

Terrain Analysis and Landslide Monitoring: Advances in Conventional and Remote Sensing Techniques for Hazard Assessment and Early Warning

Efthymia Koliokosta

efigrx@yahoo.com

University of the Aegean: Panepistemio Aigaiou <https://orcid.org/0000-0001-5439-5536>

Systematic Review

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Abstract

Landslides are among the most destructive natural hazards worldwide, posing increasing risks to human lives, infrastructure, ecosystems and socioeconomic development under changing climatic conditions. Advances in terrain analysis, remote sensing and geospatial technologies have fundamentally transformed landslide monitoring over the past three decades, enabling more accurate characterization of slope instability and supporting operational hazard assessment. This study presents a systematic review of contemporary approaches to terrain analysis and landslide monitoring following the RepOrting standards for Systematic Evidence Syntheses (ROSES) framework. A comprehensive literature search was conducted using the Scopus and Web of Science Core Collection databases, yielding 991 records, of which 244 peer-reviewed studies met the predefined eligibility criteria. The review synthesizes the evolution of conventional terrain investigation methods, Geographic Information Systems (GIS), Digital Elevation Models (DEMs), optical remote sensing, Synthetic Aperture Radar (SAR) interferometry, Light Detection and Ranging (LiDAR), Unmanned Aerial Vehicles (UAVs), artificial intelligence and multi-source data fusion for landslide detection, susceptibility assessment and continuous monitoring. Bibliometric analysis reveals a clear shift from traditional engineering geological investigations towards integrated, data-driven monitoring systems supported by machine learning, cloud computing, Digital Twins and near-real-time Earth observation platforms. Despite substantial technological advances, important challenges remain, including limited integration of conventional and remote sensing techniques, inconsistent validation procedures, uncertainty quantification in artificial intelligence models and the incorporation of climate change projections into operational early warning systems. The review identifies current knowledge gaps and proposes future research priorities aimed at developing integrated, intelligent and climate-resilient landslide monitoring frameworks to support disaster risk reduction and sustainable infrastructure management.

1. Introduction

Landslides are among the most destructive natural hazards worldwide, posing persistent threats to human life, critical infrastructure, economic development and environmental sustainability. They occur across diverse geological and climatic settings and are triggered by the complex interaction of terrain morphology, lithology, geological structures, hydrological conditions, land use, vegetation cover, seismic activity and increasingly anthropogenic disturbances (Varnes, 1978; Cruden & Varnes, 1996; Guzzetti et al., 1999; Hungr et al., 2014). Globally, landslides are responsible for thousands of fatalities each year and generate billions of dollars in direct and indirect economic losses, highlighting their significance as a major component of global disaster risk (Petley, 2012; Froude & Petley, 2018). According to the United Nations Office for Disaster Risk Reduction (UNDRR), landslides represent one of the most frequent secondary hazards associated with extreme meteorological events, earthquakes, volcanic eruptions and human-induced landscape modifications (UNDRR, 2022).

The increasing frequency and intensity of extreme weather events associated with climate change are expected to further amplify landslide occurrence in many regions worldwide. Changes in precipitation regimes, including more extreme precipitation occurrences, prolonged wet periods, glacier retreat, permafrost degradation and accelerated weathering processes, have already altered slope stability conditions in mountainous and high-latitude environments (Gariano & Guzzetti, 2016; IPCC, 2022). Several studies have demonstrated strong correlations between changing climatic conditions and increasing landslide activity, particularly in regions characterized by steep topography and rapidly expanding urban development (Kirschbaum et al., 2015; Gariano & Guzzetti, 2016). Consequently, accurate terrain characterization and continuous monitoring have become essential components of disaster risk reduction, supporting susceptibility assessment, hazard forecasting, infrastructure management and operational early warning systems (Casagli et al., 2017).

Terrain analysis provides the quantitative basis for understanding the spatial distribution of landslide susceptibility by describing the Earth's surface through digital representations of topography. Advances in Digital Elevation Models (DEMs) have enabled the extraction of numerous morphometric parameters (including slope, aspect, elevation, curvature, terrain roughness, drainage density, flow accumulation, Topographic Wetness Index (TWI), Stream Power Index (SPI) and Terrain Ruggedness Index (TRI)), that strongly influence slope instability (Moore et al., 1991; Wilson & Gallant, 2000; Tarolli, 2014). Integrated within Geographic Information Systems (GIS), these terrain derivatives are routinely combined with geological, hydrological, climatic and land-cover information to develop increasingly sophisticated vulnerability, hazard and risk assessment models (Aleotti & Chowdhury, 1999; Reichenbach et al., 2018).

Historically, terrain investigations relied predominantly on conventional field-based approaches, including geological and geomorphological mapping, borehole investigations, laboratory testing, inclinometers, extensometers, piezometers, total stations and Global Navigation Satellite System (GNSS) observations (Turner & Schuster, 1996; Duncan & Wright, 2005). These techniques remain indispensable because they provide direct measurements of lithological properties, discontinuities, groundwater conditions and subsurface deformation that cannot yet be fully captured through remote sensing (Turner & Schuster, 1996; Duncan & Wright, 2005; Jaboyedoff et al., 2012; Casagli et al., 2017). Moreover, field observations continue to provide the reference data required for calibrating and validating remotely sensed observations and numerical models. However, conventional methods are generally constrained by limited spatial coverage, high operational costs, difficult accessibility in mountainous terrain and the inability to provide continuous observations over large geographical areas (Corsini et al., 2005; Casagli et al., 2017).

Over the past three decades, remote sensing technologies have fundamentally transformed terrain analysis and landslide monitoring by enabling systematic, repetitive and spatially extensive observations of the Earth's surface. Satellite-based optical imagery, Synthetic Aperture Radar (SAR), airborne and terrestrial Light Detection and Ranging (LiDAR), Unmanned Aerial Vehicles (UAVs), hyperspectral imaging, thermal infrared sensors, airborne laser scanning and ground-based radar interferometry now provide unprecedented capabilities for mapping terrain morphology, detecting surface deformation, monitoring vegetation dynamics and quantifying slope movements with increasing spatial and temporal resolution (Mantovani et al., 1996; Guzzetti et al., 2012; Jaboyedoff et al., 2012; Casagli et al., 2017). Among these technologies, radar interferometric techniques, including Differential Interferometric Synthetic Aperture Radar (DInSAR), Persistent Scatterer Interferometry (PSInSAR) and Small Baseline Subset (SBAS), have become indispensable for monitoring slow-moving landslides because they enable millimetre-scale deformation measurements over extensive areas independent of daylight and cloud conditions (Ferretti et al., 2001; Berardino et al., 2002; Crosetto et al., 2016).

Simultaneously, the availability of freely accessible Earth observation missions has revolutionized large-scale landslide monitoring. The European Space Agency (ESA)'s Copernicus Programme, particularly the Sentinel-1 and Sentinel-2 missions, together with the National Aeronautics and Space Administration (NASA) Landsat archive, has dramatically increased access to high-quality satellite imagery for both scientific research and operational applications (Drusch et al., 2012; Torres et al., 2012; Wulder et al., 2019). These developments have been further accelerated by cloud-based geospatial platforms such as Google Earth Engine, which enable large-scale processing of petabyte-scale satellite archives without requiring extensive local computational resources (Gorelick et al., 2017). At local scales, advances in UAV technology combined with Structure-from-Motion (SfM) photogrammetry have enabled rapid acquisition of ultra-high-resolution orthophotos, dense point clouds and three-dimensional terrain models at relatively low cost, substantially improving post-event assessment and local monitoring capabilities (Westoby et al., 2012; Turner et al., 2015).

Recent years have witnessed a paradigm shift toward data-driven modelling supported by artificial intelligence (AI). Machine learning algorithms, including Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Gradient Boosting Machines (GBM), Extreme Gradient Boosting (XGBoost) and deep learning architectures, such as Convolutional Neural Networks (CNNs), have demonstrated remarkable capability for integrating heterogeneous geospatial datasets and modelling the highly nonlinear relationships governing landslide occurrence (Reichenbach et al., 2018; Merghadi et al., 2020). These approaches frequently outperform traditional statistical susceptibility models by effectively exploiting large datasets derived from remote sensing products, terrain attributes, geological information, rainfall observations and land-use variables. More recently, explainable artificial intelligence (XAI), physics-informed machine learning, Digital Twins and hybrid modelling frameworks have emerged as promising directions for improving model transparency, uncertainty quantification and operational applicability (Samek et al., 2021; Casagli et al., 2023).

Despite these remarkable technological advances, several scientific and operational challenges remain. Differences in spatial and temporal resolution among sensors, uncertainties associated with Digital Elevation Models, vegetation-induced signal attenuation, atmospheric effects in radar observations, inconsistent validation methodologies and the integration of heterogeneous datasets continue to limit the operational implementation of many monitoring systems (Crosetto et al., 2016; Reichenbach et al., 2018). Furthermore, while numerous review studies have focused on individual technologies, such as LiDAR (Jaboyedoff et al., 2012), UAV photogrammetry (Turner et al., 2015), SAR interferometry (Crosetto et al., 2016) or machine learning (Merghadi et al., 2020),

comparatively few have comprehensively synthesized conventional surveying techniques together with the rapidly evolving spectrum of remote sensing technologies and artificial intelligence within a unified terrain analysis framework.

To address this knowledge gap, the present review provides a comprehensive and systematic synthesis of contemporary approaches to terrain analysis and landslide monitoring. Specifically, it aims to: (i) examine the evolution of conventional and remote sensing techniques used for terrain characterization, (ii) critically evaluate the capabilities, strengths and limitations of the principal monitoring technologies, (iii) analyse the integration of multi-source datasets within GIS and artificial intelligence frameworks, (iv) identify emerging trends in real-time monitoring, Digital Twins and early warning systems and (v) highlight current research gaps and future directions for developing integrated, operational and climate-resilient landslide monitoring systems. By bringing together advances in geomorphology, engineering geology, remote sensing, geospatial analytics and artificial intelligence, this review seeks to provide researchers, engineers, practitioners and policymakers with a comprehensive overview of the rapidly evolving landscape of terrain analysis and landslide monitoring while identifying priorities for future scientific research and operational implementation.

2. Review Methodology

2.1 Review Design

This review was conducted following a Systematic Literature Review methodology to ensure transparency, reproducibility and methodological rigor. In contrast to traditional narrative reviews, systematic reviews adopt predefined and explicit procedures for identifying, screening, selecting, appraising and synthesizing scientific evidence, thereby reducing selection bias and enhancing the reliability and reproducibility of the review process (Haddaway et al., 2018; Snyder, 2019).

The review protocol was developed according to the RepORting standards for Systematic Evidence Syntheses (ROSES) framework proposed by Haddaway et al. (2018). ROSES was specifically designed for environmental management and geoscience research to improve the consistency, transparency and reporting quality of systematic evidence syntheses. Compared with other systematic review protocols, ROSES provides a flexible yet rigorous framework that is particularly well suited to multidisciplinary environmental studies involving heterogeneous datasets, diverse analytical methods and multiple evidence sources. Consequently, it has been increasingly adopted in studies addressing natural hazards, environmental monitoring, climate change, ecosystem management and geospatial sciences (Haddaway et al., 2018).

Following the ROSES protocol, the review consisted of five sequential stages: (i) formulation of the review objectives and research questions, (ii) systematic identification of relevant studies through a structured database search, (iii) screening and eligibility assessment based on predefined inclusion and exclusion criteria, (iv) quality appraisal and standardized data extraction and (v) qualitative thematic synthesis and bibliometric analysis of the selected literature. This structured workflow ensures that the review process is transparent, reproducible and minimizes potential bias throughout the selection and synthesis of the scientific evidence.

2.2 Literature Search Strategy

The literature search was conducted using two of the most comprehensive multidisciplinary scientific databases, Scopus and the Web of Science Core Collection (WoS). These databases were selected because of their extensive coverage of high-quality peer-reviewed literature across the fields of Earth sciences, engineering, environmental sciences, remote sensing and geospatial technologies. Both databases are widely recognized as reliable sources for systematic literature reviews and bibliometric analyses owing to their rigorous indexing standards, comprehensive citation information and broad international journal coverage (Falagas et al., 2008; Martín-Martín et al., 2018; Mongeon & Paul-Hus, 2016).

To maximize the retrieval of relevant publications while minimizing the inclusion of irrelevant records, a comprehensive search strategy was developed based on the review objectives and research questions. The search syntax combined Boolean operators (AND, OR), wildcard operators (*), phrase searching using quotation marks and multiple synonyms describing the principal concepts of the review, namely landslides, terrain analysis, monitoring technologies and remote sensing.

The search strategy was iteratively refined through several pilot searches to improve both sensitivity and specificity. The final search query was as follows:

("landslide*" OR "slope failure*" OR "mass movement*" OR "rockfall*" OR "debris flow*") AND ("terrain analysis" OR "topographic analysis" OR "terrain modelling" OR geomorphology OR "digital elevation model" OR "DEM" OR "DTM" OR "Digital Terrain Model" OR "DSM" OR "Digital Surface Model" OR "topography OR morphometry) AND ("remote sensing" OR satellite* OR "Earth observation" OR "LiDAR" OR "Light Detection and Ranging" OR "Unmanned Aerial Vehicle" OR "UAV" OR "UAS" OR "Unmanned Aircraft System" OR "drone*" OR "photogrammetry OR "structure from motion" OR "Structure-from-Motion" OR "SfM" OR "Synthetic Aperture Radar" OR "SAR" OR "Interferometric Synthetic Aperture Radar" OR "InSAR" OR "Differential Interferometric Synthetic Aperture Radar" OR "DInSAR" OR 'Persistent Scatterer Interferometric Synthetic Aperture Radar' OR "PSInSAR" OR " Small Baseline Subset" OR "SBAS" OR "Global Navigation Satellite System" OR "GNSS" OR " Global Positioning System" OR "GPS" OR "ground-based radar" OR "terrestrial laser scanning" OR "TLS" OR "airborne laser scanning" OR "ALS" OR "GIS" OR "Geographic Information System" OR "Deep Learning" OR "Machine Learning" OR " Convolutional Neural Network" OR "Random Forest" OR "Support Vector Machine") AND (monitor* OR "detection" OR "mapping" OR "inventory" OR "susceptibility" OR "hazard" OR "vulnerability" OR "risk" OR "forecasting" OR "project*" OR "Early warning"). The abbreviations explanation and terms description is provided in Table 1.

