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Landslides: Visualization of the Global Conceptual Trend

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Purpose: This study discovers the global knowledge structure of landslide research over the past twenty years in Researchers' research outputs.

Methodology: This study uses co-word analysis to determine and visualize the global structure of landslide knowledge, track the most widely used subjects, and choose the conceptual dynamics in research on landslides. This scientometric method was used to study data from the Web of Science Core Collection (WOSCC) regarding 9185 landslide research publications produced from 2000 to 2020. **Findings:** The keyword "geographic information systems (GIS)" had the highest frequency, and the phrase "landslide susceptibility" was the most often used co-word pair. Co-word analysis produced 15 thematic clusters. Cluster 8 has the highest density among the clusters, and the highest centrality was seen in Cluster 1. Most of the thematic clusters are located in the third quadrant of the strategic diagram, indicating either emerging or declining clusters. The maturity and cohesion of each cluster show their trends.

Conclusion: Co-word analysis, as a suitable and powerful tool, can visualize the scientific and intellectual structure of landslides and track the most used topics, and determine the conceptual dynamics and areas of Landslide research, and its results will be of great help to research and practical planners and policymakers. The results of the study significantly help researchers and applied planners and policymakers in adopting appropriate measures to reach more effective solutions in the shortest possible time. Also, develop research evaluation policies, and university managers aimed to create research evaluation policies.

Value: The research has also explored the complex relationships governing international studies, illuminates angles, highlights research gaps, and leads scholars and analyses. These results will pave the paths forward for planners and policymakers in organizations and centers actively addressing landslide management's strategic plans. Subsequent studies could focus on the examination of the networks of collaboration between centers and researchers, and their impacts on decision-making.

Keywords: Landslide, Scientometrics, Co-word analysis, Cluster analysis, Strategic diagram

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Extended Abstract Introduction

Landslide is one of the significant natural and environmental disasters that has always been a serious threat to human life (Pourghasemi et al., 2018). Landslide is also known to be a significant natural geological hazard (Wu et al., 2015). Landslides are movements of dense, unconsolidated sedimentary layers on sloping surfaces. They are significant natural events that are often hazards (Wu et al., 2015), posing threats to human lives and properties (Pourghasemi et al., 2018). Whether natural or anthropogenic, landslides have had far-reaching social, economic, and environmental impacts, have caused significant financial losses, destruction of infrastructure, and damage to natural environments, and have killed thousands of people around the world (Penna and Borga, 2013; Hess et al., 2017). They are produced from interactions of geological, geomorphological, topographical, and seismic factors that occur either slowly (developing events), or suddenly and rapidly. Landslides occur where layers become unstable (Forbes, Walters, and Farrow, 2020). The factors that drive the landslide process can be divided into two groups: conditioning factors (such as slope degree, aspect, elevation, faults, lithology, drainage density, land use, and soil) and triggering factors (for instance, precipitation events, earthquakes, and human activities) (Bailey, Reynolds and King, 2011; Abuzied et al., 2016). Landslide activity can be exacerbated by poor soil management practices (Günther et al., 2012).

Given this importance, the present study aims to represent the dynamics of thematic change, the conceptual clusters structure, the hidden patterns discovery, and the emerging issues in landslide subject area in clusters visualization.

Methodology

The present study is an applied scientific research done through the word co-occurrence method using an analytical approach. Co-word analysis is a Scientometric tool enabling the tracking of scientific domains by providing data for visualizing their structures, concepts, and components (Ahmadi and Osareh, 2017). On the other side, Cluster analysis is a method used in co-word analysis that can be used to reveal the directions in which research areas or disciplines have taken. Co-occurrence matrices give shapes and paths to co-word analyses and the results of cluster analyses (Zhu and Zhang, 2020). Co-occurrence assumes that the words and concepts used within documents indicate their conceptual content. Therefore, by calculating similarity levels among research publications, the thematic structure of different sciences can be discerned (Giannakos et al., 2020).

Based on advice from several experts, the following search strategy was used to search the advanced Web of Science Core Collection (WOSCC).

Findings

The 14,397 keywords from 7,138 documents indexed in WOSCC were classified and analyzed (Table 1). The keyword "geographic information systems (GIS)" had the highest frequency (612) in the literature.

the keyword "Geographic Information Systems (GIS)" is a high-frequency keyword with a frequency of 612. The terms "Landslide susceptibility," "Remote sensing," "Slope stability," and "Shallow landslides" ranked second to fifth with frequencies 357, 205, 196, and 190, respectively. The results indicate that researchers pay more attention to these keywords in this period.



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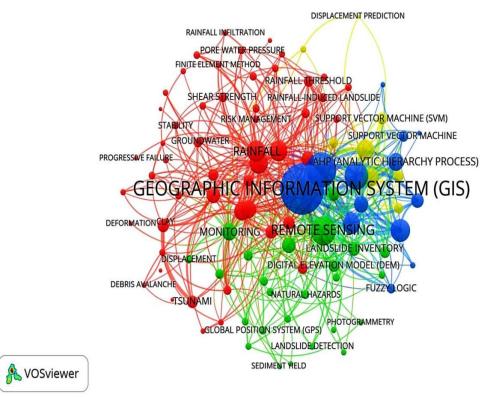


Figure 1. The network structure of high-frequency keywords in Landslide (2000-2020)

After preparing a co-word matrix based on a threshold of 5, the keywords were ranked from highest to lowest. The top third of the total are the hottest topics. The hot topics based on frequency were revealed with the VOSviewer (Figure 1). In this figure, the size of each node indicates its weight among keywords, the colors represent clusters that are formed, and the width of each line represents the relationship between keywords. Topics with the highest frequency co-occurrence are at the center of the network. Keywords around them are less frequent. The larger the size (i.e., frequency) of each node (keyword), the more important the keyword in its network.

