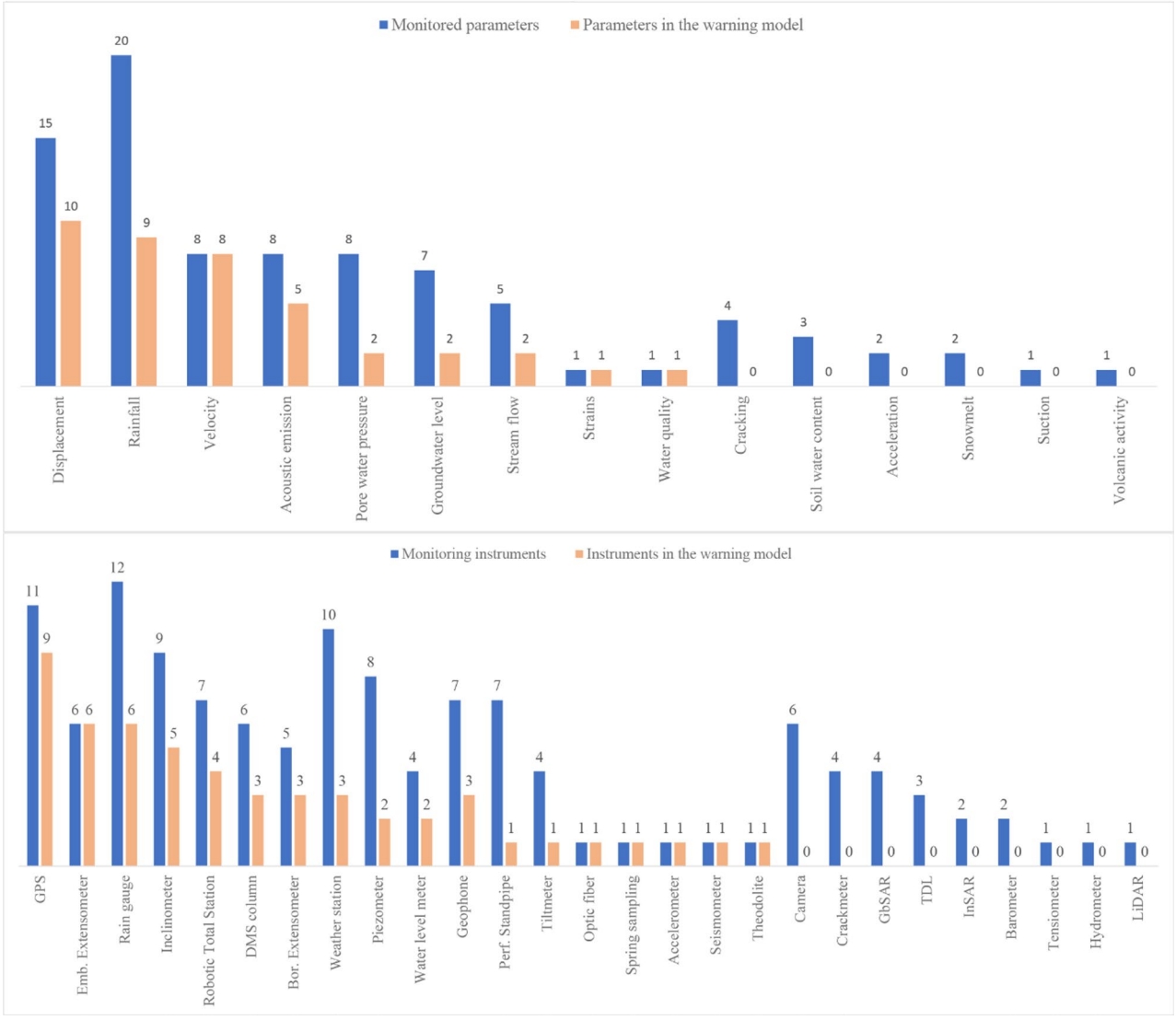


Fig. 11 The top panel illustrates the total number of monitored parameters forming the monitoring networks (blue), and those directly utilized for issuing warnings (red). The bottom panel shows the total number of instruments comprising the monitoring networks (blue), and those used explicitly for issuing warnings (orange). The plots were generated based on the summarized findings of the study by (Pecoraro et al. 2019)