Table 1
Common abbreviations used in terrain analysis and landslide monitoring

Abbreviation	Full term	Description	Representative reference
DEM	Digital Elevation Model	Digital representation of the bare Earth's surface elevation used to derive terrain attributes such as slope, aspect, curvature and hydrological indices.	Moore et al. (1991); Wilson & Gallant (2000)
DTM	Digital Terrain Model	Three-dimensional representation of the bare terrain surface that may include breaklines and additional geomorphological information beyond elevation values.	Wilson & Gallant (2000); Tarolli (2014)
DSM	Digital Surface Model	Digital model representing the elevation of the Earth's surface, including vegetation, buildings and other above-ground objects.	Tarolli (2014); Wulder et al. (2019)
LiDAR	Light Detection and Ranging	Active laser remote sensing technology producing dense three-dimensional point clouds for highly accurate terrain characterization.	Jaboyedoff et al. (2012); Tarolli (2014)
UAV	Unmanned Aerial Vehicle	Pilotless aerial platform used for acquiring high-resolution imagery and topographic data.	Westoby et al. (2012); Turner et al. (2015)
UAS	Unmanned Aircraft System	Complete aerial system comprising the UAV, sensors, communication links, navigation system and ground control station.	Turner et al. (2015)
SfM	Structure-from-Motion	Photogrammetric technique that reconstructs three-dimensional terrain from overlapping images.	Westoby et al. (2012)
SAR	Synthetic Aperture Radar	Active microwave imaging system capable of acquiring data independently of cloud cover and daylight conditions.	Ferretti et al. (2001); Torres et al. (2012)
InSAR	Interferometric Synthetic Aperture Radar	Radar interferometry technique that measures surface deformation using phase differences between repeated SAR acquisitions.	Ferretti et al. (2001); Crosetto et al. (2016)
DInSAR	Differential Interferometric Synthetic Aperture Radar	InSAR technique that removes the topographic component to estimate ground displacement.	Berardino et al. (2002); Crosetto et al. (2016)
PSInSAR	Persistent Scatterer Interferometric Synthetic Aperture Radar	Multi-temporal InSAR approach that measures millimetre-scale deformation using stable radar targets.	Ferretti et al. (2001); Crosetto et al. (2016)
SBAS	Small Baseline Subset	Multi-temporal InSAR method that estimates deformation through interferograms generated from images with small spatial and temporal baselines.	Berardino et al. (2002); Crosetto et al. (2016)
GNSS	Global Navigation Satellite System	Generic term for global satellite navigation constellations used for positioning and deformation monitoring.	Corsini et al. (2005); Casagli et al. (2017)
GPS	Global Positioning System	United States satellite navigation system and one of the principal GNSS constellations used in geodetic monitoring.	Corsini et al. (2005)
TLS	Terrestrial Laser Scanning	Ground-based LiDAR technology providing high-resolution three-dimensional measurements of slopes, cliffs and infrastructure.	Jaboyedoff et al. (2012)
ALS	Airborne Laser Scanning	Airborne LiDAR surveying technique used to generate high-resolution Digital Terrain Models over large areas.	Jaboyedoff et al. (2012); Tarolli (2014)
GIS	Geographic Information System	Computer-based framework for storing, managing, analysing and visualising spatial data.	Wilson & Gallant (2000); Reichenbach et al. (2018)

Abbreviation	Full term	Description	Representative reference
EO	Earth Observation	Collection of environmental information acquired from satellite, airborne, or ground-based sensors for monitoring Earth system processes.	Drusch et al. (2012); Wulder et al. (2019)
ML	Machine Learning	Artificial intelligence methods that learn patterns from data to support prediction and classification.	Merghadi et al. (2020)
DL	Deep Learning	Subset of machine learning based on multi-layer neural networks for automated feature extraction.	Samek et al. (2021)
CNN	Convolutional Neural Network	Deep learning architecture widely used for image classification and automated landslide detection.	Samek et al. (2021); Ghorbanzadeh et al. (2019)
RF	Random Forest	Ensemble machine learning algorithm widely applied to landslide susceptibility mapping.	Reichenbach et al. (2018); Merghadi et al. (2020)
SVM	Support Vector Machine	Supervised machine learning algorithm commonly used for landslide classification and prediction.	Reichenbach et al. (2018); Merghadi et al. (2020)
ANN	Artificial Neural Network	Computational model inspired by biological neural systems for nonlinear pattern recognition.	Reichenbach et al. (2018); Merghadi et al. (2020)
XGBoost	Extreme Gradient Boosting	Advanced ensemble learning algorithm based on gradient boosting decision trees with high predictive performance.	Merghadi et al. (2020)
NDVI	Normalized Difference Vegetation Index	Spectral vegetation index widely used to assess vegetation cover and disturbance.	Wulder et al. (2019)
TWI	Topographic Wetness Index	Hydrological terrain index estimating the spatial distribution of soil moisture.	Moore et al. (1991)
SPI	Stream Power Index	Terrain index representing the erosive power of concentrated surface runoff.	Moore et al. (1991)
TRI	Terrain Ruggedness Index	Quantitative measure of terrain heterogeneity and surface roughness.	Wilson & Gallant (2000); Tarolli (2014)

The search was conducted in June 2026 and initially retrieved 991 records from the two databases. Following the ROSES protocol (Haddaway et al., 2018), all retrieved references were exported into a reference management software, where duplicate records originating from overlapping database coverage were identified and removed prior to the screening process.

To ensure the scientific quality and relevance of the review, several eligibility criteria were applied. Only peer-reviewed journal articles and review papers published in English were considered for further analysis. Conference papers, editorials, notes, book reviews, errata and non-peer-reviewed publications were excluded. Furthermore, studies were required to explicitly address terrain analysis, landslide monitoring, susceptibility assessment or the application of conventional surveying, remote sensing, geospatial analysis or artificial intelligence to landslide-related problems. Publications focusing exclusively on other natural hazards without a direct landslide component were excluded.

The search covered publications from 1990 to June 2026, reflecting the period during which GIS, digital terrain modelling, satellite remote sensing, LiDAR, UAV technologies and artificial intelligence experienced substantial development and operational adoption in landslide research. To ensure consistency and relevance, explicit inclusion and exclusion criteria were established before screening the retrieved publications (Table 2).

Table 2
Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Peer-reviewed journal articles	Conference abstracts
English-language publications	Non-English publications
Studies focusing on landslide monitoring or terrain analysis	Studies unrelated to slope instability
Studies employing conventional or remote sensing techniques	Purely theoretical papers without monitoring applications
Full-text available	Editorials, Notes, corrigenda
Original research or review articles	Duplicate records

Initially, duplicate records were removed. Subsequently, titles and abstracts were independently screened to eliminate studies clearly outside the scope of the review. Full-text articles were then assessed against the predefined eligibility criteria. Studies were excluded when they (i) focused exclusively on earthquakes or floods without landslide applications; (ii) addressed purely geotechnical laboratory experiments without terrain analysis; (iii) lacked sufficient methodological information and (iv) did not include monitoring, mapping, susceptibility assessment or terrain characterization. The final database consisted of studies that directly contributed to understanding terrain analysis and landslide monitoring using conventional and remote sensing technologies.

The complete search and selection procedure is summarized in the ROSES flow diagram (Fig. 1)

2.3 Data Extraction

Following the eligibility assessment, information from each selected study was systematically extracted using a standardized data extraction form specifically developed for this review. The use of a structured extraction protocol ensured consistency throughout the review process, facilitated comparison among studies and minimized the risk of subjective interpretation during data collection (Haddaway et al., 2018; Snyder, 2019). Standardized data extraction is considered a fundamental component of systematic literature reviews because it enables transparent synthesis of heterogeneous evidence while supporting reproducibility and reducing potential reviewer bias.

For each eligible publication, both bibliographic and methodological information were recorded. Bibliographic data included the publication year, country of application and geographical location of the study area, allowing the identification of temporal research trends and the spatial distribution of landslide investigations. Information describing the physical characteristics of the investigated terrain, including terrain type and geomorphological setting, was also extracted to examine how monitoring approaches vary across different environmental conditions.

Particular emphasis was placed on documenting the monitoring methodologies employed in each study. Accordingly, information was collected regarding the conventional surveying techniques and remote sensing technologies adopted, including field investigations, geotechnical instrumentation, Global Navigation Satellite System (GNSS), optical satellite imagery, Synthetic Aperture Radar (SAR), Interferometric SAR (InSAR), Light Detection and Ranging (LiDAR), Unmanned Aerial Vehicles (UAVs), terrestrial laser scanning (TLS), airborne laser scanning (ALS), photogrammetry and other emerging Earth observation technologies. Where applicable, the specific satellite missions, sensors or acquisition platforms used were also recorded.

To evaluate the contribution of terrain analysis to landslide assessment, the morphometric and environmental variables incorporated into each study were systematically documented. These included commonly used terrain parameters such as slope, elevation, aspect, profile and plan curvature, terrain roughness, drainage density, flow accumulation, Topographic Wetness Index (TWI), Stream Power Index (SPI), lithology, land use, vegetation indices, rainfall and other conditioning factors. In addition, the spatial and temporal resolution of the datasets were extracted whenever reported, providing insight into the scale and monitoring capabilities of different technologies. Methodological information was further collected regarding the analytical and modelling

approaches adopted by each study, including statistical methods, physically based models, Geographic Information System (GIS) analyses, machine learning algorithms, deep learning architectures and hybrid modelling frameworks

Finally, the principal findings and reported limitations of each publication were extracted to facilitate critical comparison among studies and to identify common strengths, methodological limitations, emerging research trends and remaining knowledge gaps. The resulting standardized database formed the foundation for the subsequent bibliometric assessment, qualitative thematic synthesis and comparative analysis of conventional surveying methods, remote sensing technologies, terrain analysis techniques and artificial intelligence applications in landslide monitoring. This systematic and standardized data extraction process ensured that all studies were evaluated according to consistent criteria, thereby enhancing the reliability, transparency and reproducibility of the review.

2.4 Data Synthesis

Given the considerable heterogeneity among the reviewed studies in terms of monitoring technologies, study objectives, geographical settings, spatial and temporal scales, analytical approaches and reported outcome measures, a quantitative meta-analysis was not considered appropriate. The reviewed publications employed a wide variety of data sources, methodological frameworks, validation procedures and performance metrics, making statistical comparison and pooled quantitative synthesis both impractical and methodologically inappropriate. Consequently, the findings were synthesized using a qualitative thematic synthesis approach, which is widely recommended for systematic literature reviews involving diverse research designs and multidisciplinary evidence (Snyder, 2019).

Thematic synthesis was selected because it enables the systematic identification, comparison and interpretation of recurring concepts, methodological developments and emerging research trends while preserving the contextual information provided by individual studies. Following the standardized data extraction process, the selected publications were classified according to their primary methodological focus and technological application. This categorization facilitated a structured comparison of the evolution of terrain analysis and landslide monitoring techniques and enabled the identification of common strengths, limitations and research gaps across the literature.

Based on their principal objectives and methodologies, the reviewed studies were organized into six thematic categories: (i) conventional terrain investigation methods, including geological mapping, geomorphological surveys, geotechnical investigations and ground-based monitoring; (ii) optical remote sensing technologies for landslide detection, inventory mapping and change analysis; (iii) radar interferometry, encompassing Synthetic Aperture Radar (SAR), Differential Interferometric SAR (DInSAR), Persistent Scatterer Interferometry (PSInSAR) and Small Baseline Subset (SBAS) techniques for ground deformation monitoring; (iv) Light Detection and Ranging (LiDAR) and Unmanned Aerial Vehicle (UAV) applications for high-resolution terrain characterization and three-dimensional modelling; (v) terrain analysis and landslide susceptibility modelling, including the extraction and analysis of morphometric, geological, hydrological and environmental conditioning factors; and (vi) artificial intelligence and multi-source data fusion approaches, incorporating machine learning, deep learning, cloud computing and integrated monitoring frameworks.

Within each thematic category, studies were critically compared with respect to the monitoring technologies employed, spatial and temporal resolution, terrain variables analysed, modelling techniques, validation strategies, principal findings and reported limitations. Particular emphasis was placed on identifying technological advances, methodological innovations, operational applications and emerging research directions. The synthesis also examined how conventional field investigations are increasingly integrated with remote sensing technologies and artificial intelligence to develop more comprehensive, reliable and operational landslide monitoring systems.

This thematic synthesis provided the foundation for the subsequent results and discussion by enabling a comprehensive evaluation of current scientific knowledge, identifying prevailing research trends, highlighting methodological challenges and revealing opportunities for future research in terrain analysis and landslide monitoring.

2.5 Bibliometric Analysis

To complement the systematic literature review, a bibliometric analysis was conducted to quantitatively evaluate the evolution of scientific research on terrain analysis and landslide monitoring. Bibliometric analysis has become an increasingly important tool

for objectively assessing research productivity, identifying influential publications, revealing collaboration patterns and detecting emerging research themes within rapidly evolving scientific disciplines (Donthu et al., 2021). By combining bibliometric techniques with thematic synthesis, this review provides both a quantitative overview of the research landscape and a qualitative interpretation of technological developments in landslide monitoring.

The bibliometric analysis was performed using the final dataset obtained after the ROSES screening and eligibility process. Bibliographic metadata extracted from the selected publications were analysed to examine the temporal evolution, geographical distribution, scientific impact and thematic development of the research field. The analysis focused on several key indicators, including annual publication trends, citation performance, the most productive journals, leading countries and institutions, patterns of international scientific collaboration and the evolution of research topics over time.

Particular emphasis was placed on keyword analysis to investigate the conceptual structure of the discipline. Author keywords and indexed keywords were analysed using keyword co-occurrence techniques to identify the most frequently investigated research topics and to examine relationships among conventional terrain investigation methods, remote sensing technologies, terrain analysis techniques, machine learning algorithms and landslide monitoring applications. Co-occurrence analysis enables the identification of thematic clusters that reflect the principal research directions within the scientific literature while also highlighting emerging technologies and interdisciplinary linkages (Donthu et al., 2021).