The design and the thematic fields covered by landslide researchers and the evolution of the conceptual relationships were determined by analyzing each of the 15 clusters.

Cluster 1: "Geographic information systems (GIS)" is the most frequently used keyword. The keywords "landslide susceptibility map," "AHP," and "fuzzy logic" demonstrate the use of these methods in mapping landslide sensitivity with GIS. Cluster 2: The second most frequently used keyword was "landslide susceptibility." Three factors – "frequency ratio," "weight of evidence," and "logistic regression" – support landslide susceptibility prediction. Cluster 3: This group includes several machine-learning models used for landslide susceptibility mapping. Cluster 4: This cluster represents the technologies used for monitoring and detecting landslides. Cluster 5: This cluster is similar to Cluster 4, but focuses more on digital imaging and mapping. Cluster 6: This topic is landslide morphology and earthquakes. Cluster 7: This group regards zonal analyses of landslide risk, hazard, and vulnerability. Cluster 8: This research focuses on underwater landslides and the generation of tsunamis. Cluster 9: This focus is on the hydro-geomorphological consequences of landslides. Cluster 10: The low energy, slowly moving "landslides" involving soil creep and solifluction in clay is the nature of this group. Cluster 11 is the largest landslide cluster with 21 keywords. In this cluster, there are many popular keywords such as "Earthquake," "Debris flow," and "Numerical Model." The



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various keywords in this cluster cover a variety of subject areas. Those keywords to name are "Natural hazards," "Hazard assessment," "Risk assessment," "Factor of Safety," and "Hazard map" and include a range of concepts that together make the term "landslides hazard and risk" well visible. Similar topics such as "Geomorphology," "Dendrogeomorphology," "Slopes," "Mass Movement," "Debris Avalanche," "Deformation," "Slope Failure," and "Sediment yield" include the concepts of a spectrum. In Cluster 12, which has six keywords, the keywords "Slope stability," "Pore pressure," "Groundwater," and "Liquefaction," where thematically count as "soil mechanics," and "Geotechnics." In Cluster 13, which has nine keywords, the ones such as "Rainfall Threshold," "Rainfall-Induced Landslide", "Rainfall infiltration," and "Pore water pressure," where it is soil changes that gave rise to the notion of the factors such as landslides. Cluster 14 contains two keywords: "Three Gorges Reservoir", and "Displacement Prediction." TGRA is considered necessary in Geohazard, and it is affected by landslides. The usage of this vital keyword brings to mind "Displacement Prediction of Reservoir Landslide" (Junwei, 2020). Subjects used in Cluster 15 consisted of 11 keywords, the most important of which is "Rainfall," which is very diverse. According to the topics discussed in this cluster, some of the keywords are "ERT," "Numerical simulation," "FEM," "Stability Analysis," and "Sensitivity analysis," as well as concepts related to statistical analysis, simulation, and computer modeling in a landslide. Additionally, it brings to mind some topics such as "Rainfall," "Deep-seated landslide," "loess landslide," and "landscape evolution" that can also be seen in this cluster.



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Conclusions

Co-word analysis, as a suitable and powerful tool, can visualize the scientific and intellectual structure of landslides and track the most used topics, and determine the conceptual dynamics and areas of Landslide research, and its results will be of great help to research and practical planners and policymakers. The results of the study significantly help researchers and applied planners and policymakers in adopting appropriate measures to reach more effective solutions in the shortest possible time. Also, develop research evaluation policies, and university managers aimed to create research evaluation policies.

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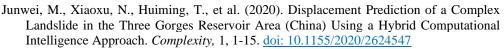
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Article type: Research article

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1.Introduction

Landslide is one of the significant natural and environmental disasters that has always been a serious threat to human life (Pourghasemi et al., 2018). Landslide is also known to be a significant natural geological hazard (Wu et al., 2015). Landslides are movements of dense, unconsolidated sedimentary layers on sloping surfaces. They are significant natural events that are often hazards (Wu et al., 2015), posing threats to human lives and properties (Pourghasemi et al., 2018). Whether natural or anthropogenic, landslides have had far-reaching social, economic, and environmental impacts, have caused significant financial losses, destruction of infrastructure, and damage to natural environments, and have killed thousands of people around the world (Penna and Borga, 2013; Hess et al., 2017). They are produced from interactions of geological, geomorphological, topographical, and seismic factors that occur either slowly (developing events), or suddenly and rapidly. Landslides occur where layers become unstable (Forbes, Walters, and Farrow, 2020). The factors that drive the landslide process can be divided into two groups: conditioning factors (such as slope degree, aspect, elevation, faults, lithology, drainage density, land use, and soil) and triggering factors (for instance, precipitation events, earthquakes, and human activities) (Bailey, Reynolds and King, 2011; Abuzied et al., 2016). Landslide activity can be exacerbated by poor soil management practices (Günther et al., 2012).

