

LANDSLIDE DETECTION AND MONITORING TECHNIQUES: A BIBLIOMETRIC ANALYSIS AND FUTURE DIRECTIONS

Hassan Khan^{1,2}, Afiqah Ismail^{1,*}, and Ahmad Safuan A. Rashid¹

Received: January 21, 2024; Revised: April 08, 2024; Accepted: July 24, 2024

Abstract

The devastating consequences of landslides demand rigorous assessment and effective management strategies to minimise risks. In this context, landslide detection and monitoring are crucial in identifying potential hazards and implementing proactive mitigation measures. This study uses the Scopus database to present a bibliometric analysis of 1,112 peer-reviewed journal articles on landslide detection and monitoring techniques published between 2002 and 2022. The analysis reveals a remarkable surge in publications, from 4 in 2002 to 180 in 2022, with the last five years (2018-2022) accounting for over 60% of the total publications. Over 3,259 unique researchers from 75 countries contributed to this field, with a significant portion originating from Asia, Europe, and North America. China and Italy emerged as the leading countries, producing over half of the articles. Nicola Casagli, from Italy, authored the most publications and garnered the highest number of citations. *Remote Sensing* emerged as the most preferred journal for authors, while *Landslides* garnered the highest total citations, and *Geomorphology* has the most normalised citations per article. The Chinese Academy of Sciences, China University of Geosciences, and the University of Florence in Italy were the most productive research institutions. The Natural Science Foundation of China (NSFC) emerged as the top funding agency. “Landslide”, “landslide monitoring”, and “early warning systems” were the top three most frequently used keywords. Keyword analysis identified landslide detection and monitoring advancements in remote sensing, analytical methods, and in-situ techniques. Co-occurrence analysis of trending research terms highlighted three distinct thematic clusters: remotely sensed data with machine learning and image analysis for landslide detection, field instrumentation for continuous deformation monitoring, and development of early warning systems for landslide hazard assessment and mitigation.

Keywords: Bibliometric Analysis; In-Situ Monitoring; Landslide Detection; Landslide Monitoring; Remote Sensing

¹ Department of Geotechnics and Transportation, Faculty of Civil Engineering, Universiti Teknologi Malaysia, Johor Bahru 81310, Malaysia, E-mail: afiqah.ismail@utm.my; ahmadsafuan@utm.my

² Department of Civil Engineering, Jalozaï Campus, University of Engineering and Technology Peshawar, 25000, Pakistan. E-mail: hassankhan@graduate.utm.my

* Corresponding author

DOI: <https://doi.org/10.55766/sujst-2024-04-e03362>

Suranaree J. Sci. Technol. 31(4):010318(1-22)

Introduction

Landslides, defined as the movement of rocks, debris or earthflow down a slope under gravity, have affected human life and environment (DM, 1996; Fell *et al.*, 2008; Guzzetti *et al.*, 2012). Triggered by nature or human activities, landslides have resulted in significant loss of life and infrastructure on a global scale. For instance, between 2004 and 2016, approximately 55,997 lives were lost in 4,862 different landslide events worldwide (Froude and Petley, 2018). Regarding economic losses, landslides have claimed USD 20 billion per year from 1980-2013, constituting 17% of the total global disaster losses (Klose, 2015). Since many countries are affected by landslide geohazards, their assessment and management are crucial for preventing and controlling the casualties and economic losses.

Landslide detection and monitoring are crucial steps in landslide risk assessment and management. Landslide detection involves collecting data and information on landslides' presence, distribution, and intensity and identifying elements affected by the deformative process. Following detection, measuring the movements and deformations over time is essential. Therefore, landslide detection and monitoring techniques refer to the methods and tools employed to detect landslide areas and measure their surface and sub-surface deformations over time. Over the past three decades, landslide research has significantly advanced. The initial decade, from 1990 to 2000, focused primarily on developing a theoretical and experimental understanding of landslide dynamics (Carrión-Mero *et al.*, 2021). Research findings from the past two decades have documented substantial advancements in applying the latest technology to assess and manage landslide hazards effectively. For instance, UAV technology (Walter *et al.*, 2009), interferometric synthetic-aperture radar (Hilley *et al.*, 2004), laser scanning (Pieraccini *et al.*, 2006), and other remote sensing techniques (Kirschbaum *et al.*, 2015) are predominantly used in landslide assessment, with their utilisation steadily increasing since the 2000s due to ongoing technological advancements (Casagli *et al.*, 2023). These advancements encompass the development of algorithms (Crosetto *et al.*, 2016) that considerably enhance the quality of monitoring data, as well as the launch of satellites with progressively higher acquisition frequency and spatial resolution (Casagli *et al.*, 2017; Mondini *et al.*, 2021).

Due to the complex nature of landslide hazards and the vast array of available detection and monitoring techniques, existing review papers

typically focus on a single method. For instance, (Scaioni *et al.*, 2014) presented an overview of remote sensing techniques with fuzzy classification based on their expertise, (Tehrani *et al.*, 2022) summarised and critically evaluated machine learning algorithms recently used for landslide detection and spatial and temporal forecasting (Whiteley *et al.*, 2019) appraised the state-of-the-art geophysical monitoring, (Kumar, 2020) discussed the applications of time domain reflectometry in open-cast mines, and (Yadav *et al.*, 2019) focused on unifying WSN and IoT technology for slope monitoring. It is challenging for researchers to evaluate the entire spectrum of landslide detection and monitoring techniques in a review paper. Bibliometric analysis can be a more effective tool to comprehensively explore trending methods with their respective performances, recently gaining widespread attention in different research fields.

Bibliometric analysis is a widely used approach for the scientific analysis of large datasets. The recent surge in the popularity of bibliometric analysis stems from advancements, accessibility, and availability of digital databases and bibliometric software such as Biblioshiny, Gephi, and VOSviewer (Donthu *et al.*, 2021). Due to the rapid development of computers and the internet, bibliometric analysis is attracting increasing attention from researchers (Bar-Ilan, 2008). By applying bibliometric analysis, one can uncover advancements in a specific research field and identify research directions and leading topics (Wang *et al.*, 2014a). Additionally, bibliometric analysis aids in identifying research gaps within a particular research area (Gall *et al.*, 2015). It can be a valuable tool for researchers and institutions to explore collaborations and funding opportunities in fields of interest. Moreover, bibliometric analysis can help policymakers and funding agencies make informed decisions regarding fund allocation (Ugolini *et al.*, 2015). Despite bibliometric analysis having gained widespread application across various fields, comprehensive studies on global landslide research remain limited. Existing bibliometric studies focus on the entire landslide literature rather than specific detection and monitoring techniques. Gokceoglu and Sezer (2009) analysed all types of landslide papers published between 1945 and 2008, providing an overview of publication trends, contributing authors, and the most frequently used keywords. Similarly, Wu *et al.* (2015) conducted a bibliometric analysis of landslide research from 1991 to 2014, summarising document type, language, research

trends, scientific categories, journals, keyword evolution, and collaboration networks. However, these studies targeted the entire field of landslides instead of focusing on specific detection and monitoring techniques. Other studies like Sassa *et al.* (2015) and Mikoš (2017) restricted their studies to the research results published by the journal *Landslides* and discussed the status and ranking of the journal within the research field. Similarly, Mikoš (2018) studied 52 books published by the International Consortium on Landslides, emphasising metrics like views, downloads, and citations. Likewise, Carrera *et al.* (2021) presented a bibliometric analysis of landslide literature from 2000 to 2019 but restricted their study to Latin America and covered the entire field of landslide research. Carrión-Mero *et al.* (2021) investigated the bibliometric characteristics of 632 documents indexed in the Scopus database, with a bias towards the intellectual structure of various landslides based on the USGS classification. The latest study by Huang *et al.* (2022) used a machine learning method (LDA) for topic modelling in addition to conventional bibliometrics. Although these works offer valuable insights and contribute to advancing knowledge within the field, their scope is often too broad, resulting in a lack of specific focus on landslide detection and monitoring techniques.

In summary, the current bibliometric analyses of landslide research are limited and have certain shortcomings, such as restricted geographical locations specific to one journal, considering the broader scope of landslide research and lack of focus on the advancement of landslide detection and monitoring techniques and their key players. Moreover, these studies often include all types of documents in their analysis, including review papers. While review papers are valuable for summarising the existing literature, journal articles are considered the preferred source of novel findings. Therefore, this study highlights the advancement of landslide detection and monitoring techniques over the past two decades, drawing solely from peer-reviewed journal articles indexed in the Scopus database.

This study aims to perform a bibliometric analysis concentrating on techniques for detecting and monitoring landslides, highlighting important data sources, methodologies, and recent research trends. Through the synthesis of existing information and examination of emerging challenges, this research contributes to the continual improvement of our understanding of landslide monitoring techniques. Bibliometric analysis, a potent quantitative tool for assessing scientific literature, is increasingly recognized across diverse research domains (Donthu *et al.*, 2021). The specific

objectives of this paper are: (1) to analyse publication and citation trends on the advancement of landslide detection and monitoring techniques from 2002 to 2022, (2) to identify the leading countries, authors, journals, institutions, and funding organisations contributing to the development of these techniques, (3) to explore collaborations among authors and countries through co-authorship analysis, and (4) to highlight the famous author keywords and trending research terms used in these articles. This study will guide researchers, academicians, practitioners, and policymakers in streamlining their future landslide hazard assessment and management endeavours.

Materials and Methodology

Data Search and Collection Strategies

The data used for the analysis were electronically retrieved from the Scopus database, utilizing the latest available version up to October 2023. Scopus was selected due to its recent advancements as a highly comprehensive online repository for academic articles, surpassing competitors like Web of Science and Google Scholar in terms of regular updates and expansion (Falagas *et al.*, 2008; Kulkarni *et al.*, 2009; Harzing and Alakangas, 2016; Powell *et al.*, 2017).

This study focused on investigating landslide detection and monitoring techniques used and enhanced during the period 2002-2022. To cover all relevant publications, we started with a simple keyword of “landslide monitoring” and added up several possible terms turn by turn to search in the titles, abstracts and keywords section of the database. This process of deciding the initial search query was finalised on September 16, 2023, with thirteen terms, each enclosed in double quotation marks and separated by the Boolean operator “OR”. The search input used was: (TITLE-ABS-KEY (“Landslide monitoring” OR “Landslide detection” OR “Landslide early warning” OR “slope monitoring” OR “Landslide monitoring system” OR “Slope displacement monitoring” OR “Slope failure monitoring” OR “Slope failure detection” OR “Slope deformation monitoring” OR “Landslide remote sensing” OR “Landslide sensor*” OR “Rockfall monitoring” OR “Rockslide monitoring”)).

The above search string retrieved 3,043 documents published from 1973 to 2023. It is required to apply certain exclusion criteria and filter out the search string to get the most relevant materials on any scientific database (Abbate *et al.*, 2023). The search string refinement was carried out in four steps, as shown in Figure 1.

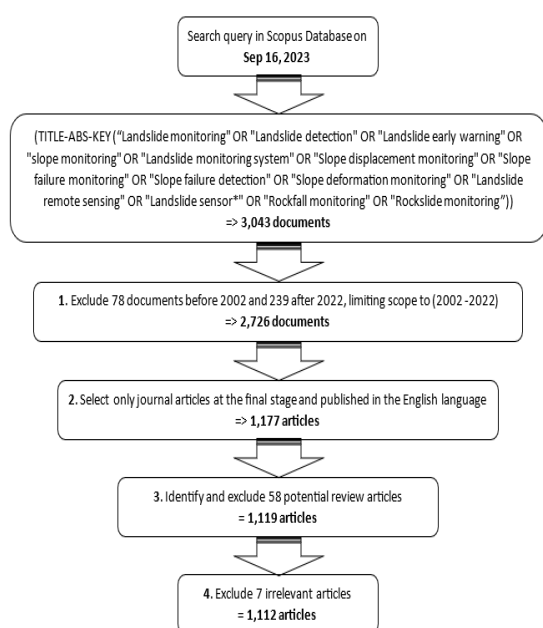


Figure 1. Flowchart for data search and refinement strategies

In Step 1, the EXCLUDE PUBYEAR command was used to exclude documents published before 2002 (78 documents) and during 2023 (242 documents), resulting in 2,723 documents published during the last two decades.

It should be noted that we used “Exclude” for all filters and found that there was a difference in the number of documents when “Limit to” was used. Step 2, only articles as document type, journal as source type, publication stage as final, and published in English were selected. Most researchers prefer articles because of their scientific reliability and acceptance (Saravanan *et al.*, 2022). Review papers were not considered because they aimed to summarise the existing literature and did not present the original research results. Step 3, Potential review articles were identified by terms like “review”, “overview”, “state of the art”, “comprehensive analysis”, “critical review”, “current perspectives”, “advances in the field”, “progress reports”, “recent developments”, “state of the discipline”, and “research trends” appearing in the title of the papers. This identified 58 potential review papers that were excluded with the help of the Boolean operator “AND NOT”. In the last step, seven irrelevant articles were identified by going through articles titles and abstracts. These articles were removed with the help of their electronic identification numbers (EIDs) and using the “AND NOT” operator in the search string. The exclusion refinement of the search string avoids any bias

introduced by any review and irrelevant paper. Finally, 1,112 peer-reviewed journal articles were selected, and data comprising citation information, bibliographical information, abstracts and keywords, funding details, and other information were exported into a comma-separated values (CSV) file for further analysis.

Bibliometric Mapping/Analytical Tools and Methods/Data Analysis

The retrieved information in the CSV file was reviewed and exported to a Microsoft Excel spreadsheet for data reliability and analysis. MS Office Excel 2019 was utilised to analyse trends in the data, including annual publications, citations, top authors, institutions, contributing countries, journals, and funding organisations. These results were then verified and further elaborated by the VOSviewer software (version 1.6.19). VOSviewer is a Java-based tool known for efficiently constructing and visualising bibliometric networks (van Eck and Waltman, 2010). The VOSviewer co-authorship analysis helps to understand the relationships between co-authored publications, while the co-occurrence analysis reveals the number of articles cited together and published jointly (Leydesdorff *et al.*, 2013). A VOSviewer bibliometric network map consists of several nodes and connecting lines with distinct colours for each category (i.e., cluster). The node size represents the number of publications for different parameters (i.e., countries or journals), while the number of lines emerging from a node shows the number of connections. The thickness of the lines, referred to as link strength, reflects the strength of the connection based on the number of documents involved. The VOSviewer software generates clusters to represent sets of nodes that are associated with related subjects.

The co-authorship analysis based on the unit of country was performed to determine collaborations among various countries. Out of the total 75 contributing countries, 67 related to at least one article published collaboratively. The clusters were based on the continents of the corresponding countries to make a similar/better visual interpretation of the global distribution map. In addition, the first letter of the country's name was capitalised by utilising the “PROPER” command in MS Excel. For the co-authorship analysis of authors on landslide detection and monitoring techniques, a visual overlay map was created by setting the threshold of a minimum of 1 document with minimum citations of 0. Based on this criterion, only 673 authors were connected out of the total 3,259 in

28 distinct clusters. It is important to note that, in the CSV file extracted from the updated version of the Scopus database, authors' names were separated by semicolon (;), and the VOSviewer cannot read it. To make it readable for the VOSviewer, we replaced the semicolon between the author's name and a comma (,) in the author's column. Moreover, the first letters of the second names and initials were capitalised.