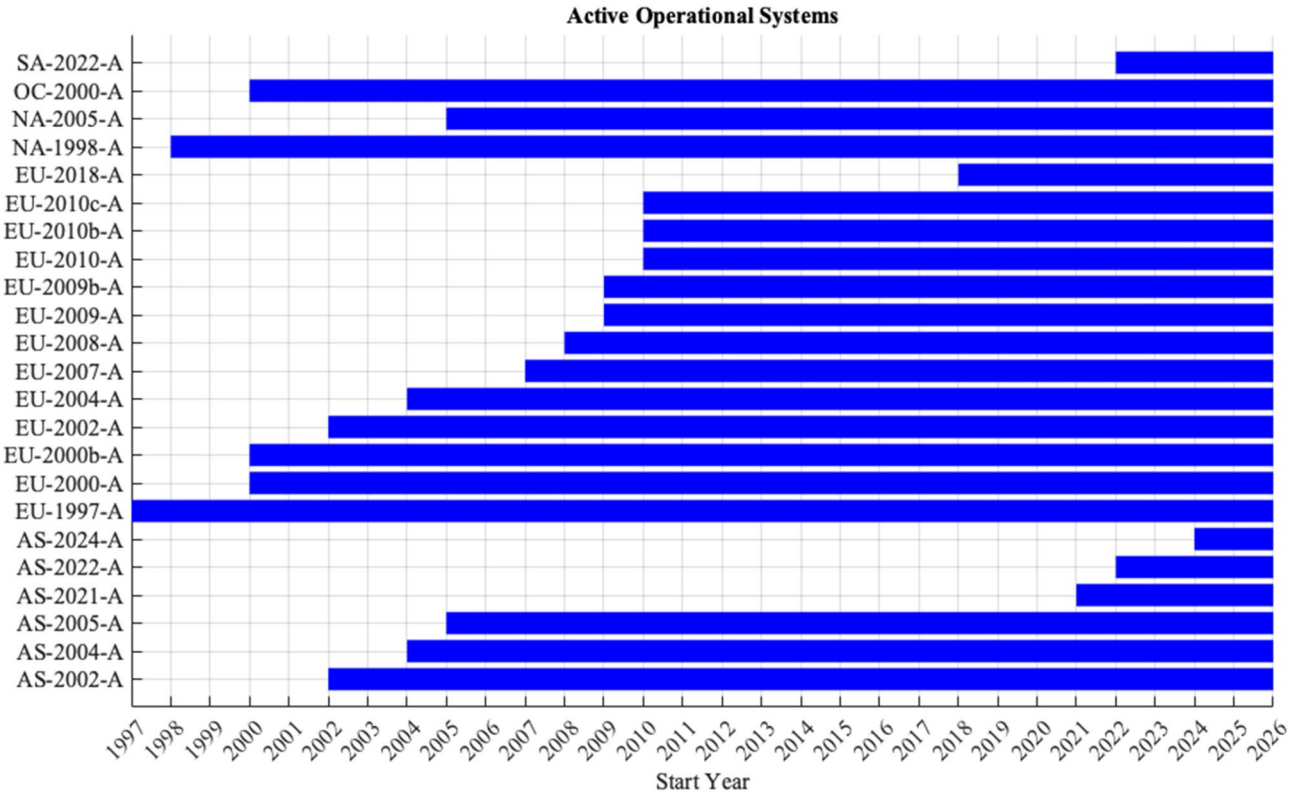


Fig. 12 Operational timelines for some of the active landslide early warning systems around the world. Each bar represents a specific landslide early warning system, identified by a three-part code: region SA (South America), OC (Oceania), NA (North America), EU (Europe), and AS (Asia), year of initiation, and active operational status (A). This Figure is regenerated from Pecoraro et al. 2019

authorities to plan emergency services, evacuation routes, shelters, and preparedness drills before a disaster strikes. Zheng (2020) developed a geospatial information-based emergency response system that utilizes UAVs for high-resolution mapping and AI for rapid interpretation of disaster information, such as affected areas and damaged infrastructure. ESRI's suite of GIS applications, including real-time dashboards, ArcGIS Field Maps, and GeoForce, further supports landslide management by providing dynamic data presentations, field data collection, and real-time hazard notifications.

Damage assessment Following a landslide, accurate damage assessment is crucial for effectively deploying resources and supporting community recovery. GIS mobile tools assist in data collection and reporting, facilitating the monitoring of debris removal and the evaluation of incident impacts. ESRI's emergency management solutions enable rapid analysis, damage assessments, resource deployment, and public engagement through scalable GIS maps, thus aiding in the post-disaster recovery process.

Geospatial technology, combined with advanced data analytics and robust communication networks, has become an indispensable asset in landslide management. Its application supports all stages of disaster management, from prevention to recovery, ultimately enhancing the effectiveness and coordination of disaster response efforts.

Current challenges and future trends

This section will discuss some of the challenges and future trends in geospatial technologies' applications in landslide studies.

One of the foremost challenges is **data management and analysis**. Advanced geospatial technologies can collect vast amounts of data on different types of slope instabilities across multiple scales, utilizing various sensors, data acquisition methods, and algorithms. This enables the detection of both slow-moving and rapid landslides in otherwise inaccessible areas. However, managing these extensive datasets presents significant hurdles. To effectively utilize the data, well-planned strategies, improved interpretation techniques, and more robust algorithms are required.

Another challenge is the **complexity of landslide identification**. Landslides often lack distinct spectral, spatial, or temporal characteristics, making them difficult to identify. Other land covers can conceal them, and their surface features vary due to diverse geological, geomorphological, hydrological, and weather conditions.

Since a landslide is not homogeneous, with elements like the main scarp, tongue, depression, and terrace exhibiting different features, identification using simple criteria becomes difficult.