Specialists have used computational modeling to assess landslide potential, to identify the causes of the deadliest landslides, or to mitigate unexpected landslides. Publications reporting the results of scientific research are abundant in scientific databases. Co-word analysis is an efficient content-analysis technique. It assesses word co-occurrence patterns and can be used to identify the relationships between networks, ideas, concepts, terminology, and subjects (Callon et al., 1983; Callon, Courtial, and Laville, 1991; He, 1999). Thus, visualization has been used to discover the structures of science. Beyond discernment of the forms of thematic networks, the processes of identification of the prominent and critical issues of subject areas, viewing the gradual evolution of a realm of science, and revealing the connections of concepts in a particular field of science are essential abilities (Bredillet, 2006; Wang and Inaba, 2009; Kumar and Jan, 2012; Wang et al., 2019). Co-word analysis can also be used to determine the array of subjects, trends, and most important concepts present in the works of specific scholars (Ryan and Bernard, 2003; Kumar and Jan, 2012). Hence, combining analyses of keywords, clusters, networks, and clustering positions can make visible the conceptual structures of research (Callon et al., 1983; Callon, Courtial, and Laville, 1991).

Given this importance, the present study aims to represent the dynamics of thematic change, the conceptual clusters structure, the hidden patterns discovery, and the emerging issues in landslide subject area in clusters visualization. To discover and identify conceptual relationships in scientific research in Landslide and to present a more comprehensive picture of the above subject area, the present study focuses on 1. hierarchical clusters and visualizing clustering, 2. presenting top keywords, and 3. drawing strategic charts. By clarifying the basic, emphatic concepts and thematic tendencies through interaction between keywords in scientific research, experts who are considered the appropriate criterion for assessing the progress of science will help policymakers and researchers in this way. This study also identifies the strengths and weaknesses of this research subject area, besides the discovery of the necessary potentialities, its main concerns and challenges, and the analysis of opportunities that experts, planners, decision-makers, and policymakers face. It also helps in identifying the neglected, emerging, or mature aspects of research work to form and use it to support this category. Given the strategic importance of this research, the lack of comprehensive evaluations of it, and the need to study the approaches to studying landslides via conceptual clusters, there is an urgent for this type of study. Finally, heading toward greater scientific effectiveness to achieve solutions in the shortest possible time is the way forward for planners, decision-makers, and policymakers. Given the strategic importance of this research and the lack of such



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comprehensive study with such approach and method, coherence and also the analysis of emerging events in landslides conceptual clusters that annually cause severe and irreparable damages to communities around the world, the urgent doing such research has been felt more than ever.

Many researchers have used the scientometric and word co-occurrence analysis tools as one of the most essential methods for examining the conceptual network in different fields. Through this article, some important and related backgrounds regarding scientific analysis with an analytical approach will be reviewed.

A literature review shows that there is a diversity of studies using scientometric techniques. They include studies of children's interactions with computers (Giannakos et al., 2020), conceptual networks of human papillomavirus (HPV) research (Danesh and Ghavidel, 2020a), geographical studies (Yagun et al., 2020), studies of halal food (Mostafa, 2020), mental health research (Zeinoun, Maalouf and Meho, 2020), andrology research (Bigdeloo and Makkizadeh, 2019), visualization of clusters in and the dynamics of HPV research (Danesh and Ghavidel, 2020b), soil and water conservation studies (Wang et al., 2019), biomedical keywords analyses (Qin, Wang and Ye, 2019), nanomedicine research (Makkizadeh, 2019), the study of big data in medicine (Liao et al., 2018), natural hazards research (Emmer, 2018), natural disasters research (Shen et al., 2018), the analyses of heavy metals in agricultural soils and aquatic systems (Ouyan et al., 2018), global geo-ontology research (Li et al., 2017), soil erosion studies (Zhuang et al., 2015), examination of citation networks in hazards and vulnerability research (Gall, Nguyen and Cutter, 2015), and studies of earthquakes (Liu et al., 2012a), Others have employed scientometric semantic cluster analysis to study landslide citations from 1977 to 2015 (Yang et al., 2019), from an international consortium on landslides (Matjaž, 2018a), from a review of landslide-focused journals (Matjaž, 2017), from a bibliographic analysis of the global landslide research trends (Wu et al, 2015), and from hazard and risk mapping of landslides.

In line with the above studies, there have also been some other ones (550 maps) using Scientometrics and about landslide fields, including Semantic Cluster Analysis and Landslide Citations from 1977 to 2015 (Yang et al., 2019), International Consortium on Landslides (Matjaž, 2018), The Review of Landslide Journals (Matjaž, 2017), The Bibliographic Analysis of The Global Research Trends In Landslide (Wu et al. 2015) and The Drawing Of Hazard And Risk Maps related to landslides.