Keywords significantly improve the search capability and accessibility of publications as they offer essential connections to the publications indexed in scientific databases. The VOSviewer co-occurrence analysis of author keywords is a powerful tool for knowledge extraction and mining (Wang *et al.*, 2021). The co-occurrence analysis revealed that a total of 2,763 keywords were used by authors in these articles. However, 194 author keywords were finalised for further analysis after renaming the synonyms, removing locations/countries' names, and setting the threshold of minimum occurrences of an author keyword to 3. Furthermore, we considered the most frequently appearing 32 keywords for exploration of technological developments in three distinct areas of this field.

Results and Discussion

Annual Publications and Citations

The extracted data was organized chronologically and presented in Figure 2 to find publication growth rates from 2002 to 2022. One thousand one hundred twelve peer-reviewed journal articles focusing on landslide detection and monitoring techniques were published during this period. The two oldest articles on landslide detection and monitoring research that appeared in the database were published in 1973 (Franklin and Denton, 1973; Norell, 1973). The global publication trend is continuously increasing, with a minimum of 4 and a maximum of 181 articles published in 2002 and 2022, respectively. The pattern indicates a slower-growing trend in the initial decade, totaling only 154 articles (14%), while the remaining 86% of articles were published in the last decade. Based on the data presented in the figure, only 47 papers were published in the first six years (2002 to 2007). However, Scientific interest experienced a significant increase following the year 2007. The number of annual publications increased significantly between 2008 and 2017, ranging from 14 to 77 articles. Surprisingly, there has been a notable increase in research output in this field, with annual publications rising from 103 to 181 between 2018 and 2022. This increase constitutes

a substantial portion, precisely 60%, of total publications recorded in the Scopus database from 2002 to 2022. This surge in research is often referred to as a "blossom period", signifying a period of rapid growth in scholarly publications (Ding and Yang, 2022).

Moreover, the consistent nonlinear rise in the cumulative number of publications indicates that the research interest is poised to keep growing in the years ahead. According to Scopus data, landslide detection and monitoring has become a prominent research topic, especially in the last five years. This growth can be attributed to factors like improved laboratory facilities, the increased availability of remote sensing data, advances in sensor technology, better programming algorithms, collaborative research efforts, increased scientific impact, and the significant societal and environmental benefits of this research (Okaiyeto *et al.*, 2020). The total number of citations serves as a metric for measuring the academic achievement of a research area, indicating its scientific impact and accessibility to a broad community of scholars (Shuaib *et al.*, 2015; Omoregie *et al.*, 2022). Figure 3 presents the total citations and normalized

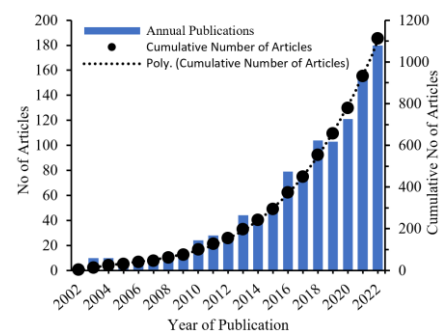


Figure 2. Number of articles on landslide detection and monitoring techniques published during 2002-2022 and indexed in the Scopus database

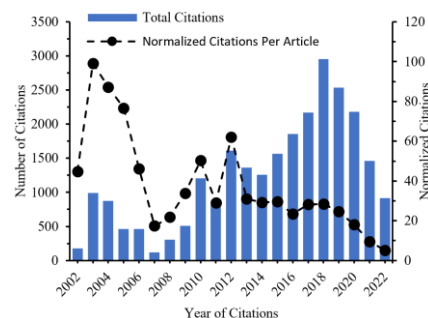


Figure 3. Citation trends of articles on landslide detection and monitoring techniques

citations per article for the yearly published articles from 2002-2022. These articles garnered a cumulative citation of 25,796. Over the years, there has been a fluctuating pattern in total citations, with occasional ups and downs.

Articles published in 2018 recorded the most citations (2,954), while publications of 2007 received the least number of citations (122). Table 1 provides further details, indicating that 1,017 articles have been cited at least once in the whole period of study. This means that other publications have referenced 91% of the total articles. In terms of normalized citations, 2003 received the highest value of 99, while 2022 had only five citations per paper. This makes sense because it takes time for articles to be cited after publication. Like total citations, the h-index serves as a prominent metric frequently employed for assessing scientific productivity (Engqvist and Frommen, 2008). In this study, the h-index for the selected articles stands

at 72. This means that out of the 1,112 articles, 72 had been cited at least 72 times, with the potential for this number to increase over time (Sweileh *et al.*, 2016). Notably, the year 2018 marked the apex for the *h*-index, registering at 33, while the years 2002 and 2007 exhibited the lowest *h*-index values, each standing at 4.

Furthermore, Table 1 demonstrates the highest cited article of each year and the total citations received. The article (McKean and Roering, 2004), with 441 citations, is the most cited article ever. This article presented a novel approach to detecting and mapping deep-seated landslides based on the topographic roughness, assessed through statistical, Laplacian, and spectral analyses of the DEM (Digital Elevation Model). This approach helped identify specific morphological zones within the landslide complex and detect the relatively recent activity.

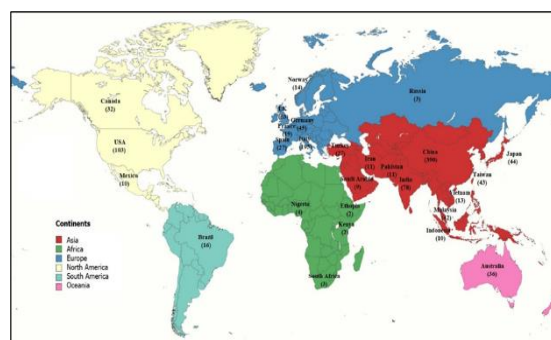
Table 1. Total publications and citations on landslide detection and monitoring techniques during 2002-2022

Year	Total Publications	Total Citations	<i>h</i> -Index	Articles Cited (%)	Highest cited paper of the year	Citations Received
2022	180	917	13	82	Landslide detection using deep learning and object-based image analysis (Ghorbanzadeh <i>et al.</i> , 2022)	47
2021	154	1,463	20	93	A comprehensive transferability evaluation of U-Net and ResU-Net for landslide detection from Sentinel-2 data (Ghorbanzadeh <i>et al.</i> , 2021)	56
2020	121	2,181	26	93	Landslide detection from an open satellite imagery and digital elevation model dataset using attention-boosted convolutional neural networks (Ji <i>et al.</i> , 2020)	143
2019	103	2,534	27	90	Evaluation of different machine-learning methods and deep-learning convolutional neural networks for landslide detection (Ghorbanzadeh <i>et al.</i> , 2019a)	439
2018	104	2,954	33	97	The Maoxian landslide as seen from space: detecting precursors of failure with Sentinel-1 data (Intrieri <i>et al.</i> , 2018)	249
2017	77	2,171	30	96	Spaceborne, UAV, and ground-based remote sensing techniques for landslide mapping, monitoring, and early warning (Casagli <i>et al.</i> , 2017)	199
2016	79	1,858	26	89	Landslide detection and susceptibility mapping using LiDAR and an artificial neural network approach: a case study in the Cuyahoga Valley National Park, Ohio (Gorsevski <i>et al.</i> , 2016)	112
2015	53	1,566	25	89	Automatic case-based reasoning approach for landslide detection: Integration of object-oriented image analysis and a genetic algorithm (Dou <i>et al.</i> , 2015)	113
2014	43	1,256	19	91	Design, development, and deployment of a wireless sensor network for detection of landslides (Ramesh, 2014)	171
2013	44	1,362	21	91	Automatic landslide detection from remote-sensing imagery using a scene classification method based on boVW and pLSA (Cheng <i>et al.</i> , 2013)	205
2012	26	1,615	17	100	Large-area landslide detection and monitoring with ALOS/PALSAR imagery data over Northern California and Southern Oregon, USA (Zhao <i>et al.</i> , 2012)	212
2011	28	814	15	96	Towards a real-time susceptibility assessment of rainfall-induced shallow landslides on a regional scale (Montrasio <i>et al.</i> , 2011)	94
2010	24	1,207	14	96	Early warning of rainfall-induced shallow landslides and debris flows in the USA (Baum and Godt, 2010)	398
2009	15	507	11	100	Test on application of distributed fibre optic sensing technique into soil slope monitoring (Wang <i>et al.</i> , 2009)	135
2008	14	305	7	93	Analysing the relationship between typhoon-triggered landslides and critical rainfall conditions (Chang <i>et al.</i> , 2008)	80
2007	7	122	4	71	Inclinometer monitoring of the Castelrotto landslide in Italy (Simeoni and Mongioli, 2007)	60
2006	10	461	7	100	Permanent Scatterers for landslide investigations: outcomes from the ESA-SLAM project (Farina <i>et al.</i> , 2006)	221
2005	6	460	6	100	Satellite remote sensing for detailed landslide inventories using change detection and image fusion (Nichol and Wong, 2005)	233
2004	10	872	6	100	Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry (McKean and Roering, 2004)	441
2003	10	992	7	100	Landslide monitoring by using ground-based SAR interferometry: An example of application to the Tessina landslide in Italy (Tarchi <i>et al.</i> , 2003)	316
2002	4	179	4	100	Neural networks for slope movement prediction (Mayoraz and Vulliet, 2002)	69

Table 2. Top 10 leading countries in landslide detection and monitoring research during 2002-2022

Rank	Country Name	Total publications	Total citations	<i>h</i> -Index	Single country publication (%)	Normalised citations
1	China	390	8,318	46	35	21
2	Italy	195	7,198	48	18	37
3	United States	103	3,917	34	9	38
4	India	78	1,142	20	7	15
5	United Kingdom	63	1,618	23	6	26
6	Germany	45	959	19	4	21
7	Japan	44	826	18	4	19
8	Taiwan	43	717	13	4	17
9	Malaysia	42	573	11	4	14
10	Austria	38	1,484	18	3	39

On the other hand, the article (Ghorbanzadeh *et al.*, 2019a) with 2nd most citations (439) evaluated the performance of artificial neural networks (ANN), support vector machines (SVM), random forest (RF), and different convolutional neural networks (CNNs) in detecting landslides. The authors concluded that convolutional neural networks (CNNs) consistently outperform other methods, contrary to the common belief. Furthermore, CNNs are still in an early stage of development, and their performance depends heavily on factors like layer depth, window size, and training strategies.

**Figure 4. Global distribution of research publications on landslide detection and monitoring techniques from 2002 to 2022**

Contributing Countries

During 2002-2022, research was conducted in 75 different countries, with a significant portion originating from Asia, Europe, and North America. Table 2 displays the top 10 countries with the greatest number of publications, while Figure 4 illustrates how publications are spread worldwide in this field.

Remarkably, the top ten countries contributed 94% of the total publications. China (390), Italy (195), the USA (103), India (78), the UK (63), Germany (45), Japan (44), Taiwan (43), Malaysia (42), and Austria (38) collectively contributed 1,041 publications, which received a total of 26,747 citations and achieved a combined *h*-index of 250. China is the most prolific and frequently cited country (8,318 citations), accounting for 35% of the total research output in landslide detection and monitoring. This means that Chinese authors have produced more articles on this subject than authors from other countries. Italy comes second in total number of articles and citations (7,195). Although the total number of publications from Italy was much lower than in China, it is essential to highlight that these articles were particularly appealing and significant to researchers.

This is evident from the fact that this country achieved the highest *h*-index value of 48 and received a substantial number of citations. Similarly, the USA followed with 103 publications, 3,918 total citations, and produced the highest-cited

article (McKean and Roering, 2004) in this field. Interestingly, Austria produced the 2nd most cited article (Ghorbanzadeh *et al.*, 2019b) and achieved the highest normalized citations (39) with only 38 publications.

Research output from other nations around the globe was insignificant when compared to the top 10 countries. Fifty out of the 75 countries could only publish between 1 and 10 papers. The research contribution of a single country during the study period was heterogeneous. Among the top 10 contributing countries, China and Italy had the highest percentage of publications from a single country, while the remaining eight countries had lower percentages, ranging from 3% to 9%. Analysis of the historical trends in publications allows us to identify the countries that have consistently ranked in the top three positions in terms of research output (Chang *et al.*, 2020). Italy was the only country that ranked among the top three for the whole period of consideration, followed by China, which remained among the top three all the time except in 2002, 2004, and 2007, when China did not contribute. It is worth noting that from 2002 to 2012, the USA was only among the top three positions three times (2004, 2007, and 2010) among the top three positions, however, in the last ten years, it has consistently occupied 3rd position except in 2016 and 2022.

It is important to note that differences in co-authorship from various countries do not necessarily reflect the quality of research or publications but rather offers insights into potential collaborations between countries and research institutions. In addition, the zeal for extended research frontiers, improved funding prospects, and the demand for specialised equipment/experiments all promote international collaborations (Melkers and Kiopa, 2010).

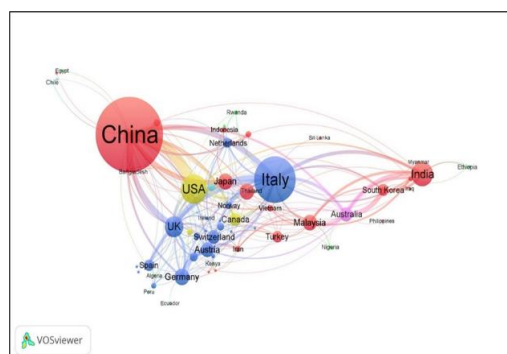


Figure 5. Collaboration network of contributing countries during 2002-2022. To view online click: [VOSviewer Online](#)

The VOSviewer software has proven to be a valuable tool for exploring the relationship among authors, their countries, and the co-occurrences of keywords (Loh *et al.*, 2022). Figure 5 shows the co-authorship analysis of the contributing countries. The network visualisation map revealed that out of 75 contributing countries, 67 collaborated with 269 links and a total link strength of 593. The collaborating countries are divided into 6 clusters, each with a distinct colour: Asia (represented by red), Africa (green), Europe (blue), North America (yellow), South America (cyan), and Oceania (algae colour). The node's size reflects the number of articles published by the country, while the thickness of the line represents the strength of the collaboration between connecting countries.

China emerged as the most central player in international collaboration, boasting the maximum total link strength (131) and the most linkages (32) with other nations. Italy followed with a total link strength of 111 and 29 ties to other countries. Notably, the link strength between China and the USA stood at 27, surpassing all other collaborating countries.

On the other hand, Italy had a link strength of 12 each with China and the UK. Similarly, a collaboration between Italy and Spain, Italy and India, China and Canada, the USA and the UK all have a link strength of 8. The total link strength represents co-authorship ties with other countries

and authors. In contrast, the link strength between countries and authors reveals the number of publications jointly authored by two linked countries and their respective authors (Loh *et al.*, 2022).