In addition, thematic evolution analysis was undertaken to explore how research priorities have changed over time. This analysis provides insights into the transition from traditional engineering geological investigations and field-based monitoring toward advanced Earth observation technologies, artificial intelligence, cloud computing and integrated multi-sensor monitoring systems. The identification of temporal research trends also facilitates the recognition of emerging scientific topics and potential future research directions.

The bibliometric results were presented using a combination of descriptive statistics and scientific knowledge mapping techniques. Publication trends, country productivity and journal distributions were summarized using statistical charts, whereas keyword co-occurrence networks, thematic maps and collaboration networks were used to visualize relationships among authors, institutions, countries and research themes. These complementary analyses provide a comprehensive overview of the scientific development of terrain analysis and landslide monitoring while supporting the identification of knowledge gaps and future research priorities.

The integration of bibliometric analysis with the qualitative thematic synthesis enhances the robustness of this review by combining quantitative evidence of research activity with critical evaluation of methodological advances and technological innovations. Consequently, this dual approach provides a more comprehensive understanding of the evolution of terrain analysis and landslide monitoring than either bibliometric or narrative review methods alone.

2.6 Limitations

Although Scopus and WoS provide the most comprehensive collections of peer-reviewed scientific literature, restricting the search to those databases may have excluded a limited number of relevant publications indexed elsewhere, such as the IEEE Xplore. Furthermore, only English-language publications were included, introducing the possibility of language bias. Nevertheless, previous comparative studies have shown that Scopus and WoS provide excellent coverage of Earth sciences, engineering, remote sensing and environmental hazard research, making it appropriate sources for systematic reviews in this domain (Falagas et al., 2008; Martín-Martín et al., 2018).

Finally, the rapid pace of technological innovation in remote sensing, artificial intelligence and Earth observation means that new methodologies continue to emerge. Consequently, this review should be regarded as a comprehensive synthesis of the state of the art up to June 2026, while recognizing that the field will continue to evolve.

3. Results

3.1 Temporal Evolution of Research

The systematic review identified 256 peer-reviewed publications related to terrain analysis and landslide monitoring, demonstrating a substantial increase in scientific interest over the past three decades. The earliest studies primarily focused on conventional geomorphological investigations, engineering geological mapping and geotechnical monitoring, whereas research published after 2000 increasingly incorporated Geographic Information Systems (GIS), Digital Elevation Models (DEMs) and satellite remote sensing technologies.

A marked acceleration in publication output was observed during the last decade, reflecting rapid technological developments in Earth observation systems, cloud computing, unmanned aerial vehicles (UAVs) and artificial intelligence (AI). The launch of freely available satellite missions such as Sentinel-1 and Sentinel-2 under the Copernicus Programme has significantly expanded access to high-resolution remote sensing datasets, facilitating both regional and global landslide investigations (Drusch et al., 2012; Torres et al., 2012).

Recent years have also witnessed a growing emphasis on machine learning, deep learning and multi-source data fusion approaches, indicating a transition from descriptive terrain mapping toward predictive and operational monitoring systems. Similar publication trends have been reported in previous bibliometric studies of landslide susceptibility modelling and remote sensing applications (Reichenbach et al., 2018; Merghadi et al., 2020).

Figure 2 illustrates the annual evolution of publications between 2000 and 2026.

3.2 Geographic Distribution of Research

The bibliometric analysis reveals a pronounced geographical imbalance in the global distribution of research on terrain analysis and landslide monitoring. Scientific output is concentrated primarily in countries that combine high landslide susceptibility with strong research infrastructure, long-standing expertise in engineering geology and substantial investment in Earth observation technologies. This pattern reflects both the spatial occurrence of landslide hazards and national priorities for disaster risk reduction, infrastructure protection and environmental monitoring.

Among all countries, China has emerged as the most prolific contributor to the literature, reflecting its extensive mountainous terrain, rapid infrastructure development, frequent landslide disasters and sustained investment in remote sensing technologies, artificial intelligence and national hazard monitoring programmes. The large number of publications also reflects the increasing availability of high-resolution satellite imagery, UAV platforms and large-scale geospatial datasets that support landslide susceptibility modelling and deformation monitoring.

Within Europe, Italy represents one of the leading centres of excellence in landslide research. The country's long tradition in engineering geology, geomorphology and geotechnical engineering, together with pioneering developments in radar interferometry and operational landslide monitoring, has resulted in a substantial scientific contribution. Italian researchers have played a particularly important role in advancing InSAR methodologies, early warning systems and integrated multi-sensor monitoring frameworks (Casagli et al., 2017).

Significant research activity is also observed in India, Japan and the United States, where frequent rainfall-induced and earthquake-triggered landslides, combined with extensive transportation infrastructure in mountainous environments, have stimulated continuous methodological development. Additional contributions originate from Spain, Switzerland and Norway, where research has focused on mountainous terrain, alpine hazards, rock slope stability and climate-induced geomorphological processes.

The observed geographical distribution closely corresponds with global landslide susceptibility patterns reported by previous worldwide assessments (Kirschbaum et al., 2015; Froude & Petley, 2018). Regions characterized by steep topography, active tectonics, intense precipitation, glacier retreat, or rapid urban expansion consistently exhibit higher scientific output, reflecting both greater hazard exposure and increased investment in monitoring technologies.

Despite the growing internationalization of landslide research, important regional disparities remain evident. Comparatively few studies originate from many countries in Africa, South America and parts of Southeast Asia, despite the high vulnerability of many of these regions to rainfall-induced slope failures. Limited access to high-resolution geospatial datasets, insufficient long-term

monitoring infrastructure, scarce landslide inventories and restricted research funding continue to constrain scientific development and operational hazard assessment. Addressing these geographical disparities through international collaboration, open-access Earth observation initiatives, technology transfer and capacity-building programmes represents an important priority for future research and global disaster risk reduction.

Overall, the bibliometric findings indicate that landslide research is progressively becoming more internationally collaborative; however, significant opportunities remain to expand monitoring capabilities and scientific knowledge in data-scarce regions where landslide risk is expected to increase under future climate change scenarios.

3.3 Evolution of Monitoring Technologies

The evolution of landslide monitoring technologies over the past four decades represents one of the most significant advances in natural hazard research, driven by rapid developments in geospatial technologies, Earth observation systems, digital terrain analysis and computational modelling. Traditionally, landslide investigations relied predominantly on field-based geological and geomorphological surveys, geotechnical instrumentation and site-specific monitoring to characterize slope conditions and failure mechanisms (Varnes, 1978; Cruden & Varnes, 1996; Turner & Schuster, 1996). Although these conventional approaches continue to provide essential information on subsurface conditions and slope stability, their limited spatial coverage and high operational costs have encouraged the adoption of increasingly sophisticated remote sensing technologies capable of monitoring large and inaccessible areas (Aleotti & Chowdhury, 1999; Duncan & Wright, 2005).

The widespread implementation of Geographic Information Systems (GIS), Digital Elevation Models (DEMs), satellite remote sensing and Global Navigation Satellite Systems (GNSS) during the 1990s and early 2000s marked a fundamental shift from localized investigations toward spatially explicit terrain analysis and regional susceptibility assessment (Moore et al., 1991; Wilson & Gallant, 2000; Guzzetti et al., 1999). Since then, continuous advances in Synthetic Aperture Radar (SAR) interferometry, Light Detection and Ranging (LiDAR), Unmanned Aerial Vehicles (UAVs), airborne and terrestrial laser scanning and high-resolution optical satellite imagery have substantially enhanced the capability to detect, characterize and monitor landslide processes across multiple spatial and temporal scales (Ferretti et al., 2001; Berardino et al., 2002; Jaboyedoff et al., 2012; Tarolli, 2014; Crosetto et al., 2016; Casagli et al., 2017).

More recently, the availability of freely accessible Earth observation missions such as Sentinel-1, Sentinel-2 and Landsat, together with cloud-based geospatial platforms such as Google Earth Engine, has enabled the systematic processing of large volumes of satellite data for regional and global landslide monitoring (Drusch et al., 2012; Torres et al., 2012; Gorelick et al., 2017; Wulder et al., 2019). Simultaneously, advances in machine learning, deep learning and multi-source data fusion have transformed landslide monitoring from a predominantly descriptive discipline into a predictive and data-driven science capable of supporting near-real-time deformation analysis, susceptibility modelling and operational early warning systems (Reichenbach et al., 2018; Merghadi et al., 2020; Samek et al., 2021; Casagli et al., 2023).

Overall, this technological evolution has fundamentally improved the accuracy, spatial coverage, temporal frequency and operational applicability of landslide investigations, facilitating the transition from isolated field assessments to integrated monitoring frameworks that combine conventional surveying techniques, remote sensing observations, artificial intelligence and geospatial analytics for comprehensive hazard assessment and disaster risk reduction (Casagli et al., 2017; Froude & Petley, 2018; IPCC, 2022).

Table 3
Evolution of landslide monitoring technologies

Period	Dominant Technologies	Main Applications	Advantages	Principal Limitations	Representative References
Before 1990	Geological mapping, geomorphological surveys, boreholes, inclinometers, extensometers, piezometers	Site characterization, failure mechanism identification	Direct observations, high geotechnical accuracy	Local coverage, labour-intensive, expensive	Varnes (1978); Cruden & Varnes (1996); Turner & Schuster (1996)
1990–2000	GIS, DEMs, GNSS, Digital Terrain Analysis	Terrain characterization, susceptibility mapping	Spatial analysis, integration of multiple datasets	Limited temporal monitoring	Moore et al. (1991); Wilson & Gallant (2000); Guzzetti et al. (1999)
2000–2010	Optical satellite imagery, SAR, InSAR, DInSAR, PSInSAR, SBAS	Inventory mapping, deformation monitoring	Regional coverage, repeated observations	Atmospheric effects, vegetation interference	Ferretti et al. (2001); Berardino et al. (2002); Crosetto et al. (2016)
2010–2020	LiDAR, TLS, ALS, UAVs, SfM photogrammetry, Sentinel-1/2	High-resolution terrain modelling, change detection, rapid post-event assessment	Centimetre-scale resolution, rapid data acquisition	Cost, limited UAV coverage, weather dependence	Jaboyedoff et al. (2012); Tarolli (2014); Westoby et al. (2012); Turner et al. (2015); Drusch et al. (2012); Torres et al. (2012)
2020–Present	Cloud computing, Google Earth Engine, Machine Learning, Deep Learning, Multi-source data fusion	Automated landslide detection, susceptibility modelling, near-real-time monitoring	High automation, predictive capability, large-scale processing	Data heterogeneity, model interpretability, computational requirements	Gorelick et al. (2017); Reichenbach et al. (2018); Merghadi et al. (2020); Samek et al. (2021); Casagli et al. (2023)

3.3.1 Conventional Terrain Investigation Methods

Before the widespread adoption of remote sensing and advanced geospatial technologies, landslide investigations relied predominantly on conventional field-based techniques to characterize terrain conditions, identify instability mechanisms and evaluate slope behaviour. Geological mapping, geomorphological surveys, borehole investigations, laboratory testing, geophysical surveys, inclinometers, extensometers, piezometers, crack meters, total stations as well as Global Navigation Satellite System (GNSS) observations formed the foundation of engineering geological investigations and remain essential components of contemporary landslide assessment (Turner & Schuster, 1996; Cruden & Varnes, 1996; Duncan & Wright, 2005).

These conventional approaches provide direct observations and measurements of the physical processes governing slope instability. Geological and geomorphological mapping enable the identification of lithological units, structural discontinuities, fault systems, weathering profiles, drainage conditions and geomorphological features such as scarps, tension cracks, displaced blocks and erosion patterns that control landslide initiation and evolution (Turner & Schuster, 1996; Duncan & Wright, 2005).. Borehole investigations and laboratory testing further provide detailed information on subsurface stratigraphy, soil and rock mechanical properties, permeability and shear strength parameters, which are fundamental for slope stability analyses and geotechnical design (Turner & Schuster, 1996; Duncan & Wright, 2005).

Ground-based instrumentation has also evolved considerably over recent decades. Inclinometers remain one of the most reliable techniques for monitoring subsurface displacement and identifying the depth and geometry of slip surfaces, while piezometers provide continuous measurements of groundwater levels and pore-water pressure, two of the most critical factors influencing slope failure. Similarly, extensometers and crack meters enable the detection of progressive surface deformation, whereas GNSS observations and robotic total stations provide high-precision measurements of surface displacement, frequently achieving centimetre- to millimetre-level accuracy under favourable monitoring conditions (Corsini et al., 2005; Casagli et al., 2017). Collectively, these techniques remain indispensable because they provide direct measurements of lithological properties,

geological discontinuities, hydrogeological conditions and subsurface deformation that cannot yet be fully captured through remote sensing technologies alone (Turner & Schuster, 1996; Duncan & Wright, 2005; Casagli et al., 2017).

The reviewed literature demonstrates that conventional investigations continue to play a fundamental role in validating remotely sensed observations and calibrating both physically based and data-driven landslide models. Field measurements are frequently used to verify deformation detected by radar interferometry, validate Digital Elevation Models (DEMs), assess the accuracy of UAV-derived products and provide ground-truth information for machine learning applications. Consequently, despite the rapid development of Earth observation technologies, conventional surveying methods remain an essential component of integrated landslide monitoring systems.

Nevertheless, these methods also present important limitations. Most conventional monitoring techniques provide information only at discrete locations and therefore may not adequately represent the spatial variability of large or complex landslide systems. Their implementation often requires permanent field installations, specialized equipment, regular maintenance and repeated site visits, resulting in considerable financial and logistical costs. Accessibility constraints in steep, densely vegetated, or hazardous terrain may further restrict data collection, particularly immediately following major landslide events. In addition, conventional surveys are generally unsuitable for continuous regional-scale monitoring because their spatial coverage is inherently limited (Aleotti & Chowdhury, 1999; Guzzetti et al., 2012).

