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From Heuristic Models to GeoAI: A Scientometric and Thematic Evolution of Landslide Susceptibility Mapping Approaches

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Abstract

Landslide susceptibility mapping (LSM) has evolved considerably over the past two decades due to advances in Geographic Information Systems (GIS), remote sensing, machine learning, and geospatial artificial intelligence (GeoAI). This study presents a Scientometric and thematic evolution analysis of global LSM research published between 2006 and 2026 using the PRISMA framework, SciMAT, and VOSviewer. A total of 795 peer-reviewed publications retrieved from Scopus, Web of Science, IEEE, and Springer databases were systematically analyzed across four temporal periods (2006-2012, 2013-2018, 2019-2022, and 2023-2026). The findings reveal a clear transition from heuristic and statistical susceptibility approaches toward ensemble machine

learning, deep learning, LiDAR, InSAR, and GeoAI-driven susceptibility frameworks. Scientific mapping identified “landslide-modeling”, “hazard-mapping”, “machine learning (ML)”, “remote sensing techniques”, and “landslide conditioning factors” as dominant themes across different periods, while explainable artificial intelligence (XAI), hybrid ensemble models, and advanced geospatial intelligence emerged as growing research frontiers in recent years. The study further highlights persistent challenges related to data uncertainty, model interpretability, inventory quality, and transferability of susceptibility models across heterogeneous terrains. This work provides a comprehensive understanding of the intellectual structure and evolution of LSM research and offers future research directions toward explainable, transferable, and real-time GeoAI-based landslide prediction systems for sustainable hazard mitigation and infrastructure resilience.

Keywords

Bibliometric review; Geospatial artificial intelligence (GeoAI); Thematic evolution, Deep learning; SciMAT

1. Introduction

Landslides remain one of the most destructive geomorphological hazards worldwide, causing substantial loss of life, environmental degradation, economic disruption, and severe damage to critical infrastructure systems such as highways, railways, pipelines, and urban settlements. The increasing frequency and intensity of landslide events in recent decades have been associated with a combination of natural and anthropogenic factors, including extreme rainfall, seismic activities, rapid urbanization, deforestation, unregulated slope modification, and climate-induced environmental changes (Alcántara-Ayala, 2025; Guzzetti et al., 2005; Shrestha et al., 2025; Turner, 2018). Mountainous and tectonically active regions are particularly vulnerable because of their

1 complex geological settings, steep terrain morphology, and dynamic hydrological conditions,
2 while some low-moderate terrain regions also experience landslide occurrence due to prolonged
3 rainfalls among some other factors (Chakraborty, 2021; Shano et al., 2021). Consequently,
4 landslide susceptibility mapping (LSM) has become an essential component of hazard mitigation,
5 land-use planning, transportation corridor management, environmental sustainability, and disaster
6 risk reduction (Yadawa, 2024).

7 LSM refers to the spatial prediction of areas that are likely to experience future landslides based
8 on the relationships between historical landslide occurrences and conditioning factors such as
9 slope, lithology, elevation, rainfall, land use/land cover, curvature, soil type, drainage density, and
10 proximity to roads or faults (Lee, 2019; Pacheco Quevedo et al., 2023). Over the last two decades,
11 LSM research has evolved considerably due to advances in Geographic Information Systems
12 (GIS), remote sensing technologies, spatial modeling techniques, computational intelligence, and
13 high-resolution terrain datasets (Lu et al., 2024; Zhong et al., 2020). Early susceptibility studies
14 largely relied on heuristic and knowledge-driven approaches, including expert-based weighting
15 methods, inventory overlays, and multi-criteria decision-making techniques such as the Analytic
16 Hierarchy Process (AHP) and fuzzy logic (Barman et al., 2024; Das et al., 2022). Although these
17 approaches offered practical solutions in data-scarce environments, they were often criticized for
18 subjectivity, limited transferability, and reduced predictive generalization (Wang & Nanekaran,
19 2024).

20 The increasing availability of geospatial big data, high-resolution Digital Elevation Models
21 (DEMs), satellite imagery, Light Detection and Ranging (LiDAR), and cloud-based computing
22 infrastructures has accelerated the transition from heuristic susceptibility frameworks toward data-
23 driven and artificial intelligence-based approaches (Dritsas & Trigka, 2025; Ramamoorthy, 2026).