Italy and China consistently have high research output due to their significant contributions and active participation in international collaborations. China's substantial research output is driven by its extensive collaboration network and investment in research infrastructure, while Italy's consistent performance is attributed to its long-standing expertise in the field and strong ties with other research institutions. In summary, 89.33% of the contributing countries actively participated in international collaborations, highlighting the global nature of knowledge sharing and joint research efforts in the field of landslide detection and monitoring. A strong international collaboration has been found to exist among the countries. The observed collaborative research likely resulted from several motivating factors, such as the need to secure research funding, facilitate information sharing, obtain access to research facilities, and engage in co-authorship of publications (Bezak *et al.*, 2021). Despite the prevalence of international collaboration, some countries, such as Albania, Bhutan, Estonia, Jordan, Romania, Serbia, Singapore, and Slovenia, exhibit limited or no links with other countries, indicating a lack of international collaboration. This could be due to various factors such as limited resources, research infrastructure, or opportunities for collaboration within their respective regions. In summary, the high research output of certain countries in landslide detection and monitoring is influenced by factors such as research infrastructure, funding opportunities, collaborative networks, and motivation for knowledge sharing and joint research efforts on a global scale.

Top Prolific Authors

The analysis of 1,112 papers on landslide detection and monitoring techniques revealed that a total of 3,259 unique researchers authored these publications. The Scopus database assessed the authors' performance in publishing significant research articles. Table 3 presents the top prolific authors in this field, ranked by the number of articles they contributed.

According to the data, the top 10 authors collectively published 135 articles, representing 12% of all publications (1,112 articles) on this topic. The top 10 prolific authors were found to be from four different countries. A substantial representation

Table 3. Top 10 most prolific authors and their contributions

Rank	Author	TP	TC	HI	Scopus ID	Country	Highest cited article	CHCA
1	Nicola Casagli	26	2,134	23	56962779300	Italy	Landslide monitoring by using ground-based SAR interferometry: An example of application to the Tessina landslide in Italy (Tarchi <i>et al.</i> , 2003)	316
2	Biswajeet Pradhan	16	542	12	12753037900	Australia	Landslide Detection Using Residual Networks and the Fusion of Spectral and Topographic Information (Sameen and Pradhan, 2019)	87
3	Qiang Xu	15	604	10	56506033600	China	Successive land sliding and damming of the Jinsha River in eastern Tibet, China: prime investigation, early warning, and emergency response (Fan <i>et al.</i> , 2019)	143
4	Samuele Segoni	14	508	12	35272973800	Italy	Technical note: Use of remote sensing for landslide studies in Europe (Tofani <i>et al.</i> , 2013)	111
5	Huiming Tang	13	409	10	58132262400	China	Identification of causal factors for the Majiagou landslide using modern data mining methods (Ma <i>et al.</i> , 2017)	70
6	Emanuele Intrieri	12	975	10	53865165900	Italy	The Maoxian landslide as seen from space: detecting precursors of failure with Sentinel-1 data (Intrieri <i>et al.</i> , 2018)	250
7	Filippo Catani	10	501	10	7003483555	Italy	Displacement prediction of step-like landslide by applying a novel kernel extreme learning machine method (Zhou <i>et al.</i> , 2018a)	121
8	Weile Li	10	395	8	25936551300	China	Successive landsliding and damming of the Jinsha River in eastern Tibet, China: prime investigation, early warning, and emergency response (Fan <i>et al.</i> , 2019)	143
9	Bo Yu	10	216	8	57190156260	China	Landslide detection based on a contour-based deep learning framework in case of the national scale of Nepal in 2015 (Yu <i>et al.</i> , 2020)	71
10	Maneesha Vinodini Ramesh	9	418	8	55411983300	India	Design, development, and deployment of a wireless sensor network for detection of landslides (Ramesh, 2014)	170

is observed from China and Italy, with four authors originating from each nation. Moreover, one author from Australia and India also secured positions among the top 10 prolific authors.

Nicola Casagli had the most publications (26), received the maximum citations (2,134) and had the highest *h*-index (23) among this group. Followed by Biswajeet Pradhan (542 citations) and Qiang Xu (604 citations) with 16 and 15 articles, respectively. On the other hand, with 12 articles, Emanuele Intrieri achieved the 2nd highest citations (975), although one of his articles has not yet been cited. The remaining nine top authors' articles had already been cited at least once. Furthermore, Nicola Casagli's earliest publication within this group dates back to 2003, while Weile Li's most recent first publication emerged in 2019. In addition, the article (Tarchi *et al.*, 2003) co-authored by Nicola Casagli received the most citations (316), followed by Emanuele Intrieri's work (Intrieri *et al.*, 2018) with 250 citations.

Nicola Casagli, a professor at the University of Florence, Italy, was the most productive author. His main contribution is using various remote sensing techniques for landslide detection and monitoring. Specifically, the application of the ground-based interferometric synthetic aperture radar (GB-InSAR) to create highly detailed and accurate temporal maps of surface deformations of two landslides located in Italy (Pieraccini *et al.*, 2003; Tarchi *et al.*, 2003). His most cited article (Tarchi *et al.*, 2003) revealed that ground-based

radar interferometry can generate highly accurate 2D temporal deformation maps with detailed coverage area and high frequency.

On the other hand, Biswajeet Pradhan is a distinguished professor at the University of Technology Sydney, Australia. He is an internationally recognised scientist in the field of Geospatial Information Systems (GIS), image processing, machine learning, and remote sensing of earth observation. His work mainly contributed to the development of soft computing techniques, including machine learning (Mezaal *et al.*, 2017a; Sameen and Pradhan, 2019), image processing (Pradhan *et al.*, 2016; 2020), and information fusion (Mezaal *et al.*, 2017b; 2018; Sameen and Pradhan, 2019) for landslide detection and monitoring.

Figure 6 shows the overlay visualisation map of researchers' collaboration for developing landslide detection and monitoring technology from 2002 to 2022. In this bibliometric map, 673 authors are organised into 28 groups, connected by 3,278 links with a combined link strength 4,087. The map highlights that Nicola Casagli (Casagli N.) holds the highest total link strength (124) and relates to 54 other authors. Following closely are Emanuele Intrieri (42 links) and Qiang Xu (41 links), with link strengths of 65 and 63, respectively. The co-authorship map also shows that Nicola Casagli collaborated on seven articles each with Emanuele Intrieri (Intrieri E.) and Samuele Segoni (Segoni S.). In contrast, Biswajeet Pradhan, despite having the second-highest number of articles on this topic,

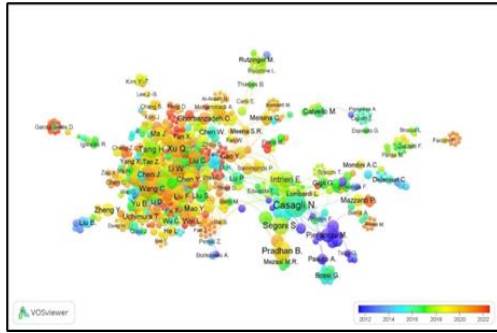


Figure 6. Overlay visualisation of co-authorship of authors. To view online click: [VOSviewer Online](#)

had lower collaboration, with a total link strength of 31 and 8 links to other authors. Notably, the top two authors, Casaghi and Pradhan, do not have a direct connection.

Productive Journals

The Scopus database was analysed to identify the most significant journals in the field. Table 4 summarises the top-performing journals on

landslide detection and monitoring techniques. It offers insights into their total article count, citations, and additional pertinent information, including the most cited article, publisher names, CiteScore, and *h*-index. The list of the top ten journals with the most publications on landslide detection and monitoring includes five distinct academic publishers: MDPI (3 journals), Springer Nature (3 journals), Elsevier Ltd (2 journals), Taylor & Francis Ltd (1 journal), and Copernicus (1 journal).

The top ten journals contributed 402 articles to the field, generating 12,817 citations. The journal Remote Sensing occupied the foremost position in terms of overall publications, with a total of 106 articles and 2,845 citations. It was followed by Landslides with 85 articles, which, remarkably, accumulated the highest total citations of 3,547 and attained the highest *h*-index of 33. This indicated that most researchers preferred to publish their work in Remote Sensing. However, articles published in Landslides were more likely to be cited. Besides, the fact that Remote Sensing is an open-source journal.

The Scopus CiteScore is a vital tool for evaluating journal performance by reflecting the average citations received per article over four

Table 4. The top ten most productive Journals on landslide detection and monitoring techniques from 2002 to 2022 and their most cited articles

Rank	Journal	Publisher	TP	TC	NCPA	PCA	HI	CiteScore (2022)	SJR (2022)	SNIP (2022)	Q	Highest cited article	CHCA
1	Remote Sensing	MDPI	106	2,845	27	97	28	7.9	1.136	1.532	Q1	Evaluation of different machine-learning methods and deep-learning convolutional neural networks for landslide detection (Ghorbanzadeh <i>et al.</i> , 2019b)	439
2	Landslides	Springer Nature	85	3,547	42	100	33	11.6	1.928	2.025	Q1	Early warning of rainfall-induced shallow landslides and debris flows in the USA (Baum and Godt, 2010)	398
3	Engineering Geology	Elsevier	45	2,283	51	96	24	12	2.342	2.373	Q1	Landslide monitoring by using ground-based SAR interferometry: An example of application to the Tessina landslide in Italy (Tarchi <i>et al.</i> , 2003)	316
4	Natural Hazards	Springer Nature	28	601	21	100	15	5.5	0.747	1.151	Q1	Developing an early warning system for a very slow landslide based on displacement monitoring (Macciotta <i>et al.</i> , 2016)	59
5	Sensors	MDPI	27	543	20	100	15	6.8	0.764	1.317	Q1	Automated landslide detection for mountain cities using multi-temporal remote sensing imagery (Chen <i>et al.</i> , 2018b)	60
6	Natural Hazards and Earth System Sciences	Copernicus	25	570	23	100	14	6.8	1.094	1.289	Q1	Technical Note: An operational landslide early warning system at a regional scale based on space-time-variable rainfall thresholds (Segoni <i>et al.</i> , 2015)	71
7	Geomatics Natural Hazards and Risk	Taylor & Francis	20	451	23	100	12	7.3	0.813	1.184	Q1	Performance of low-cost GNSS receiver for landslides monitoring: test and results (Cina and Piras, 2015)	79
8	Geomorphology	Elsevier	19	1,221	64	100	17	7.8	1.207	1.309	Q2	Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry (McKean and Roering, 2004)	441
9	Applied Sciences (Switzerland)	MDPI	17	260	15	82	8	4.5	0.492	0.974	Q2	Optimized neural architecture for automatic landslide detection from high-resolution airborne laser scanning data (Mezaal <i>et al.</i> , 2017c)	63
10	Environmental Earth Sciences	Springer Nature	15	408	27	100	9	5.2	0.599	0.931	Q1	Landslide HotSpot Mapping by means of Persistent Scatterer Interferometry (Bianchini <i>et al.</i> , 2012)	106

years. For example, CiteScore 2022 is the average journal citations received per published article from 2019 to 2022. Based on the CiteScore 2022, there were seven journals with CiteScores greater than 6. Among the top 10 most productive journals, Engineering Geology received the highest CiteScore of 12 and the highest SJR (2.342) and SNIP (2.373) scores. Moreover, eight of these top ten journals held a prestigious Q1 ranking in their respective subject categories, signifying their esteemed status and dedication to publishing cutting-edge research. This esteemed reputation is a powerful magnet, attracting high-quality research that further elevates their performance (Wu *et al.*, 2021). Consequently, future impactful publications in landslide detection and monitoring are anticipated to find their place in these leading journals.

Table 4 also presents the most cited papers published by the top ten journals. The Journal of Geomorphology published the most cited article (McKean and Roering, 2004). Subsequently followed by the articles (Tarchi *et al.*, 2003; Baum and Godt, 2010; Ghorbanzadeh *et al.*, 2019b) published in Journal of Remote Sensing (439 citations), Landslide (398 citations), and Engineering Geology (316 citations), respectively.

On the other hand, the Journal of Applied Sciences garnered the fewest citations (260) and held the ninth position among the most productive journals in total publications (17 articles). This journal also had the lowest journal metrics in this group, even though it is an open-access journal.

This observation suggests that open-access status alone may not guarantee high citation impact, and other factors such as journal reputation, editorial standards, and quality of research also play a significant role.

Productive Institutions and Funding Organizations

The data retrieved from the Scopus database was analysed to extract the top 10 most prolific institutions in landslide detection and monitoring from 2002 to 2022. As indicated in Table 5, eight of these institutions are located in China, while the remaining two are in Italy and Switzerland. These ten institutions contributed (330 articles) 30% of the total publications received 9,789 citations and generated a combined *h*-index of 170 from the considered topic between 2002 and 2022. Chinese Academy of Sciences (CAS) is the leading institution in total publications (55 articles), closely followed by the China University of Geosciences and the University of Florence, Italy, each contributing 53 articles. However, regarding citations, the University of Florence, Italy, emerges as the leading institution with the highest total number of citations (3,304).

It is followed by the China University of Geosciences (1,280 citations) and the Chinese Academy of Sciences (1,262 citations). Notably, ETH Zurich was the only university in this list

Table 5. Top 10 productive institutions in advancing landslide detection and monitoring techniques during 2002-2022

Rank	Institution	Location	TP	TC	PCA	HI	Highest cited article	CHCA
1	Chinese Academy of Sciences	Beijing, China	55	1,262	96	20	Susceptibility assessment of earthquake-induced landslides using Bayesian network: A case study in Beichuan, China (Song <i>et al.</i> , 2012)	131
2	China University of Geosciences	Hubei, China	53	1,280	98	21	Forested landslide detection using LiDAR data and the random forest algorithm: A case study of the Three Gorges, China (Chen <i>et al.</i> , 2014b)	152
3	University of Florence	Florence, Italy	53	3,304	92	31	Landslide monitoring by using ground-based SAR interferometry: An example of application to the Tessina landslide in Italy (Tarchi <i>et al.</i> , 2003)	316
4	Wuhan University	Hubei, China	30	761	97	15	Landslide detection from an open satellite imagery and digital elevation model dataset using attention boosted convolutional neural networks (Ji <i>et al.</i> , 2020)	140
5	Chengdu University of Technology	Chengdu, China	28	757	93	13	Successive landsliding and damming of the Jinsha River in eastern Tibet, China: prime investigation, early warning, and emergency response (Fan <i>et al.</i> , 2019)	143
6	University of Chinese Academy of Sciences	Beijing, China	26	542	88	14	Landslide detection of hyperspectral remote sensing data based on deep learning with constraints (Ye <i>et al.</i> , 2019)	72
7	Chongqing University	Chongqing, China	24	405	83	11	Wireless self-powered sensor networks driven by triboelectric nanogenerator for in-situ real-time survey of environmental monitoring (Zhou <i>et al.</i> , 2018b)	88
8	Central South University	Hunan, China	22	322	86	10	Towards slow-moving landslide monitoring by integrating multi-sensor InSAR time series datasets: The Zhouqu case study, China (Sun <i>et al.</i> , 2016a)	48
9	Chang'an University	Shaanxi, China	20	522	95	10	Large-area landslide detection and monitoring with ALOS/PALSAR imagery data over Northern California and Southern Oregon, USA (Zhao <i>et al.</i> , 2012)	211
10	ETH Zürich	Zurich, Switzerland	19	636	100	12	Four-dimensional imaging of moisture dynamics during landslide reactivation (Uhlemann <i>et al.</i> , 2017)	106

Table 6. Top 10 funding organisations and their achievements in landslide detection and monitoring techniques during 2002-2022