Yang et al.'s (2019), study using co-word analysis to study earthquake research provides a template for our study. Still, there are significant differences in our approach, which include: We have modified searching strategies and improved efficiency. Yang et al. (2019), used the Science Citation Index (SCI). This study is based on the Web of Science Core Collection. Yang et al. (2019), focused on the keywords of the study populations, whereas we also included examinations of the methodologies, countries of origin, and keywords co-occurrence. We also used different statistics and software to analyze the data. Yang et al.'s (2019), evaluations were based on three indicators: the mean, the silhouettes, and the annual modularity of cluster members. In the present study, our analysis, the capabilities of the Co-word analysis technique, and strategic diagram have been used for New and different explanations, Yang et al.'s (2022), also analyzed the four main topics in studies related to Landslide Susceptibility Prediction using data mining tools and bibliometric analysis methods, 600 documents that have been indexed in the Web of Science and Scopus databases over the past 40 years. The results of this research had good suggestions for improving the prediction accuracy of landslide disaster susceptibility. In this paper, it was found that various coupling models, integration models, and hybrid models have more advantages in model fitting and prediction performance. Still, these models often make the model design and calculation complicated. Therefore, it is suggested that when multiple models need to be involved in landslide disaster analysis, the model shall be simplified as much as possible while ensuring accuracy and reliability to promote the



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application of the model and guide the work and practice of landslide disaster prevention and control. In another study, Lima et al.'s (2022) evaluated the texts on landslide susceptibility in 2585 DdLSM publications (from 1985 to 2020) that were indexed in the Web of Science database using bibliometric analysis and machine learning approaches (classification techniques). This article has shown, the outcomes of landslide susceptibility maps generated through DdLSM are highly reliant on many factors. Bovi (2022) also studied the emerging global trends of dendrogeomorphology in 286 articles in Web of Science and Scopus (1900 to 2020) using bibliometric evaluation methods. Topics such as soil erosion, debris flow, landslide, flood/flashflood, snow avalanche, and rockfall activity were identified as among the issues discussed in dendrogeomorphology.

The primary purpose of this study is to discover the clusters, and the dynamics of landslide research. To achieve this, we sought to determine the ranks of keywords based on co-word analysis, the top co-word pairs, the emergence of "hot" topics based on keyword frequencies, subject clusters using cluster analysis, and the densities and centralities of clusters. The maturity or coherence of thematic clusters was revealed using strategic diagramming of landslide research.

2. Methodology

The present study is an applied scientific research done through the word co-occurrence method using an analytical approach. Co-word analysis is a Scientometric tool enabling the tracking of scientific domains by providing data for visualizing their structures, concepts, and components (Ahmadi and Osareh, 2017). On the other side, Cluster analysis is a method used in co-word analysis that can be used to reveal the directions in which research areas or disciplines have taken. Co-occurrence matrices give shapes and paths to co-word analyses and the results of cluster analyses (Zhu and Zhang, 2020). Co-occurrence assumes that the words and concepts used within documents indicate their conceptual content. Therefore, by calculating similarity levels among research publications, the thematic structure of different sciences can be discerned (Giannakos et al., 2020).

Based on advice from several experts, the following search strategy was used to search the advanced Web of Science Core Collection (WOSCC).

TI= (Landslide*)) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Article) Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=2000-2020.

WOSCC is the world's most authoritative citation database (Birkle et al., 2020). WOSCC contains data for all scientific publications since 1900 with complete citation and reference indexing. It allows for the downloading of data that far outweighs the information available from other databases (Analytics, 2020).

The population of publications was 9185 articles published between 2000 and 2020. This period was chosen to depict the most recent developments in this subject area. From this population, 14,397 keywords were extracted. The keywords were ranked by frequency. The VOSviewer 1.6.13 was used to visualize the keywords. The top one-third of the keywords were identified as the core. The second third of the keywords were classified as close to thecenter. From the set of 14,397 keywords, 101 had frequencies of at least 20.

After integrating the keywords, it is necessary to select a threshold for preparing the matrix and then analyzing the word co-occurrence. Though several points have been used to determine the top keywords for analysis in other co-word studies (Liu, Hu, and Wang, 2012b; Hu et al., 2013), the matrix threshold was set to 5 by Bradford's law. The co-word matrix was created with Ravar Matrix: Ravar PreMap, and was used to generate a correlation or co-occurrence matrix that was transferred to SPSS16. Of the multivariate statistical methods, hierarchical clustering can be used to identify the clustering of keywords to reveal the relationships between them. Ward's hierarchical clustering criterion-generating method was applied, and the squared



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Euclidean distance for each co-word cluster was calculated. Co-word clusters were visualized with a dendrogram. With this, the analysis generated 15 clusters. This method has been used to analyze hierarchical clusters in other co-word analysis studies (Ding, Chowdhury, and Foo, 2001; Lee and Jeong, 2008; Neff and Corley, 2009; Zong et al., 2013).

The centrality and density characteristics of the co-word matrix network were displayed with UCINET 6.689 as a strategic diagram, in which the x-axis represents centrality and the y-axis represents density (Hu et al., 2013; Melcer et al., 2015). This revealed the evolution and trends of landslide research. The more critical a keyword cluster is, the higher its centrality. The more mature it is, the higher its density will be.

3.Findings

Ranking landslide research keywords based on co-word analysis

The 14,397 keywords from 7,138 documents indexed in WOSCC were classified and analyzed (Table 1). The keyword "geographic information systems (GIS)" had the highest frequency (612) in the literature. The top 20 keywords indicate the terms that researchers used most often during the study period.

