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To cite this article: Zhengli Yang, Heng Lu, Zhijie Zhang, Chao Liu, Ruihua Nie, Wanchang Zhang, Gang Fan, Chen Chen, Lei Ma, Xiaoai Dai, Min Zhang & Donghui Zhang (2023) Visualization analysis of rainfall-induced landslides hazards based on remote sensing and geographic information system-an overview, International Journal of Digital Earth, 16:1, 2374-2402, DOI: [10.1080/17538947.2023.2229797](https://doi.org/10.1080/17538947.2023.2229797)

To link to this article: <https://doi.org/10.1080/17538947.2023.2229797>



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Published online: 30 Jun 2023.



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Visualization analysis of rainfall-induced landslides hazards based on remote sensing and geographic information system-an overview

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ABSTRACT

In recent years, RS and GIS technologies have played an increasingly important role in various aspects of rainfall induced landslide research. In order to systematically understand their application situation, this paper extensively used various visualization analysis technologies for in-depth analysis of 1,161 documents collected by the WOS data platform in the past 27 years by combining quantitative and qualitative methods. Then, this article focuses on sub domain analysis from four aspects: landslide detection and monitoring, prediction models, sensitivity mapping, and risk assessment. The study found that the number of literature in this field has steadily increased and is expected to continue to rise. This literature review has attracted widespread attention from the academic community, but it is challenging to meet research needs. Frequent and effective cooperation between countries, institutions, and authors is very beneficial for promoting progress in this field. The future development direction is a new intelligent hybrid model that integrates multiple research methods. This study can provide researchers in this field with the core research force, hot topic evolution, and future development trends of future rainfall-induced landslides and contribute to landslide prevention and control decision-making and achieving the United Nations'sustainable development goals.

ARTICLE HISTORY

Received 29 December 2022
Accepted 21 June 2023

KEYWORDS

Landslide; rainfall-induced; detection and monitoring; predictive model; sensitivity mapping; risk assessment; visual analysis

1. Introduction

The landslide is a complex system dynamics process controlled by multiple factors. Many factors trigger landslide hazards, among which rainfall is the most critical inducing factor (Donati and Tur-rini 2002; Li et al. 2021; Mekrshu et al. 2022). The hazard caused by the deformation and failure of

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slopes due to rainfall is called rainfall-induced landslides hazards (Wieczorek and Glade 2005), the world's most widely distributed and most frequent landslide hazard. Ubydul Haque et al. conducted a statistical analysis of landslides in 128 countries around the world from 1995 to 2014. They found that rainfall-induced landslides accounted for 85%, and there was a significant correlation between landslides and rainfall events in space and time (Haque et al. 2019). Melanie, J. F. and David, N.P. made a spatiotemporal analysis of the global non-seismic landslide dataset during 2004–2016. The result showed that 79% of the non-seismic landslide events were caused by rainfall (Froude and Petley 2018). During 2011–2016, Fanyu Zhang et al. collected all landslides in China and proved that 94.2% of the landslides were related to rainfall (Zhang and Huang 2018). These rainfall-induced landslides disasters have caused heavy losses of life and property (Aristizábal and Sánchez 2020; Jain et al. 2021; Martha et al. 2019; Matziaris et al. 2015; Orense and Sapuay 2006; Park, Oh, and Park 2021;), and aroused widespread concern in society and great attention from various countries (Dai, Lee, and Wang 2003; Yilmaz 2009).

However, rainfall landslides mainly occur in mountainous and hilly areas and are accompanied by severe rainstorm weather. Sudden, hidden, and challenging field investigations characterize them. Their research has always been one of the hard problems in natural disasters. (Pourghasemi, Mohammady, and Pradhan 2012; Sharma and Shakya 2008). It is difficult to find hidden dangers and guarantee the timeliness and accuracy of spatiotemporal information analysis of landslide hazards by the traditional manual investigation and screening methods. With the rapid development of geo-information science and new generation of information technology, RS and GIS technologies have been widely used in recent decades, providing more reliable research methods for rainfall-induced landslides (Chen, Chue, and Chen 2013; Manfré et al. 2012). The environmental factors such as topography, landform, vegetation coverage, and land use type can be obtained, calculated, and analyzed under the advantages of RS and GIS technologies, which are very suitable for researching rainfall-induced landslides hazards (Abdallah et al. 2005). Scholars explored the essential characteristics, influencing factors, instability mechanism, deformation mechanism, stability, and dynamic aspects of rainfall-induced landslides by widely using RS and GIS technologies for the effective detection, forecast, early warning, prevention, and control of rainfall-induced landslides hazards. We have reviewed previous literature and used it as the starting point for our research. The essential documents that are up-to-date, most cited, most frequently used at all times, and most used in the last 180 days in the research field of rainfall-induced landslides hazards can be found by the sorting function of WOS. See Table 1 for the review of the four representative documents, which are the core references in this research.

Although scholars have done a lot of research in this field, there is still a lack of comprehensive and detailed sorting and summary on the study of RS and GIS technology in rainfall landslides. These documents show the readers such problems from different angles:

- (1) What is the temporal and spatial distribution of the number of documents issued in this field? What is the highly cited literature? What is the status quo of scientific research cooperation analysis?
- (2) What are the representative concerns of these documents? What is the development trend in the future?
- (3) What research methods do scholars prefer in terms of central topics in this field, such as landslide detection and monitoring, prediction model, sensitivity mapping, analysis and evaluation, and how effective are they?

If the above problems are analyzed in depth, it will help the rainfall landslide researchers to broaden their thinking and carry out adequate research combined with their work. Analyzing previous review papers, it was found that most of them mainly focused on describing a particular region rather than the world, and the comprehensiveness of the research was lacking. Furthermore, few people have paid attention to the bibliometric analysis of literature in this

Table 1. Table for the Review of Representative Documents.

Characteristic	References	Approach	Contribution
Date: newest first (2021)	Khasanov et al. 2021	79 articles published during 2000–2020 on the causes and effects of landslides in Central Asia were reviewed via the Scopus database, and rainfall was studied as a major landslide hazard-causing factor.	It was found that GIS and RS technologies were not widely used in papers from 2000 to 2010 but gradually applied to the research of rainfall-induced landslides in Central Asia in the last ten years.
Citations: highest first(794)	Dai, Lee, and Ngai 2002b	The latest progress in landslide risk assessment and management (updated to 2002) was reviewed, and the applicability of landslide risk assessment models with rainfall data was discussed.	A landslide risk assessment and management framework that can reduce landslide risks was proposed, and the empirical and theoretical relationships between rainfall characteristics and landslide occurrence were summarized.
Usage (all time): most first	Van Westen, Castellanos, and Kuriakose 2008	The trend of collecting spatial information on landslide environmental factors (updated to 2008) was reviewed, spatial data were analyzed hierarchically, and a schematic diagram of landslide frequency associated with rainfall events was drawn	The methods of capturing and using spatial information such as triggers (rainfall included) and environmental factors and the importance of prioritizing methods for risk assessment that are appropriate for available data and analysis scales were discussed.
Usage (last 180 days): most first	Chae et al. 2017	The latest progress and development in the essential components of landslide hazard assessment (updated to 2017) was summarized, and different models for simulating possible landslides with rainfall data were compared and analyzed.	The probability method and physical method of susceptibility assessment were mainly analyzed, an early landslide warning was conducted based on the landslide remote sensing monitoring technology, and the remote sensing methods and primary reference materials of different rainfall monitoring were introduced in detail.

field, which has a low degree of visualization and is difficult to intuitively reflect the application of RS technology and GIS technology in studying rainfall-induced landslides disasters. In addition, the literature database samples are old, and difficult to track emerging technologies and methods, which cannot reflect the research hotspots in this field in recent years and predict future development trends. Given this, this paper retrieved 1,161 documents published during 1995–2022 from the document data platform of WOS based on the comprehensive analysis of previous research results and comprehensively reviewed the achievements of the global RS and GIS technologies in the rainfall-induced landslides hazards geoinformatics research. The paper deeply explored the research topics and hotspots through the scientific application of document analysis functions of the WOS document data platform and various document visualization tools, mainly introducing the research progress in four landslide detection and monitoring sub-fields, predictive model analysis, susceptibility mapping, and risk assessment. Then, the limitations of literature data, four sub-areas, and econometric analysis results during this study were discussed, corresponding solutions were proposed, and how the study could provide some assistance to policymakers and UN SDGs. Finally, the advantages of using bibliometric analysis software for visual analysis in this study were summarized, revealing the core research strengths, hot topic evolution, and future trends of rainfall-induced landslides geoinformatics in the future.