Rank	Funding Agency	Country	TP	TC	PCA	HI	Highest cited article	HCAC
1	National Natural Science Foundation of China, (NSFC)	China	217	4,528	93	37	Large-area landslide detection and monitoring with ALOS/PALSAR imagery data over Northern California and Southern Oregon, USA (Zhao <i>et al.</i> , 2012)	211
2	National Key Research and Development Program of China, (NKRDP)	China	75	1,152	93	18	Landslide detection from an open satellite imagery and digital elevation model dataset using attention boosted convolutional neural networks (Ji <i>et al.</i> , 2020)	140
3	Fundamental Research Funds for the Central Universities, (FRFCU)	China	43	728	91	14	Forested landslide detection using LiDAR data and the random forest algorithm: A case study of the Three Gorges, China (Chen <i>et al.</i> , 2014b)	152
4	European Space Agency, (ESA)	France	25	634	92	11	Permanent Scatterers for landslide investigations: outcomes from the ESA-SLAM project (Farina <i>et al.</i> , 2006)	221
5	European Commission, (EC)	Belgium	23	666	91	12	Correlation of multi-temporal ground-based optical images for landslide monitoring: Application, potential and limitations (Travalletti <i>et al.</i> , 2012)	158
6	China Scholarship Council, (CSC)	China	19	678	100	12	Large-area landslide detection and monitoring with ALOS/PALSAR imagery data over Northern California and Southern Oregon, USA (Zhao <i>et al.</i> , 2012)	211
7	Natural Environment Research Council, (NERC)	UK	19	572	100	12	A semi-automated object-based approach for landslide detection validated by persistent scatterer interferometry measures and landslide inventories (Höbling <i>et al.</i> , 2012)	122
8	Japan Society for the Promotion of Science, (JSPS)	Japan	17	330	94	12	Data Driven Cyber-Physical System for Landslide Detection (Liu <i>et al.</i> , 2019)	39
9	Chinese Academy of Sciences, (CAS)	China	15	514	93	10	Susceptibility assessment of earthquake-induced landslides using Bayesian network: A case study in Beichuan, China (Song <i>et al.</i> , 2012)	131
10	National Science Foundation, (NSF)	USA	15	237	100	8	A stable reference frame for landslide monitoring using GPS in the Puerto Rico and Virgin Islands region (Wang <i>et al.</i> , 2014b)	47

whose articles have been cited at least once. Furthermore, the article (Tarchi *et al.*, 2003) originated from the University of Florence and had the most citations (316) among this group. This was followed by articles (Zhao *et al.*, 2012; Chen *et al.*, 2014b) originating from Chang'an University, China (211 citations) and the China University of Geosciences (152 citations), respectively.

Table 6 summarises the top ten leading funding organisations in the technological development of landslide detection and monitoring research. The ranking is based on the number of manuscripts funded by these organisations. Five out of 10 leading funding sponsors belong to China (NSFC, NKRDP, FRFCU, CSC, CAS). The remaining five sponsors were from Japan (JSPS), France (ESA), Belgium (EC), the UK (NERC), and the USA (NSF). The National Natural Science Foundation of China (NSFC) was the most productive sponsor in terms of the maximum number of publications (216 articles), the most citations (4,528), and the highest h-index (37).

This was followed by the National Key Research and Development Program of China (NKRDP), which had 75 publications and generated 1,152 citations with an 18 *h*-index in this category. Furthermore, the article (Farina *et al.*, 2006) sponsored by the European Space Agency (ESA, France) had the highest cumulative citations (221) in this particular group. This was followed by a publication (Zhao *et al.*, 2012) that was sponsored collaboratively by the National Natural Science

Foundation of China (NSFC) and the China Scholarship Council (CSC).

Trending Keywords

Keywords are the keys to opening the door to the most relevant and specific publications in the broad spectrum of a scientific database. Specifically, author keywords are considered more significant as they link to the information presented in the articles. The VOSviewer software was utilised to conduct a co-occurrence analysis of the author keywords and explore research priorities and interests of researchers in landslide detection and monitoring technologies.

Initially, this tool identified 2,763 author keywords, showcasing its analytical power in revealing complicated keyword relationships. However, a data cleaning process was conducted to simplify the results by replacing different synonyms with a common term and removing a few country/location names. Finally, 194 author keywords grouped into 15 distinct clusters were identified with minimum occurrences of 3. As shown in Figure 7, "landslide" was the most frequently used author keyword, appearing 292 times, with a link strength of 585 and 149 connections to other terms. The average citation of this keyword was 27.53, while its average publication year was 2017.24. This was followed by the author's keyword "landslide monitoring", with

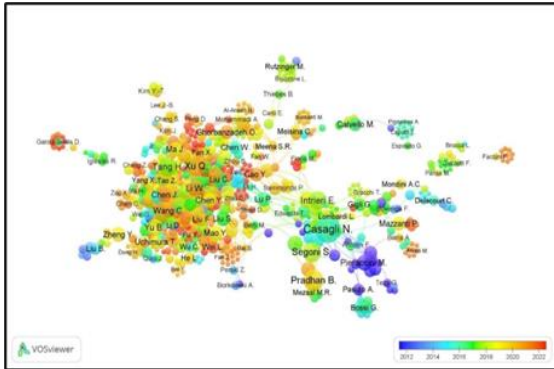


Figure 7. Overlay visualisation of co-occurrence analysis of author keywords. To view online click: [VOSviewer Online](#)

238 occurrences, 129 links, and 25.45 average citations.

In addition, the VOSviewer analysis revealed that 8 of the top 10 most frequently used author keywords in this field were “early warning systems”, “landslide detection”, “remote sensing”, “slope monitoring”, “wireless sensor network”, “interferometric synthetic aperture radar”, “slope stability”, and “rainfall”. These keywords were used more frequently than the other 184 author keywords. Furthermore, “Landslide” had the highest association with “landslide monitoring”, “early

warning systems”, “remote sensing”, and “interferometric synthetic aperture radar” of link strengths 54, 52, 23, and 17, respectively. This indicates that remote sensing techniques play an essential role by providing early information about landslide detection.

Trending Techniques and Their Temporal Analysis

The VOSviewer co-occurrence analysis unveiled significant keywords, enabling a clearer understanding of the most prevalent research focuses and trends within landslide detection and monitoring techniques. To explore various technologies utilized for landslide detection and monitoring during 2002–2022, we selected the top 32 most frequently used author keywords with frequency ranging from 10 to 61. These keywords were classified into three classes, namely, (I) In-Situ Monitoring Techniques (7 keywords), (II) Remote Sensing Techniques (15 keywords), and (III) Analytical Techniques (10), as shown in Figure 8.

The temporal evolution of landslide detection and monitoring techniques was traced with the help of trending keywords. The development process can be divided into two distinct periods: the initial decade (2002–2012) and the recent decade

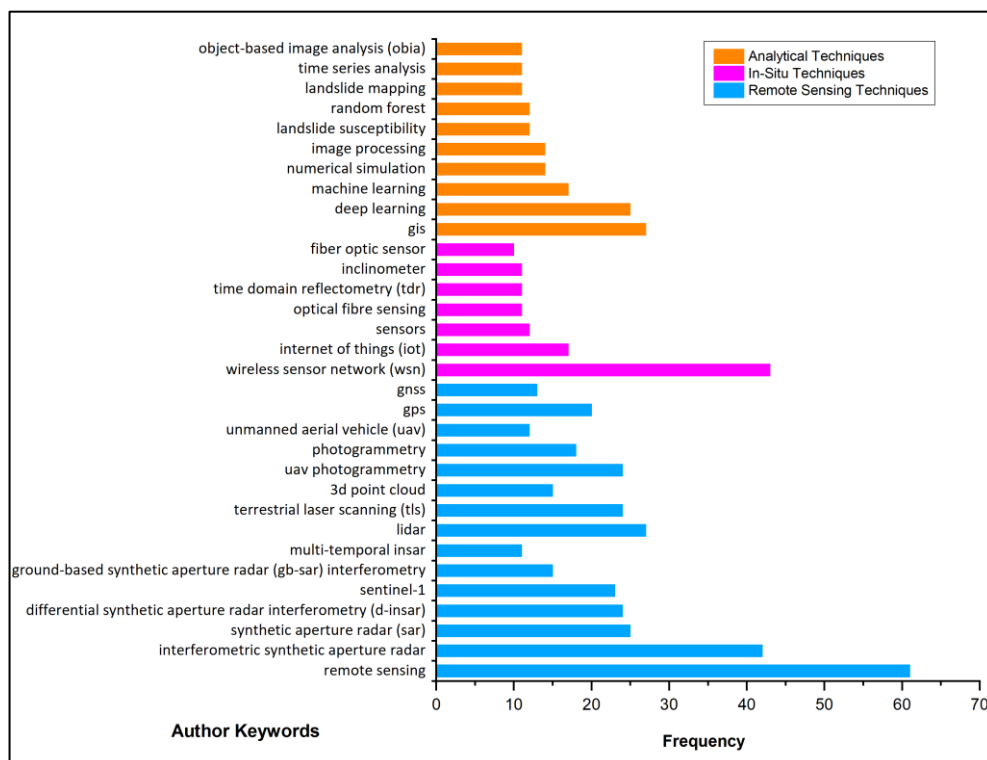


Figure 8. Most popular author keywords and their classification

Table 7. Temporal evolution of landslide detection and monitoring techniques during the past two decades

Method	Period (2002 – 2012)	Period (2013 – 2022)
In-Situ Monitoring Techniques	Inclinometers, Fiber Optic Sensing, Time Domain Reflectometry	Optical Time Domain Reflectometry, Brillouin Optical Time Domain Reflectometry (BOTDR), Wireless Sensor Network
Remote Sensing Techniques	Ground-Based Synthetic Aperture Radar (GB-InSAR), satellite-based Interferometric Synthetic Aperture Radar (InSAR), Global Navigation Satellite System (GNSS) and Global Positioning System (GPS)	Persistent Scatterer Interferometry (PS-Insar), Small Baseline Subset (SBAS-Insar), And Multi-Temporal Insar (MT-Insar), Light Detection and Ranging (Lidar), Airborne Laser Scanning (ALS), Terrestrial Laser Scanning (TLS), Unmanned Aerial Vehicle (UAV)
Analytical Techniques	Geographic Information System (GIS), Machine Learning Algorithms, Neural Networks, Numerical Simulation, Pixel-Based Image Analysis	Deep Learning, Convolutional Neural Networks (CNNs), Random Forest, Time Series Analysis, Object-Based Image Analysis (OBIA), High-Resolution Remote Sensing

(2013-2022). The temporal evolution of each class in the last two decades is shown in Table 7 and discussed here in detail.

In-Situ Monitoring Techniques

In-situ monitoring in this paper refers to methods of slope monitoring performed directly on-site by placing/installing instruments, sensors, or measurement devices at the location of interest to gather data in real time or over a specific period. Inclinometers have a long and distinguished history as one of the earliest geotechnical instruments employed for in-situ slope monitoring. Prior to the year 2000, they served as the primary tool for this purpose. During the initial decade (2002-2012), researchers started to improve the performance of the inclinometer by some modifications. For instance, Lollino *et al.* (2002), highlighted the effectiveness of an automatic inclinometer system for detecting deep soil movements in Italy.

In addition, this period saw the rise of light and electromagnetic wave-based techniques for detecting changes in physical properties. As a result, experimental research in this field diverted towards optical fiber-based inclinometers (Yoshida *et al.*, 2002; Moore *et al.*, 2010) and time domain reflectometry (TDR) techniques (Singer *et al.*, 2006; Lin, 2009; Lin *et al.*, 2009; Lei *et al.*, 2010).

The recent decade (2013-2022) has emphasized on further improving the accuracy and practicality by introducing Optical Time Domain Reflectometry (OTDR) (Zheng *et al.*, 2019a) and Brillouin Optical Time Domain Reflectometry (BOTDR) (Sun *et al.*, 2016b). On the other hand, a surge in Wireless Sensor Network (WSN) combined with the Internet of Things (IoT), has transformed landslide detection and monitoring during these ten years. Wireless Sensor Network (WSN) refers to a network of spatially distributed sensors to measure several landslide-related parameters autonomously. The

adoption of WSN technology for real-time slope monitoring is evidenced by many studies (Li and Yuan, 2013; Ramesh, 2014; Yunus *et al.*, 2015; Giorgetti *et al.*, 2016; Bhatta and Thangadurai, 2016; Gan and Jin, 2018; Khoa and Takayama, 2018; Latupapua *et al.*, 2018; Mucchi *et al.*, 2018; Giri *et al.*, 2018, 2019; Hemalatha *et al.*, 2019; Kumar *et al.*, 2020; Sharma *et al.*, 2020; Ciampalini *et al.*, 2021; Dhanagopal and Muthukumar, 2021; Ragnoli *et al.*, 2022; Sugimoto and Ishizuka, 2022; Yadav *et al.*, 2022). Despite its advantages, WSN technology faces several challenges such as power consumption, limited processing and storage, data fusion and interpretation, high costs, and security concerns, which need further research explorations.

To sum up, the development of in-situ monitoring methods has been characterized by technological progress, particularly in fiber optic sensing and WSN technologies, which have significantly advanced the capabilities for real-time monitoring of slopes.

Remote Sensing Techniques

In contrast to the in-situ methods that rely on physical instruments placed directly on the slope, remote sensing (RS) leverages various technologies like radar, LiDAR, and satellite imagery to gather information about the Earth's surface from a distance. This capability is particularly advantageous for studying dangerous or inaccessible slopes.

The initial decade (2002-2012) witnessed the emergence of specialized novel remote sensing tools and techniques offering greater precision and detailed information on slope movements. Synthetic Aperture Radar (SAR) emerged as a game-changer in landslide detection and monitoring. This technology leverages radar waves to create high-resolution images, offering a crucial advantage: its ability to penetrate vegetation cover.

This capability makes SAR particularly valuable in situations where traditional optical methods might be hindered by dense vegetation. Leva *et al.* (2003) and Tarchi *et al.* (2003) demonstrated the efficacy of the ground-based interferometric synthetic aperture radar (GB-InSAR) in detecting landslide movements, laying foundation for the subsequent advancements. The GB-InSAR is a ground based terrestrial remote sensing imaging system that provides displacement maps with high spatial and temporal resolutions and accuracy (Tarchi *et al.*, 2003), thanks to its high acquisition frequency (up to one image every minute) and a rapid deployment, which makes it a promising tool for managing local (at a single slope scale) emergencies (Leva *et al.*, 2003; Tarchi *et al.*, 2003; Noferini *et al.*, 2005 and 2008). During this period, the utilization of satellite-based Interferometric Synthetic Aperture Radar (InSAR) experienced a surge in popularity. Noteworthy studies conducted by Ge *et al.* (2009), Herrera *et al.* (2011), and other researchers demonstrated the effectiveness of InSAR in examining landslide deformations. This era witnessed the initial incorporation of satellite platforms into landslide monitoring endeavors, providing a wider coverage area and enhanced accessibility in contrast to traditional ground-based methods. Moreover, the adoption of Global Navigation Satellite System (GNSS) and Global Positioning System (GPS) technologies emerged for the purpose of landslide detection and monitoring.