These limitations have been a major driving force behind the rapid development and adoption of remote sensing technologies over the past three decades. Satellite observations, airborne surveys, LiDAR, UAV photogrammetry and radar interferometry have substantially expanded monitoring capabilities by providing continuous, spatially extensive and repeatable observations of terrain dynamics. Rather than replacing conventional investigations, however, these technologies increasingly complement field-based measurements within integrated monitoring frameworks that combine the accuracy of in situ observations with the extensive spatial and temporal coverage offered by Earth observation systems (Casagli et al., 2017). Such multidisciplinary approaches are now widely recognised as the most effective strategy for comprehensive landslide characterization, hazard assessment and operational early warning.

3.3.2 Development of Geographic Information Systems and Digital Terrain Analysis

The introduction of Geographic Information Systems (GIS) during the 1980s and 1990s marked a fundamental turning point in landslide research by enabling the systematic integration, management, analysis and visualization of spatial data within a unified analytical framework. Prior to the widespread adoption of GIS, landslide investigations relied primarily on manual interpretation of topographic maps, aerial photographs and field observations, making regional-scale analyses time-consuming and often subjective. GIS transformed these conventional approaches by facilitating the integration of diverse environmental datasets—including topography, geology, geomorphology, hydrology, land use, vegetation, soils, infrastructure and climatic information—thereby significantly improving the efficiency and reproducibility of landslide susceptibility assessment and hazard mapping (Wilson & Gallant, 2000; Guzzetti et al., 1999).

A major advancement accompanying the development of GIS was the increasing availability of Digital Elevation Models (DEMs), which enabled quantitative characterization of terrain morphology through Digital Terrain Analysis (DTA). DEMs provide digital representations of the Earth's surface from which a wide range of morphometric parameters can be automatically derived. Commonly extracted terrain variables include elevation, slope gradient, aspect, profile and plan curvature, terrain roughness, drainage density, flow accumulation, flow direction, Topographic Wetness Index (TWI), Stream Power Index (SPI), Topographic Position Index (TPI) and Terrain Ruggedness Index (TRI). These morphometric indices describe the geometric, hydrological and geomorphological characteristics that influence slope stability and have become fundamental explanatory variables in both physically based and data-driven landslide susceptibility models (Moore et al., 1991; Wilson & Gallant, 2000; Tarolli, 2014; Reichenbach et al., 2018).

The reviewed literature demonstrates that GIS-based terrain analysis has substantially improved the capability to identify areas susceptible to slope failure by integrating terrain attributes with geological, hydrological, climatic and anthropogenic conditioning factors. More broadly, GIS and satellite-based geospatial frameworks have demonstrated considerable value for integrating

spatially heterogeneous hazard, exposure and vulnerability indicators within multi-criteria natural-hazard risk assessments (Koliokosta, 2023c). In landslide research, this capability has facilitated the transition from descriptive geomorphological mapping toward quantitative, reproducible and spatially explicit analyses capable of supporting susceptibility assessment, regional planning, infrastructure management and disaster risk reduction (Guzzetti et al., 1999; Reichenbach et al., 2018).

The continuous improvement in DEM quality has further enhanced the reliability of terrain analysis. Freely available global datasets such as the Shuttle Radar Topography Mission (SRTM), ASTER Global DEM, ALOS World 3D and the Copernicus DEM, together with high-resolution airborne LiDAR-derived terrain models, have significantly increased the spatial detail available for landslide investigations. Higher-resolution terrain models enable the identification of subtle geomorphological features—including scarps, drainage anomalies, slope breaks, erosion channels and ancient landslide deposits—that may remain undetected in coarser elevation datasets (Tarolli, 2014; Wulder et al., 2019). Consequently, DEM resolution has become a critical factor influencing the accuracy of susceptibility modelling and terrain characterization.

More recently, GIS has evolved beyond a mapping platform into an integrated geospatial decision-support environment. Modern GIS applications increasingly combine Digital Terrain Analysis with remote sensing, LiDAR, Synthetic Aperture Radar (SAR), UAV-derived datasets, machine learning and cloud computing to process large volumes of heterogeneous geospatial information. The integration of these technologies enables automated terrain characterization, dynamic susceptibility assessment and continuous monitoring of slope instability while supporting operational early warning systems and infrastructure management (Casagli et al., 2017; Gorelick et al., 2017).

Despite these advances, several challenges remain. The quality of Digital Terrain Analysis is strongly dependent on the spatial resolution, vertical accuracy and acquisition method of the underlying DEM. Differences among elevation datasets may substantially influence derived morphometric parameters and consequently affect susceptibility modelling results. Furthermore, terrain variables alone cannot fully explain landslide occurrence without considering geological structure, hydrological processes, land-cover dynamics and triggering mechanisms such as extreme rainfall or seismic activity. Consequently, recent studies increasingly emphasize the integration of terrain analysis with multi-source environmental data and advanced analytical techniques to improve the robustness and transferability of susceptibility models (Reichenbach et al., 2018).

Overall, the development of GIS and Digital Terrain Analysis has fundamentally reshaped landslide research by providing quantitative, reproducible and spatially explicit methods for characterizing terrain and modelling slope instability. As higher-resolution elevation datasets, cloud-based geospatial platforms and artificial intelligence continue to evolve, GIS-based terrain analysis is expected to remain the core analytical framework underpinning next-generation landslide susceptibility assessment, hazard mapping and operational monitoring systems.

3.3.3 Expansion of Optical Remote Sensing

The rapid development of **optical remote sensing** has fundamentally transformed landslide investigation by enabling systematic, repetitive and spatially extensive observations of the Earth's surface. Since the late 1990s, continuous improvements in satellite sensor technology have significantly enhanced the spatial, spectral and temporal resolution of optical imagery, allowing increasingly detailed characterization of terrain morphology, vegetation dynamics and surface changes associated with slope instability. These advances have shifted landslide investigations from localized field-based assessments toward regional and global monitoring programmes capable of supporting hazard mapping, inventory development and post-disaster response (Mantovani et al., 1996; Guzzetti et al., 2012).

Early landslide applications primarily relied on the Landsat programme, whose long-term archive provides one of the most valuable Earth observation datasets for analysing landscape evolution and historical landslide activity over more than four decades. The subsequent development of higher-resolution satellite missions—including SPOT, ASTER, WorldView, GeoEye, PlanetScope, Pleiades and particularly the Copernicus Sentinel-2 constellation—has substantially improved the capability to detect small-scale geomorphological changes and monitor rapidly evolving landslide processes (Drusch et al., 2012; Wulder et al., 2019). The availability of multispectral imagery has also facilitated the use of vegetation indices, surface reflectance characteristics and land-cover classifications for identifying indirect indicators of slope instability, including vegetation stress, bare-soil exposure, erosion and post-failure environmental changes.

The reviewed literature demonstrates that optical satellite imagery is now routinely applied across a wide range of landslide-related applications. These include landslide inventory mapping, terrain and geomorphological interpretation, change detection, land-cover and vegetation monitoring, post-event damage assessment, debris-flow mapping and long-term environmental monitoring. Multi-temporal image analysis has proved particularly valuable for detecting progressive landscape changes and evaluating the temporal evolution of unstable slopes, while very-high-resolution commercial imagery enables detailed mapping of individual landslides and associated geomorphological features (Guzzetti et al., 2012).

One of the principal advantages of optical remote sensing is its ability to provide broad spatial coverage, high spectral resolution and frequent image acquisition, allowing consistent monitoring of extensive and often inaccessible mountainous regions. The operational implementation of the Copernicus Sentinel-2 mission has further enhanced these capabilities by providing freely available multispectral imagery with spatial resolutions of up to 10 m and revisit periods of approximately five days, significantly improving the feasibility of routine monitoring and large-scale susceptibility assessments (Drusch et al., 2012). Moreover, the increasing availability of open-access satellite archives has greatly expanded research opportunities and facilitated the development of automated processing workflows using cloud-based platforms such as Google Earth Engine.

Despite these significant advantages, optical remote sensing also presents important limitations. Image acquisition remains highly dependent on cloud cover, atmospheric conditions, solar illumination and seasonal vegetation, which can substantially reduce image quality or completely prevent observations during extreme rainfall events when landslides are most likely to occur. Dense forest cover may also obscure geomorphological features, making the identification of landslide scarps and subtle surface deformation particularly challenging. Furthermore, optical imagery primarily captures surface characteristics and is generally unable to detect slow ground deformation or subsurface processes that precede slope failure.

Consequently, the reviewed studies increasingly advocate the integration of optical remote sensing with complementary technologies such as Synthetic Aperture Radar (SAR), LiDAR, UAV photogrammetry, Digital Elevation Models (DEMs) and field-based geotechnical investigations. Such multi-sensor approaches exploit the strengths of each technology while compensating for their individual limitations, resulting in more comprehensive characterization of terrain conditions and improved landslide detection, susceptibility modelling and hazard assessment (Casagli et al., 2017).

Overall, optical remote sensing remains a cornerstone of contemporary landslide research owing to its accessibility, extensive historical archives and continuous technological development. Future advances in higher-resolution satellite missions, hyperspectral imaging, artificial intelligence and cloud-based geospatial processing are expected to further enhance automated landslide detection and strengthen the role of optical imagery within integrated, near-real-time monitoring and early warning systems.

3.3.4 Radar Interferometry and Surface Deformation Monitoring

Among contemporary remote sensing technologies, Synthetic Aperture Radar (SAR) has arguably had the greatest impact on landslide deformation monitoring, fundamentally transforming the ability to detect and quantify ground movements over large geographical areas. Unlike optical remote sensing systems, SAR sensors actively transmit microwave signals and operate independently of solar illumination and cloud cover, enabling continuous observations under virtually all weather conditions and during both day and night. These characteristics make SAR particularly suitable for monitoring landslide-prone regions, where adverse meteorological conditions frequently coincide with periods of increased slope instability (Ferretti et al., 2001; Casagli et al., 2017).

A major breakthrough in landslide monitoring occurred with the development of Interferometric Synthetic Aperture Radar (InSAR), which enables the detection of millimetre-scale ground deformation by comparing the phase information of repeated SAR acquisitions obtained over the same area. By exploiting differences in radar signal phase between successive images, InSAR provides highly accurate measurements of surface displacement, allowing researchers to identify slow-moving landslides, quantify deformation rates and detect pre-failure movements that are often imperceptible using conventional surveying methods (Ferretti et al., 2001). Consequently, InSAR has become one of the most widely applied techniques for long-term deformation monitoring, supporting both scientific investigations and operational hazard management.

Continuous methodological developments have further enhanced the capabilities of radar interferometry. Differential Interferometric Synthetic Aperture Radar (DInSAR) represented one of the first operational techniques for detecting surface deformation by removing the topographic contribution from interferometric phase measurements. Subsequently, Persistent Scatterer Interferometry (PSInSAR) significantly improved measurement accuracy by analysing stable radar targets that remain coherent throughout long image time series, thereby reducing the effects of atmospheric disturbances and temporal decorrelation (Ferretti et al., 2001). More recently, the Small Baseline Subset (SBAS) approach has expanded monitoring capabilities by exploiting multiple interferometric pairs acquired with short temporal and spatial baselines, allowing accurate deformation measurements over natural terrains characterized by lower coherence (Berardino et al., 2002; Crosetto et al., 2016). Together, these methodological advances have considerably increased the reliability, spatial coverage and temporal continuity of satellite-based deformation monitoring.

The operational deployment of new satellite missions has further accelerated the application of radar interferometry in landslide research. In particular, the European Space Agency's Sentinel-1 mission, launched as part of the Copernicus Programme, has revolutionized operational monitoring by providing free, systematic and globally available C-band SAR imagery with revisit intervals of six to twelve days, depending on satellite configuration (Torres et al., 2012). Combined with long-term archives from missions such as ERS-1/2, ENVISAT, TerraSAR-X, COSMO-SkyMed, ALOS and RADARSAT, Sentinel-1 has enabled continuous regional and national surveillance of ground deformation while significantly expanding the availability of operational InSAR products for scientific research, infrastructure management and civil protection (Casagli et al., 2017).

The reviewed literature demonstrates that radar interferometry is now routinely applied across a broad range of applications, including landslide inventory updating, deformation monitoring of active and dormant landslides, infrastructure stability assessment, transportation corridor surveillance, mining activities, dam safety and urban subsidence analysis. Its ability to provide repeated observations over extensive geographical areas makes InSAR particularly valuable for identifying unstable slopes that require more detailed field investigation or high-resolution monitoring using complementary technologies such as LiDAR, UAV photogrammetry, or geotechnical instrumentation.

Despite its considerable advantages, radar interferometry is not without limitations. Measurement accuracy may be affected by dense vegetation, rapid ground movements exceeding the detectable displacement threshold, geometric distortions associated with steep terrain and loss of signal coherence caused by temporal or environmental changes. Furthermore, InSAR measures displacement only along the satellite's line-of-sight (LOS), which may not fully represent the true three-dimensional movement of complex landslide systems. Consequently, radar interferometry is increasingly employed within multi-sensor monitoring frameworks, where its strengths are complemented by field observations, GNSS measurements, LiDAR-derived terrain models, UAV surveys and numerical modelling to provide a more comprehensive understanding of landslide dynamics (Crosetto et al., 2016; Casagli et al., 2017).

Overall, SAR interferometry has become one of the cornerstones of modern landslide monitoring. Ongoing developments in higher-resolution satellite missions, advanced time-series interferometric techniques, cloud-based processing platforms and artificial intelligence are expected to further enhance its operational capabilities, supporting near-real-time deformation monitoring and next-generation early warning systems. Through its integration with complementary Earth observation technologies and geotechnical investigations, InSAR is likely to remain a key component of intelligent, multi-source monitoring frameworks designed to improve landslide forecasting and disaster risk reduction.

3.3.5 LiDAR and High-Resolution Terrain Characterization

The development of Light Detection and Ranging (LiDAR) has fundamentally transformed terrain analysis and geomorphological investigations by enabling the acquisition of highly accurate three-dimensional representations of the Earth's surface. Unlike conventional surveying techniques and passive optical remote sensing, LiDAR actively emits laser pulses to measure the distance between the sensor and the terrain, producing dense point clouds from which high-resolution Digital Terrain Models (DTMs), Digital Surface Models (DSMs) and three-dimensional topographic representations can be generated. These capabilities have significantly enhanced the detection, characterization and monitoring of landslide-prone terrain across a wide range of spatial scales (Jaboyedoff et al., 2012; Tarolli, 2014).