1 Statistical models such as logistic regression (LR), frequency ratio (FR), weights-of-evidence
2 (WoE), and certainty factor methods became widely adopted because of their ability to establish
3 quantitative relationships between conditioning variables and landslide occurrences (Ding et al.,
4 2017; Farooq & Akram, 2021). Subsequently, machine learning (ML) algorithms, including
5 Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forest (RF),
6 Decision Trees (DT), Naïve Bayes, and ensemble learning frameworks, gained substantial
7 attention owing to their improved predictive performance and capacity to model complex
8 nonlinear relationships (Ali et al., 2022; Arabameri et al., 2022; Nhu et al., 2020). More recently,
9 deep learning architectures, convolutional neural networks (CNNs), explainable artificial
10 intelligence (XAI), and GeoAI-driven frameworks have emerged as dominant research frontiers in
11 susceptibility assessment and geospatial hazard prediction (Mubeen & Saeed, 2023).

12 Parallel to methodological evolution, remote sensing technologies have significantly transformed
13 the acquisition, processing, and integration of landslide-related datasets (Casagli et al., 2023).
14 Optical Imagery, Synthetic Aperture Radar (SAR), Interferometric SAR (InSAR), LiDAR-derived
15 topographic and hydrographic products, and unmanned aerial vehicle (UAV)-based
16 photogrammetry have enhanced the capability to detect terrain deformation, monitor slope
17 instability, generate landslide inventories, and improve susceptibility model accuracy (Joyce et al.,
18 2014; Li & Xiao, 2025; Lissak et al., 2020). These developments have also promoted the
19 integration of multi-source datasets and hybrid modeling strategies capable of capturing both
20 spatial complexity and environmental uncertainty (Xiao et al., 2025; Ye et al., 2025). Also, the
21 field of LSM has expanded from traditional Geographic Information System (GIS)-based
22 susceptibility assessment toward multidisciplinary and computationally intensive GeoAI

1 ecosystems integrating remote sensing, geospatial analytics, artificial intelligence, and
2 environmental modeling (Wang & Nanekaran, 2024).

3 Despite the substantial growth of LSM research, several challenges remain unresolved. Existing
4 review studies have predominantly focused on methodological comparisons, regional applications,
5 machine learning performance evaluations, or systematic literature summaries (Ado et al., 2022;
6 Chicas et al., 2024; Zhong et al., 2020). Although a few bibliometric investigations have explored
7 publication trends and citation structures in landslide research, limited attention has been given to
8 the longitudinal thematic evolution of susceptibility mapping approaches, particularly the
9 transition from heuristic frameworks to GeoAI-driven paradigms. In addition, many previous
10 studies depended on and sourced articles from a single database and inadequately examined the
11 evolution of remote sensing integration, the emergence of explainable AI, the role of advanced
12 ensemble learning, and the shifting knowledge structure of LSM research across temporal periods.
13 Furthermore, the rapid expansion of publications after 2018, especially in deep learning and
14 geospatial artificial intelligence, necessitates an updated scientometric assessment capable of
15 identifying dominant themes, emerging research frontiers, and future methodological directions
16 (Dong et al., 2023; Huang et al., 2022; Mehmood et al., 2026).

17 To address these gaps, this study presents a comprehensive scientometric and thematic evolution
18 analysis of global landslide susceptibility mapping research published between 2006 and 2026
19 using the PRISMA framework, SciMAT, and VOSviewer. After screening over 2,100 articles
20 (including peer reviewed research articles and well-reviewed conference articles that capture most
21 recent LSM techniques) using the PRISMA framework, a total of 795 peer-reviewed publications
22 retrieved from Scopus, Web of Science, IEEE, and Springer databases were systematically
23 analyzed to evaluate publication growth, thematic structures, methodological evolution, and

collaborative research patterns. Literature retrieval across selected databases was concluded on May 8, 2026. The major goal of the research seeks to answer the following questions:

Q1: How has landslide susceptibility mapping research evolved thematically and methodologically between 2006 and 2026?