Table 1. Top 20 Landslide keywords ranking based on co-word analysis (2000-2020)

Rank	Keywords	Frequency	Rank	Keywords	Frequency
1	Geographic Information Systems (GIS)	612	11	Monitoring	137
2	landslide susceptibility	357	12	Submarine landslide	131
3	Remote sensing	205	13	Landslide dam	122
4	Slope stability	196	14	Numerical Model	115
5	shallow landslides	190	15	landslide Susceptibility Map	111
6	Rainfall	182	16	Tsunami	102
7	Earthquake	179	17	Frequency ratio (FR)	102
8	Debris flow	164	18	Artificial Neural Network (ANN)	93
9	Logistic regression (LR)	162	19	Light Detection and Ranging (LIDAR)	93
10	Susceptibility	139	20	Early Warning System	86



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As can be seen in Table 1, the keyword "Geographic Information Systems (GIS)" is a high-frequency keyword with a frequency of 612. The terms "Landslide susceptibility," "Remote sensing," "Slope stability," and "Shallow landslides" ranked second to fifth with frequencies 357, 205, 196, and 190, respectively. The results indicate that researchers pay more attention to these keywords in this period.

3-1.Ranking high-frequency co-word pairs in landslide research from 2000 to 2020

Co-word coupling was measured based on the common occurrence of the keyword pairs in publications, assuming each couple had conceptual closeness. The couples were ranked (Table 2). The top 20 illustrate the most often associated concepts, methods, or technologies in landslide research during this period. The keyword pair of "geographic information systems" and "landslide susceptibility" had the highest frequency (139 appearances).

Table 2. The top 20 landslide-research co-word pairs (2000-2020)

Rank	Keywords	Frequency of co- Word pairs
1	Geographic Information Systems (GIS)** Landslide Susceptibility	139

2	Remote Sensing ** Geographic Information Systems (GIS)	100
3	Susceptibility ** Geographic Information Systems (GIS)	59
4	Frequency Ratio (FR)** Geographic Information Systems (GIS)	57
5	Landslide Susceptibility ** Logistic Regression	50
6	Logistic Regression ** Geographic Information Systems (GIS)	49
7	Artificial Neural Network (Ann)** Geographic Information Systems (GIS)	38
8	Landslide Susceptibility Map** Geographic Information Systems (GIS)	35
9	Submarine Landslide ** Tsunami	34
10	Shallow Landslides ** Geographic Information Systems (GIS)	16
11	Rainfall ** Shallow Landslides	15
12	Light Detection and Ranging (LIDAR)** Geographic Information Systems (GIS)	15
13	Slope Stability ** Rainfall	14
14	Earthquake ** Geographic Information Systems (GIS)	14
15	Numerical Model ** Tsunami	12
16	Debris Flow ** Rainfall	11
17	Monitoring ** Early Warning System	11
18	Early Warning System ** Rainfall Threshold	9
19	Landslide Dam ** Debris Flow	8
20	Tsunami ** Earthquake	5



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3-2. Ranking and determining hot topics in landslide research

After preparing a co-word matrix based on a threshold of 5, the keywords were ranked from highest to lowest. The top third of the total are the hottest topics. The hot topics based on frequency were revealed with the VOSviewer (Figure 1). In this figure, the size of each node indicates its weight among keywords, the colors represent clusters that are formed, and the width of each line represents the relationship between keywords. Topics with the highest frequency co-occurrence are at the center of the network. Keywords around them are less frequent. The larger the size (i.e., frequency) of each node (keyword), the more important the keyword in its network.

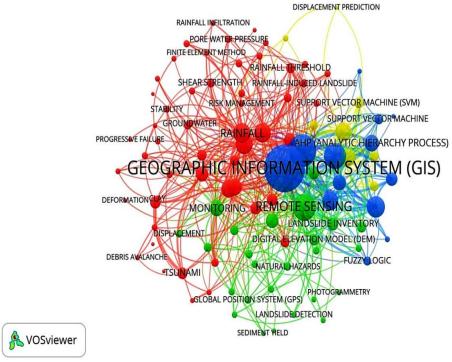


Figure 1. The network structure of high-frequency keywords in Landslide (2000-2020)

3-3. The structure of the landslide research based on cluster analysis

Using SPSS, the hierarchical clustering analysis was run. A dendrogram displaying the clustering of the keywords was created (Figure 2). Fifteen thematic clusters were formed.

The design and the thematic fields covered by landslide researchers and the evolution of the conceptual relationships were determined by analyzing each of the 15 clusters (Table 3). Cluster 1: "Geographic information systems (GIS)" is the most frequently used keyword. The keywords "landslide susceptibility map," "AHP," and "fuzzy logic" demonstrate the use of these methods in mapping landslide sensitivity with GIS. Cluster 2: The second most frequently used keyword was "landslide susceptibility." Three factors - "frequency ratio," "weight of evidence," and "logistic regression" – support landslide susceptibility prediction. Cluster 3: This group includes several machine-learning models used for landslide susceptibility mapping. Cluster 4: This cluster represents the technologies used for monitoring and detecting landslides. Cluster 5: This cluster is similar to Cluster 4, but focuses more on digital imaging and mapping. Cluster 6: This topic is landslide morphology and earthquakes. Cluster 7: This group regards zonal analyses of landslide risk, hazard, and vulnerability. Cluster 8: This research focuses on underwater landslides and the generation of tsunamis. Cluster 9: This focus is on the hydro-geomorphological consequences of landslides. Cluster 10: The low energy, slowly moving "landslides" involving soil creep and solifluction in clay is the nature of this group. Cluster 11 is the largest landslide cluster with 21 keywords. In this cluster, there are many popular keywords such as "Earthquake," "Debris flow," and "Numerical Model." The various keywords in this cluster cover a variety of subject areas. Those keywords to name are "Natural hazards," "Hazard assessment," "Risk assessment," "Factor of Safety," and "Hazard map" and include a range of concepts that together make the term "landslides hazard and risk" well visible. Similar topics such as "Geomorphology," "Dendrogeomorphology," "Slopes," "Mass Movement," "Debris Avalanche," "Deformation," "Slope Failure," and "Sediment yield" include the concepts of a spectrum. In Cluster 12, which has six keywords, the keywords