2. Material and methods

2.1. Document retrieval and processing

This paper took the WOS document data platform as the data source for analysis, and the retrieval time was July 18, 2022. The search settings were TS = ‘landslide’ AND ‘GIS’ AND ‘rain*’ and TS

= 'landslide' AND 'RS', of which '*' represented a wildcard character, 'rain*' contained multiple subject words: 'rainfall-induced', 'rainfall', 'rainfall-triggered', 'torrential rain', 'high-rainfall', 'heavy rainfall' and so forth. We set the data source as 'Search in: Web of Science Core Collection' in the WOS document data platform. Selected the citation index as 'Editions: All', the document fields as 'Topic' and the retrieval time as 'Publication: All years (1900-2022)'. 1,328 records from 1995 to 2022 were retrieved from the WOS document data platform. To ensure the accuracy and relevance of the document and facilitate the document management and visualization analysis of the software, the raw data needs to be downloaded in different formats and provided with preparations such as terms unification, sorting and deduplication, and item-by-item screening. For this, a flow chart (Figure 1) was drawn to illustrate the strategies of document data collection, screening, and sorting.

Firstly, the retrieved documents were 'added to the tag list' in the resulting interface of the WOS document data platform so that the bibliometric analysis function of WOS could be used to analyze the retrieval results quantitatively. Then, the data format (*.ris) was used to download, which was convenient for Endnote to browse documents and manage references. The tabular data format (*.xls) was adopted to download to realize document collation and data analysis in Excel. The data format (*.txt) was applied to download to facilitate visualization analysis of the software. Since different papers used different names for terms with the same meaning to improve the accuracy of document analysis, the words were unified, as shown in Table 2. After being de-duplicated according to title and DOI, the two researchers screened and summarized the documents based on the document inclusion and exclusion criteria and the document information, such as titles, keywords, and abstracts. The inclusion criteria were that the research object is a rainfall-induced landslides and the research contents involve the application of RS and GIS technologies in geoinformatics. The exclusion criteria were as follows: (1) the study subjects were not rainfall-type landslides, such as earthquakes, tsunamis, hurricanes, forest fires, human activities, and other landslides as the main inducing factors. (2) Literature with no correlation between the research content and RS and GIS technology. After the ambiguous and uncertain contents were submitted to the third researchers for judgment and determined through group meetings, 1,161

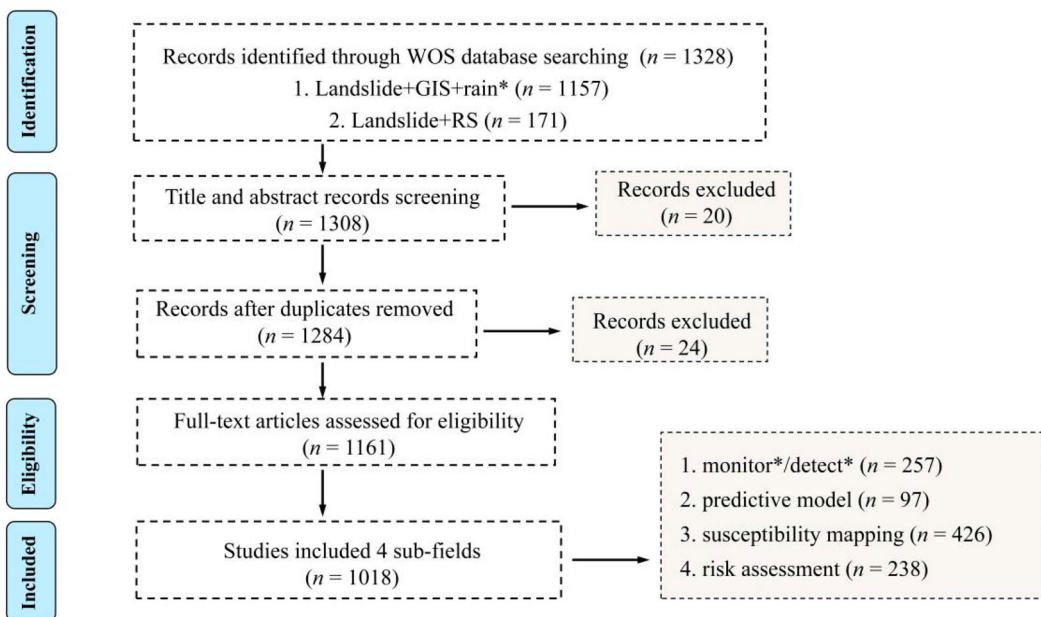


Figure 1. Number of documents published and cited quantity.

Table 2. Unified terms.

After the merger	Before the merger	After the merger	Before the merger	After the merger	Before the merger
ANN	Artificial Neural Network	AHP	Analytic Hierarchy Process	DEM	Digital Elevation Model
EBF	Evidential Belief Function	FR	Frequency Ratio	GIS	Geographic Information Systems
LSM	Landslide susceptibility mapping, LSM, Landslide Susceptibility Model, Landslide Susceptibility Modeling, Landslide Susceptibility Modelling	NDVI	Normalized Difference Vegetation Index	ROC	Receiver Operating Characteristic
RF	Random Forest	SVM	Support Vector Machine	WLC	Weighted Linear Combination

accurate records were obtained to form a document sample database. Finally, in the result of the document sample database, the keywords such as ‘monitor*’, ‘detect*’, ‘predictive model’, ‘susceptibility mapping’, ‘risk assessment’ were further retrieved for document refining, and the keys documents in the four sub-fields were extracted, sorted and combed according to time, number of citations and download counts in combination with professional knowledge.

2.2. Visualization analysis method

Visualization analysis is mainly applied for massive data correlation analysis and can perform a correlation analysis of data and make a complete analysis chart with the aid of manual operation (Elejalde, De Elejalde, and Heitman 1985). This paper made a visualization analysis of the application and development trend of RS and GIS technologies in the rainfall-induced landslides geoinformatics research field by extensively using various document analysis tools such as WOS document data platform, VOSviewer, SCImago Graphica, Pajek and Citespace. First, click on the ‘Analyze Retrieval Results’ in the WOS document data platform and select the publication year, country/region, publication title, research direction, and other functional modules from the list of marked document results to provide primary data for the visualization analysis of this paper.

VOSviewer is a kind of software for the visualization analysis of documents. In 2009, Van Eck and Waltman (2010) proposed VOSviewer at the 12th International Conference on Scientometrics and Informetrics (ISSI), attracting attention from the academic circle. Retrieval found that a document on the VOSviewer program was cited more than 4,000 times, indicating that VOSviewer had been widely used for document analysis in various fields (Cobo et al. 2011; Leydesdorff, Carley, and Rafols 2013). However, VOSviewer has only been used in research on landslide hazards in recent three years (Bovi et al. 2022; Kaur and Sood 2020; Yang et al. 2022a). This paper mainly made inter-country cooperation analysis and high-frequency keywords analysis with VOSviewer (version 1.6.16) software, used SCImago Graphics for global geographic visualization analysis of the document, and combined with Pajek for keyword node separation. As two easy-to-use document visualization analysis software, SCImago Graphica and Pajek can be downloaded and used for free at <https://graphica.app/> and <http://mrvar.fdv.uni-lj.si/pajek/be2.htm>.

With apparent advantages in co-occurrence networks and research trend visualization analysis (Chen 2017; Ding et al. 2021; Yang et al. 2017), CiteSpace has been favored by many scholars since it was developed. In particular, CiteSpace, together with VOSviewer for visualization analysis, can achieve complementary advantages and is a good tool for mining research hotspots and development trends (Ding and Yang 2020; Markscheffel and Schröter 2021; Xu, Yu, and Wang 2019; Yang et al. 2022b). In light of this, this paper used Citespace (version 6.1. R2) for author cooperation, institutional cooperation, keyword clustering analysis, and timeline analysis and also combined with VOSviewer for research hotspots and trend analysis.