Q2: What are the dominant and emerging approaches, datasets, and technological frameworks driving modern landslide susceptibility modeling?

Q3: What future research directions and knowledge gaps exist in the transition from traditional susceptibility assessment toward GeoAI-driven landslide prediction systems?

2. Materials and Methods

2.1 Methodology

This study adopted a systematic scientometric framework to evaluate the intellectual structure, thematic evolution, and methodological transitions in LSM research between 2006 and 2026. The methodological workflow integrated systematic literature retrieval, PRISMA-based screening, bibliometric preprocessing, scientific mapping using SciMAT, and collaboration network visualization using VOSviewer. The workflow Figure 1 was designed to ensure transparency, reproducibility, and thematic consistency throughout the analysis.

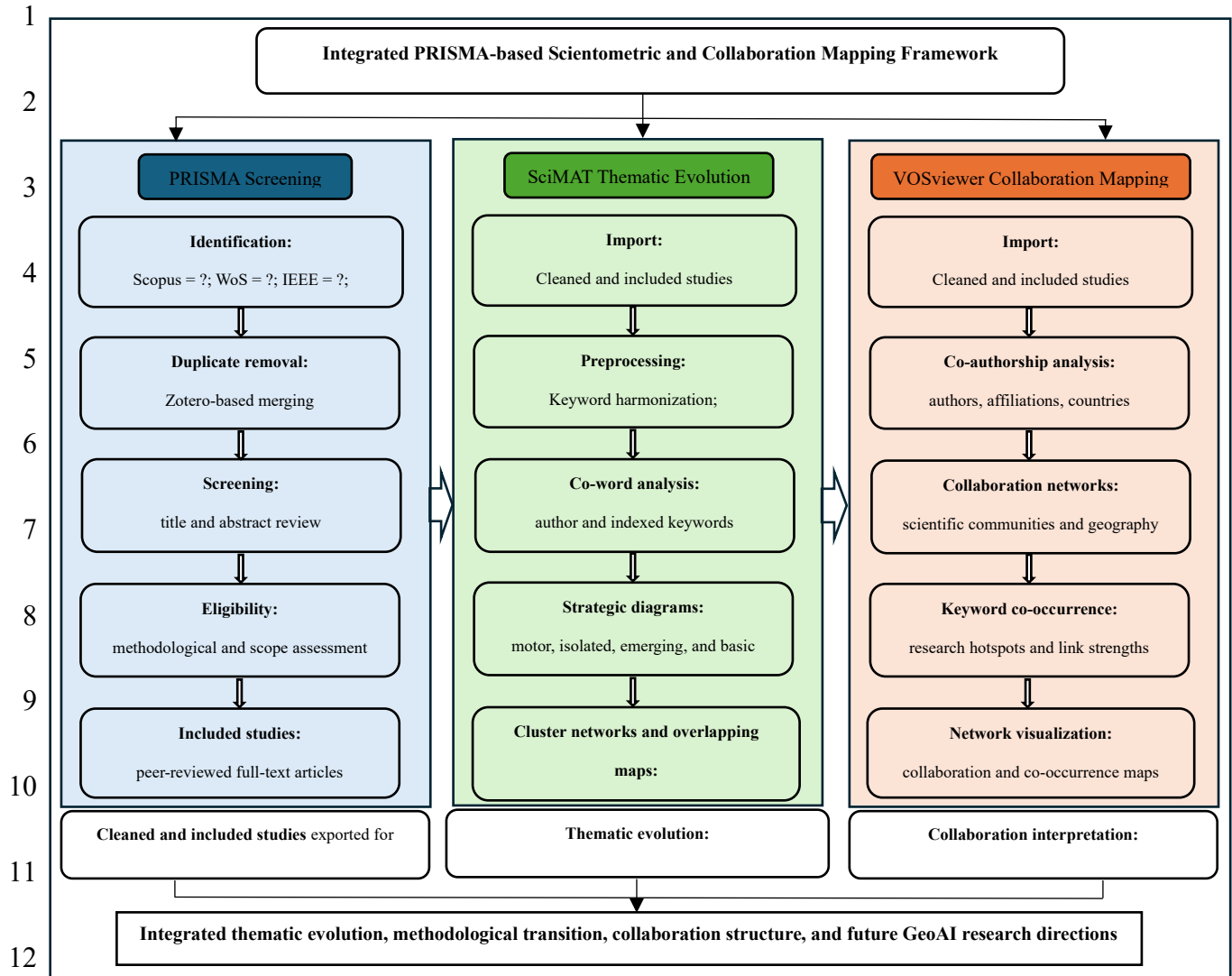


Figure 1. Connected PRISMA-SciMAT-VOSviewer framework for landslide bibliometric review.