Among LiDAR technologies, Airborne Laser Scanning (ALS) has become one of the most effective tools for regional terrain characterization. One of its principal advantages is the ability of laser pulses to partially penetrate vegetation canopies, enabling the generation of bare-earth Digital Terrain Models even in densely forested environments where conventional optical imagery often fails to accurately represent ground morphology. As a result, ALS has greatly improved the identification of subtle geomorphological features associated with both active and dormant landslides, including scarps, tension cracks, displaced blocks, hummocky terrain, lateral ridges, erosion channels and relict landslide deposits that may remain undetected using traditional mapping techniques (Jaboyedoff et al., 2012; Tarolli, 2014). Furthermore, high-density point clouds provide detailed information on terrain roughness, slope geometry, drainage networks and surface morphology, supporting more reliable susceptibility mapping and hazard assessment.

Complementing airborne surveys, Terrestrial Laser Scanning (TLS) provides exceptionally high-resolution observations for local-scale investigations. Fixed or mobile laser scanners repeatedly measure three-dimensional surface geometry with millimetre- to centimetre-level precision, allowing continuous monitoring of rock slopes, cliffs, open-pit mines, engineered embankments and unstable escarpments. Repeated TLS surveys enable the quantification of deformation rates, volumetric changes, rockfall activity and progressive slope movements, making the technology particularly valuable for infrastructure monitoring, engineering applications and validation of numerical stability models (Jaboyedoff et al., 2012).

The reviewed literature demonstrates that LiDAR has become an essential source of topographic information for landslide susceptibility modelling. High-resolution terrain derivatives-including slope, aspect, curvature, roughness, terrain ruggedness, flow accumulation and drainage characteristics-can be extracted with considerably greater accuracy than from conventional Digital Elevation Models. These morphometric parameters constitute fundamental explanatory variables in both physically based and data-driven susceptibility models, contributing substantially to improved prediction accuracy (Tarolli, 2014; Reichenbach et al., 2018).

Recent technological developments have further expanded LiDAR applications through the deployment of UAV-mounted LiDAR systems, which combine the flexibility of unmanned aerial platforms with the high accuracy of laser scanning. These systems enable rapid acquisition of high-density point clouds over inaccessible terrain while significantly reducing operational costs compared with conventional airborne surveys. In addition, increasing integration of LiDAR datasets with optical imagery, Synthetic Aperture Radar (SAR), UAV photogrammetry and machine learning algorithms has enhanced the automated identification of landslide features and improved multi-source terrain characterization (Casagli et al., 2017).

Despite its numerous advantages, LiDAR also presents several limitations. Airborne LiDAR campaigns remain relatively expensive compared with freely available satellite imagery, while data acquisition is often episodic rather than continuous, limiting temporal monitoring capabilities. Processing dense point clouds requires substantial computational resources and specialized expertise and the quality of terrain products may be influenced by flight parameters, point density, vegetation structure and interpolation techniques. Consequently, LiDAR is increasingly used as a complementary component within integrated monitoring systems rather than as a standalone technology.

Overall, LiDAR has revolutionized high-resolution terrain characterization by providing unprecedented detail in three-dimensional surface representation. Its ability to accurately map terrain morphology, detect subtle geomorphological features and generate precise morphometric variables has established LiDAR as one of the most valuable technologies for contemporary landslide research. When integrated with remote sensing observations, geotechnical investigations, Geographic Information Systems (GIS) and artificial intelligence, LiDAR forms a cornerstone of next-generation terrain analysis and operational landslide monitoring frameworks.

3.3.6 UAV-Based Monitoring

Over the past decade, Unmanned Aerial Vehicles (UAVs) have emerged as one of the most rapidly advancing technologies in landslide investigation, offering unprecedented flexibility for high-resolution terrain characterization and repeated monitoring. Their relatively low acquisition and operational costs, rapid deployment and ability to access hazardous or difficult-to-reach environments have made UAVs an increasingly valuable tool for both scientific research and operational hazard management (Westoby et al., 2012; Turner et al., 2015).

Modern UAV platforms can be equipped with a wide range of sensors, including high-resolution optical cameras, multispectral and hyperspectral sensors, thermal infrared cameras and increasingly lightweight LiDAR systems. These payloads enable the acquisition of ultra-high-resolution imagery and three-dimensional spatial information that significantly exceeds the resolution of most satellite-based observations. When combined with Structure-from-Motion (SfM) photogrammetry, UAV imagery facilitates the generation of centimetre-scale orthophotos, dense point clouds, Digital Surface Models (DSMs), Digital Terrain Models (DTMs) and highly detailed three-dimensional reconstructions of unstable slopes (Westoby et al., 2012). These products provide valuable information for identifying landslide scarps, tension cracks, displaced blocks, erosion features, debris accumulation zones and subtle geomorphological changes that may indicate progressive slope instability.

The reviewed literature demonstrates that UAVs have become particularly valuable for post-event reconnaissance, rapid damage assessment, monitoring of active landslides, rockfall investigations, infrastructure inspections and change detection through repeated surveys. Their ability to conduct frequent acquisitions enables the quantification of deformation rates, volumetric changes, erosion processes and sediment transport with exceptional spatial accuracy. Furthermore, the integration of UAV-derived datasets with LiDAR surveys, GNSS observations and satellite imagery has substantially improved the accuracy of landslide inventories and deformation analyses while providing high-quality validation data for remote sensing products and susceptibility models (Jaboyedoff et al., 2012; Turner et al., 2015).

Recent technological developments have further expanded UAV capabilities through the incorporation of real-time kinematic (RTK) and post-processed kinematic (PPK) positioning systems, autonomous flight planning, obstacle avoidance technologies and cloud-based processing platforms. These innovations have improved georeferencing accuracy, reduced field survey times and facilitated the production of high-quality terrain models suitable for engineering applications and emergency response. In addition, the growing integration of UAV observations with machine learning algorithms has enabled increasingly automated identification and classification of landslide features from high-resolution imagery.

Despite these significant advantages, several limitations continue to restrict the widespread operational use of UAVs. Flight duration remains constrained by battery capacity, limiting coverage over extensive areas. Data acquisition is also highly dependent on favourable weather conditions, with strong winds, precipitation and poor visibility frequently restricting flight operations. Regulatory requirements governing UAV deployment vary considerably among countries and may constrain data collection, particularly in populated areas or near critical infrastructure. Moreover, although UAVs provide exceptional spatial resolution, their limited spatial coverage makes them less suitable for regional or national monitoring programmes, where satellite-based Earth observation remains more efficient. Consequently, UAVs are increasingly regarded as complementary components of multi-sensor monitoring systems, combining local-scale, high-resolution observations with the extensive spatial and temporal coverage provided by satellite remote sensing, LiDAR, geotechnical instrumentation and Geographic Information Systems (GIS). This integrated approach offers a more comprehensive understanding of landslide dynamics and is expected to play an increasingly important role in next-generation operational monitoring and early warning systems.

3.3.7 Multi-Sensor Integration

One of the most significant developments identified throughout the reviewed literature is the transition from single-sensor applications toward integrated multi-sensor monitoring frameworks. Rather than relying on individual datasets, contemporary landslide investigations increasingly combine conventional field observations with Earth observation technologies to exploit the complementary strengths of different monitoring approaches. This evolution reflects the recognition that landslide processes are inherently complex and involve interactions among geological, geomorphological, hydrological, climatic and anthropogenic factors that cannot be adequately captured by any single monitoring technique (Casagli et al., 2017; Reichenbach et al., 2018).

Conventional geotechnical investigations remain indispensable because they provide direct information on lithological properties, structural discontinuities, groundwater conditions, pore-water pressures, soil and rock mechanical properties and subsurface deformation. However, these measurements are generally restricted to discrete locations and often require permanent instrumentation, making them unsuitable for large-scale monitoring. Conversely, remote sensing technologies offer extensive spatial coverage and repeated observations but primarily measure surface characteristics and deformation. Consequently, combining field instrumentation with satellite observations enables simultaneous characterization of both surface and subsurface

processes, resulting in more comprehensive assessments of slope behaviour (Turner & Schuster, 1996; Duncan & Wright, 2005; Casagli et al., 2017).

Among remote sensing technologies, strong complementarities have also emerged. Optical satellite imagery provides detailed information on land cover, vegetation dynamics, geomorphological changes and post-event damage but is affected by cloud cover and illumination conditions. Synthetic Aperture Radar (SAR) and Interferometric SAR (InSAR) overcome these limitations by operating independently of daylight and weather conditions while providing millimetre-scale deformation measurements over extensive regions (Ferretti et al., 2001; Crosetto et al., 2016). LiDAR contributes highly accurate three-dimensional terrain models capable of identifying subtle geomorphological features beneath dense vegetation, whereas UAV photogrammetry provides ultra-high-resolution imagery that is particularly valuable for localized investigations, inaccessible terrain and rapid post-disaster surveys (Jaboyedoff et al., 2012; Westoby et al., 2012). The integration of these complementary datasets significantly improves terrain characterization by combining the regional coverage of satellites with the high spatial resolution of airborne and ground-based observations.

The review further indicates that Geographic Information Systems (GIS) have become the principal platform for integrating heterogeneous datasets within unified analytical environments. GIS enables the combination of Digital Elevation Models, geological maps, land-use information, rainfall records, hydrological variables, remote sensing products and field observations into comprehensive spatial databases suitable for susceptibility assessment, hazard mapping and risk analysis (Wilson & Gallant, 2000). More recently, cloud-based geospatial platforms such as Google Earth Engine have expanded these capabilities by facilitating the rapid processing of petabyte-scale satellite archives and enabling near-real-time analysis of continuously updated Earth observation datasets (Gorelick et al., 2017). These technological developments have substantially improved the scalability of integrated monitoring systems, allowing regional and national monitoring programmes that were previously computationally infeasible.

Artificial intelligence has become a key component of modern integrated monitoring frameworks. Machine learning and deep learning algorithms are increasingly employed to fuse heterogeneous datasets derived from optical imagery, SAR interferometry, LiDAR point clouds, UAV surveys, meteorological observations, geotechnical measurements and terrain derivatives. Unlike conventional statistical approaches, these algorithms can identify complex nonlinear relationships among conditioning factors while automatically extracting relevant spatial patterns from high-dimensional datasets (Merghadi et al., 2020). Consequently, AI-based data fusion has significantly enhanced the accuracy of landslide susceptibility mapping, automated landslide detection, deformation forecasting and operational decision support.

Despite these advances, the review also highlights several important challenges associated with multi-sensor integration. Differences in spatial resolution, temporal frequency, acquisition geometry, coordinate reference systems, sensor accuracy and data quality often complicate the integration of heterogeneous datasets. Furthermore, satellite observations, UAV surveys, LiDAR campaigns and in situ monitoring systems frequently operate on different temporal scales, creating difficulties in synchronizing observations for dynamic landslide processes. Additional challenges include the large computational requirements associated with high-resolution datasets, limited interoperability among data formats and the absence of standardized protocols for data fusion and validation (Reichenbach et al., 2018).

Future integrated monitoring systems are therefore expected to evolve toward intelligent, interoperable and continuously adaptive platforms. Emerging technologies such as Digital Twins, Internet of Things (IoT) sensor networks, edge computing, 5G communications and real-time data assimilation have the potential to create dynamic monitoring environments capable of continuously updating hazard assessments as new observations become available (Casagli et al., 2023). In these systems, remotely sensed observations, field instrumentation, meteorological forecasts, numerical simulations and artificial intelligence algorithms will operate within unified decision-support frameworks, enabling continuous risk assessment and adaptive early warning. Such integrated architectures represent one of the most promising directions for future landslide research and are expected to play a central role in enhancing disaster preparedness, infrastructure resilience and climate change adaptation.

Overall, the reviewed literature demonstrates that the future of landslide monitoring lies not in the continued development of individual technologies, but in their effective integration. By combining the complementary strengths of conventional investigations, remote sensing, geospatial analysis, artificial intelligence and real-time environmental monitoring, multi-sensor

frameworks provide a more comprehensive understanding of landslide processes than any individual method. Their continued development will be essential for improving predictive capability, reducing uncertainty and supporting operational landslide early warning systems under increasingly dynamic environmental conditions.

3.3.8 Artificial Intelligence and the Next Generation of Monitoring Systems

The rapid expansion of Earth observation data, advances in computational power and the increasing availability of high-resolution geospatial datasets have positioned artificial intelligence (AI) at the forefront of next-generation landslide monitoring. The reviewed literature demonstrates a clear transition from conventional statistical susceptibility models toward data-driven approaches capable of integrating heterogeneous datasets and modelling the highly nonlinear interactions among geological, geomorphological, hydrological, climatic and anthropogenic factors that control slope instability (Reichenbach et al., 2018; Merghadi et al., 2020). Consequently, AI has become a fundamental component of modern terrain analysis, supporting not only landslide susceptibility assessment but also automated detection, deformation forecasting and operational early warning.

Among machine learning techniques, Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Extreme Gradient Boosting (XGBoost) and Gradient Boosting Machines (GBM) are the most widely applied algorithms for susceptibility modelling. These methods have consistently demonstrated superior predictive performance compared with many traditional statistical approaches because they effectively capture complex nonlinear relationships, manage high-dimensional datasets and accommodate interactions among multiple conditioning factors without requiring strong assumptions regarding data distributions (Reichenbach et al., 2018; Merghadi et al., 2020). More recently, deep learning architectures, particularly Convolutional Neural Networks (CNNs), have enabled automated extraction of spatial features directly from optical imagery, LiDAR-derived terrain models and Synthetic Aperture Radar (SAR) products, substantially improving landslide detection, inventory mapping and image classification.

The emergence of cloud computing has further accelerated the operational application of artificial intelligence. Platforms such as Google Earth Engine provide access to petabyte-scale archives of Earth observation data while offering distributed computational resources capable of processing large volumes of satellite imagery in near real time (Gorelick et al., 2017). These platforms enable the integration of multi-temporal optical imagery, SAR observations, Digital Elevation Models (DEMs), climatic variables, land-use information and other geospatial datasets within unified analytical environments, thereby facilitating regional and even global-scale susceptibility assessments that were previously computationally prohibitive.