3. Results

3.1. Spatio-temporal distribution of number of documents published

Statistics of the number of papers published and cited in this research field during 1995–2022 were made according to time sequence, as shown in [Figure 2](#). The results indicated that the number of documents published and cited shows an increasing trend as a whole, reflecting that the application of RS and GIS technologies in this field has attracted more and more attention from many scholars.

The first stage (1995–2007) was the preliminary application stage: The number of documents published and cited in this stage was small, but there were research results every year. The research in this field began in 1995 and coincided with the ‘An International Decade for Natural Hazard Reduction’ mid-term of the United Nations. Under the background that the landslide hazard research was being carried out in full swing after first applying GIS technology to the analysis of rainfall-induced landslides hazards, WU, WM. et al. proposed a slope stability model (dSLAM) (Wu and Sidle 1995) and integrated the contour-line topographic analysis and GIS technology for spatial data extraction and display, which had a significant impact on subsequent scholars (Ozdemir and Turoglu 2007; Qiao 2004; Tarantino, Blonda, and Pasquariello 2004; Wang et al. 2007; Yang et al. 2001). The second stage (2008–2014) was the development and application stage: a few scholars began to focus on integrating RS and GIS technologies and predicting rainfall-induced landslides through artificial intelligence modeling (Kavoura and Sabatakakis 2020 Liu, Du, and Yi 2022;; Park et al. 2011). What contributed most was that in 2013, Tehrany, Pradhan, and Jebur (2013) researched the spatial prediction of flood-prone areas by using the statistical model integrated with the decision tree (DT) and GIS, which was cited 371 times, indicating that the hybrid intelligence method integrating RS and GIS technologies and artificial intelligence method has significantly contributed to the subsequent research on rainfall-induced landslides hazards. The third stage (2015–2022) was a rapid development stage: The number of documents published and cited increased significantly compared with that of the previous two stages. The number of papers published in 2017 exceeded 100, reached a peak of 159 in 2020, but declined slightly in 2021, showing an increasing trend as a whole. In 2022, although there was no complete statistics on research results, the number of a document published reached 69, and the number of citations also acquired 4,399, which showed that scholars had paid more attention to the research value of this field (Jiang et al. 2020 Mondal and Mandal 2018;).

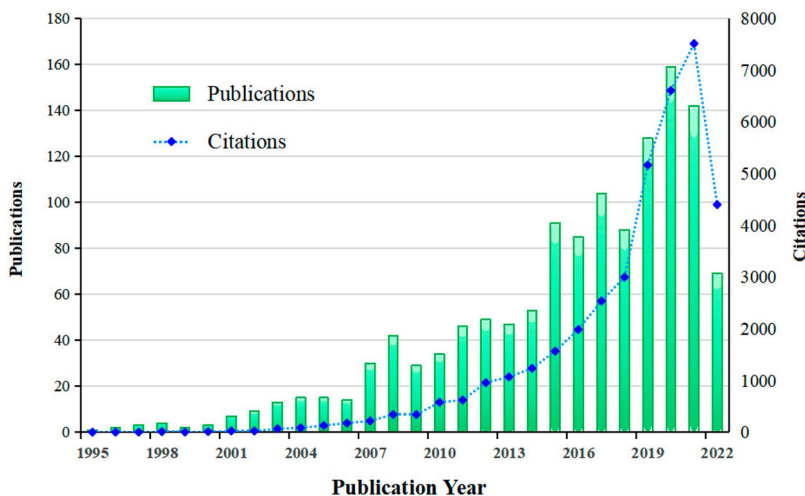


Figure 2. Number of documents published and cited quantity.

The analysis of the document results in the WOS document data platform showed that 89 countries or regions had published papers in this field. From Figure 3, it is clearly seen that the research in this field was widely distributed worldwide. The circular node represents the number of publications in the country. The larger the number of publications, the larger the node. The specific numbers are shown in the legend below Figure 3. The connections between nodes indicate the relations between countries. With the most significant number of papers published, China is the only country that has published more than 300 papers, which correlates closely with the characteristics of high density, high frequency, and wide distribution of rainfall-induced landslides in China and the large number of funds invested in landslide hazard prevention and control research. According to the statistical data of Petley (2012), the number of deaths caused by landslide hazards in China during 2004–2010 was 6,860, which ranked first in the world and was significantly higher than that of other countries. Besides, countries such as Italy and the United States, etc., were deeply affected by rainfall-induced landslides hazards.

The detailed distribution of the journals that rank in the top 5 in the number of documents published was obtained after the document sample database was processed, as shown in Table 3. The journals that rank in the top 10 in the number of documents published were authoritative journals with international reputations, indicating that high-level international researchers have gradually recognized the research in this field. It can be seen intuitively from Table 3 that with the most significant number of papers published, Natural Hazards has published 84 articles, accounting for 7.24% of the total number of papers published. Since 2002, Natural Hazards has published papers in this field and successively posted documents on RS and GIS technologies in landslide spatial analysis (Wang, Sassa, and Xu 2007), landslide susceptibility mapping (Yalcin and Bulut 2007), risk analysis (Gentile, Bisantino, and Trisorio Liuzzi 2008), hazard zoning (Kouli et al. 2010), etc., with a total number of citations of 2,462 and an average number of sources of 123 per year. The journal not only had the highest total number of documents published but also was more frequently published (4) and cited every year, which showed that its influence ranks first. In 1999 (Bonomi and Cavallin 1999), Geomorphology was the first to publish papers in this field, with the highest total number of citations (4,334) and the highest average annual number of citations (188), showing that the journal has made significant contributions to this research field. With the highest annual average number of papers published, Environmental Earth Sciences published five articles, which meant that the journal focuses more on this research field. Although Remote Sensing was the last concern about this field (Teshebaeva et al. 2015), it had a prominent position in the number of papers published or the annual number of articles cited. Journals such as Catena

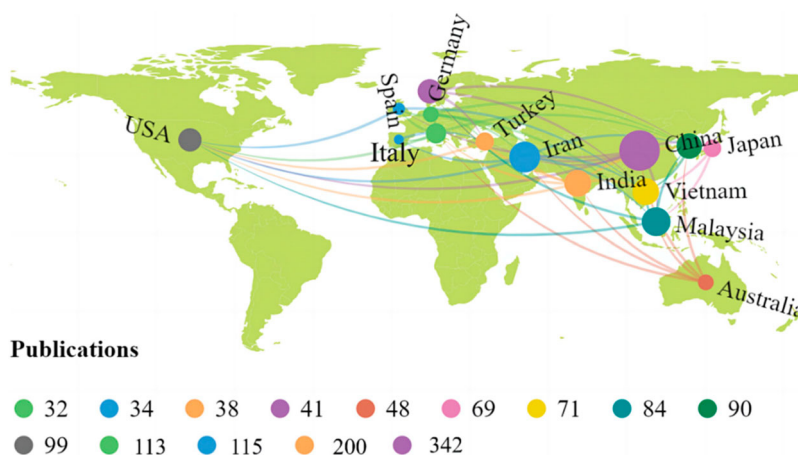


Figure 3. National Geographic visualization with more than 30 articles posted (by VOSviewer and Scimago).

Table 3. Distribution of journals(TOP 5).

NO.	Journal name	Post volume	A percentage of the total documents posted	The total number of citations	Start the year	Annual output	The annual number of citations
1	Natural Hazards	84	7.21	2462	2002	4	123
2	Environmental Earth Sciences	62	5.34	1942	2009	5	149
3	Landslides	60	5.17	2872	2005	4	169
4	Geomorphology	57	4.91	4334	1999	2	188
5	Geomatics Natural Hazards Risk	34	2.93	845	2011	3	77

(25), Journal of Mountain Science (22), and Sustainability (21) had a relatively large number of papers published and were the primary sources of documents in this field. Most of these journals originated from geoscience, engineering technology, environmental science, and other areas, playing an essential role in promoting the development of this field. Furthermore, 25 journals published more than ten papers, accounting for 59.17% of the published papers. In general, the distribution of journals was diverse and scattered, and it was a common consensus to pay attention to the importance of applying RS and GIS technologies to the research of rainfall-induced landslides geo-informatics field.