The methodological contribution of this study lies in the integration of PRISMA-based systematic literature screening with SciMAT thematic mapping and VOSviewer collaboration network analysis. The combined framework enables simultaneous examination of thematic evolution, methodological development, and research collaboration patterns, providing a comprehensive assessment of the intellectual and scientific structure of LSM research between 2006 and 2026.

2.2 Literature Search Strategy and Data Sources

The literature search was conducted using four major scientific databases: Scopus, Web of Science (WoS), IEEE Xplore, and Springer. These databases were selected because of their extensive coverage of geospatial science, engineering geology, remote sensing, computer science, artificial intelligence, and environmental hazard research. The search process focused on peer-reviewed studies related to landslide susceptibility mapping, zonation, prediction, detection, machine learning, GIS, remote sensing, LiDAR, InSAR, and GeoAI applications.

Boolean search expressions were constructed using combinations of keywords associated with susceptibility mapping methodologies, geospatial technologies, and artificial intelligence techniques. The search process covered publications from January 2006 to May 08, 2026. The initial search produced 2,119 records as shown in Table 1, these include documents from Scopus, WoS, IEE Xplore, and Springer databases.

Table 1. Boolean operators used within databases consulted and records retrieved.

Database	Boolean Query	Retrieved Records	Comments
Scopus	ALL(("landslide susceptibility" OR "landslide prediction" OR "landslide mapping") AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "GeoAI") AND ("GIS" OR "remote sensing" OR "geospatial analysis") AND ("LiDAR" OR "DEM" OR "digital elevation model" OR "InSAR")) AND	1,426	Review articles were intentionally retrieved to examine some of the review articles that exist prior to this study.

	("AHP" OR "analytic hierarchy process" OR "multi-criteria decision analysis" OR "MCDA") AND ("physics-based" OR "physically-based" OR "data-driven" OR "hybrid model")) AND PUBYEAR > 2006 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT- TO (DOCTYPE, "re") OR LIMIT-TO (DOCTYPE,"cp")) AND (LIMIT-TO (LANGUAGE, "English"))	However, these review articles were not included as part of records in this study and were filtered before screening process begins.
WoS	TS= (("landslide susceptibility" OR "landslide susceptibility mapping" OR "landslide prediction" OR "landslide hazard mapping") AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "GeoAI" OR "geospatial artificial intelligence") AND (GIS OR "remote sensing" OR LiDAR OR DEM OR "digital elevation model" OR "DEM of Difference" OR InSAR) AND (AHP OR "analytic hierarchy process" OR MCDA OR "multi-criteria decision analysis"))	538
IEEE	"Abstract": (landslide susceptibility OR landslide	76
Xplore	prediction) AND (machine learning OR deep learning) AND (GIS OR Remote Sensing) AND	

(Physics-based OR physically based) AND (AHP
OR MCDA OR "multi-criteria decision analysis")
AND (LiDAR) AND (GeoAI)

Springer ("landslide susceptibility" OR "landslide 79
prediction" OR "landslide mapping") AND
("machine learning" OR "deep learning") AND
("AHP" OR "analytic hierarchy process" OR
"multi-criteria decision analysis" OR "MCDA")
AND ("Physics-based" OR "Physically based")
AND ("GIS" OR "remote sensing" OR "LiDAR"
OR "DEM" OR "InSAR") AND (GeoAI)

2.3 PRISMA Screening and Eligibility Assessment

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework
Figure 2 was adopted to ensure a transparent and reproducible literature selection process. All
retrieved records were exported into Zotero reference management software for metadata
organization, duplicate removal, and preliminary screening. This method was introduced to make
sure irrelevant studies were not included in the review processes, and that selection of the said
included studies were identified systematically and transparently unlike previous bibliometric
reviews that solely depended on direct retrieved studies from academic databases.