Beyond machine learning, the literature indicates a growing shift toward intelligent monitoring ecosystems that integrate artificial intelligence with emerging digital technologies. Explainable Artificial Intelligence (XAI) is increasingly recognised as a means of improving the transparency and interpretability of complex predictive models, thereby enhancing confidence among practitioners and decision-makers (Samek et al., 2021). At the same time, Digital Twin technologies are beginning to enable the creation of dynamic virtual representations of unstable slopes by continuously assimilating data from remote sensing platforms, geotechnical instrumentation, meteorological observations and numerical simulations. Complementing these developments, Internet of Things (IoT) sensor networks and edge computing architectures facilitate continuous acquisition, transmission and processing of environmental data, supporting real-time monitoring while reducing latency and improving system responsiveness (Casagli et al., 2023).

Despite these significant advances, several important challenges remain before AI can be fully integrated into operational landslide monitoring systems. Many predictive models function as black-box algorithms, providing limited insight into the physical processes underlying their predictions. Furthermore, the performance of AI models is highly dependent on the quality, completeness and representativeness of training datasets, while differences in spatial resolution, data availability and regional environmental conditions often limit model transferability. The review also highlights that relatively few studies systematically evaluate uncertainty, model robustness, or long-term operational performance, indicating that greater emphasis should be placed on uncertainty quantification, standardized validation protocols and hybrid approaches that combine data-driven techniques with physically based process models (Reichenbach et al., 2018; Merghadi et al., 2020).

Looking forward, the convergence of artificial intelligence, cloud computing, multi-source data fusion, Digital Twins, IoT sensor networks, 5G communications and real-time data assimilation is expected to fundamentally transform landslide monitoring over the coming decade. Rather than functioning as isolated analytical tools, future monitoring systems are likely to operate as intelligent, adaptive and continuously learning platforms capable of assimilating diverse streams of geospatial and environmental information, updating hazard assessments dynamically and supporting automated decision-making. Such integrated AI-driven frameworks have the potential to shift landslide management from a predominantly reactive activity focused on post-event assessment toward a proactive, predictive and operational discipline capable of enhancing early warning, infrastructure resilience and climate adaptation strategies.

3.3.9 Emerging Research Trends

The bibliometric analysis revealed a pronounced evolution in the thematic focus of landslide research over the past four decades, reflecting the rapid technological advances that have transformed terrain analysis and monitoring practices (Fig. 3 and **Table 4**). The progression of author keywords and indexed terms demonstrates a clear transition from traditional engineering geological investigations toward integrated, data-driven monitoring systems that combine remote sensing, artificial intelligence (AI), cloud computing and real-time decision support.

During the early stages of landslide research, studies were primarily centred on engineering geology, slope stability, geomorphology, field mapping, geotechnical investigations and failure mechanism analysis. Research during this period focused largely on understanding the geological and geomorphological controls governing slope instability through field observations, laboratory testing and conventional surveying techniques. Geographic Information Systems (GIS) and Digital Elevation Models (DEMs) subsequently became increasingly prominent, facilitating quantitative terrain analysis and spatial susceptibility mapping through the integration of topographic, geological, hydrological and land-use datasets (Moore et al., 1991; Wilson & Gallant, 2000; Guzzetti et al., 1999).

From the early 2000s onwards, advances in Earth observation technologies substantially reshaped research priorities. Keywords related to Synthetic Aperture Radar (SAR), Interferometric SAR (InSAR), Persistent Scatterer InSAR (PSInSAR), Small Baseline Subset (SBAS), Light Detection and Ranging (LiDAR), Unmanned Aerial Vehicles (UAVs) and Structure-from-Motion (SfM) photogrammetry became increasingly frequent, reflecting the growing adoption of remote sensing for regional landslide inventory mapping, high-resolution terrain characterization and millimetre-scale deformation monitoring (Ferretti et al., 2001; Berardino et al., 2002; Jaboyedoff et al., 2012; Crosetto et al., 2016). Simultaneously, the launch of freely accessible satellite missions such as Sentinel-1, Sentinel-2 and the continued availability of the Landsat archive significantly expanded opportunities for operational monitoring by providing systematic, high-resolution and globally consistent Earth observation data (Drusch et al., 2012; Torres et al., 2012; Wulder et al., 2019).

The most recent literature demonstrates an even more pronounced shift toward intelligent geospatial analytics. Keywords such as machine learning, deep learning, Random Forest, Support Vector Machine (SVM), Convolutional Neural Networks (CNNs), Explainable Artificial Intelligence (XAI), cloud computing, Google Earth Engine, multi-source data fusion, Digital Twins and the Internet of Things (IoT) have experienced substantial growth over the last decade. These developments indicate a transition from descriptive mapping and retrospective hazard assessment toward automated feature extraction, predictive modelling, continuous deformation monitoring and operational early warning systems capable of processing large volumes of heterogeneous geospatial data in near real time (Gorelick et al., 2017; Reichenbach et al., 2018; Merghadi et al., 2020; Samek et al., 2021).

Another emerging trend identified in the reviewed literature is the increasing emphasis on multi-sensor integration. Rather than relying on a single monitoring technique, contemporary studies increasingly combine conventional field investigations, geotechnical instrumentation, GNSS observations, LiDAR surveys, UAV photogrammetry, optical satellite imagery, SAR interferometry, meteorological observations and numerical modelling within integrated Geographic Information System (GIS) environments. This multidisciplinary approach improves monitoring reliability by exploiting the complementary strengths of different technologies while reducing uncertainties associated with individual datasets (Casagli et al., 2017).

Furthermore, the literature demonstrates growing interest in the development of operational landslide early warning systems, particularly those integrating continuous monitoring with rainfall thresholds, deformation measurements, machine learning

algorithms and real-time data transmission. Advances in cloud computing and high-performance geospatial processing have enabled the implementation of scalable monitoring frameworks capable of supporting national and regional hazard surveillance, infrastructure management and disaster risk reduction initiatives (Gorelick et al., 2017; Casagli et al., 2023).

Overall, the evolution of research themes illustrates a clear technological progression from conventional engineering geological investigations toward integrated, intelligent and automated monitoring systems. Future research is expected to focus increasingly on the fusion of multi-source Earth observation data, explainable artificial intelligence, Digital Twins, edge computing, Internet of Things (IoT) sensor networks and climate-resilient early warning systems. These emerging technologies have the potential to transform landslide monitoring from a predominantly reactive process into a proactive, predictive and continuously adaptive framework capable of supporting real-time decision-making under changing environmental conditions.

Table 4 Evolution of monitoring technologies for landslide investigations

Section	Monitoring Approach	Key Technologies / Tools	Typical Applications	Main Advantages	Main Limitations	Representative References
3.3.1	Conventional Terrain Investigation Methods	Geological mapping, geomorphological surveys, boreholes, laboratory testing, inclinometers, extensometers, piezometers, total stations, GNSS	Slope characterization, failure mechanism analysis, groundwater monitoring, geotechnical investigations, engineering design	Direct measurements; high geotechnical reliability; accurate local-scale observations	Limited spatial coverage; point measurements; expensive and labour-intensive; difficult access in mountainous terrain	Turner & Schuster (1996); Cruden & Varnes (1996); Duncan & Wright (2005); Corsini et al. (2005); Casagli et al. (2017)
3.3.2	GIS and Digital Terrain Analysis	GIS, DEM, DTM, terrain derivatives (slope, aspect, curvature, TWI, SPI, drainage density, flow accumulation)	Terrain characterization, susceptibility mapping, spatial modelling, hydrological analysis	Integrates multiple datasets; quantitative terrain analysis; supports regional assessments	Strongly dependent on DEM quality and spatial resolution; requires accurate input datasets	Moore et al. (1991); Wilson & Gallant (2000); Guzzetti et al. (1999); Tarolli (2014)
3.3.3	Optical Remote Sensing	Landsat, Sentinel-2, SPOT, ASTER, WorldView, PlanetScope	Landslide inventory mapping, vegetation disturbance analysis, change detection, post-disaster assessment	Wide spatial coverage; multispectral information; frequent image acquisition; freely available datasets (Sentinel-2, Landsat)	Cloud cover; atmospheric interference; limited night-time capability	Mantovani et al. (1996); Guzzetti et al. (2012); Drusch et al. (2012); Wulder et al. (2019)
3.3.4	Radar Interferometry	SAR, InSAR, DInSAR, PSInSAR, SBAS, Sentinel-1	Millimetre-scale deformation monitoring, regional landslide surveillance, infrastructure stability assessment	All-weather operation; day/night monitoring; high temporal frequency; very high deformation accuracy	Atmospheric effects; temporal decorrelation; vegetation interference; requires advanced processing	Ferretti et al. (2001); Berardino et al. (2002); Crosetto et al. (2016); Torres et al. (2012)
3.3.5	LiDAR and High-Resolution Terrain Characterization	ALS, TLS, airborne LiDAR, terrestrial LiDAR	High-resolution terrain modelling, identification of scarps, displaced blocks, rock slopes, ancient landslides	Very high spatial resolution; accurate 3D terrain models; vegetation penetration (ALS)	High acquisition cost; specialised processing; campaign-based acquisition	Jaboyedoff et al. (2012); Tarolli (2014)
3.3.6	UAV-Based Monitoring	UAV, UAS, Structure-from-Motion (SfM), UAV-LiDAR, multispectral and thermal sensors	Ultra-high-resolution mapping, rapid post-disaster assessment, repeat surveys, infrastructure inspection	Low cost; flexible deployment; centimetre-scale resolution; rapid data collection	Limited flight duration; weather sensitivity; regulatory restrictions; limited spatial extent	Westoby et al. (2012); Turner et al. (2015)
3.3.7	Multi-Sensor Integration	Field investigations, GNSS, LiDAR, UAV, SAR/InSAR, optical imagery, meteorological and geotechnical data integrated within GIS	Comprehensive monitoring, validation, susceptibility modelling, decision support, early warning systems	Combines complementary datasets; improves spatial and temporal completeness; reduces uncertainty	Data heterogeneity; interoperability issues; complex processing workflows	Casagli et al. (2017)

Section	Monitoring Approach	Key Technologies / Tools	Typical Applications	Main Advantages	Main Limitations	Representative References
3.3.8	Artificial Intelligence and Next-Generation Monitoring	Random Forest, SVM, ANN, XGBoost, CNN, deep learning, Google Earth Engine, Digital Twins, IoT, Explainable AI	Automated landslide detection, susceptibility modelling, deformation forecasting, real-time monitoring, early warning	Handles large datasets; captures nonlinear relationships; supports automation and operational decision-making	Requires high-quality training data; computationally demanding; limited model interpretability	Gorelick et al. (2017); Reichenbach et al. (2018); Merghadi et al. (2020); Samek et al. (2021); Casagli et al. (2023)

3.4 Integrated Monitoring Frameworks for Landslide Risk Assessment

The systematic review demonstrates that no single monitoring technology is capable of addressing the full complexity of landslide processes. Slope instability results from the interaction of geological, geomorphological, hydrological, climatic and anthropogenic factors that operate across multiple spatial and temporal scales. Consequently, effective landslide monitoring increasingly relies on the integration of complementary monitoring techniques rather than the application of individual technologies in isolation (Casagli et al., 2017; Reichenbach et al., 2018).

Conventional geotechnical investigations remain fundamental for characterizing lithological conditions, discontinuity systems, groundwater behaviour and the mechanical properties of soils and rocks. Borehole investigations, inclinometers, piezometers, extensometers and GNSS observations provide direct measurements of subsurface processes that cannot currently be obtained using remote sensing technologies alone (Turner & Schuster, 1996; Duncan & Wright, 2005). However, these methods are generally restricted to individual sites and require permanent instrumentation and regular maintenance.

Remote sensing technologies complement these limitations by providing continuous observations over much larger areas. Optical satellite imagery enables regional landslide inventory mapping and land-cover monitoring, while Synthetic Aperture Radar (SAR) interferometry provides millimetre-scale measurements of ground deformation independent of cloud cover and daylight conditions (Ferretti et al., 2001; Crosetto et al., 2016). Similarly, airborne and terrestrial LiDAR produce high-resolution three-dimensional terrain models capable of identifying subtle geomorphological features, whereas UAV-based photogrammetry offers flexible and cost-effective monitoring of rapidly evolving slopes (Jaboyedoff et al., 2012; Westoby et al., 2012; Tarolli, 2014).

The reviewed studies increasingly demonstrate that combining these complementary datasets substantially improves monitoring reliability and reduces the uncertainties associated with individual sensors. Multi-source data fusion enables the integration of optical imagery, SAR observations, LiDAR-derived terrain models, UAV surveys, geotechnical measurements, meteorological observations and numerical modelling within unified Geographic Information System (GIS) environments. Such integrated frameworks improve the characterization of terrain morphology, deformation dynamics, hydrological processes and triggering mechanisms while supporting more robust susceptibility assessment and hazard mapping (Casagli et al., 2017; Merghadi et al., 2020).

Artificial intelligence has emerged as a key enabling technology for integrating heterogeneous datasets. Machine learning algorithms—including Random Forest, Support Vector Machines, Artificial Neural Networks, Gradient Boosting and deep learning models—are capable of analysing complex nonlinear relationships among terrain characteristics, geological conditions, rainfall, vegetation and remotely sensed observations. These approaches facilitate automated feature extraction, susceptibility modelling and continuous monitoring while accommodating the increasing volume of Earth observation data generated by modern satellite constellations (Reichenbach et al., 2018; Merghadi et al., 2020).

Recent advances in cloud computing have further accelerated this integration. Platforms such as Google Earth Engine allow rapid processing of multi-petabyte satellite archives and facilitate near-real-time analyses at regional and global scales (Gorelick et al., 2017). Together with Digital Twins, Internet of Things (IoT) sensor networks, edge computing and explainable artificial intelligence, these technologies are paving the way for intelligent monitoring systems capable of continuously assimilating new observations and updating hazard assessments dynamically (Samek et al., 2021; Casagli et al., 2023).