3.2. Analysis of highly cited documents

In the document sample database in this paper, the top 5 copies with the highest number of citations are shown in Table 4. The highly cited articles that rank first and second were both from Dai, F.C. Team. In nearly 27 years of research in this field, the two papers of the team have been cited 29 and 26 times per year, respectively, which showed that Dai, F.C. et al. had made significant influences in this field, and also proved that the small number of review documents have essential reference value for subsequent research, and more review documents in this field need to be systematically summarized and deeply analyzed in the future.

With the third highest number of citations, and as a review paper, it was cited 684 times, which further explained the necessity and importance of the review documents. Having been studied earlier, documents ranked fourth in the number of citations were the documents at the beginning of the second research stage (2008-2014) in this research field, and also the early documents on the combination of RS and GIS technologies with intelligent methods, which were forward-looking.

Table 4. Highly cited literature information table(TOP 5).

Author	Cite Frequency	Year	Publication type	Main Contribution
Dai, Lee, and Ngai 2002b	794	2002	Review	A landslide risk assessment and management framework that can reduce landslide risks was proposed, and the research status of landslides was critically reviewed.
Dai and Lee 2002a	718	2002	Article	The GIS database was used to describe the statistical relationship among the physical characteristics of landslides, the landslide frequency, and the physical parameters that cause landslides.
Van Westen, Castellanos, and Kuriakose 2008	684	2008	Review	The spatial information was discussed and used for landslide susceptibility, hazard, and vulnerability assessment.
Yalcin 2008	493	2008	Article	Analytic hierarchy process (AHP), statistical index (WI), and weighting factor (WF) was used to generate susceptibility maps, and the performance of the three methods was compared.
Wu and Sidle 1995	439	1995	Article	A slope stability model (dSLAM) was proposed and integrated with the GIS for spatial data extraction and display.

In the follow-up research, many documents on new hybrid intelligent algorithms were published one after another, which once again proved that mixed intelligent methods are hot topics in this research field. Finally, although the document with the fifth highest number of citations was published at the preliminary exploration stage of this research field, its popularity has not decreased. It has been cited 439 times, playing an essential role in guiding subsequent scholars to use GIS technology to carry out rainfall-induced landslides research and showing that this field has been widely concerned by the academic circle.

3.3. Analysis of scientific research cooperation

In terms of the analysis of author cooperation and high productivity author, the data in the document sample database was retrieved and imported into CiteSpace (version 6.1.R2) for processing. To facilitate the clear display of the documents-based knowledge mapping (Chen 2004; Chen 2006; Chen 2016), the software parameters were set first, and the time span was selected as 1995–2022. The time slice was set as follows: the node type was selected as Author, Pathfinder, and MST were chosen for tailoring the network mapping, and the remaining parameters were selected as default values. Using the CiteSpace author co-occurrence and cooperation analysis function, the core author groups and their cooperative relationships were visualized in Figure 4. The authors published more than 30 papers, and their representative works are shown in Table 4. In Figure 4, a dot represents an author. The large the dot radius is, the more papers the author publishes. The lines between the dots represent the scientific research cooperation between the authors. Figure 4 shows a specific relationship between most authors, which is reflected in multiple core author groups. The largest core author group is centered on PRADHAN B, and the core author group is closely related to other author groups. Table 4 indicates that the team publishes 57 papers, which have been cited 6,106 times in total, and ranks first in the number of articles published and the total number of citations, showing that the team is the most influential core author group in this field. The second-ranked core author group is the BUI T author group. Figure 4 indicates that the core author group is also closely related to other core author groups. Still, its scientific research cooperation is not as extensive as that of the PRADHAN B core author group. Table 4 intuitively shows that the BUI T team publishes 40 papers, which have been cited 4,507 times, and makes a lot of contributions to this field. Figure 4 demonstrates that although the core author groups of the

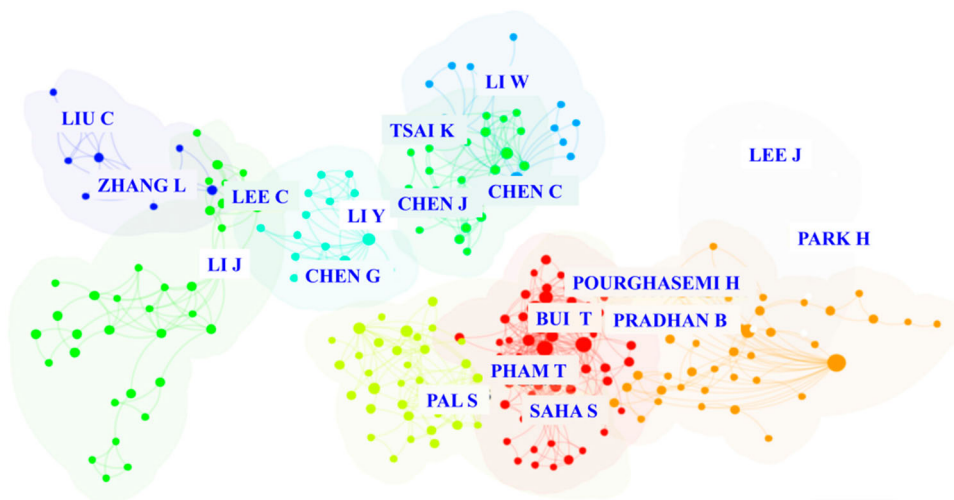


Figure 4. The authors' partnership is co-present (by CiteSpace).

third-ranked PHAMT and the fourth-ranked CHEN W have more academic exchanges with other scientific research teams, their cooperation is not as extensive and close as that of the previous two core author groups.

Table 5 also seems to suggest that the PHAMT and CHEN W author groups are weaker than the previous two core author groups in terms of both the number of papers published and the total number of citations, indicating that the more they cooperate with other research teams, the more articles they will print and the more the papers will be cited. In addition, except for a few large core author groups, the nodes of the remaining author groups are scattered and not closely correlated with each other and do not form a robust clustering, suggesting that the scientific research teams have not established close cooperation and communication and started a trend of cooperative research, and also indicating that they mainly carry out independent research in this field. Still, the breadth and depth of their study are inferior to that of the previous core author groups. Overall, the number of author nodes in this field is large, showing that the application of RS and GIS technologies in the geoinformatics analysis of rainfall-induced landslides is a research field that researchers are very interested in.

The data downloaded from the WOS document data platform was imported VOSviewer (version 1.6.16) to obtain a visualization analysis network map of cooperation between countries relying on the county cooperation function of VOSviewer software and taking the country name as the node. As shown in Figure 5, the number of rectangular nodes represents the number of countries, and the larger the area of the rectangular node is, the more papers are published by the government. The line between rectangular nodes reflects the cooperation between countries. The more the number of lines, the more extensive the scientific research cooperation is. The closer the lines are, the closer the relationship between them is.

The research results have showed that the lines between rectangular nodes are dense and complex, indicating that there are many cooperative relationships between different countries. With the largest area of corresponding rectangular nodes, and the largest number of papers published, China has the largest area of corresponding rectangular nodes, published the most papers, and connected more rectangular nodes. Although cooperation with other countries is frequent to some extent, it is still in a marginal position and has not yet become an essential bridge in international collaboration. Countries that are second only to China regarding the number of papers published and cooperative influence are India, Italy, Iran, etc. The rectangular nodes where these countries are located are large

Table 5. High Productivity Authors and Representative Works (Over 30).

Authors	Post volume	Cite Frequency	Masterpiece	Representative contribution
Pradhan and Lee 2010	57	6106	Regional landslide susceptibility analysis using back-propagation neural network model at Cameron Highland, Malaysia	Modeling was made by the hybrid intelligent method via remote sensing data and GIS technology to realize the susceptibility mapping of landslide hazards.
Bui et al. 2012	40	4507	Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS	Modeling was made based on the GIS-integrated artificial intelligence method for the regional spatial prediction of landslide hazards.
Pham et al. 2017	34	3043	Landslide susceptibility assessment in the Uttarakhand area (India) using GIS: a comparison study of prediction capability of naïve bayes, multilayer perceptron neural networks, and functional trees methods	The predicted performance of several technologies, such as function trees, multilayer perceptron neural networks, and Naive Bayes in landslide susceptibility assessment, was compared with the GIS.
Chen et al. 2017	31	2335	GIS-based landslide susceptibility modeling: a comparative assessment of kernel logistic regression, Naive-Bayes tree, and alternating decision tree models	Some potential applications of complex machine learning technology in landslide susceptibility mapping were explored based on GIS technology.