The use of **satellite imagery** also comes with its own set of issues. Satellite images often require corrections for varying shadow angles and lighting conditions. Factors such as atmospheric distortions, geometric discrepancies, and temporal decorrelation can compromise the quality of DInSAR results. In regions prone to landslides, such as mountainous or humid areas, weather conditions like clouds and snow, along with daylight limitations, can hinder the acquisition of clear imagery, complicating landslide detection.

The Limitations of DInSAR and InSAR technologies further complicate the situation. DInSAR is most effective in areas with high interferogram coherence, but low coherence in forests, vegetated regions, and areas with snow or moisture can lead to unreliable data. Likewise, InSAR faces challenges related to geometrical effects, phase aliasing, and the presence of vegetation. Certain slopes and orientations, particularly north-south facing slopes, may not be easily detected by these technologies, necessitating alternative ground-based sensors for more comprehensive monitoring.

Moreover, **model transferability and data quality** are critical issues in the application of ML for landslide detection. Models trained on specific datasets often struggle to perform well in new regions, and the success of ML approaches is heavily dependent on data quality. As much as 80% of the effort in ML projects is devoted to data preprocessing (Ma et al. 2021), and poor data quality can severely degrade model performance.

Unmanned Aerial Vehicles (UAVs) present another challenge. Although UAVs offer high-resolution imagery, the images often lack detailed spectral information, making manual interpretation difficult. This limits the utility of UAVs for quickly capturing emergency data during landslide events, when time is of the essence.

The **integration of remote sensing with DL** offers significant potential, but also presents notable difficulties. Remote sensing images are highly complex, often containing hundreds of bands that make processing challenging. DL methods, such as CNNs, require large amounts of labeled data, which is often limited in remote sensing applications. The performance of these models depends on various factors like layer depth, input size, and training strategies, making their application in landslide mapping still in the experimental phase. Future research must focus on optimizing CNN designs, expanding training datasets, and refining augmentation strategies to improve performance.

Another issue is the **scalability of AI models**. Applying AI at a global scale across varied geological, geomorphological, and climatic settings remains a challenge, requiring significant computational resources. Data latency between event occurrences and satellite image availability can delay emergency response. Moreover, the lack of updated Digital Terrain Models (DTMs) post-landslide complicates analysis, as achieving globally updated DTMs with the necessary resolution to capture small events is still an unresolved issue.

The **limitations in rapid landslide information extraction** also pose a significant barrier to effective disaster response. Accurately and quickly obtaining landslide data after events like earthquakes is critical, but current methods involve considerable manual intervention, delaying the availability of vital information.

Both **geodesic and remote sensing methods** have their own sets of limitations. Geodesic methods, such as GPS and extensometers, offer high precision but are expensive when applied across large areas. Remote sensing, on the other hand, provides broader spatial coverage but is less precise and is often constrained by time, weather, and topographical challenges such as shadowing on steep slopes.

Time constraints in InSAR processing remain a key obstacle. InSAR is time-consuming and may not be suitable for areas experiencing significant displacements or challenging topography, further complicating landslide detection efforts.

Despite these challenges, **citizen science** is emerging as a promising approach in landslide monitoring. Platforms like GPS, Google MyMaps, and Esri ArcGIS allow communities to contribute to landslide inventories by involving the public in data collection and analysis. Initiatives like the USGS's "Did You See It?" project and NASA's Cooperative Open Online Landslide Repository (COOLR) are examples of how global crowdsourcing can enhance landslide data collection through applications like Landslide Reporter and Landslide Viewer.

These challenges underscore the importance of continued advancements in data processing, algorithm development, and cross-disciplinary collaboration. As geospatial technologies evolve, overcoming these barriers will be essential to fully leveraging their potential in landslide studies.

Conclusion

This review has provided a thorough examination of both conventional and advanced geospatial techniques used in landslide detection and modeling, offering valuable insights into the evolution of these technologies. From widely used tools like GIS and satellite imagery to cutting-edge methods such as real-time monitoring and ML, the review underscores the significant contributions these approaches have made to landslide management and prediction. Despite these advancements, challenges

remain, particularly in areas like data integration, predictive model accuracy, and real-time monitoring of landslide-prone regions. Addressing these issues is critical for improving landslide response and mitigation strategies. The paper highlights the need for continued research and technological innovations that can enhance the reliability and efficiency of geospatial tools, ultimately contributing to better disaster preparedness and resilience. By focusing on these future directions, this review aims to guide the development of more effective geospatial solutions for managing landslide risks in vulnerable areas.

Supplementary Information

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Supplementary Material 1

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Generative AI statement
The authors affirm that no generative AI tools were used in the creation of the content, analysis, results, figures, or tables presented in this work. However, AI and Grammarly was used to improve the text's readability and style and to ensure accuracy in grammar, spelling, punctuation, and tone.

Author contributions
Mahyat Shafapourtehrany: Writing – original draft, Writing – review & editing, Supervision, Data curation, Conceptualization, Maryna Batur: Writing – original draft, Writing – review & editing, Validation, Data curation, Haluk Özener: Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization, Niloufar Lorestani: Writing – review & editing, Validation, Data curation, Bahareh Kalantar: Writing – review & editing, Validation, Farzin Shabani: Writing – review & editing, Project administration.

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