The past decade (2013-2022) has marked a significant development in the application of remote sensing techniques for landslide monitoring. In this period however, satellite-based InSAR remains a dominant tool as used by several studies (Shi *et al.*, 2016; Bru *et al.*, 2018; Dong *et al.*, 2018; Ramsey and Rangoonwala, 2021) to investigate landslide deformations. Additionally, advancements in InSAR techniques like Persistent Scatterer Interferometry (PS-InSAR), Small Baseline Subset (SBAS-InSAR), and multi-temporal InSAR (MT-InSAR) (Ding *et al.*, 2022; Guo *et al.*, 2022; Shankar *et al.*, 2022) offer improved precision. These advancements lead to more accurate detection and mapping of landslide movements due to enhanced spatial and temporal resolution. However, factors such as the availability of suitable radar targets, data processing, and the specific characteristics of the study area can influence the effectiveness of these methods. Additionally, interpretation and validation of results remain critical in ensuring the reliability of deformation measurements.

In parallel, Light Detection and Ranging (LiDAR) techniques, including both Airborne Laser Scanning (ALS) and Terrestrial Laser Scanning (TLS), have seen increased adoption for landslide

monitoring. Several Studies (Kuhn and Prüfer, 2014; Matano *et al.*, 2016; Pradhan *et al.*, 2016; Pfeiffer *et al.*, 2018; Huang *et al.*, 2019; Tyszkowski and Cebulski, 2019; Yin *et al.*, 2020) demonstrated the applications of LiDAR and highlighted the benefits of LiDAR in providing detailed and accurate 3D point clouds, particularly in densely vegetated terrain where traditional methods may be limited. However, the high cost of data acquisition and requirements for advanced data processing skills are still challenging in LiDAR applications.

Photogrammetry is one of the earliest remote sensing techniques traditionally performed by manned aircraft. Technological advancement makes it possible to use low-cost unmanned aerial vehicles (UAVs) to capture site details. Research articles (Huang *et al.*, 2017; Eker *et al.*, 2018; Koukouvelas *et al.*, 2020; Xu *et al.*, 2020; Gantimurova *et al.*, 2021; Cho *et al.*, 2022) employed UAV photogrammetry for landslide monitoring. Moreover, the integration of different remote sensing techniques has further expanded the capabilities of landslide monitoring efforts (Jia *et al.*, 2022; Jiang *et al.*, 2022). This synergistic approach allows for more comprehensive assessments of landslide displacements.

Overall, remote sensing has revolutionized landslide detection and monitoring over the last two decades. From early aerial photography to sophisticated InSAR and LiDAR techniques, the field has witnessed continuous advancements. As technology evolves and researchers explore innovative applications, remote sensing will remain an indispensable tool in mitigating landslide risks and ensuring safer slopes.

Analytical Techniques

In addition to the evolution in data collection techniques, the realm of landslide detection and monitoring has witnessed a remarkable advancement in analytical techniques. The first decade (2002-2012) saw the utilization of Geographic Information Systems (GIS) for landslide susceptibility mapping (Lee and Choi, 2004; Wu and Chen, 2009), alongside the adoption of machine learning algorithms, including neural networks (Mayoraz and Vulliet, 2002; Mondino *et al.*, 2009), for predicting and detecting landslides. Additionally, numerical simulation methods (Eberhardt, 2008; Guihong *et al.*, 2012) and time series analysis (Lauknes *et al.*, 2010; Behling *et al.*, 2014) were employed during this time.

From 2013 to 2022, further advancements in analytical techniques continued to enhance landslide detection and monitoring. Deep learning methods (He *et al.*, 2021; Han *et al.*, 2022) and

random forest algorithms (Chen *et al.*, 2018a; Krkač *et al.*, 2020) became prominent for landslide prediction and detection. Moreover, there was a transition from pixel-based image analysis to more accurate object-based image analysis (OBIA) (Dou *et al.*, 2015; Amatya *et al.*, 2021) during this period.

In summary, the initial decade (2002-2012) witnessed the utilization of traditional instruments with some modifications, the initial application of innovative remote sensing technologies, and the emergence of analytical techniques. In contrast, the recent decade (2013-2022) saw remarkable progress in the in-situ monitoring with technologies like fiber optic sensing, wireless sensors network (WSN), and the Internet of Things (IoT). This decade experienced the refinement and expansion of remote sensing methods for landslide detection and monitoring, reflecting technological advancements and a heightened focus on precision and accuracy in evaluating hazards. Furthermore, this era has seen a paradigm shift towards advanced analytical techniques, driven by the increasing availability of high-resolution remote sensing data and computational resources.

Key Research Themes

The VOSviewer co-occurrence analysis explores the breadth and width of a research topic. Text data from titles and abstracts of publications was utilised to identify trending key research themes. Figure 9 presents the resulting visualisation network map with a minimum term occurrence threshold of 20 and binary count selection. The analysis yielded three distinct clusters (red, green, and blue) encompassing 109 terms with 5,533 connecting links and a total link strength 52,284. The red cluster comprised 35 research terms, while the green and blue clusters contained 30 and 44 terms, respectively.

The first cluster (red) revealed a dominant research theme centred on “image,” with 233 occurrences, a hefty total link strength of 2,352, and 107 connections to other research terms. Notably, “image” linked to 100 articles on “landslide detection,” 78 on “accuracy,” 68 on “landslide monitoring,” and 52 on “algorithm”. Analysis of research terms in this cluster indicated that researchers had utilised remotely sensed data obtained through satellites or ground-based radar, lidar, and unmanned aerial vehicles to detect landslide events. In addition, several analytical techniques, including image analysis and machine learning algorithms, have been deployed to predict landslide hazards.

The second cluster (green) focused on the term “monitoring” with 429 occurrences and 3985 total link strength and connected to all (108) terms considered in the analysis. This term “monitoring” had a strong connection with the terms “landslide monitoring,” “deformation”, and “displacement” of link strength 139, 126, and 123, respectively. This cluster indicated that researchers tested various field instruments to monitor slope movements (deformation and displacements).

The third cluster (blue) presented that these articles were mainly focusing on two terms, “slope” and “system”. These two terms were connected to all 107 terms and had a total link strength of 3,244 and 3,224 to other research topics. There were 99 articles in which these two terms are linked together. One hundred fifty-five studies link “slopes” to “monitoring”, 98 to “displacement”, 97 to “deformation” and 78 to rainfall. Whereas 170 articles connect the word “system” with “monitoring”, 120 with “landslide monitoring”, and 44 with “landslide early warning system”. This cluster revealed that researchers were interested in developing an early warning system to protect human lives and infrastructures against the natural disaster of landslides.

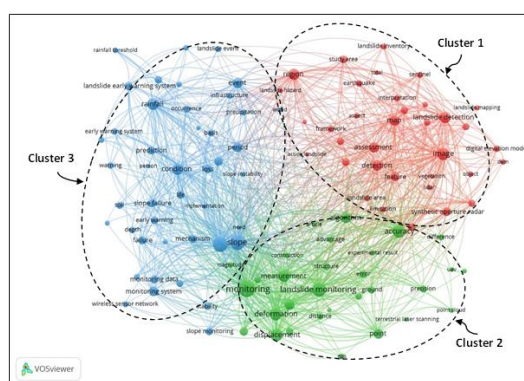


Figure 9. Network visualization map of trending themes from co-occurrence analysis of research terms used in the titles and abstracts. To view online click: [VOSviewer Online](#)

In summary, the co-occurrence analysis of trending research terms uncovers distinct thematic clusters in the landscape of landslide research. The first cluster centres on “image” and its associations, highlighting the significant role of remotely sensed data, machine learning, and image analysis in landslide detection. The second cluster emphasises monitoring slope movements, reflecting the substantial research on field instrumentation for deformation and displacement observation. The third cluster’s focus on “slope” and “system”

underscores the interest in developing early warning systems to mitigate the impacts of landslides, protecting both lives and infrastructure. These findings offer valuable insights into the research priorities within this critical field.

Limitations

This study, like previous bibliometric reviews, has its limitations. We based our analysis solely on data from the Scopus database. This means some research articles related to our field might not be included because they were not indexed in Scopus. We did our best to create a comprehensive search query to find as many relevant publications as possible, but we may have missed some articles that used different terms in their titles, keywords, and abstracts. Our data collection only included articles published between 2002 and 2022, so anything published before 2002 or after 2022 is not part of this analysis. Additionally, we focused on journal articles published in English, excluding other document types and languages.

Conclusions

This study presents a bibliometric analysis of 1,112 original research articles on landslide detection and monitoring techniques published between 2002 and 2022 and indexed in the Scopus database. Microsoft Excel and the VOSviewer applications helped in analyzing publication trends, contributing countries, prolific authors, productive journals, institutions, funding organizations, popular keywords, and research terms. This comprehensive analysis equips researchers with a clear overview of trending landslide detection and monitoring techniques, paving the way for future landslide hazard assessment and management advancements.

The key findings of this study are as follows.

1. The initial decade (2002-2012) saw a relatively modest output of 154 research articles, accounting for 14% of the total publications. However, this period laid the foundation for future developments with the improvements in traditional in-situ monitoring tools (inclinometer, tiltmeter), utilization of novel remote sensing technologies (SAR, LiDAR, GNSS), and the emergence of new analytical techniques (numerical simulation, machine learning, GIS).

2. The recent decade (2013-2022) has seen a remarkable surge in the number of articles, with the last five years (2018-2022) alone contributing 60% of the total articles on this topic. This period

witnessed remarkable progress in the in-situ monitoring with technologies like fiber optic sensing, wireless sensors network (WSN), and the Internet of Things (IoT). This decade experienced the refinement and expansion of remote sensing methods for landslide detection and monitoring, reflecting technological advancements and a heightened focus on precision and accuracy. Furthermore, this era has seen a paradigm shift towards advanced analytical techniques, driven by the increasing availability of high-resolution remote sensing data and computational resources.

3. China and Italy emerged as the top two contributors, collectively accounting for over half (52.6%) of the total articles. China stood out as the most prolific country, boasting the highest number of publications and international collaborations. Italy is in the second position, well behind in publications and collaborations, but its articles garnered greater attention among researchers, as evidenced by its highest h-index.

4. The top ten most prolific authors hail from China (4 authors), Italy (4 authors), Australia (1 author), and India (1 author). Nicola Casagli, from Italy, authored the most publications and garnered the most citations among all authors.

5. Authors most frequently chose to publish in Remote Sensing, while Landslides garnered the most citations among academic journals.

6. The Chinese Academy of Sciences (CAS), China University of Geosciences, and the University of Florence, Italy, were the most productive institutions. The University of Florence, Italy, achieved the highest number of citations and h-Index among all institutions.

7. The Natural Science Foundation of China (NSFC) emerged as the top funding agency, with the highest number of publications and citations among all funding organizations.

8. "Landslide", "Landslide Monitoring", and "Early Warning Systems" were the top 3 most frequently used keywords. Moreover, keywords analysis reveals that remote sensing was the most frequently used technique among the three classes (i.e. in-situ, remote sensing, and analytical) of landslide detection and monitoring.

9. The co-occurrence analysis of trending research terms effectively unravels the thematic landscape of research, highlighting the pivotal roles of remote sensing and machine learning algorithms in landslide detection and field instrumentations in deformation monitoring, contributing to the development of early warning systems and the advancement of landslide hazard mitigation strategies.