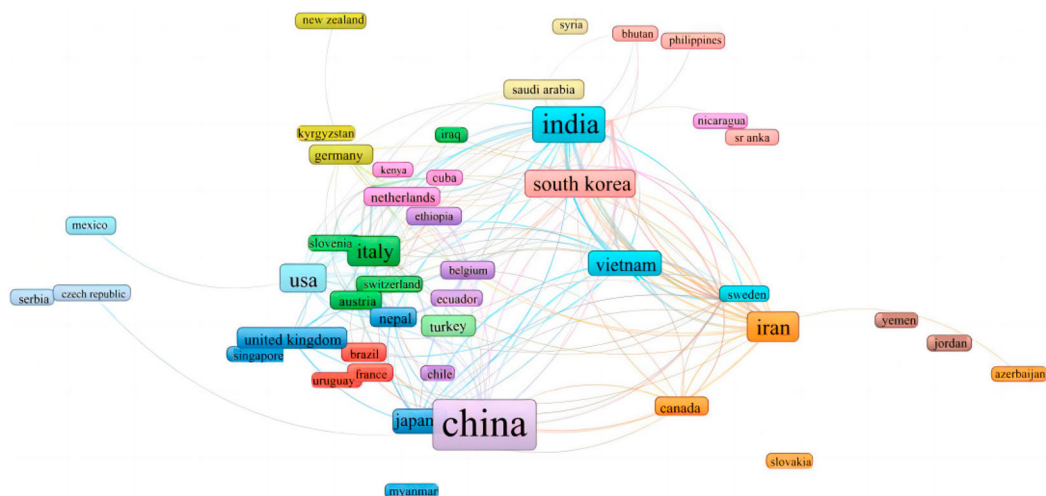


Figure 5. Network diagram of cooperation between countries(by VOSviewer).

in area, and there are more lines between the rectangular nodes and other countries, suggesting that these countries occupy relatively core positions in this research field with more significant research influence. Other sporadically scattered countries are not directly linked to other countries but can be indirectly linked to other countries through neighboring countries. The analysis shows that these relatively discrete countries, due to limited scientific research resources, are difficult to form their advantages in the field of disciplines, coupled with geographical constraints and other factors, cannot directly cooperate with more countries in scientific research.

According to the WOS document data platform statistics, 1,292 research institutions have carried out research in this field, of which only one institution has published more than 50 papers, and 58 institutions have published more than ten papers. From Figure 6(a), it can be seen that the largest cooperative relationship group includes Chinese Acad Sci, China Univ Geosci, Univ Chinese Acad Sci, Xian Univ Sci & Technol, Chengdu Univ Technol, and China Univ Min & Technol, etc., which have formed a stable and close relationship and are from China, indicating that these institutions are significantly affected by geographical factors.

In order to reflect the time sequence and duration of research carried out by various institutions in this field, the 'Burstterms' function of the CiteSpace software has been applied for the mutation detection of institution names during 1995–2022 to obtain the top 25 mutation institution names in this field, representing the famous institutions during this period. As shown in Figure 6(b), Column 1 is the short name of institution names, and Column 2 is the year in which the research started. Column 3 represents the increased intensity of the citation frequency of the institution, which can also be understood as the quantized value of the institution's influence in this research field. The years in Columns 4 and 5 represent the years when the institution appeared and ended in this research field respectively. The red strip represents the mutation duration. It's not hard to see that US Geol Survey first stood out in this field in 2000, followed by Univ Hong Kong and Chinese Acad Sci, which became active in this research field in 2001, of which Chinese Acad Sci is an institution for mutation research, with the most extended period of 9 years from 2001 to 2010. Univ Putra Malaysia had the most significant increase in the intensity value of the citation frequency, which was 11.35, suggesting that the institution's research results had attracted much attention during 1995–2022. The four institutions of Univ Gour Banga, Univ Technol Sydney, Univ Chinese Acad Sci, and Tarbiat Modares Univ have been actively engaged in the geoinformatics analysis of rainfall-induced landslides until now. They will continue to conduct relevant research in the future. Because the cooperation among countries, institutions, and disciplines is limited by geographical

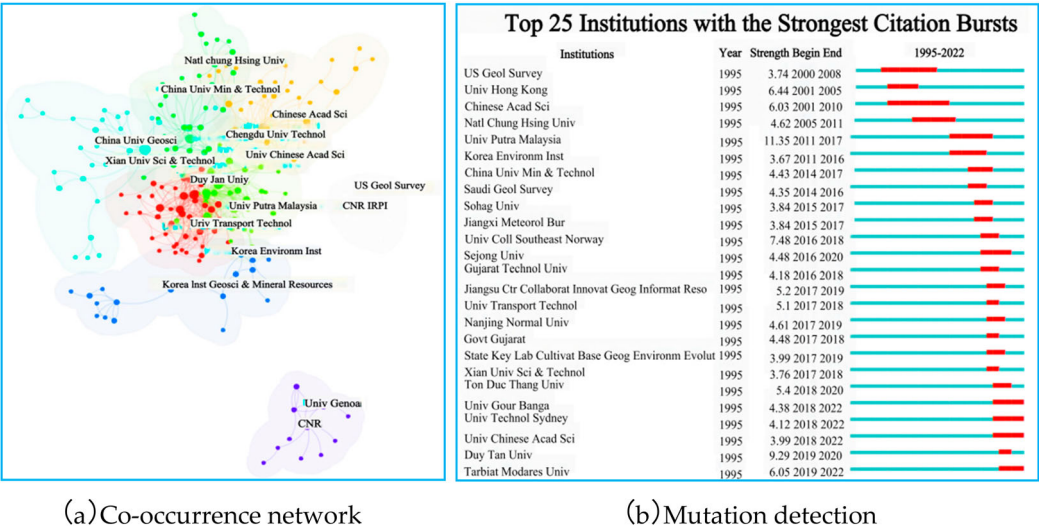


Figure 6. Cooperative analysis and mutation testing (by CiteSpace).

location, it is suggested that researchers abandon the concept of space and strengthen academic exchanges using network meetings without considering geographical boundaries.

3.4. Analysis of research hotspots and trend

The keywords involved in this field were displayed in a collinear network relation topic mapping by making use of the visualization method of VOSviewer software, taking keywords as the node and combining with Pajek’s node separation function, as shown in Figure 7. The width of rectangular nodes represents the keyword frequency. The wider the rectangle is, the more prominent the node is, indicating that the keyword frequency is higher. The line between rectangular nodes represents the correlation between keywords. The thicker the line is, the darker the color is, and the closer the connection between keyword nodes will be. The same color of rectangular nodes means that the keywords belong to the same topic. A total of 6 keyword topics have been obtained through the analysis of keyword frequency. It is not difficult to see that as the most frequent keyword, ‘gis’ is at the core of the red topic and is also the focus and hotspot of the topic research.

For the keywords like ‘model’, ‘landslide’, and ‘rainfall’ that are closely related to it have the same red color as ‘gis’. Moreover, the rectangular nodes where these keywords are located have large widths, prominent integrity, and more divergent lines, indicating that they are high-frequency words and also hot topics of the topic research. Besides, the View clearly shows that keywords such as ‘prediction’, ‘logistic regression’, ‘ann’, ‘risk assessment’, and ‘national hazard’ appear more frequently. Their rectangular nodes are green, light blue, yellow, purple, and cyan, meaning these are the core keywords in the topic they belong to. However, the closer the case to the right is, the more discrete the node is. The fewer the lines between rectangular nodes and other nodes are, indicating that the main research topics in this field are different in heat or depth, and the closer to the right side of the view is, the more it will show a downward trend.

To more clearly show the node topic of keywords and mine research hotspots (Chen, Ibekwe-SanJuan, and Hou 2010), CiteSpace software was used to cluster the document keywords into 10 clusters (Saha et al. 2021; Van Dao et al. 2020; Zhu et al. 2021). The color of the clustering tags was consistent with the color of the clustering nodes. The keyword clustering analysis map is shown in Figure 8 after sorting.