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"Slope stability," "Pore pressure," "Groundwater," and "Liquefaction," where thematically count as "soil mechanics," and "Geotechnics." In Cluster 13, which has nine keywords, the ones such as "Rainfall Threshold," "Rainfall-Induced Landslide", "Rainfall infiltration," and "Pore water pressure," where it is soil changes that gave rise to the notion of the factors such as landslides. **Cluster 14** contains two keywords: "Three Gorges Reservoir", and "Displacement Prediction." TGRA is considered necessary in Geohazard, and it is affected by landslides. The usage of this vital keyword brings to mind "Displacement Prediction of Reservoir Landslide" (Junwei, 2020). Subjects used in **Cluster 15** consisted of 11 keywords, the most important of which is "Rainfall," which is very diverse. According to the topics discussed in this cluster, some of the keywords are "ERT," "Numerical simulation," "FEM," "Stability Analysis," and "Sensitivity analysis," as well as concepts related to statistical analysis, simulation, and computer modeling in a landslide. Additionally, it brings to mind some topics such as "Rainfall," "Deep-seated landslide," "loess landslide," and "landscape evolution" that can also be seen in this cluster.



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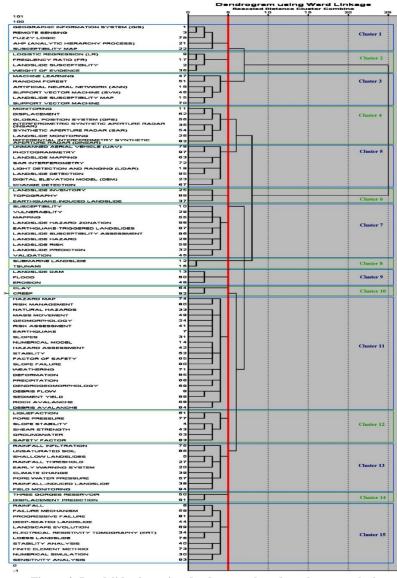


Figure 2. Landslide clustering dendrogram based on cluster analysis

Table 3. Clustering of landslide based on cluster analysis

240	de 5. Clustering of fandshue based on cluster an	Number
Cluster	Keywords	of
Number	Keyworus	Keywords
1	Geographic Information Systems (GIS); Remote	5
1	Sensing; Fuzzy Logic; Analytic Hierarchy Process	3
	(AHP); Susceptibility Map;	
2	Logistic Regression (LR); Frequency Ratio (FR);	4
	Landslide Susceptibility; Weight of Evidence	-
3	Machine Learning; Random Forest; Artificial	6
	Neural Network (ANN); Support Vector Machine	O
	(SVM); Landslide Susceptibility Map; Support	
	Vector Machine	
4	Monitoring; Displacement; Global Positioning	7
·	System (GPS); Interferometric Synthetic Aperture	
	Radar (INSAR); Synthetic Aperture Radar (SAR);	
	Landslide Monitoring; Differential Interferometry	
	Synthetic Aperture Radar (DINSAR)	
5	Unmanned Aerial Vehicle (UAV);	8
	Photogrammetry; Landslide Mapping; SAR	
	Interferometry; Light Detection and Ranging	
	(LIDAR); Landslide Detection; Digital Elevation	
	Model (DEM); Change Detection	
6	Landslide Inventory; Topography; Earthquake-	3
	Induced Landslide	
7	Susceptibility; Vulnerability; Mapping; Landslide	10
	Hazard Zonation; Earthquake-Triggered Landslides;	
	Landslide Susceptibility Assessment; Landslide	
	Hazards; Landslide Risk; Landslide Prediction;	
	Validation	
8	Submarine Landslide; Tsunami	2
9	Landslide Dam; Flood; Erosion	3
10	Clay; Creep	2
11	Hazard Map; Risk Management; Natural Hazards;	21
	Mass Movement; Geomorphology; Risk	
	Assessment; Earthquake; Slopes; Numerical Model;	
	Hazard Assessment; Stability; Factor Of Safety;	
	Slope Failure; Weathering; Deformation;	
	Precipitation; Dendrogeomorphology; Debris Flow;	
	Sediment Yield; Rock Avalanche; Debris	
	Avalanche	
12	Liquefaction; Pore Pressure; Slope Stability; Shear	6
	Strength; Groundwater; Safety Factor	
13	Rainfall Infiltration; Unsaturated Soil; Shallow	9
	Landslides; Rainfall Threshold; Early Warning	
	System (EWS); Climate Change; Pore Water	
	Pressure; Rainfall-Induced Landslide; Field	
1.4	Monitoring There Course Bernstein Divide course Brediction	2
14	Three Gorges Reservoir; Displacement Prediction	2
15	Rainfall; Failure Mechanisms; Progressive Failure;	11
	Deep-Seated Landslide; Landscape Evolution;	
	Electrical Resistivity Tomography (ERT); Loess	
	Landslide; Sensitivity Analysis; Finite Element	
	Method (FEM); Numerical Simulation; Stability	
	Analysis	