References

- Abbate, S., Centobelli, P., Cerchione, R., Oropallo, E., and Riccio, E. (2023). Investigating healthcare 4.0 transition through a knowledge management perspective. *IEEE Transactions on Engineering Management*, 70(9):3297-3310. <https://doi.org/10.1109/TEM.2022.3200889>
- Amatya, P., Kirschbaum, D., Stanley, T., and Tanyas, H. (2021). Landslide mapping using object-based image analysis and open-source tools. *Engineering geology*, 282:106000. <https://doi.org/10.1016/j.enggeo.2021.106000>
- Bar-Ilan, J. (2008). Informetrics at the beginning of the 21st century-A review. *Journal of Informetrics*, 2(1):1-52. <https://doi.org/10.1016/j.joi.2007.11.001>
- Baum, R.L. and Godt, J.W. (2010). Early warning of rainfall-induced shallow landslides and debris flows in the USA. *Landslides*, 7:259-272. <https://doi.org/10.1007/s10346-009-0177-0>
- Behling, R., Roessner, S., Segl, K., Kleinschmit, B., and Kaufmann, H. (2014). Robust automated image co-registration of optical multi-sensor time series data: Database generation for multi-temporal landslide detection. *Remote Sensing*, 6(3):2572-2600. <https://doi.org/10.3390/rs6032572>
- Bezák, N., Mikoš, M., Borrelli, P., Alewell, C., Alvarez, P., Anache, J.A.A., Baartman, J., Ballabio, C., Biddocci, M., Cerdà, A., Chalise, D., Chen, S., Chen, W., De Girolamo, A.M., Gessesse, G.D., Deumlich, D., Diodato, N., Efthimiou, N., Erpul, G., Fiener, P., Freppaz, M., Gentile, F., Gericke, A., Haregeweyn, N., Hu, B., Jeanneau, A., Kaffas, K., Kiani-Harchegani, M., Villuendas, I.L., Li, C., Lombardo, L., López-Vicente, M., Lucas-Borja, M.E., Maerker, M., Miao, C., Modugno, S., Möller, M., Naipal, V., Nearing, M., Owusu, S., Panday, D., Patault, E., Patriche, C.V., Poggio, L., Portes, R., Quijano, L., Rahdari, M.R., Renima, M., Ricci, G.F., Rodrigo-Comino, J., Saia, S., Samani, A.N., Schillaci, C., Syrris, V., Kim, H.S., Spinola, D.N., Oliveira, P.T., Teng, H., Thapa, R., Vantas, K., Vieira, D., Yang, J.E., Yin, S., Zema, D.A., Zhao, G., and Panagos, P. (2021). Soil erosion modelling: A bibliometric analysis. *Environmental Research*, 197:111087. <https://doi.org/10.1016/j.envres.2021.111087>
- Bhatta, N.P. and Thangadurai, N. (2016). Effective approach for landslide monitoring using wireless sensor networks. *International Journal of Civil Engineering and Technology*, 7(6):378-385.
- Bianchini, S., Cigna, F., Righini, G., Proietti, C., and Casagli, N. (2012). Landslide HotSpot Mapping by means of Persistent Scatterer Interferometry. *Environmental Earth Sciences*, 67(4):1155-1172. <https://doi.org/10.1007/s12665-012-1559-5>
- Bru, G., Escayo, J., Fernández, J., Mallorqui, J.J., Iglesias, R., Sansosti, E., Abajo, T., and Morales, A. (2018). Suitability assessment of X-band satellite SAR data for geotechnical monitoring of site scale slow moving landslides. *Remote Sensing*, 10(6):936. <https://doi.org/10.3390/rs10060936>
- Carrera, A.C.V., Mendoza, M.E., Allende, T.C., and Macías, J.L. (2021). A review of recent studies on landslide hazard in Latin America. *Physical Geography*, 44(3):243-286. <https://doi.org/10.1080/02723646.2021.1978372>
- Carrión-Mero, P., Montalván-Burbano, N., Morante-Carballo, F., Quesada-Román, A., and Apolo-Masache, B. (2021). Worldwide research trends in landslide science. *International Journal of Environmental Research and Public Health*, 18(18):9445. <https://doi.org/10.3390/ijerph18189445>
- Casagli, N., Frodella, W., Morelli, S., Tofani, V., Ciampalini, A., Intrieri, E., Raspini, F., Rossi, G., Tanteri, L., and Lu, P. (2017). Spaceborne, UAV and ground-based remote sensing techniques for landslide mapping, monitoring and early warning. *Geoenvironmental Disasters*, 4(1):9. <https://doi.org/10.1186/s40677-017-0073-1>
- Casagli, N., Intrieri, E., Tofani, V., Gigli, G., and Raspini, F. (2023). Landslide detection, monitoring and prediction with remote-sensing techniques. *Nature Reviews Earth and Environment*, 4(1):51-64. <https://doi.org/10.1038/s43017-022-00373-x>
- Chang, K.T., Chiang, S.H., and Lei, F. (2008). Analysing the relationship between typhoon-triggered landslides and critical rainfall conditions. *Earth Surface Processes and Landforms*, 33(8):1261-1271. <https://doi.org/10.1002/esp.1611>
- Chang, X., Zhang, R., Xiao, Y., Chen, X., Zhang, X., and Liu, G. (2020). Mapping of publications on asphalt pavement and bitumen materials: A bibliometric review. *Construction and Building Materials*, 234:117370. <https://doi.org/10.1016/j.conbuildmat.2019.117370>
- Chen, F., Yu, B., and Li, B. (2018a). A practical trial of landslide detection from single-temporal Landsat8 images using contour-based proposals and random forest: a case study of national Nepal. *Landslides*, 15(3):453-464. <https://doi.org/10.1007/s10346-017-0884-x>
- Chen, W., Li, X., Wang, Y., Chen, G., and Liu, S. (2014b). Forested landslide detection using LiDAR data and the random forest algorithm: A case study of the Three Gorges, China. *Remote Sensing of Environment*, 152:291-301. <https://doi.org/10.1016/j.rse.2014.07.004>
- Chen, Z., Zhang, Y., Ouyang, C., Zhang, F., and Ma, J. (2018b). Automated landslides detection for mountain cities using multi-temporal remote sensing imagery. *Sensors*, 18(3):821. <https://doi.org/10.3390/s18030821>
- Cheng, G., Guo, L., Zhao, T., Han, J., Li, H., and Fang, J. (2013). Automatic landslide detection from remote-sensing imagery using a scene classification method based on boVW and pLSA. *International Journal of Remote Sensing*, 34(1):45-59. <https://doi.org/10.1080/01431161.2012.705443>
- Cho, J., Lee, J., and Lee, B. (2022). Application of UAV photogrammetry to slope-displacement measurement. *KSCSE Journal of Civil Engineering*, 26(4):1904-1913. <https://doi.org/10.1007/s12205-021-1374-1>
- Ciampalini, A., Farina, P., Lombardi, L., Nocentini, M., Taurino, V., Guidi, R., Pina, F.D., and Tavarini, D. (2021). Integration of satellite InSAR with a wireless network of geotechnical sensors for slope monitoring in urban areas: The Pariana landslide case (Massa, Italy). *Remote Sensing*, 13(13):2534. <https://doi.org/10.3390/rs13132534>
- Cina, A. and Piras, M. (2015). Performance of low-cost GNSS receiver for landslides monitoring: test and results. *Geomatics, Natural Hazards and Risk*, 6(5-7):497-514. <https://doi.org/10.1080/19475705.2014.889046>
- Crosetto, M., Monserrat, O., Cuevas-González, M., Devanthéry, N., and Crippa, B. (2016). Persistent scatterer interferometry: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 115:78-89. <https://doi.org/10.1016/j.isprsjprs.2015.10.011>
- Dhanagopal, R. and Muthukumar, B. (2021). A model for low power, high speed and energy efficient early landslide detection system using IoT. *Wireless Personal Communications*, 117(4):2713-2728. <https://doi.org/10.1007/s11277-019-06933-7>
- Ding, L., Li, C., Wei, L., Guo, Z., Jia, P., Wang, W., and Gao, Y. (2022). Slope deformation prediction based on MT-InSAR and Fbprophet for deep excavation section of south-north water transfer project. *Sustainability*, 14(17):10873. <https://doi.org/10.3390/su141710873>
- Ding, X. and Yang, Z. (2022). Knowledge mapping of platform research: a visual analysis using VOSviewer and CiteSpace. *Electronic Commerce Research*, 22(3):787-809. <https://doi.org/10.1007/s10660-020-09410-7>
- DM, C. (1996). Landslide types and processes. *Landslides, investigation and mitigation: special report* 247:36-75.
- Dong, J., Liao, M., Xu, Q., Zhang, L., Tang, M., and Gong, J. (2018). Detection and displacement characterization of landslides using multi-temporal satellite SAR interferometry: A case study of Danba County in the Dadu River Basin. *Engineering Geology*, 240:95-109. <https://doi.org/10.1016/j.enggeo.2018.04.015>
- Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., and Lim, W.M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133:285-296. <https://doi.org/10.1016/j.jbusres.2021.04.070>
- Dou, J., Chang, K.T., Chen, S., Yunus, A.P., Liu, J.K., Xia, H., and Zhu, Z. (2015). Automatic case-based reasoning approach for landslide detection: Integration of object-oriented image analysis and a genetic algorithm. *Remote Sensing*, 7(4):4318-4342. <https://doi.org/10.3390/rs70404318>
- Eberhardt, E. (2008). Twenty-ninth Canadian Geotechnical Colloquium: The role of advanced numerical methods and geotechnical field measurements in understanding complex deep-seated rock slope failure mechanisms. *Canadian Geotechnical Journal*, 45(4):484-510. <https://doi.org/10.1139/T07-116>
- Eker, R., Aydın, A., and Hübl, J. (2018). Unmanned aerial vehicle (UAV)-based monitoring of a landslide: Gallenzerkogel landslide (Ybbs-Lower Austria) case study. *Environmental Monitoring and Assessment*, 190(1):28. <https://doi.org/10.1007/s10661-017-6402-8>
- Engqvist, L. and Frommen, J.G. (2008). The h-index and self-citations. *Trends in Ecology and Evolution*, 23(5):250-252. <https://doi.org/10.1016/j.tree.2008.01.009>
- Falagas, M.E.; Pitsouni, E.I.; Malietzis, G.A.; Pappas, G. (2008). Comparison of pubmed, scopus, web of science, and google scholar: strengths and weaknesses. *FASEB Journal*, 22(2):338-342. <https://doi.org/10.1096/fj.07-9492LSF>
- Fan, X., Xu, Q., Alonso-Rodriguez, A., Subramanian, S.S., Li, W., Zheng, G., Dong, X., and Huang, R. (2019). Successive landsliding and damming of the Jinsha River in eastern Tibet, China: prime investigation, early warning, and emergency response. *Landslides*, 16(5):1003-1020. <https://doi.org/10.1007/s10346-019-01159-x>
- Farina, P., Colombo, D., Fumagalli, A., Marks, F., and Moretti, S. (2006). Permanent Scatterers for landslide investigations: outcomes from

- the ESA-SLAM project. *Engineering geology*, 88(3-4):200-217. <https://doi.org/10.1016/j.enggeo.2006.09.007>
- Fell, R., Corominas, J., Bonnard, C., Cascini, L., Leroi, E., and Savage, W.Z. (2008). Guidelines for landslide susceptibility, hazard and risk zoning for land use planning. *Engineering geology*, 102(3):85-98. <https://doi.org/10.1016/j.enggeo.2008.03.022>
- Franklin, J. and Denton, P. (1973). The monitoring of rock slopes. *Quarterly Journal of Engineering Geology and Hydrogeology*, 6(3-4):259-286. <https://doi.org/10.1144/GSL.QJEG.1973.006.03.10>
- Froude, M.J. and Petley, D.N. (2018). Global fatal landslide occurrence from 2004 to 2016. *Natural Hazards and Earth System Sciences*, 18(8):2161-2181. <https://doi.org/10.5194/nhess-18-2161-2018>
- Gall, M., Nguyen, K.H., and Cutter, S.L. (2015). Integrated research on disaster risk: Is it really integrated? *International Journal of Disaster Risk Reduction*, 12:255-267. <https://doi.org/10.1016/j.ijdr.2015.01.010>
- Gan, B. and Jin, S. (2018). Design of early warning system based on wireless sensor network. *International Journal of Online Engineering*, 14(1):66-76. <https://doi.org/10.3991/ijoe.v14i01.8060>
- Gantimurova, S., Parshin, A., and Erofeev, V. (2021). GIS-based landslide susceptibility mapping of the circum-baikal railway in Russia using UAV data. *Remote Sensing*, 13(18):3629. <https://doi.org/10.3390/rs13183629>
- Ge, L., Ng, A.H.M., Rizos, C., Wang, H., and Wang, H. (2009). Crustal deformation in Australia measured by satellite radar interferometry using ALOS/PALSAR imagery. *Journal of Applied Geodesy*, 3(1):47-53. <https://doi.org/10.1515/JAG.2009.005>
- Ghorbanzadeh, O., Blaschke, T., Gholamnia, K., Meena, S.R., Tiede, D., and Aryal, J. (2019a). Evaluation of different machine learning methods and deep-learning convolutional neural networks for landslide detection. *Remote Sensing*, 11(2):196. <https://doi.org/10.3390/rs11020196>
- Ghorbanzadeh, O., Crivellari, A., Ghamisi, P., Shahabi, H., and Blaschke, T. (2021). A comprehensive transferability evaluation of U-Net and ResU-Net for landslide detection from Sentinel-2 data (case study areas from Taiwan, China, and Japan). *Scientific Reports*, 11(1):14629. <https://doi.org/10.1038/s41598-021-94190-9>
- Ghorbanzadeh, O., Meena, S.R., Blaschke, T., and Aryal, J. (2019b). UAV-based slope failure detection using deep-learning convolutional neural networks. *Remote Sensing*, 11(17):2046. <https://doi.org/10.3390/rs11172046>
- Ghorbanzadeh, O., Shahabi, H., Crivellari, A., Homayouni, S., Blaschke, T., and Ghamisi, P. (2022). Landslide detection using deep learning and object-based image analysis. *Landslides*, 19(4):929-939. <https://doi.org/10.1007/s10346-021-01843-x>
- Giorgetti, A., Lucchi, M., Tavelli, E., Barla, M., Gigli, G., Casagli, N., Chiani, M., and Dardari, D. (2016). A robust wireless sensor network for landslide risk analysis: System design, deployment, and field testing. *IEEE Sensors Journal*, 16(16):6374-6386. <https://doi.org/10.1109/JSEN.2016.2579263>
- Giri, P., Ng, K., and Phillips, W. (2018). Laboratory simulation to understand translational soil slides and establish movement criteria using wireless IMU sensors. *Landslides*, 15(12):2437-2447. <https://doi.org/10.1007/s10346-018-1055-4>
- Giri, P., Ng, K., and Phillips, W. (2019). Wireless sensor network system for landslide monitoring and warning. *IEEE Transactions on Instrumentation and Measurement*, 68(4):1210-1220. <https://doi.org/10.1109/TIM.2018.2861999>
- Gokceoglu, C. and Sezer, E. (2009). A statistical assessment on international landslide literature (1945-2008). *Landslides*, 6(4):345-351. <https://doi.org/10.1007/s10346-009-0166-3>
- Gorsevski, P.V., Brown, M.K., Panter, K., Onasch, C.M., Simic, A., and Snyder, J. (2016). Landslide detection and susceptibility mapping using LiDAR and an artificial neural network approach: a case study in the Cuyahoga Valley National Park, Ohio. *Landslides*, 13(3):467-484. <https://doi.org/10.1007/s10346-015-0587-0>
- Guihong, P., Xianguo, D., and Le, Y. (2012). Optimization layout of slope displacement monitoring points based on numerical computation. *Electronic Journal of Geotechnical Engineering*, 17U:2851-2860.
- Guo, H., Yi, B., Yao, Q., Gao, P., Li, H., Sun, J., and Zhong, C. (2022). Identification of Landslides in Mountainous Area with the Combination of SBAS-InSAR and Yolo Model. *Sensors*, 22(16):6235. <https://doi.org/10.3390/s22166235>
- Guzzetti, F., Mondini, A.C., Cardinali, M., Fiorucci, F., Santangelo, M., and Chang, K.-T. (2012). Landslide inventory maps: New tools for an old problem. *Earth-Science Reviews*, 112(1):42-66. <https://doi.org/10.1016/j.earscirev.2012.02.001>
- Han, J., Yang, H., Liu, Y., Lu, Z., Zeng, K., and Jiao, R. (2022). A Deep Learning Application for Deformation Prediction from Ground-Based InSAR. *Remote Sensing*, 14(20):5067. <https://doi.org/10.3390/rs14205067>
- Harzing, A.W. and Alakangas, S. (2016). Google Scholar, Scopus and the Web of Science: A longitudinal and cross-disciplinary comparison. *Scientometrics*, 106:787-804. <https://doi.org/10.1007/s11192-015-1798-9>
- He, F., Liu, C., and Liu, H. (2021). Integration and fusion of geologic hazard data under deep learning and big data analysis technology. *Complexity*, 2021:2871770. <https://doi.org/10.1155/2021/2871770>
- Hemalatha, T., Ramesh, M.V., and Rangan, V.P. (2019). Effective and accelerated forewarning of landslides using wireless sensor networks and machine learning. *IEEE Sensors Journal*, 19(21):9964-9975. <https://doi.org/10.1109/JSEN.2019.2928358>
- Herrera, G., Notti, D., García-Davalillo, J.C., Mora, O., Cooksley, G., Sánchez, M., Arnaud, A., and Crosetto, M. (2011). Analysis with C- and X-band satellite SAR data of the Portalet landslide area. *Landslides*, 8(2):195-206. <https://doi.org/10.1007/s10346-010-0239-3>
- Hilley, G.E., Burgmann, R., Ferretti, A., Novati, F., and Rocca, F. (2004). Dynamics of slow-moving landslides from permanent scatterer analysis. *Science*, 304(5679):1952-1955. <https://doi.org/10.1126/science.1098821>
- Höbling, D., Füreder, P., Antolini, F., Cigna, F., Casagli, N., and Lang, S. (2012). A semi-automated object-based approach for landslide detection validated by persistent scatterer interferometry measures and landslide inventories. *Remote Sensing*, 4(5):1310-1336. <https://doi.org/10.3390/rs4051310>
- Huang, H., Long, J., Lin, H., Zhang, L., Yi, W., and Lei, B. (2017). Unmanned aerial vehicle based remote sensing method for monitoring a steep mountainous slope in the Three Gorges Reservoir, China. *Earth Science Informatics*, 10(3):287-301. <https://doi.org/10.1007/s12145-017-0291-9>
- Huang, R., Jiang, L., Shen, X., Dong, Z., Zhou, Q., Yang, B., and Wang, H. (2019). An efficient method of monitoring slow-moving landslides with long-range terrestrial laser scanning: a case study of the Dashu landslide in the Three Gorges Reservoir Region, China. *Landslides*, 16(4):839-855. <https://doi.org/10.1007/s10346-018-1118-6>
- Huang, Y., Xu, C., Zhang, X., and Li, L. (2022). Bibliometric analysis of landslide research based on the WOS database. *Natural Hazards Research*, 2(2):49-61. <https://doi.org/10.1016/j.nhres.2022.02.001>
- Intrieri, E., Raspini, F., Fumagalli, A., Lu, P., Del Conte, S., Farina, P., Allievi, J., Ferretti, A., and Casagli, N. (2018). The Maoxian landslide as seen from space: detecting precursors of failure with Sentinel-1 data. *Landslides*, 15:123-133. <https://doi.org/10.1007/s10346-017-0915-7>
- Ji, S., Yu, D., Shen, C., Li, W., and Xu, Q. (2020). Landslide detection from an open satellite imagery and digital elevation model dataset using attention boosted convolutional neural networks. *Landslides*, 17(6):1337-1352. <https://doi.org/10.1007/s10346-020-01353-2>
- Jia, H., Zhu, G., Guo, L., He, J., Liang, B., and He, S. (2022). An improved point clouds model for displacement assessment of slope surface by combining TLS and UAV photogrammetry. *Applied Sciences*, 12(9):4320. <https://doi.org/10.3390/app12094320>
- Jiang, N., Li, H.B., Li, C.J., Xiao, H.X., and Zhou, J.W. (2022). A fusion method using terrestrial laser scanning and unmanned aerial vehicle photogrammetry for landslide deformation monitoring under complex terrain conditions. *IEEE Transactions on Geoscience and Remote Sensing*, 60:4707214. <https://doi.org/10.1109/TGRS.2022.3181258>
- Khoa, V.V. and Takayama, S. (2018). Wireless sensor network in landslide monitoring system with remote data management. *Measurement: Journal of the International Measurement Confederation*, 118:214-229. <https://doi.org/10.1016/j.measurement.2018.01.002>
- Kirschbaum, D., Stanley, T., and Zhou, Y. (2015). Spatial and temporal analysis of a global landslide catalog. *Geomorphology*, 249:4-15. <https://doi.org/10.1016/j.geomorph.2015.03.016>
- Klose, M. (2015). *Landslide databases as tools for integrated assessment of landslide risk*. Springer. <https://doi.org/10.1007/978-3-319-20403-1>
- Koukouvelas, I.K., Nikolakopoulos, K.G., Zygouri, V., and Kyriou, A. (2020). Post-seismic monitoring of cliff mass wasting using an unmanned aerial vehicle and field data at Egremni, Lefkada Island, Greece. *Geomorphology*, 367:107306. <https://doi.org/10.1016/j.geomorph.2020.107306>
- Krkač, M., Bernat Gazibara, S., Arbanas, Ž., Sećanj, M., and Mihalčić Arbanas, S. (2020). A comparative study of random forests and multiple linear regression in the prediction of landslide velocity. *Landslides*, 17(11): 2515-2531. <https://doi.org/10.1007/s10346-020-01476-6>
- Kuhn, D. and Prüfer, S. (2014). Coastal cliff monitoring and analysis of mass wasting processes with the application of terrestrial laser scanning: A case study of Rügen, Germany. *Geomorphology*, 213:153-165. <https://doi.org/10.1016/j.geomorph.2014.01.005>