After removing duplicate records (n = 63), a total of 2,056 studies were screened based on titles
and abstracts. Publications unrelated to landslide susceptibility research, editorials, opinion papers,
records lacking methodological clarity, and studies outside the thematic scope of the review were
excluded during screening. Full-text eligibility assessment was subsequently conducted on the

remaining studies using predefined inclusion and exclusion criteria. Following the eligibility review, 795 peer-reviewed publications were retained for scientometric analysis.

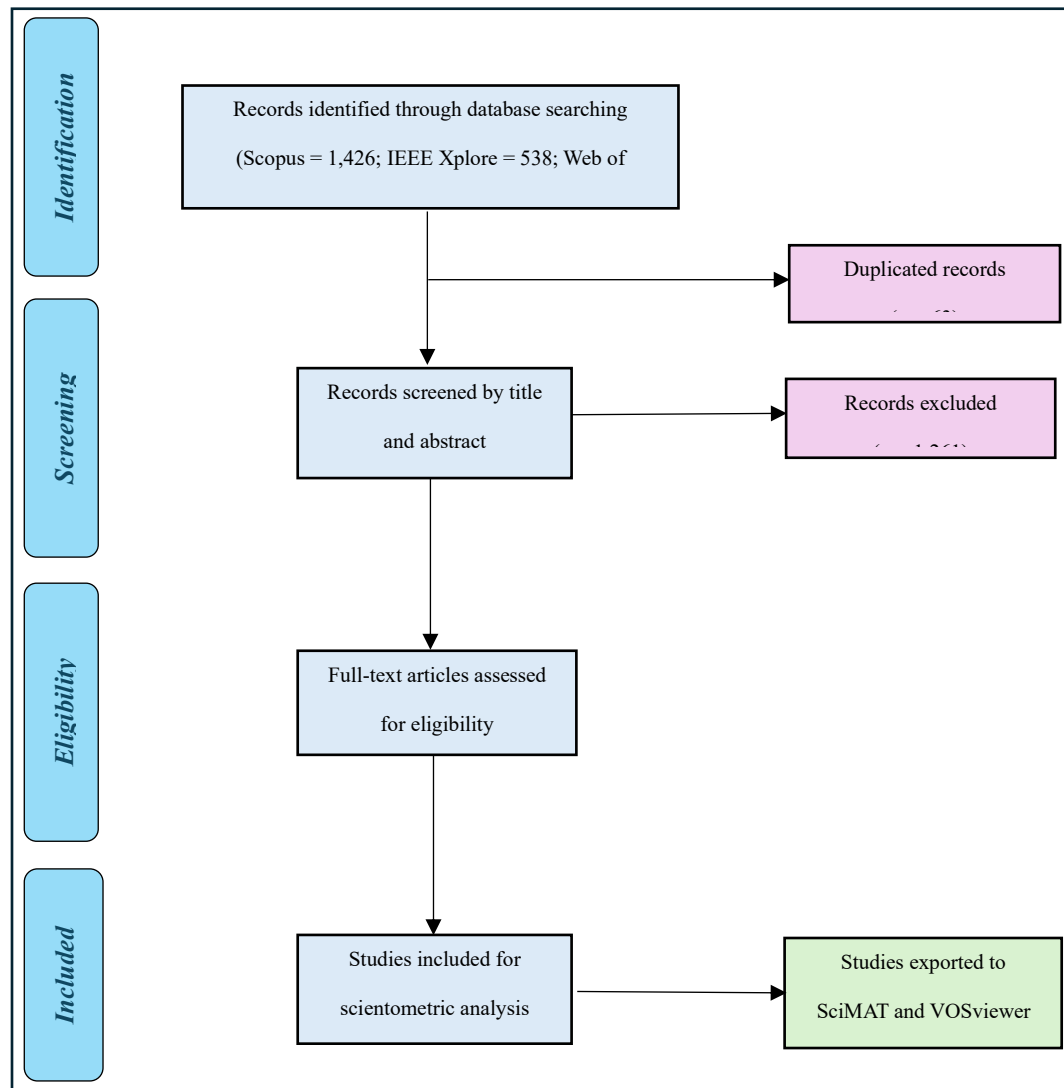


Figure 3. PRISMA flow diagram showing identification, screening, eligibility, and inclusion stages.