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This broad array of 21 keywords aligns with the modeling of landslide dynamics and hazard. Cluster 12: This topic concerns the role of groundwater hydrodynamics of soil in the production of landslides. Cluster 13: Like Cluster 12, this cluster studies the processes behind precipitation-induced landslides. Cluster 14: A narrowly focused cluster reflects research on the landslide-inducing impacts of the Three Gorges Reservoir project in China (Junwei et al., 2020). Cluster 15: This group is akin to Cluster 13, but its focus is on computer simulation and modeling of the role of precipitation in landslide genesis.

3-4. Density and centrality and a strategic diagram of the clusters

Using UCINET for each of the fifteen clusters, a large matrix and a correlation matrix were created. The mean, centrality, rank, and network density (or the internal communication power) of each cluster were calculated following the methods of Borgatti and Everett (Borgatti and Everett, 2006)(Table 4).

Table 4. Density and centrality of the clusters from co-word analysis

Clusters	Centrality	Density
Cluster 1	42.6667	21.9
Cluster 2	14.6667	25.3333
Cluster 3	5.5	4.3333
Cluster 4	2.5	2.381
Cluster 5	2.6667	1.4286
Cluster 6	1.5	3
Cluster 7	1.0278	0.8444
Cluster 8	1	34
Cluster 9	2	5.3333
Cluster 10	1	3
Cluster 11	1.1395	0.619
Cluster 12	4	2.3333
Cluster 13	2.7143	1.8889
Cluster 14	1	4
Cluster 15	1.6667	0.8364
Total	85.0484	111.2315
Average	5.669893	7.415433



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Clusters 1, 2, and 3 have the highest centralities, and 8, 2, and 1 have the highest densities. Density and centrality are network measurement methods (Wasserman and Faust, 1994).

The centrality and density of all 15 clusters were also mapped in a strategic diagram (Figure 3). The horizontal axis of this matrix is the degree of centrality, and the vertical axis is density. The first quadrant contains coherent and central clusters. The second quadrant contains coherent but separated clusters. The third quadrant includes emerging or declining clusters, and the fourth quadrant is clusters that have not yet matured, but may become primary foci (Melcer et al., 2015).

The higher the centrality of a cluster, the more criticaland central to the subject area the cluster is. A higher cluster density indicates has a greater capacity for longevity and development. The internal relationship between clusters is also measured by density (Liu et al., 2012a; Liu, Hu, and Wang, 2012b; Law et al., 1988; Soheili, Shaban, and Khasseh, 2016). Cluster 8 is the densest (34), and the most central is Cluster 1 (42.6667). The origin of the strategic diagram is based on the means of centrality and density, which are located at 5.669893 on the x-axis and at 7.415433 on the y-axis. Clusters 1 and 2 are in Quadrant 1, and cluster 8 is in Quadrant 2 clusters 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, and 15 are in Quadrant 3. There are no clusters in quadrant 4.

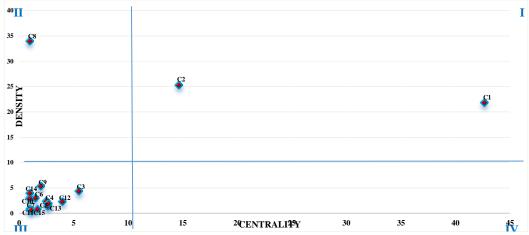


Figure 3. Strategic Diagram of the Structure of Landslide Research (2000-2020)

Co-word analysis enables an accurate visualization of the internal and external structures of the relationships between themes. Social network analysis and cluster analysis are two of the most common methods used in co-word study and provide micro- and macro-perspectives of research networks and domains, research hotspots, and subject evolution rules (Zhu and Zhang, 2020). Accordingly, in this study, the structures of the concepts and topics in landslide research can be identified, emerging issues can be exposed, and hidden conceptual relationships can be revealed over 20 years (2000–2020).

4.Conclusion

The results show that "geographic information systems (GIS)" was the most common keyword in landslide research from 2000 to 2020. The above result is precisely consistent with the results of Lima et al.'s (2022). This is not surprising, considering that most researchers use information systems to compile, process, and analyze their data. Hierarchical clustering can reveal the intellectual structure of landslide research. Here the process led to the emergence of 15 thematic clusters. Cluster 11, the most significant thematic cluster, contains 21 keywords. The other topics found in the remaining 14 clusters are: "mapping landslide sensitivity with GIS," "landslide susceptibility," "landslide susceptibility prediction," "machine learning models for landslide susceptibility mapping," "technologies used for monitoring and detecting landslides," "digital imaging and mapping for landslide monitoring," "landslide morphology and earthquakes," "zonal analyses of landslide risk, hazard, and vulnerability," "underwater landslides and tsunami," "hydro-geomorphological consequences of landslides," "low energy, slowly moving landslides," "groundwater hydrodynamics of soil in the production of landslides," "the processes behind precipitation-induced landslides," "the landslide-inducing impacts of the Three Gorges Reservoir," and "simulation and modeling the role of precipitation in landslide genesis." In Yang et al.'s (2022) research, 14 clusters were identified, and topics such as "debris flow," "underlying surface structure," and "rainfall" were identified as research hotspots.