Nevertheless, the review indicates that fully integrated operational monitoring systems remain relatively uncommon. Many published studies continue to evaluate individual technologies independently, while comparatively few combine conventional field investigations, remote sensing observations, geotechnical instrumentation, numerical modelling and artificial intelligence within a single operational framework. Furthermore, challenges related to data interoperability, uncertainty propagation, computational requirements and standardized validation procedures continue to hinder the implementation of integrated monitoring systems.

Future research should therefore prioritize interoperable monitoring architectures capable of integrating multi-source observations across different spatial and temporal scales. Such frameworks should combine field-based measurements, Earth observation technologies, machine learning, climate information and dynamic numerical modelling within standardized decision-support systems. The development of these integrated platforms represents one of the most promising directions for enhancing landslide forecasting, strengthening early warning systems and supporting climate-resilient disaster risk reduction strategies.

3.5 Research Gaps and future directions

Despite the remarkable technological advances achieved in terrain analysis and landslide monitoring over the past four decades, the present review demonstrates that several important scientific, methodological and operational challenges remain unresolved (Table 5). Although remote sensing technologies, geospatial analysis and artificial intelligence have substantially enhanced landslide detection and monitoring capabilities, their integration into reliable, operational and globally transferable monitoring systems remains incomplete. Addressing these knowledge gaps will be essential for developing the next generation of intelligent, climate-resilient landslide monitoring and early warning systems.

One of the most significant research gaps concerns the limited integration of conventional geotechnical investigations with modern remote sensing technologies. While field observations, borehole investigations, inclinometers, piezometers, extensometers and Global Navigation Satellite System (GNSS) measurements continue to provide the most reliable information regarding subsurface conditions and slope behaviour, they are frequently applied independently from satellite observations and Earth observation technologies. Conversely, many remote sensing studies rely exclusively on surface observations without incorporating detailed geotechnical information describing internal slope conditions or failure mechanisms. Consequently, relatively few studies have developed integrated monitoring frameworks that combine field instrumentation, geotechnical measurements, remote sensing observations and numerical modelling within a unified operational platform. Such multidisciplinary approaches are likely to improve both model reliability and the interpretation of complex landslide processes (Casagli et al., 2017).

A second major challenge relates to the increasing use of artificial intelligence and machine learning for landslide susceptibility assessment. Although machine learning algorithms—including Random Forest, Support Vector Machines, Artificial Neural Networks, Extreme Gradient Boosting and deep learning architectures—have consistently demonstrated superior predictive performance compared with many conventional statistical techniques, relatively little attention has been devoted to model uncertainty, robustness and interpretability (Reichenbach et al., 2018; Merghadi et al., 2020). Most published studies emphasize predictive accuracy while providing only limited assessment of uncertainty propagation, confidence intervals, sensitivity analysis, or the influence of input data quality. Furthermore, many advanced deep learning models remain difficult to interpret, reducing confidence among practitioners responsible for hazard management and decision-making. Consequently, future research should place greater emphasis on uncertainty quantification, explainable artificial intelligence (XAI), probabilistic modelling and transparent model validation to enhance the operational credibility of AI-based landslide monitoring systems (Samek et al., 2021).

Another important limitation identified throughout the reviewed literature concerns the lack of standardized validation procedures. Considerable variability exists in the selection of validation datasets, sampling strategies, performance metrics and evaluation methodologies adopted by different studies. Accuracy measures such as the Area Under the Receiver Operating Characteristic Curve (AUC), overall accuracy, precision, recall, F1-score, Cohen's Kappa coefficient, Root Mean Square Error (RMSE) and cross-validation techniques are often reported inconsistently, making direct comparison among published susceptibility models particularly difficult (Reichenbach et al., 2018). The absence of internationally accepted benchmarking datasets and standardized evaluation protocols further limits reproducibility and hampers objective assessment of methodological performance. Developing common validation frameworks and reporting standards would therefore represent a significant step toward improving methodological consistency across landslide research.

The review also highlights the relatively limited operational implementation of Digital Twin technologies, Internet of Things (IoT) sensor networks and real-time data assimilation. Although these technologies have received increasing attention within the broader fields of smart infrastructure, digital engineering and environmental monitoring, their application to landslide hazard assessment remains at an early stage. Digital Twins have the potential to create dynamic virtual representations of unstable slopes by continuously integrating remote sensing observations, geotechnical measurements, meteorological information and numerical simulations. Similarly, IoT sensor networks can provide continuous, high-frequency measurements of displacement, groundwater levels, rainfall, soil moisture and environmental conditions, while real-time data assimilation techniques enable monitoring systems to update predictions dynamically as new observations become available. However, relatively few studies have successfully integrated these technologies into fully operational landslide monitoring and early warning systems, indicating substantial opportunities for future interdisciplinary research (Casagli et al., 2023).

A further research gap concerns the integration of multi-source Earth observation data within unified analytical frameworks. Although numerous studies employ optical imagery, Synthetic Aperture Radar (SAR), LiDAR, UAV photogrammetry, or geotechnical monitoring individually, comparatively few exploit the complementary strengths of these datasets simultaneously. Differences in spatial resolution, temporal frequency, coordinate systems, sensor characteristics and data quality continue to complicate multi-source integration. Future research should therefore prioritize the development of interoperable geospatial frameworks capable of combining heterogeneous datasets through advanced data fusion techniques, cloud computing platforms and standardized data architectures. Such integrated approaches have considerable potential to improve both the spatial completeness and temporal continuity of landslide monitoring while reducing uncertainties associated with individual sensors.

The review also identifies important geographical and socioeconomic disparities in the global distribution of landslide research. Most published studies originate from countries with well-established scientific infrastructure and substantial investment in Earth observation technologies, including China, Italy, Japan, the United States and several European countries. In contrast, comparatively few investigations have been conducted in many regions of Africa, South America, Southeast Asia and other low- and middle-income countries, despite their often high landslide susceptibility. Limited monitoring infrastructure, scarce historical inventories, restricted access to geospatial data and insufficient technical capacity continue to constrain research and operational implementation in these regions. Expanding international collaboration, promoting open-access Earth observation resources and strengthening local scientific capacity should therefore constitute important priorities for future research.

Finally, although climate change has become an increasingly prominent theme within the landslide literature, relatively few studies explicitly integrate future climate projections into continuous monitoring systems and adaptive early warning frameworks. Most current investigations evaluate historical rainfall thresholds or present-day environmental conditions, whereas relatively little attention has been devoted to assessing how projected changes in precipitation intensity, rainfall duration, snowmelt dynamics, glacier retreat, permafrost degradation, or extreme weather events may influence future landslide activity (Gariano & Guzzetti, 2016; IPCC, 2022). Incorporating climate model projections, long-term Earth observation datasets, dynamic susceptibility modelling and adaptive warning thresholds into operational monitoring systems represents one of the most important challenges for future landslide research. Such climate-informed monitoring frameworks will be essential for enhancing disaster preparedness and supporting resilient infrastructure planning under rapidly changing environmental conditions.

Overall, the findings of this review indicate that the future of landslide monitoring lies in the development of integrated, intelligent and adaptive monitoring frameworks that combine conventional geotechnical investigations, multi-source remote sensing, artificial intelligence, cloud computing, Digital Twins, IoT technologies and climate projections within unified decision-support systems. Achieving this objective will require greater interdisciplinary collaboration among geologists, geomorphologists, geotechnical engineers, remote sensing specialists, computer scientists and disaster risk managers. Such collaborative approaches have the potential to transform landslide monitoring from a predominantly reactive process into a predictive, continuously evolving and operationally robust component of disaster risk reduction and climate adaptation strategies.

Table 5
Major research gaps and future research priorities in terrain analysis and landslide monitoring

Research Area	Current Limitations	Implications	Future Research Priorities	Representative References
Integration of conventional and remote sensing techniques	Conventional geotechnical investigations and satellite observations are often applied independently rather than within unified monitoring frameworks.	Limited understanding of the relationship between surface deformation and subsurface failure mechanisms.	Develop integrated monitoring systems combining field instrumentation, GNSS, geotechnical measurements, LiDAR, UAVs, optical imagery, SAR/InSAR and numerical modelling.	Casagli et al. (2017); Jaboyedoff et al. (2012)
Artificial Intelligence and uncertainty quantification	Most AI models emphasize predictive accuracy while providing limited uncertainty analysis and model interpretability.	Reduced confidence for operational decision-making and hazard management.	Incorporate uncertainty quantification, probabilistic modelling, sensitivity analysis and Explainable Artificial Intelligence (XAI) into susceptibility and forecasting models.	Reichenbach et al. (2018); Merghadi et al. (2020); Samek et al. (2021)
Model validation and benchmarking	Validation procedures vary considerably among studies, with inconsistent datasets and evaluation metrics.	Difficult comparison of model performance and limited reproducibility.	Establish standardized validation protocols, benchmark datasets and harmonized reporting standards for susceptibility and monitoring studies.	Reichenbach et al. (2018)
Digital Twins and IoT-based monitoring	Operational applications of Digital Twins, Internet of Things (IoT) sensor networks and real-time data assimilation remain limited.	Continuous monitoring and dynamic forecasting capabilities are not fully exploited.	Develop intelligent Digital Twin platforms integrating real-time sensor data, remote sensing observations and numerical simulations for operational landslide management.	Casagli et al. (2023); Gorelick et al. (2017)
Multi-source data fusion	Most studies employ individual datasets rather than integrating complementary Earth observation technologies.	Reduced monitoring reliability and incomplete characterization of landslide processes.	Develop interoperable data fusion frameworks integrating optical imagery, SAR/InSAR, LiDAR, UAVs, GNSS, meteorological observations and geotechnical data.	Casagli et al. (2017); Crosetto et al. (2016)
Climate change integration	Few monitoring systems explicitly incorporate future climate projections or adaptive warning thresholds.	Future landslide hazard may be underestimated under changing climatic conditions.	Couple climate projections, Earth observation datasets and dynamic susceptibility models with adaptive early warning systems.	Gariano & Guzzetti (2016); IPCC (2022)
Geographical coverage and global equity	Research is concentrated in developed countries, while many highly susceptible regions remain underrepresented.	Limited transferability of monitoring approaches to developing countries.	Expand international collaborations, open-data initiatives and monitoring infrastructure in Africa, South America, Southeast Asia and other data-scarce regions.	Froude & Petley (2018); Kirschbaum et al. (2015)
Operational early warning systems	Many monitoring approaches remain research-oriented and are not fully operational.	Limited application in disaster preparedness and emergency response.	Develop integrated, real-time early warning systems combining remote sensing, AI, IoT, cloud computing and decision-support tools for disaster risk reduction.	Casagli et al. (2017); Gorelick et al. (2017); IPCC (2022)

5. Discussion

The findings of this systematic review demonstrate that landslide monitoring has undergone a profound transformation over the past four decades, evolving from predominantly field-based investigations toward integrated, multi-sensor and increasingly intelligent monitoring systems. This technological progression reflects broader developments in Earth observation, geospatial technologies, computational modelling and artificial intelligence, which together have fundamentally changed how terrain instability is investigated, monitored and managed. While conventional geological and geotechnical investigations continue to provide indispensable information regarding failure mechanisms and subsurface conditions, remote sensing technologies have dramatically expanded monitoring capabilities by enabling repeated, spatially continuous observations over local, regional and even global scales (Cruden & Varnes, 1996; Turner & Schuster, 1996; Casagli et al., 2017).

One of the principal findings of this review is the growing convergence of complementary monitoring technologies. Rather than replacing conventional investigations, remote sensing methods increasingly complement field measurements by providing broader spatial coverage, higher temporal resolution and more comprehensive representations of terrain dynamics. Technologies such as LiDAR, Synthetic Aperture Radar (SAR), Interferometric SAR (InSAR), UAV photogrammetry and high-resolution optical imagery have significantly improved the detection of subtle geomorphological changes, slope deformation and pre-failure indicators that were previously difficult to observe using traditional surveying methods alone (Jaboyedoff et al., 2012; Crosetto et al., 2016). This convergence has led to the emergence of integrated monitoring frameworks capable of combining surface observations with geotechnical measurements and numerical modelling, thereby improving both monitoring reliability and hazard assessment.

The bibliometric analysis further illustrates how technological innovation has reshaped research priorities. Earlier studies primarily emphasized engineering geology, geomorphology, slope stability analysis and field investigations, whereas recent publications increasingly focus on satellite interferometry, LiDAR, UAVs, machine learning, cloud computing and operational early warning systems. This transition reflects not only technological advances but also the growing availability of freely accessible Earth observation datasets, including the Copernicus Sentinel missions and the Landsat archive, which have democratized access to high-quality remote sensing information and substantially expanded research opportunities worldwide (Drusch et al., 2012; Torres et al., 2012; Gorelick et al., 2017).

Artificial intelligence represents another major development identified throughout the reviewed literature. Machine learning and deep learning algorithms have demonstrated considerable potential for integrating heterogeneous datasets and modelling the complex, nonlinear interactions among geological, geomorphological, hydrological, climatic and anthropogenic factors that influence landslide occurrence (Merghadi et al., 2020). Compared with conventional statistical approaches, these algorithms frequently achieve higher predictive performance while accommodating large volumes of multi-source geospatial data. Nevertheless, the review indicates that many AI-based studies continue to prioritize predictive accuracy over model transparency and uncertainty quantification. Limited interpretability, inconsistent validation procedures and insufficient assessment of prediction uncertainty remain significant obstacles to operational implementation, particularly in decision-making environments where transparency and reliability are essential (Reichenbach et al., 2018; Samek et al., 2021).

The review also highlights the increasing importance of cloud computing and near-real-time geospatial processing. Platforms such as Google Earth Engine enable efficient analysis of petabyte-scale Earth observation archives without requiring substantial local computational resources, facilitating large-scale monitoring and accelerating disaster response (Gorelick et al., 2017). Combined with advances in Internet of Things (IoT) technologies, Digital Twins and real-time data assimilation, these developments are gradually shifting landslide monitoring from periodic observation toward continuous surveillance and adaptive early warning. Although still at an early stage of implementation, such technologies offer significant opportunities for improving operational hazard management by integrating satellite observations, in situ monitoring, meteorological forecasting and numerical modelling within unified decision-support systems.