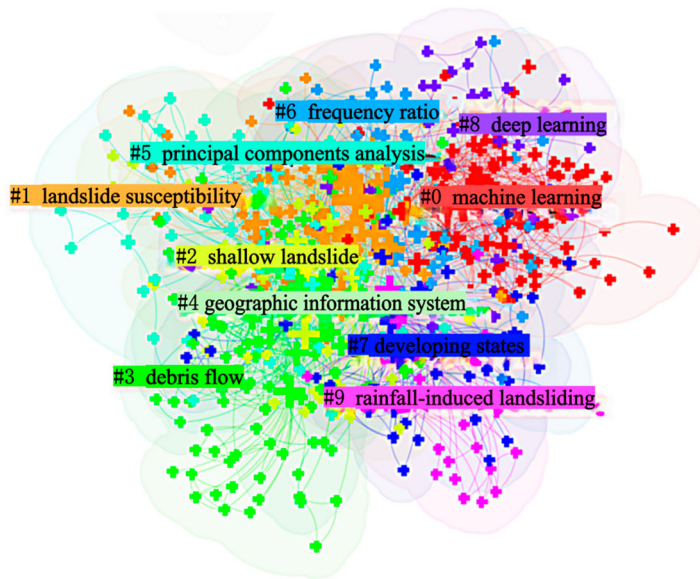


Figure 8. Keyword cluster analysis map (by CiteSpace).

and broader than that of the #3 debris flow. In addition, the most significant node appeared in the #4 geographic information system, which means the GIS technology is the foundation of the research in this field. On the whole, since 2007, there have been no new nodes, which indicates that the research enthusiasm has declined. However, the two clusters are still being studied continuously, suggesting that the two clusters are still the research directions at present and in the future. The cluster #5 principal components analysis appeared late (1997). Still, the distribution density of its nodes has remained the largest till now, showing that the research of this cluster is the most concerned hotspot direction for scholars. It's worth noting that the order in which the nodes appear shows that the annual ring-shaped nodes are denser, and will be greatly reduced

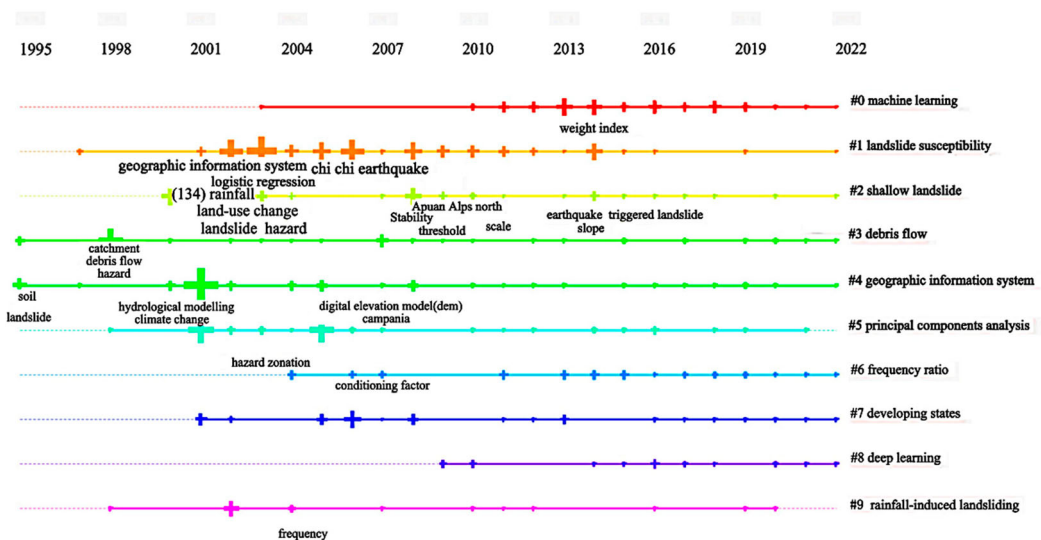


Figure 9. Keyword cluster analysis map (by CiteSpace).

in later period. Since 2014, there have been basically no new nodes, which demonstrated that susceptibility analysis has not made much breakthrough in the research of rainfall-induced landslides in recent years, and the cluster has entered a stage of steady development. By contrast, the cluster #1 machine learning appeared later (2003), and had smaller and sparser nodes in early period, but since 2011, new nodes have frequently appeared, suggesting that machine learning has entered the research booming stage, and become the development trend of this research field. The analysis found that the cluster #8 deep learning was the last to appear (2009), and did not have many nodes on the axis, which shows that the cluster has been studied for a short time, does not have many research results and has not made breakthrough research achievements. Although the #8 deep learning is still in the initial stage and has many research gaps, the timeline for this cluster has been continued to the present, indicating that it will be one of the research directions in the future.

4. Research sub-fields

As there are many classification methods in sub-fields, this paper summarized and discussed mainly the four sub-fields of landslide detection and monitoring, predictive model analysis, susceptibility mapping, and risk assessment by combining with multiple analysis results such as spatial-temporal distribution characteristics of the number of papers published, clustering analysis, hotspots, and evolution trends, keyword cloud maps and separation results and comprehensively considering the application of RS and GIS technologies in rainfall-induced landslides. Based on the WOS document data platform, the document samples related to this research content were marked 'monitor*', 'detect*', 'predictive model', 'susceptibility mapping,' and 'risk assessment' was taken as the retrieval words to extract the documents in four sub-fields.

4.1. Landslide detection and monitoring

How to quickly detect and dynamically monitor landslide data with high precision is an important research topic in geoinformatics analysis of rainfall-induced landslides hazards, which is of great significance for preventing and controlling rainfall-induced landslides hazards (Han et al. 2022; Shi et al. 2020). In 1998, people realized that it is difficult to distinguish the dangers of individual landslide hazards by qualitative methods, but quantitative methods shall be adopted. Chowdhury and Flentje (1998) conducted quantitative research on the relationship between the underground shear movement and rainfall through the historical recurrence and monitoring of individual landslides based on the GIS accurate geological and landslide map and landslide database and verified it in Australia. The continuous increase of remote sensing data and GIS functions has created opportunities for more precise and rapid detection and monitoring of rainfall-induced landslides (Hussain et al. 2005; Singh, Maurya, and Dwivedi 2021). Many scholars have successively developed many new methods based on RS and GIS technologies to further improve the stability and accuracy of landslide detection and monitoring from different perspectives. The representative cases are shown in Table 6.

High-quality remote sensing images are helpful for researchers to identify the losses before and after landslide events and the exposure of hazard-bearing bodies (Martha et al. 2012). With the aid of the GIS technology platform, a variety of remote sensing-based satellite image processing technologies can be used to extract helpful environment and hazard-causing information in landslide areas. Different remote sensing platforms have their advantages (Argyriou et al. 2022). The identification and extraction of small-scale landslide data via the uncrewed aerial vehicle (UAV) and semi-global dense matching (SGM) can achieve cm-level accuracy (Al-Rawabdeh et al. 2016). Unlike traditional optical and microwave remote sensing, airborne LiDAR can quickly obtain a high-resolution and high-precision digital elevation model (DEM), which has strong advantages in-ground detection. The obtained topographic

Table 6. Typical Cases of Landslide Detection and Monitoring.