- Kulkarni, A.V.; Aziz, B.; Shams, I.; Busse, J.W. (2009). Comparisons of citations in Web of Science, Scopus, and Google Scholar for articles published in general medical journals. *JAMA*, 302:1092-1096. <https://doi.org/10.1001/jama.2009.1307>
- Kumar, A. (2020). Time-domain reflectometry-based real-time slope stability monitoring in opencast mines: A review. *Noise and Vibration Worldwide*, 0957456520924812. <https://doi.org/10.1177/0957456520924812>
- Kumar, S., Duttgupta, S., Rangan, V.P., and Ramesh, M.V. (2020). Reliable network connectivity in wireless sensor networks for remote monitoring of landslides. *Wireless Networks*, 26(3):2137-2152. <https://doi.org/10.1007/s11276-019-02059-7>
- Latupapua, H., Latupapua, A.I., Wahab, A., and Alaydrus, M. (2018). Wireless sensor network design for earthquake's and landslide's early warnings. *Indonesian Journal of Electrical Engineering and Computer Science*, 11(2):437-445. <https://doi.org/10.11591/ijeecs.v11i2.pp437-445>
- Lauknes, T.R., Piyush Shanker, A., Dehls, J.F., Zebker, H.A., Henderson, I.H.C., and Larsen, Y. (2010). Detailed rockslide mapping in northern Norway with small baseline and persistent scatterer interferometric SAR time series methods. *Remote Sensing of Environment*, 114(9):2097-2109. <https://doi.org/10.1016/j.rse.2010.04.015>
- Lee, S. and Choi, J. (2004). Landslide susceptibility mapping using GIS and the weight-of-evidence model. *International Journal of Geographical Information Science*, 18(8):789-814. <https://doi.org/10.1080/13658810410001702003>
- Lei, G., He-lin, F., and Han-hua, T. (2010). Experimental study on application of time domain reflectometry to highway slope monitoring. *Electronic Journal of Geotechnical Engineering*, 15M:1306-1316.
- Leva, D., Nico, G., Tarchi, D., and Fortuny-Guasch, J. (2003). Temporal analysis of a landslide by means of a ground-based SAR interferometer. *IEEE Transactions on Geoscience and Remote Sensing*, 41(4 part 1):745-752. <https://doi.org/10.1109/TGRS.2003.808902>
- Leydesdorff, L., Carley, S., and Rafols, I. (2013). Global maps of science based on the new Web-of-Science categories. *Scientometrics*, 94(2): 589-593. <https://doi.org/10.1007/s11192-012-0784-8>
- Li, X. and Yuan, J. (2013). Mountain landslide monitoring based on wireless sensor network. *Information Technology Journal*, 12(15):3357-3362. <https://doi.org/10.3923/ij.2013.3357.3362>
- Lin, C.P. (2009). TDR as geo-nerve: A slope monitoring system example. *Geotechnical News*, 27(1):38-40.
- Lin, C.P., Tang, S.H., Lin, W.C., and Chung, C.C. (2009). Quantification of cable deformation with time domain reflectometry - Implications to landslide monitoring. *Journal of Geotechnical and Geoenvironmental Engineering*, 135(1):143-152. [https://doi.org/10.1061/\(ASCE\)1090-0241\(2009\)135:1\(143\)](https://doi.org/10.1061/(ASCE)1090-0241(2009)135:1(143))
- Liu, Z., Tsuda, T., Watanabe, H., Ryu, S., and Iwasawa, N. (2019). Data Driven Cyber-Physical System for Landslide Detection. *Mobile Networks and Applications*, 24(3):991-1002. <https://doi.org/10.1007/s11036-018-1031-1>
- Loh, Z.Z., Zaidi, N.S., Yong, E.L., Syafuddin, A., Boopathy, R., and Kadier, A. (2022). Current Status and Future Research Trends of Biofiltration in Wastewater Treatment: a Bibliometric Review. *Current Pollution Reports*, 8(3):234-248. <https://doi.org/10.1007/s40726-022-00224-9>
- Lollino, G., Arattano, M., and Cuccureddu, M. (2002). The use of the automatic inclinometric system for landslide early warning: The case of Cabella Ligure (North-Western Italy). *Physics and Chemistry of the Earth*, 27(36):1545-1550. [https://doi.org/10.1016/S1474-7065\(02\)00175-4](https://doi.org/10.1016/S1474-7065(02)00175-4)
- Ma, J., Tang, H., Hu, X., Bobet, A., Zhang, M., Zhu, T., Song, Y., and Ez Eldin, M.A.M. (2017). Identification of causal factors for the Majiagou landslide using modern data mining methods. *Landslides*, 14(1):311-322. <https://doi.org/10.1007/s10346-016-0693-7>
- Macciotta, R., Hendry, M., and Martin, C.D. (2016). Developing an early warning system for a very slow landslide based on displacement monitoring. *Natural Hazards*, 81(2):887-907. <https://doi.org/10.1007/s11069-015-2110-2>
- Matano, F., Iuliano, S., Somma, R., Marino, E., del Vecchio, U., Esposito, G., Molisso, F., Scepti, G., Grimaldi, G.M., Pignatola, A., Caputo, T., Troise, C., De Natale, G., and Sacchi, M. (2016). Geostructure of Coroglio tuff cliff, Naples (Italy) derived from terrestrial laser scanner data. *Journal of Maps*, 12(3):407-421. <https://doi.org/10.1080/17445647.2015.1028237>
- Mayoraz, F. and Vuillet, L. (2002). Neural networks for slope movement prediction. *International Journal of Geomechanics*, 2(2):153-173. [https://doi.org/10.1061/\(ASCE\)1532-3641\(2002\)2:2\(153\)](https://doi.org/10.1061/(ASCE)1532-3641(2002)2:2(153))
- McKean, J. and Roering, J. (2004). Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry. *Geomorphology*, 57(3-4):331-351. [https://doi.org/10.1016/S0169-555X\(03\)00164-8](https://doi.org/10.1016/S0169-555X(03)00164-8)
- Melkers, J. and Kiopa, A. (2010). The Social Capital of Global Ties in Science: The Added Value of International Collaboration. *Review of Policy Research*, 27(4):389-414. <https://doi.org/10.1111/j.1541-1338.2010.00448.x>
- Mezaal, M.R., Pradhan, B., and Rizeei, H.M. (2018). Improving landslide detection from airborne laser scanning data using optimized Dempster-Shafer. *Remote Sensing*, 10(7):1029. <https://doi.org/10.3390/rs10071029>
- Mezaal, M.R., Pradhan, B., Sameen, M.I., Mohd Shafri, H.Z., and Yusoff, Z.M. (2017a). Optimized Neural Architecture for Automatic Landslide Detection from High-Resolution Airborne Laser Scanning Data. *Applied Sciences*, 7(7):730. <https://doi.org/10.3390/app7070730>
- Mezaal, M.R., Pradhan, B., Sameen, M.I., Shafri, H.Z.M., and Yusoff, Z.M. (2017b). Optimized neural architecture for automatic landslide detection from high-resolution airborne laser scanning data. *Applied Sciences*, 7(7):730. <https://doi.org/10.3390/app7070730>
- Mezaal, M.R., Pradhan, B., Shafri, H.Z.M., and Yusoff, Z.M. (2017c). Automatic landslide detection using Dempster-Shafer theory from LiDAR-derived data and orthophotos. *Geomatics, Natural Hazards and Risk*, 8(2):1935-1954. <https://doi.org/10.1080/19475705.2017.1401013>
- Mikoš, M. (2017). Landslides: a top international journal in geological engineering and engineering geology? *Landslides*, 14(5):1827-1838. <https://doi.org/10.1007/s10346-017-0869-9>
- Mikoš, M. (2018). The bibliometric impact of books published by the International Consortium on Landslides. *Landslides*, 15(8):1459-1482. <https://doi.org/10.1007/s10346-018-1019-8>
- Mondini, A.C., Guzzetti, F., Chang, K.-T., Monserrat, O., Marth, T.R., and Manconi, A. (2021). Landslide failures detection and mapping using Synthetic Aperture Radar: Past, present and future. *Earth-Science Reviews*, 216:103574. <https://doi.org/10.1016/j.earscirev.2021.103574>
- Mondino, E.B., Giardino, M., and Perotti, L. (2009). A neural network method for analysis of hyperspectral imagery with application to the Cassas landslide (Susa Valley, NW-Italy). *Geomorphology*, 110(1-2):20-27. <https://doi.org/10.1016/j.geomorph.2008.12.023>
- Montrasio, L., Valentino, R., and Losi, G.L. (2011). Towards a real-time susceptibility assessment of rainfall-induced shallow landslides on a regional scale. *Natural Hazards and Earth System Science*, 11(7):1927-1947. <https://doi.org/10.5194/nhess-11-1927-2011>
- Moore, J.R., Gischig, V., Button, E., and Loew, S. (2010). Rockslide deformation monitoring with fiber optic strain sensors. *Natural Hazards and Earth System Science*, 10(2):191-201. <https://doi.org/10.5194/nhess-10-191-2010>
- Mucchi, L., Jayousi, S., Martinelli, A., Caputo, S., Intrieri, E., Gigli, G., Gracchi, T., Mugnai, F., Favalli, M., Fornaciari, A., and Nannipieri, L. (2018). A flexible wireless sensor network based on ultra-wide band technology for ground instability monitoring. *Sensors*, 18(9):2948. <https://doi.org/10.3390/s18092948>
- Nichol, J. and Wong, M.S. (2005). Satellite remote sensing for detailed landslide inventories using change detection and image fusion. *International Journal of Remote Sensing*, 26(9): 1913-1926. <https://doi.org/10.1080/01431160512331314047>
- Noferini, L., Pieraccini, M., Mecatti, D., Luzi, G., Atzeni, C., Tamburini, A., and Broccolato, M. (2005). Permanent scatterers analysis for atmospheric correction in ground-based SAR interferometry. *IEEE Transactions on Geoscience and Remote Sensing*, 43(7):1459-1470. <https://doi.org/10.1109/TGRS.2005.848707>
- Noferini, L., Takayama, T., Pieraccini, M., Mecatti, D., Macaluso, G., Luzi, G., and Atzeni, C. (2008). Analysis of ground-based SAR data with diverse temporal baselines. *IEEE Transactions on Geoscience and Remote Sensing*, 46(6):1614-1623. <https://doi.org/10.1109/TGRS.2008.916216>
- Norell, W. (1973). Measuring and depicting trouble areas in stereomodels. *Highway research record*, 452:45-54.
- Okaiyeto, K., Ekundayo, T.C., and Okoh, A.I. (2020). Global research trends on biofloculant potentials in wastewater remediation from 1990 to 2019 using a bibliometric approach. *Letters in Applied Microbiology*, 71(6):567-579. <https://doi.org/10.1111/lam.13361>
- Omeregbe, A.I., Muda, K., Ojuri, O.O., Hong, C.Y., Pauzi, F.M., and Ali, N.S.B.A. (2022). The global research trend on microbially induced carbonate precipitation during 2001-2021: a bibliometric review. *Environmental Science and Pollution Research*, 29(60):89899-89922. <https://doi.org/10.1007/s11356-022-24046-w>
- Pfeiffer, J., Zieher, T., Bremer, M., Wichmann, V., and Rutzinger, M. (2018). Derivation of three-dimensional displacement vectors from multi-temporal long-range terrestrial laser scanning at the Reissenschuh