Despite these advances, the review identifies several persistent methodological challenges. Considerable heterogeneity remains in monitoring approaches, spatial and temporal resolutions, terrain variables, modelling strategies and validation procedures. The absence of standardized benchmarking datasets and harmonized evaluation protocols limits reproducibility and complicates direct comparison among published studies. Furthermore, most investigations continue to focus on individual monitoring

technologies, whereas relatively few integrate conventional field observations, geotechnical instrumentation, multi-source remote sensing and artificial intelligence within fully operational monitoring frameworks. Addressing these limitations will require greater interdisciplinary collaboration, improved data interoperability and the development of standardized methodological frameworks capable of supporting transferable and reproducible landslide monitoring applications.

Finally, climate change represents one of the most important emerging challenges identified in this review. Increasing precipitation extremes, glacier retreat, permafrost degradation and changing hydrological regimes are expected to alter landslide frequency and spatial distribution in many regions worldwide (Gariano & Guzzetti, 2016; IPCC, 2022). However, relatively few monitoring systems explicitly incorporate future climate projections into susceptibility modelling, continuous monitoring, or adaptive early warning systems. Future research should therefore focus on integrating climate scenarios, long-term Earth observation records and dynamic monitoring approaches to improve preparedness under changing environmental conditions. Such climate-informed monitoring frameworks will become increasingly important for protecting infrastructure, supporting land-use planning and enhancing disaster resilience.

6. Conclusions

This review provides a comprehensive synthesis of contemporary approaches for terrain analysis and landslide monitoring, integrating evidence from conventional geotechnical investigations, remote sensing technologies, Geographic Information Systems, digital terrain analysis and artificial intelligence. The systematic review demonstrates that landslide monitoring has evolved from predominantly localized field investigations to highly integrated, multi-scale monitoring systems capable of supporting regional surveillance, continuous deformation analysis and increasingly sophisticated early warning applications.

The review confirms that conventional field investigations remain indispensable for understanding geological conditions and validating remotely sensed observations, while advances in satellite remote sensing, LiDAR, UAV photogrammetry, radar interferometry and cloud-based geospatial platforms have dramatically expanded monitoring capabilities. These technologies have significantly improved the spatial resolution, temporal frequency and operational applicability of landslide investigations, allowing the detection of subtle deformation patterns and the assessment of slope instability across extensive geographical areas.

The bibliometric assessment further demonstrates a clear evolution of scientific priorities, with recent research increasingly emphasizing Earth observation, machine learning, deep learning, explainable artificial intelligence, Digital Twins, Internet of Things technologies and integrated early warning systems. This transition reflects the broader digital transformation occurring across geosciences and highlights the growing importance of multidisciplinary approaches that combine remote sensing, computational modelling and geotechnical engineering.

Nevertheless, the review also identifies several important challenges that continue to limit operational implementation. These include the limited integration of conventional and remote sensing techniques, insufficient uncertainty quantification in artificial intelligence models, inconsistent validation methodologies, difficulties associated with multi-source data fusion and the relatively limited incorporation of climate change projections into monitoring systems and early warning frameworks. Addressing these challenges will require standardized methodological protocols, improved interoperability among heterogeneous datasets, transparent and explainable artificial intelligence models and stronger collaboration between geoscientists, engineers, computer scientists and disaster risk practitioners.

Looking ahead, future landslide monitoring systems are expected to become increasingly intelligent, automated and adaptive through the integration of multi-source Earth observation data, cloud computing, Digital Twins, IoT sensor networks, explainable artificial intelligence and real-time data assimilation. These technological developments have the potential to transform landslide monitoring from a predominantly reactive activity into a predictive and continuously evolving component of disaster risk reduction. By synthesizing current knowledge, identifying methodological limitations and highlighting emerging research directions, this review provides a comprehensive reference for researchers, practitioners and decision-makers seeking to advance the development of operational, climate-resilient and data-driven landslide monitoring systems.

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Figures

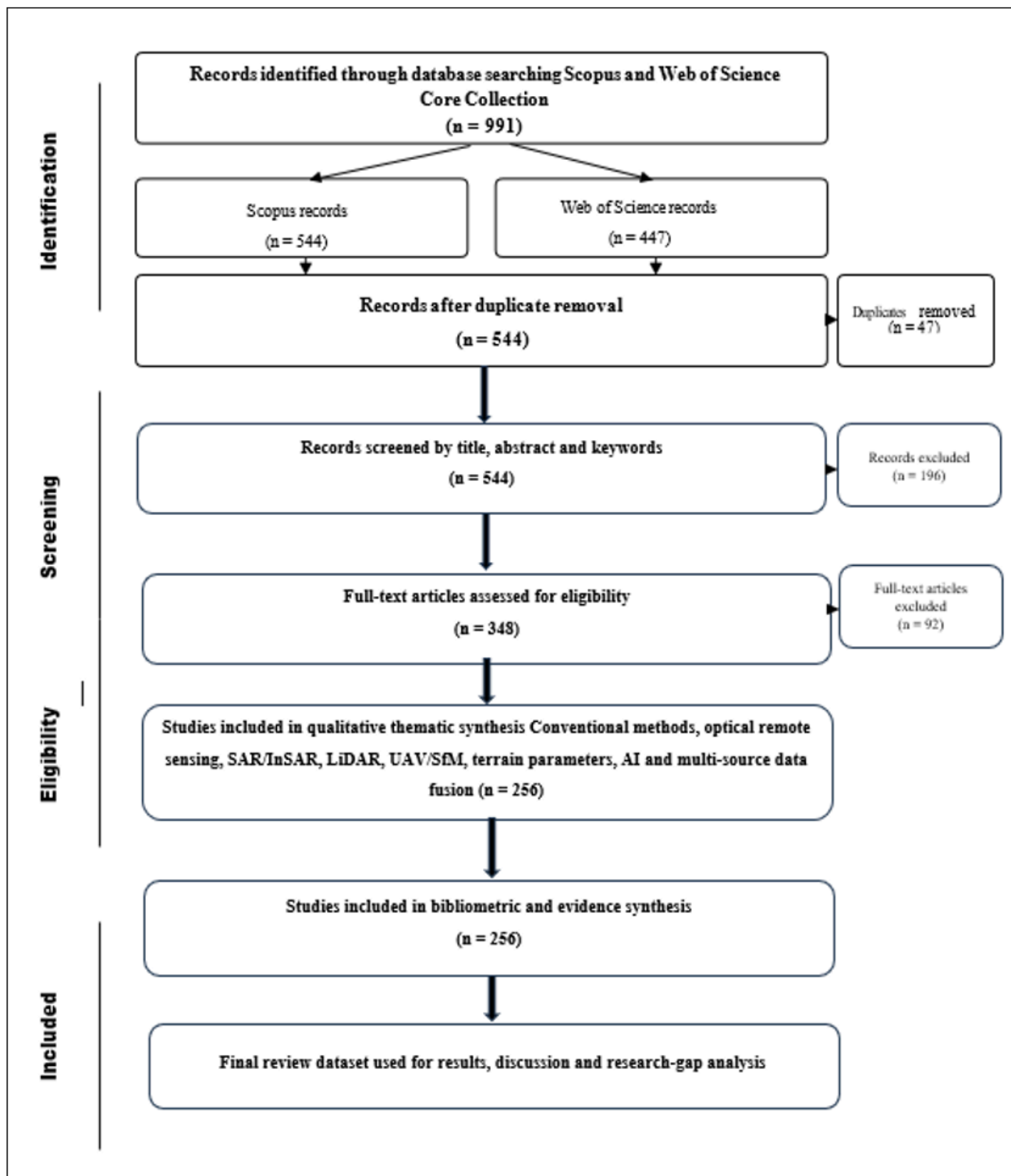


Figure 1

ROSES flow diagram for the systematic literature review

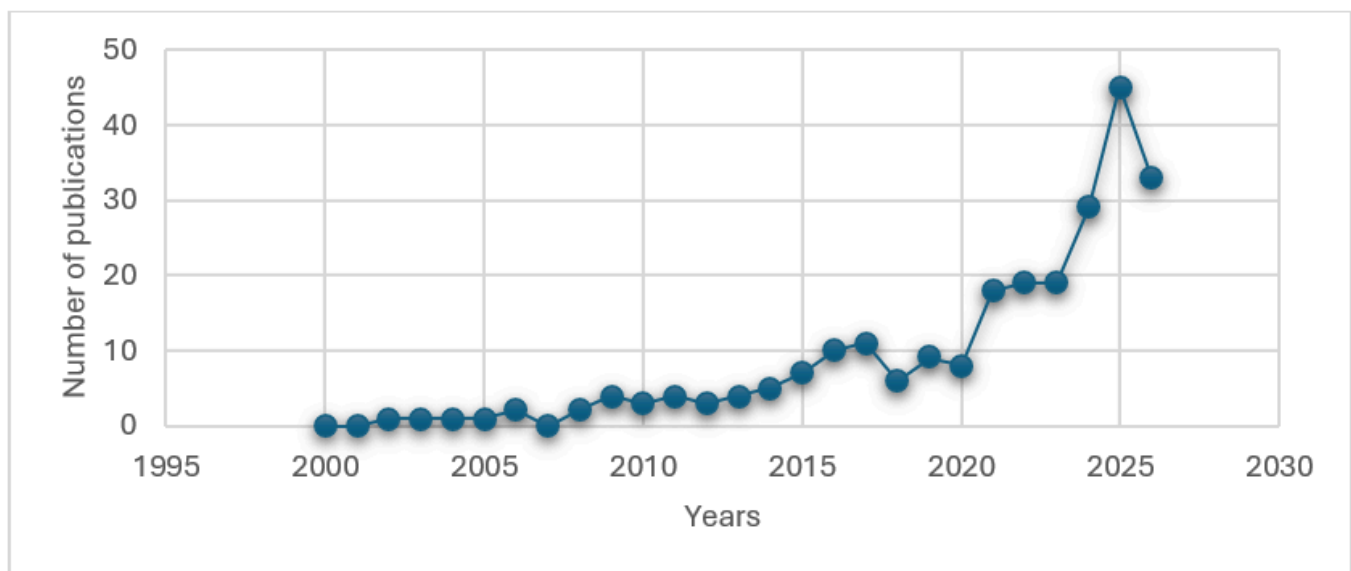


Figure 2

Geographical distribution of research studies by study areas

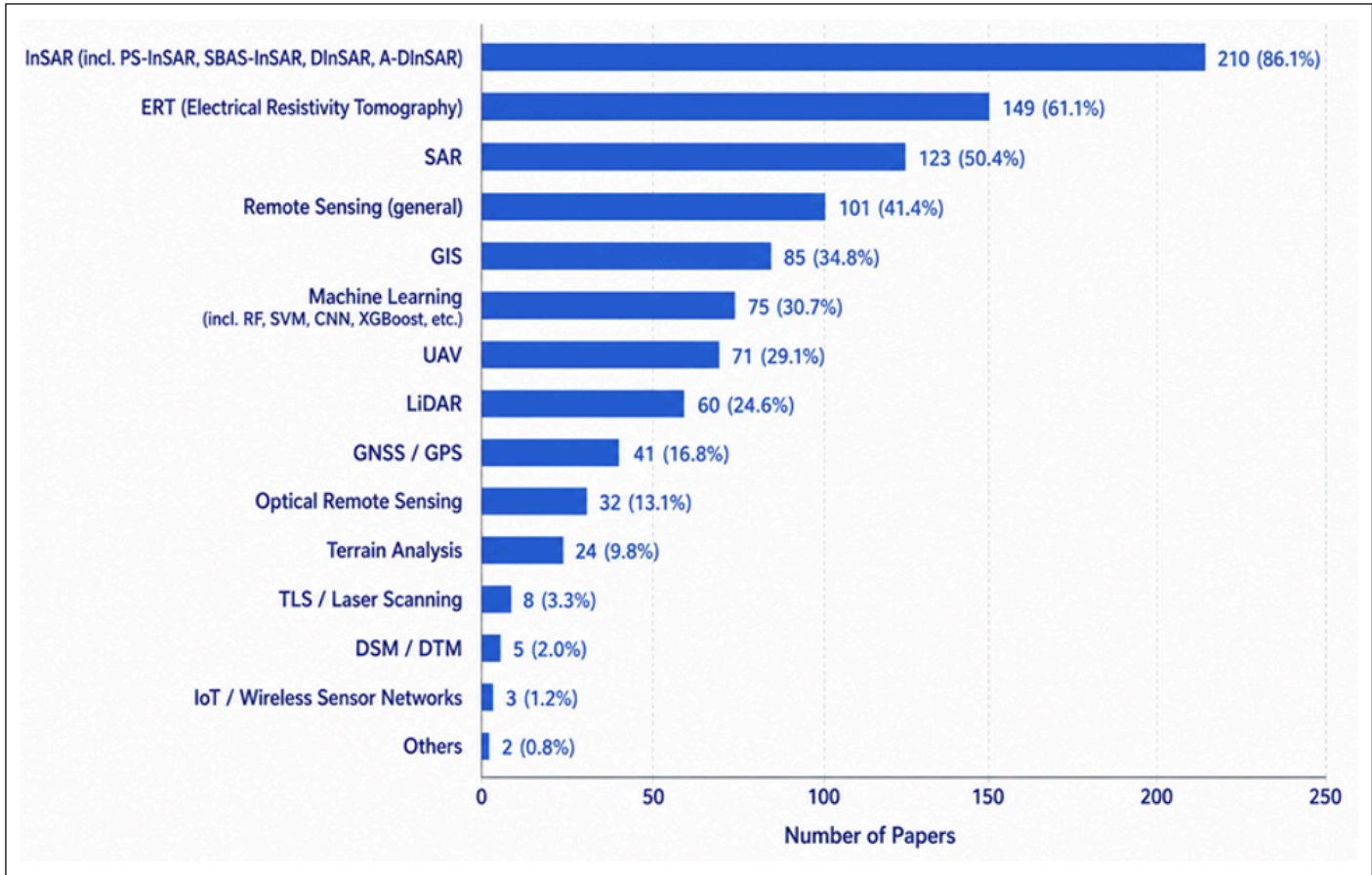


Figure 3

Distribution of Monitoring Methods in Reviewed Studies