Reference	Question	Method	Conclusion
Kelevitz et al. 2022	How to incorporate Sentinel-1 remote sensing data into landslide hazard prediction and mitigation across the UK.	The Huolin Mountain Landslide Observation Station (HHLO) was used to show the landslide process clearly and experimented with for slope stability characterization and monitoring.	InSAR measurement results were consistent with other ground measurement results.
Kontoes et al. 2021	The contributions of interferometric synthetic aperture radar InSAR data to landslide detection needed to be figured out.	The rainfall-induced landslides hazards were evaluated by heuristic and statistical methods to compare the landslide models in areas with high and low occurrence frequency in Greece	The weights of evidence (WoE) were more accurate, relying on expert opinions and landslide inventory.
Han et al. 2022	Traditional measurement had problems such as low efficiency, low accuracy, prolonged time consumption, poor classification accuracy, etc.	The object-oriented classification and extraction were provided for the Sentinel-2 and GF-1 remote sensing images before and after the occurrence of landslides to learn about the forms, constituent elements, and damage degrees.	In selecting the optimal segmentation scale, the object-oriented landslide extraction process still needs to be improved in many aspects.
Guarascio et al. 2020	The large amount of computation of the dense sensor network made integrating different remote sensing measurement information difficult.	A method based on machine learning was proposed, which used a classifier to estimate rainfall by integrated approaches, and synthesized different remote sensing measurement information.	The accurate rainfall estimation was provided without rain gauges, which was more economical than the spatial interpolation method.

data has a resolution of 1 meter in the horizontal direction and 0.15 meter in the vertical direction (Chen 2006), which is suitable for measuring the decimeter-to-meter level topographic changes in the specific research areas rainfall-induced landslides hazards. For example, the potential hazard areas of rainfall-induced landslides hazards can be easily identified using the natural topography after vegetation removal (Vega 2019). With the advantages of high spatial resolution and low comprehensive cost, interferometric synthetic aperture radar (InSAR) is particularly suitable for large-scale continuous tracking and observation. It has obvious advantages in detecting rainfall-induced landslides phenomena (Nakano et al. 2016; van Natijne et al. 2022; Zhao et al. 2012), landslide mass identification, landslide factor extraction, change monitoring, etc. In the landslide detection and monitoring stage, InSAR will continue to be the mainstream method for a long time in the future, with visible light as an auxiliary means. At the same time, the single standards will continue to be replaced by an integrated monitoring system that combines multiple monitoring technologies. Remote sensing data and multi-temporal images have become valuable alternative sources for disaster assessment in areas with limited field investigation potential. However, the complexity of rainfall-induced landslides requires effective object-oriented landslide detection methods to define object features from RS data. In the future, fast and automatic landslide detection methods, such as WebGIS systems for landslide detection and prediction (Yang et al. 2023), are worth paying attention to.

4.2. Predictive model analysis

The prediction is based on RS and GIS technology and an established spatiotemporal database, comprehensively analyzing various factors in the landslide area and using spatial analysis function and mathematical means to analyze and predict the possible location, scale, and shape of rainfall-induced landslides. The predictive model mainly processes the geographic input parameters into a single final model by various weighting and interpolation methods (i.e. statistical analysis,

probability method, machine learning, expert knowledge, etc.) (Marjanovic, Bajat, and Kovacevic 2009). With the strong ability to learn and process complex data (Wang, Tian, and Cao 2021), machine learning is a part of artificial intelligence, while deep learning is a part of machine learning (McCarthy et al. 2006). As shown in Table 7, artificial intelligence has been applied to the field of rainfall-induced landslides since 1992 (Buisson et al. 1992) and mainly concentrated on exploring how to integrate artificial intelligence with GIS technology to solve the problem of landslide prediction. As a result, machine learning began to appear in the field of rainfall-induced landslides, opening a new round of application development of artificial intelligence, which has extensively promoted the vigorous development of rainfall-induced landslides research (Qing et al. 2020; Yuan et al. 2022; Zhao et al. 2020). As a new research direction of machine learning (ML) (Prakash, Manconi, and Loew 2020), deep learning was applied to the research of rainfall-induced landslides hazards in 2009, which inspired the construction of rainfall-induced landslides prediction models. Based on the analysis of research hotspots in Section 3.4, it can be seen that machine learning has made breakthrough progress in landslide prediction, sensitivity mapping, disaster assessment, and other aspects, which have extensively promoted the vigorous development of research on rainfall-induced landslides.

4.3. Susceptibility mapping

Landslide susceptibility mapping is a meaningful way and tool for geoinformatics analysis of rainfall-induced landslides, which is of great significance for land use planning and disaster reduction decision-making (Achour, Saidani, and Touati 2021; He et al. 2021; Liu et al. 2022). The VOSviewer software can be used to visualize the document keywords related to susceptibility mapping in the document sample database. The research thermodynamic diagram (Figure 10) clearly shows that the redder the color is and the more pronounced the font is, the more research will be conducted. The font of ‘mapping’ is the most obvious, and occupies a central position in rainfall-induced landslides research, which is very important for landslide prediction (Roccati et al. 2021), risk assessment, and identification of dangerous areas.

The key to rainfall-induced landslides susceptibility mapping is to determine the influencing factors of regional landslides and select the appropriate methods. Different influencing factors were considered first. Then, the weight ratio of the factors was processed to judge the relationship between these factors and rainfall-induced landslides hazards and the influence degree. The occurrence of landslide hazards is often affected by many factors, and sometimes these factors will affect each other, so landslide susceptibility mapping is not a sample task. Fernández et al. (1999) were the

Table 7. Table of Typical Cases of Predictive Models.

Reference	Cite Frequency	Method	Contribute
Buisson et al. 1992	0	The application of AI in landslide prevention and soil erosion prediction was investigated, and enough attention was paid to the explicit expression of various knowledge, spatiotemporal reasoning, and uncertainty management capabilities embedded in artificial intelligence systems.	Artificial intelligence was first used in landslide research, and it was pointed out that the purpose of future work was to develop general-purpose methods and capabilities of the simulation system.
Qiao 2004	2	The primary environmental factors were quantitatively sampled based on RS and GIS technologies, and traditional floor plans were decoded into 3D maps.	Machine learning was first used for landslide research.
Marjanovic, Bajat, and Kovacevic 2009	33	AHP processed different model input parameters in the GIS environment to form a susceptibility mode as the training set of SVM and K-NN algorithms.	A deep learning algorithm was first used for the assessment of landslide susceptibility.

weight of evidence (WOE), logistic regression (LR), support vector machine (SVM), and random forest (RF), gradually became abundant.

From this, it can be seen that scholars have always been paying great attention to the research on the evaluation of rainfall induced landslide disasters. Based on the continuous development of RS and GIS technology, the rationality of selecting risk assessment factors, research methods, and evaluation accuracy will show a continuous trend of progress.

5. Discussion

With the development of remote sensing multi-source sensors in spatial resolution, temporal resolution, radiation resolution, and spectral resolution, and the progress of GIS in data acquisition management, analysis modeling, and mapping methods, the research on geoinformatics of rainfall-induced landslides hazards has made significant progress. This paper is based on literature visualization analysis and provides the following discussions and suggestions:

- (1) Visualization analysis results: The literature review indicates that in the past 27 years, many articles have been published, and journals have been widely distributed, indicating the importance of this field. Since 2015, there has been a sharp increase in scientific achievements in this field, highlighting the increasing awareness of RS and GIS technology's application in rainfall-induced landslides. Countries such as China, India, and Iran rank among the top three in terms of publication volume, and countries such as Italy and the United States have also shown significant interest in this field. The number of publications is not only related to the situation of rainfall-induced landslides, but also to economic development, and countries with more foreign cooperation have more publications. The largest group of institutional partnerships, mainly from China, is significantly influenced by geographical factors. On the other hand, although comprehensive literature has received a lot of attention from the academic community, the overall publication volume is too small to meet the needs of the development of this field. Of course, this study also has certain limitations, only searching the WOS English database. Although the international scientific and technological community recognizes the WOS database as a database that reflects the level of scientific research, with strict screening criteria and citation indexing mechanisms, it can broadly represent research in this field. However, the analysis results may have slight deviations from the actual situation.
- (2) Monitoring means and methods: RS technology is mainly used, while GIS technology is less applied, while in the stage of landslide analysis, GIS is more applied, while RS technology is less applied. The rapid development of remote sensing technologies such as space radar, satellite remote sensing, uncrewed aerial vehicles (UAV), and the application of GIS technology has extensively promoted the rapid development of the geoinformatics analysis of rainfall-induced landslides. The comprehensive application of RS and GIS technologies in detecting and monitoring rainfall-induced landslides is mainly for remote sensing image classification and image analytical processing of landslide objects (Liu et al. 2021; Nhu et al. 2020; Pawluszek-Filipiak and Borkowski 2020). However, the accuracy of data processing depends largely on the resolution of satellite images. The review of documents shows that only a few studies on landslide detection and monitoring have been conducted in this field (Syzykbayev, Karimi, and Karimi 2020). In particular, there is a lack of research on integrating a large number of data and correctly using high temporal, high spatial, high-radiation, and high spectral resolution. Besides, although modern remote sensing technology is superior to traditional detection and monitoring methods (Yaa'cob et al. 2020), due to their respective restrictions and shortcomings, they cannot rely on a single technical means to identify the potential hazards of rainfall-type landslides. Instead, they can better understand the spatiotemporal variation rules of rainfall-induced landslides by integrating with various standards and using multi-source data. With the rapid growth of landslide data sources, amounts, styles, and the constant improvement

of artificial intelligence algorithms. The object-based image analysis (OBIA) detection method based on deep learning algorithms has been increasingly applied to landslide detection. It has shown good performance in terms of detection speed and freeing up manual recognition workload (Ghorbanzadeh, Gholamnia, and Ghamisi 2022).