- Landslide (Tyrol, Austria). *Remote Sensing*, 10(11): 1688. <https://doi.org/10.3390/rs10111688>
- Pieraccini, M., Casagli, N., Luzi, G., Tarchi, D., Mecatti, D., Noferini, L., and Atzeni, C. (2003). Landslide monitoring by ground-based radar interferometry: A field test in Valdarno (Italy). *International Journal of Remote Sensing*, 24(6):1385-1391. <https://doi.org/10.1080/0143116021000044869>
- Pieraccini, M., Noferini, L., Mecatti, D., Atzeni, C., Teza, G., Galgaro, A., and Zaltron, N. (2006). Integration of radar interferometry and laser scanning for remote monitoring of an urban site built on a sliding slope. *IEEE Transactions on Geoscience and Remote Sensing*, 44(9):2335-2341. <https://doi.org/10.1109/TGRS.2006.873574>
- Powell, K.R. and Peterson, S.R. (2017). Coverage and quality: A comparison of Web of Science and Scopus databases for reporting faculty nursing publication metrics. *Nursing Outlook*, 65:572-578. <https://doi.org/10.1016/j.outlook.2017.03.004>
- Pradhan, B., Al-Najjar, H.A.H., Sameen, M.I., Mezaal, M.R., and Alamri, A.M. (2020). Landslide Detection Using a Saliency Feature Enhancement Technique from LiDAR-Derived DEM and Orthophotos. *IEEE Access*, 8:121942-121954. <https://doi.org/10.1109/ACCESS.2020.3006914>
- Pradhan, B., Jebur, M.N., Shafri, H.Z.M., and Tehrani, M.S. (2016). Data fusion technique using wavelet transform and taguchi methods for automatic landslide detection from airborne laser scanning data and quickbird satellite imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 54(3):1610-1622. <https://doi.org/10.1109/TGRS.2015.2484325>
- Ragnoli, M., Leoni, A., Barile, G., Ferri, G., and Stomelli, V. (2022). LoRa-Based Wireless Sensors Network for Rockfall and Landslide Monitoring: A Case Study in Pantelleria Island with Portable LoRaWAN Access. *Journal of Low Power Electronics and Applications*, 12(3):47. <https://doi.org/10.3390/jlpea12030047>
- Ramesh, M.V. (2014). Design, development, and deployment of a wireless sensor network for detection of landslides. *Ad Hoc Networks*, 13(Part A):2-18. <https://doi.org/10.1016/j.adhoc.2012.09.002>
- Ramsey, E.W. and Rangoonwala, A. (2021). Using ALOS-2 synthetic aperture radar (SAR) and interferometric SAR to detect landslides on the mountainous island of Pohnpei, federated states of Micronesia. *US Geological Survey Open-File Report*, 2021(1084). <https://doi.org/10.3133/ofr20211084>
- Sameen, M. I., and Pradhan, B. (2019). Landslide Detection Using Residual Networks and the Fusion of Spectral and Topographic Information. *IEEE Access*, 7:114363-114373. <https://doi.org/10.1109/ACCESS.2019.2935761>
- Saravanan, P., Rajeswari, S., Kumar, J. A., Rajasimman, M., and Rajamohan, N. (2022). Bibliometric analysis and recent trends on MXene research - A comprehensive review. *Chemosphere*, 286:131873. <https://doi.org/10.1016/j.chemosphere.2021.131873>
- Sassa, K., Tsuchiya, S., Fukuoaka, H., Mikos, M., and Doan, L. (2015). Landslides: review of achievements in the second 5-year period (2009-2013). *Landslides*, 12(2):213-223. <https://doi.org/10.1007/s10346-015-0567-4>
- Scaioni, M., Longoni, L., Melillo, V., and Papini, M. (2014). Remote Sensing for Landslide Investigations: An Overview of Recent Achievements and Perspectives. *Remote Sensing*, 6(10):9600-9652. <https://doi.org/10.3390/rs6109600>
- Segoni, S., Battistini, A., Rossi, G., Rosi, A., Lagomarsino, D., Catani, F., Moretti, S., and Casagli, N. (2015). Technical Note: An operational landslide early warning system at regional scale based on space-time-variable rainfall thresholds. *Natural Hazards and Earth System Sciences*, 15(4):853-861. <https://doi.org/10.5194/nhess-15-853-2015>
- Shankar, H., Singh, D., and Chauhan, P. (2022). Landslide deformation and temporal prediction of slope failure in Himalayan terrain using PSInSAR and Sentinel-1 data. *Advances in Space Research*, 70(12):3917-3931. <https://doi.org/10.1016/j.asr.2022.04.062>
- Sharma, R., Vashisht, V., and Singh, U. (2020). WOATCA: A secure and energy aware scheme based on whale optimisation in clustered wireless sensor networks. *IET Communications*, 14(8):1301-1310. <https://doi.org/10.1049/iet-com.2019.0359>
- Shi, X., Liao, M., Zhang, L., and Balz, T. (2016). Landslide stability evaluation using high-resolution satellite SAR data in the Three Gorges area. *Quarterly Journal of Engineering Geology and Hydrogeology*, 49(3):203-211. <https://doi.org/10.1144/qjgeh2015-029>
- Shuaib, W., Acevedo, J.N., Khan, M.S., Santiago, L.J., and Gaeta, T.J. (2015). The top 100 cited articles published in emergency medicine journals. *The American Journal of Emergency Medicine*, 33(8):1066-1071. <https://doi.org/10.1016/j.ajem.2015.04.047>
- Simeoni, L. and Mongiovì, L. (2007). Inclinator monitoring of the Castelrotto landslide in Italy. *Journal of Geotechnical and Geoenvironmental Engineering*, 133(6):653-666. [https://doi.org/10.1061/\(ASCE\)1090-0241\(2007\)133:6\(653\)](https://doi.org/10.1061/(ASCE)1090-0241(2007)133:6(653))
- Singer, J., Thuro, K., and Sambeth, U. (2006). Development of a continuous 3D-monitoring system for unstable slopes using TDR. *Felsbau*, 24(3):16-23.
- Song, Y., Gong, J., Gao, S., Wang, D., Cui, T., Li, Y., and Wei, B. (2012). Susceptibility assessment of earthquake-induced landslides using Bayesian network: A case study in Beichuan, China. *Computers and Geosciences*, 42:189-199. <https://doi.org/10.1016/j.cageo.2011.09.011>
- Sugimoto, S., and Ishizuka, Y. (2022). Slope deformation monitoring using wireless sensor network and evaluation of mechanical stability by FDM simulation. *International Journal of GEOMATE*, 22(94):13-20. <https://doi.org/10.21660/2022.94.97>
- Sun, Q., Hu, J., Zhang, L., and Ding, X. (2016a). Towards slow-moving landslide monitoring by integrating multi-sensor InSAR time series datasets: The Zhouqu case study, China. *Remote Sensing*, 8(11):908. <https://doi.org/10.3390/rs8110908>
- Sun, Y., Shi, B., Zhang, D., Tong, H., Wei, G., and Xu, H. (2016b). Internal Deformation Monitoring of Slope Based on BOTDR. *Journal of Sensors*, 2016: 9496285. <https://doi.org/10.1155/2016/9496285>
- Sweileh, W.M., Al-Jabi, S.W., Sawalha, A.F., AbuTaha, A.S., and Zyoude, S.E.H. (2016). Bibliometric analysis of publications on *Campylobacter*: (2000-2015). *Journal of Health, Population and Nutrition*, 35(1):39. <https://doi.org/10.1186/s41043-016-0076-7>
- Tarchi, D., Casagli, N., Fanti, R., Leva, D.D., Luzi, G., Pasuto, A., Pieraccini, M., and Silvano, S. (2003). Landslide monitoring by using ground-based SAR interferometry: An example of application to the Tessina landslide in Italy. *Engineering geology*, 68(1-2):15-30. [https://doi.org/10.1016/S0013-7952\(02\)00196-5](https://doi.org/10.1016/S0013-7952(02)00196-5)
- Tehrani, F.S., Calvellido, M., Liu, Z., Zhang, L., and Lacasse, S. (2022). Machine learning and landslide studies: recent advances and applications. *Natural Hazards*, 114(2):1197-1245. <https://doi.org/10.1007/s11069-022-05423-7>
- Tofani, V., Segoni, S., Agostini, A., Catani, F., and Casagli, N. (2013). Technical note: Use of remote sensing for landslide studies in Europe. *Natural Hazards and Earth System Science*, 13(2):299-309. <https://doi.org/10.5194/nhess-13-299-2013>
- Travellati, J., Delacourt, C., Allemand, P., Malet, J. P., Schmittbuhl, J., Toussaint, R., and Bastard, M. (2012). Correlation of multi-temporal ground-based optical images for landslide monitoring: Application, potential and limitations. *ISPRS Journal of Photogrammetry and Remote Sensing*, 70:39-55. <https://doi.org/10.1016/j.isprsjprs.2012.03.007>
- Tyszkowski, S., and Cebulski, J. (2019). Practical aspects of landslides surveys using terrestrial laser scanning in diverse geomorphological terrains: Case studies from polish carpathians and lower vistula valley. *Zeitschrift für Geomorphologie*, 62(2):107-124. <https://doi.org/10.1127/zfg/2019/0500>
- Ugolini, D., Bonassi, S., Cristaudo, A., Leoncini, G., Ratto, G.B., and Neri, M. (2015). Temporal trend, geographic distribution, and publication quality in asbestos research. *Environmental Science and Pollution Research*, 22(9):6957-6967. <https://doi.org/10.1007/s11356-014-3925-1>
- Uhlemann, S., Chambers, J., Wilkinson, P., Maurer, H., Merritt, A., Meldrum, P., Kuras, O., Gunn, D., Smith, A., and Dijkstra, T. (2017). Four-dimensional imaging of moisture dynamics during landslide reactivation. *Journal of Geophysical Research: Earth Surface*, 122(1):398-418. <https://doi.org/10.1002/2016JF003983>
- van Eck, N.J. and Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, 84(2):523-538. <https://doi.org/10.1007/s11192-009-0146-3>
- Walter, M., Niethammer, U., Rothmund, S., and Joswig, M. (2009). Joint analysis of the Super-Sauze (French Alps) mudslide by nanoseismic monitoring and UAV-based remote sensing. *first break*, 27(8). <https://doi.org/10.3997/1365-2397.27.1302.32182>
- Wang, B., Pan, S.-Y., Ke, R.-Y., Wang, K., and Wei, Y.-M. (2014a). An overview of climate change vulnerability: a bibliometric analysis based on Web of Science database. *Natural Hazards*, 74(3):1649-1666. <https://doi.org/10.1007/s11069-014-1260-y>
- Wang, B.J., Li, K., Shi, B., and Wei, G.Q. (2009). Test on application of distributed fiber optic sensing technique into soil slope monitoring. *Landslides*, 6(1):61-68. <https://doi.org/10.1007/s10346-008-0139-y>
- Wang, G., Kearns, T.J., Yu, J., and Saenz, G. (2014b). A stable reference frame for landslide monitoring using GPS in the Puerto Rico and Virgin Islands region. *Landslides*, 11(1):119-129. <https://doi.org/10.1007/s10346-013-0428-y>
- Wang, X., Xu, Z., Su, S.-F., and Zhou, W. (2021). A comprehensive bibliometric analysis of uncertain group decision making from 1980 to 2019. *Information Sciences*, 547:328-353. <https://doi.org/10.1016/j.ins.2020.08.036>

- Whiteley, J.S., Chambers, J.E., Uhlemann, S., Wilkinson, P.B., and Kendall, J.M. (2019). Geophysical Monitoring of Moisture-Induced Landslides: A Review. *Reviews of Geophysics*, 57(1):106-145. <https://doi.org/10.1029/2018RG000603>
- Wu, C.H. and Chen, S.C. (2009). Determining landslide susceptibility in Central Taiwan from rainfall and six site factors using the analytical hierarchy process method. *Geomorphology*, 112(3-4):190-204. <https://doi.org/10.1016/j.geomorph.2009.06.002>
- Wu, H., Tong, L., Wang, Y., Yan, H., and Sun, Z. (2021). Bibliometric analysis of global research trends on ultrasound microbubble: a quickly developing field. *Frontiers in Pharmacology*, 12. <https://doi.org/10.3389/fphar.2021.646626>
- Wu, X., Chen, X., Zhan, F.B., and Hong, S. (2015). Global research trends in landslides during 1991-2014: a bibliometric analysis. *Landslides*, 12(6):1215-1226. <https://doi.org/10.1007/s10346-015-0624-z>
- Xu, Q., Li, W.L., Ju, Y.Z., Dong, X.J., and Peng, D.L. (2020). Multitemporal UAV-based photogrammetry for landslide detection and monitoring in a large area: a case study in the Heifangtai terrace in the Loess Plateau of China. *Journal of Mountain Science*, 17(8):1826-1839. <https://doi.org/10.1007/s11629-020-6064-9>
- Yadav, D.K., Jayanthu, S., Das, S.K., Chinara, S., and Mishra, P. (2019). Critical review on slope monitoring systems with a vision of unifying WSN and IoT. *IET Wireless Sensor Systems*, 9(4):167-180. <https://doi.org/10.1049/iet-wss.2018.5197>
- Yadav, D.K., Mishra, P., Jayanthu, S., and Das, S.K. (2022). On the Application of IoT: Slope Monitoring System for Open-cast Mines Based on LoRa Wireless Communication. *Arabian Journal for Science and Engineering*, 47(2):1387-1398. <https://doi.org/10.1007/s13369-021-05941-9>
- Ye, C., Li, Y., Cui, P., Liang, L., Pirasteh, S., Marcato, J., Goncalves, W. N., and Li, J. (2019). Landslide detection of hyperspectral remote sensing data based on deep learning with constraints. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 12(12):5047-5060. <https://doi.org/10.1109/JSTARS.2019.2951725>
- Yin, C., Li, H., Hu, Z., and Li, Y. (2020). Application of the terrestrial laser scanning in slope deformation monitoring: Taking a highway slope as an example. *Applied Sciences*, 10(8):2808. <https://doi.org/10.3390/app10082808>
- Yoshida, Y., Kashlwai, Y., Murakami, E., Ishida, S., and Hashiguchi, N. (2002). Development of the monitoring system for slope deformations with fiber Bragg grating arrays. *Proceedings of SPIE - The International Society for Optical Engineering*, 4694:296-303. <https://doi.org/10.1117/12.472632>
- Yu, B., Chen, F., and Xu, C. (2020). Landslide detection based on contour-based deep learning framework in case of national scale of Nepal in 2015. *Computers and Geosciences*, 135:104388. <https://doi.org/10.1016/j.cageo.2019.104388>
- Yunus, M.A.M., Ibrahim, S., Khairi, M.T.M., and Faramarzi, M. (2015). The WiFi-based wireless sensor network (WSN) application in hill slope condition monitoring. *Jurnal Teknologi*, 73(3):75-84.
- Zhao, C., Lu, Z., Zhang, Q., and de la Fuente, J. (2012). Large-area landslide detection and monitoring with ALOS/PALSAR imagery data over Northern California and Southern Oregon, USA. *Remote Sensing of Environment*, 124:348-359. <https://doi.org/10.1016/j.rse.2012.05.025>
- Zheng, Y., Zhu, Z.W., Deng, Q.X., and Xiao, F. (2019a). Theoretical and experimental study on the fiber Bragg grating-based inclinometer for slope displacement monitoring. *Optical Fiber Technology*, 49:28-36. <https://doi.org/10.1016/j.yofte.2019.01.031>
- Zhou, C., Yin, K., Cao, Y., Intrieri, E., Ahmed, B., and Catani, F. (2018a). Displacement prediction of step-like landslide by applying a novel kernel extreme learning machine method. *Landslides*, 15(11):2211-2225. <https://doi.org/10.1007/s10346-018-1022-0>
- Zhou, Z., Li, X., Wu, Y., Zhang, H., Lin, Z., Meng, K., Lin, Z., He, Q., Sun, C., Yang, J., and Wang, Z.L. (2018b). Wireless self-powered sensor networks driven by triboelectric nanogenerator for in-situ real time survey of environmental monitoring. *Nano Energy*, 53:501-507. <https://doi.org/10.1016/j.nanoen.2018.08.055>