This study revealed that between 2000 and 2020, the top keywords in landslide research were "GIS" and "landslide susceptibility." Yang et al.'s (2019), study indicated that "landslide susceptibility analysis" and "machine-learning methods" were at the top. The similar sets emphasize the popularity of the two topics "susceptibility" and "modeling/mapping." Increasing numbers of landslide disasters and rising economic losses and casualties have made clear the need for landslide inventories and effective methods of modeling with GIS and machine learning (Milia MFederico, 2021and also studied thematic clusters related to "Renewable Energy Research" based on the evidence indexed in Scopus between 1992 and 2016.



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According to the results of Table 3, clusters 8, 2, and 1 have the highest density, so they have more internal coherence and correlation. Clusters 1, 2, and 3 are the most centralized, so the topics of these clusters have several relationships with other nodes, have higher centrality and power, and have an essential place in the network. Cluster 8 has the highest density can be seen among the keywords of cluster 8, and the most centrality can be seen in Cluster 1.

The results of the strategic diagram indicate that clusters 1 and 2 (GIS mapping and landslide susceptibility mapping in GIS) share the core of landslide research today (Bahrami, Hassani, and Maghsoudi, 2020). Mapping landslide susceptibility is a fundamental and essential step toward the comprehensive management of landslide hazards (Arabameri et al., 2020). The subjects of these two clusters are the primary, mature, central, and developed themes that play an essential role in landslides. At the same time highly focused clusters like Cluster 8 (submarine landslides) are well-developed but specialized and isolated. This cluster has a high internal coherence but has weak relationships with the other clusters in the network. The clusters in quadrant 3 are topics in the emerging or declining portions of the network, meaning that these are less developed and have garnered little interest in this research network. The density and centrality of these clusters are also low. Therefore, some emerging missions have been designed to promote and mature the various research areas, but others may eventually decline.

Researchers have always worked on the landslide susceptibility model, which is one of the most popular keywords. Although this is not a new phenomenon, it has not been neglected. The preparation of susceptibility mapping is an essential step in landslide's comprehensive risk management (Arabameri et al., 2020), which has been considered by researchers (clusters 1 and 2).

Today, machine learning models, such as ANN and SVM, are the focus of attention for landslide susceptibility mapping because they can be hybridized (Luo et al., 2019). Landslide monitoring is a significant breakthrough in geodetic surveying technology that has made it possible to measure and monitor terrestrial metamorphosis more accurately, efficiently, and expertly (Reyes-Carmona et al., 2020)(Cluster 4). LIDAR, DEM, and photogrammetry are digital technologies used to prepare imagery. Today, radar is used to generate ground-thrust maps (Seif and Mahmoodi, 2014; Borrelli, Conforti and Mercuri, 2019). Digital technologies, like digital photogrammetry, are used in landslide hazard analyses (Seif and Mahmoodi, 2014; Borrelli, Conforti,, and Mercuri, 2019)(Cluster 5). Because the most critical steps in the assessment of landslide risk are the identification and preparation of landslide distribution maps of these types (Kornejady, Ownegh, and Sadoddin, 2015). Landslide distribution maps will always be necessary because there are always zones of hazard and risk that are caused by either natural factors or human activities. Also, Landslide prediction is one of the complicated topics recognized by the global scientific community (Yang et al., 2022)(Cluster 7).

The most significant landslide-influencing factors are rainfall amounts, seismic activities, construction projects, and soil type. When there is a lack of vegetation at landslide locations, the events can increase their extent and severity. The challenge to address these issues has drawn many scholars into geotechnics and soil mechanics. Statistical analysis, simulation, and computer modeling of landslides (Cluster 15) are another scholars focus. The **fourth quadrant** of the strategic diagram is empty; there are no clusters we would consider comprehensive, extensive, or immature issues.

The results of this study are in line with landslide studies by Yang et al. (2019), and Matjaž. (2018a; 2017b). Accordingly, the results of this scientometric study are consistent with the strategic hierarchy clustering of the strategic diagram and the co-word analysis of international studies undertaken by Danesh and Ghavidel (2020a; 2020b) and Giannakos et al. (2020).

Using scientometric tools and technics, the intellectual structure governing landslide research is revealed by 15 conceptual clusters. The maturity and coherence of each cluster in the strategic diagram display the global trends and The intellectual design of researchers in



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landslide research. Cluster analysis and co-occurrence matrix can express and reflect the connection (hidden conceptual relationships) of high-frequency keywords in research. Keywords in a cluster are close in concept. This paper has also explored the complex relationships governing international studies, illuminates angles, highlights research gaps, and leads scholars and analyses. These results will pave the paths forward for planners and policymakers in organizations and centers actively addressing landslide management's strategic plans. Subsequent studies could focus on the examination of the networks of collaboration between centers and researchers, and their impacts on decision-making.

Nevertheless, there are some limitations to our study. First, English sources were selected only. Second, perhaps with other synonyms for the subject of landslide, there was content that may not have been considered because we used common words under the supervision of experts. The choice of 20 years was to be able to express the latest developments in the subject area, but there is a kind of limitation to the present research.

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