- (3) Predictive model: Rainfall-induced landslides prediction requires accurate numerical values, but the complexity of the hazard mechanism often leads to uncertainty in the spatial forecast, making it challenging to predict landslides. The model methods mainly include qualitative, semi-quantitative, and quantitative methods. Qualitative methods that rely on expert capabilities have the advantage of high accuracy, while the disadvantage is limited application space and are subjective. Although the semi-quantitative approach considers other relevant factors on a qualitative basis and conducts statistical analysis, the results still have one-sidedness. The advantage of quantitative methods is that they feel more influencing factors and can quantitatively predict, but their accuracy is often low (Deng et al. 2022). Compared with traditional statistical methods, although modern artificial intelligence methods can provide more convenient analysis results, as the foundation of artificial intelligence is big data, rainfall-induced landslides often have insufficient data and strong suddenness, and they do not have big data characteristics. Also, single artificial intelligence algorithms, including the most promising deep learning algorithms, may have problems with local optimum (Li et al. 2022), overfitting, low training speed, and low image recognition accuracy. It can be said that the current research on solid artificial intelligence is basically in an inactive state, and the mainstream research is mainly focused on weak artificial intelligence. Of course, the research on rainfall-induced landslides based on RS and GIS technologies is no exception. Therefore, modern spatial information technology, especially various new types of hybrid intelligent methods formed by a precise combination of RS and GIS technologies and different artificial intelligence methods, will have more potential in rainfall-induced landslides prediction. Recently, researchers have found through comparative analysis that Random Subspace Credal Decision Tree (RSCDT) models can effectively improve the accuracy of landslide prediction, and its performance details are superior to individual models. This proves that ensemble models can become a novel and promising method for the spatial prediction of landslides in specific regions (Gui et al. 2023).
- (4) Susceptibility mapping: With the continuous development of RS and GIS technologies, the research on the geoinformatics of rainfall-induced landslides is deepening, and the classification methods of landslide susceptibility mapping are also changing. Except for the classification methods adopted by Kayastha, Dhital, and De Smedt (2013), there are other classification methods for landslide susceptibility mapping, such as landslide inventory analysis, heuristic, and statistical methods. Pradhan, Seeni, and Kalantar (2017) believed that qualitative and quantitative methods could draw landslide susceptibility mapping or can also be developed by statistical (Bathrellos, Kalivas, and Skilodimou 2009; Conoscenti et al. 2016; Schicker and Moon 2012) and physical (Baum et al. 2005; Montrasio, Valentino, and Losi 2011; Park, Nikhil, and Lee 2013;) methods based on the RS data and the GIS technology. A large number of studies on landslide susceptibility mapping have found that landslide susceptibility mapping technology can be divided into direct mapping (Van Westen, Rengers, and Soeters 2003) and indirect mapping (Chen and Song 2019; Shirzadi et al. 2017). In general, no matter what classification method is used, the inherent advantages and limitations of each susceptibility mapping method should be noted during the research. There is still no method that can be universally used for landslide susceptibility mapping. In recent years, to find more suitable processes, some researchers have gradually developed a new hybrid mapping model (Aghdam, Pradhan, and Panahi 2017;; Tien Bui et al. 2017; Vasu and Lee 2016), integrated the model with GIS by various methods, and achieved good results. In Ha Giang Province, Vietnam, multiple machine learning methods and weighting techniques were compared using limited data to produce LSMs, and it was found that the combination of RF and AHP had the best performance. This study provides a new approach to creating LSMs based on weighted

machine learning methods (Trinh et al. 2022). Therefore, it is necessary to comprehensively understand each method's characteristics, advantages and disadvantages, and adaptability to improve the accuracy of rainfall-induced landslides susceptibility mapping.

- (5) Risk assessment: A landslide is a geological hazard caused by the coupling action of many factors. The difference between rainfall-induced landslides and other landslides is that they have different characteristics of inducing factors and environmental influencing factors. Using different parameters for risk assessment in a specific research area will directly affect the analysis result. Still, the selection of parameters usually depends on the local factors and data availability in the research area. Therefore, an open and comprehensive landslide inventory database is needed to link these influencing factors with rainfall-induced landslides risk assessment (Ibsen and Brunsden 1996; Martha et al. 2013; Pennington et al. 2015). Although the establishment and data update of the landslide inventory database is time-consuming and arduous, it has significant scientific research value and practical significance. It can further clarify the location, volume, type, inducement, frequency, and damage of rainfall-induced landslides (Guzzetti et al. 2012; Kirschbaum et al. 2010). Concerning the establishment and data update of the landslide inventory database, RS and GIS technologies should be widely used, and integrated with other rainfall-induced landslides risk assessment tools, to become a powerful tool for landslide inventory database establishment and risk assessment. On the other hand, landslide cataloging databases not only provide us with a large amount of risk assessment basis but also pose challenges to the integration ability of non-data businesses. The use of modern 3D GIS technology can provide intuitive and interactive 3D visualization of multi-source geographic big data, making professional landslide knowledge easier for decision-makers and the public to understand. A 3D GIS system that includes interactive route planning, real-time text, images, and other information has just been developed, and most of its functions are implemented using open-source projects (Yang et al. 2023).

With the help of information visualization technology, this study systematically combs the application process of RS and GIS technology with rainfall landslides as the research object. Excavate machine learning, landslide sensitivity, and shallow landslides as the three most critical topic groups, among which machine learning is the most popular research topic. The latest information technologies and intelligent algorithms involved in the literature review can help decision-makers quickly integrate, process, and analyze disaster data and assist them in optimizing landslide disaster information management and emergency command and control systems. This literature review clarifies that deep learning is the most promising modeling algorithm and discusses the advantages and disadvantages of various model methods. It is suggested to focus on new intelligent hybrid models in the future, which can provide some reference for makers and UN SDGs to promote landslide disaster management and regional planning.

6. Conclusions

RS and GIS technologies have been widely applied in rainfall-induced landslides, and a large number of research results are constantly emerging. The contradiction between the scattered spatiotemporal distribution of literature in this field, scattered research topics, and unclear research trends, as well as the scarcity and obsolescence of review literature, is becoming increasingly prominent, making it challenging to meet the research needs of landslides. To systematically clarify the development process of research in this field and predict future research trends, this article established a data sample library containing 1161 articles based on the WOS literature data platform. With the help of WOS literature analysis function and various literature visualization tools, relevant literature was systematically analyzed from aspects such as the spatiotemporal distribution of publication volume, highly cited literature, scientific research cooperation, research hotspots, and trends. Finally, the research progress and development trends in the four sub-areas of landslide detection

and monitoring, prediction model analysis, sensitivity mapping, and risk assessment were summarized. The results indicate that the literature in this field will continue to show an upward trend, and machine learning algorithms will be relatively active shortly. Among them, deep learning algorithms may become a cutting-edge trend, and new intelligent hybrid models are the future development direction. Ultimately, we will continue to conduct literature data mining and quantitative analysis based on the research hotspots and trends obtained in this article, providing a more scientific and reasonable basis for landslide prevention and control research.

Data availability statement

The data used in this study are available by contacting the corresponding author.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research was supported by the National Key R&D Program of China (2019YFC1510700), and the Sichuan Science and Technology Program (2023YFS0380, 2023YFS0377, 2023NSFSC1989, 2022YFS0539).

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