2.4 Inclusion and Exclusion Criteria

The literature selection process was guided by clearly defined inclusion and exclusion criteria to ensure thematic relevance and methodological consistency.

2.4.1 Inclusion Criteria

Studies were included if they:

- i. were peer-reviewed journal articles or high-quality conference papers;
- ii. were published between 2006 and 2026;
- iii. focused on landslide susceptibility mapping, modeling, detection, or prediction;
- iv. employed GIS, remote sensing, statistical, machine learning, deep learning, MCDA, or physics-based approaches; and
- v. provided clearly defined methodologies and validation procedures.

2.4.1 Inclusion Criteria

Studies were excluded if they:

- i. were duplicate records across databases;
- ii. were editorials, commentaries, opinion papers, or non-peer-reviewed materials;
- iii. were not directly related to landslide susceptibility research;
- iv. lacked methodological transparency; or
- v. presented insufficient or unclear analytical findings.

2.5 Bibliometric Data Preprocessing

The final dataset was imported into SciMAT for preprocessing and scientific mapping analysis. Prior to analysis, metadata cleaning and keyword harmonization were conducted to improve thematic consistency and reduce semantic redundancy within the co-word network. Keyword standardization involves merging synonymous expressions, abbreviations, and singular/plural variations. For example, terms such as “LSM” and “landslide susceptibility mapping,” “RF” and “random forest,” and “CNN” and “convolutional neural network” were unified during

preprocessing. Common significant terms to the study were grouped while generic terms with limited thematic significance were removed to improve clustering efficiency and thematic interpretation.

2.6 Scientific Mapping and Thematic Evolution Analysis

Scientific mapping was conducted using SciMAT to examine the conceptual structure and thematic evolution of landslide susceptibility mapping research. The analysis was based on co-word networks generated from author keywords and indexed keywords within the selected publications. To capture longitudinal evolution of LSM research, the study period was divided into four temporal intervals:

- Period 1: 2006-2012
- Period 2: 2013-2018
- Period 3: 2019-2022
- Period 4: 2023-2026

These periods were selected and grouped to reflect major methodological transitions within the field, including the early dominance of heuristic and statistical methods, the expansion of machine learning approaches, the rapid adoption of deep learning techniques, and the recent emergence of GeoAI-driven frameworks. The equivalence index was used for network normalization among other settings in Table 2, while thematic evolution was evaluated using the inclusion index.

Table 2. Science Mapping Configuration Settings

Setting	Chosen Options
Unit of analysis	Author's words / Source's words / Added words
Data reduction	Frequency reduction (checked) / Minimum frequency (2) for all periods
Kind of matrix	Co-occurrence
Network reduction	Edge value reduction (checked) / Minimum value (1) for all periods
Normalization	Equivalence index
Clustering algorithm	Simple centers algorithm / Max. size (40) / Min. size (1)
Document mapper	Core mapper
Evolution measure	Inclusion index
Quality measure	h-index / Sum citations
Longitudinal map	Evolution map (Jaccard's index) / Overlapping map (Inclusion index)

In this research using SciMAT application, three major steps were followed:

- Detection of research themes
- Drawing the thematic network structure for each research themes, and
- Conduction of performance analysis.

Figures 3 to Figure 5 show the thematic network structure. Having satisfied the configuration settings, SciMAT generates strategic diagram Figure 3. Here, research themes were divided based on their centrality and density level into four quadrants namely: *Motor themes* - Q1: Upper-right quadrant, *Highly developed and isolated themes* - Q2: Upper-left quadrant, *Emerging or declining themes* - Q3: Lower-left quadrant, and *Basic and transversal themes* - Q4: Lower-right quadrant.



Figure 3. Strategic diagram.

The cluster network map Figure 4 displays the relationship between the major theme and its subthemes. The size of each circle within the cluster network is proportional to the number of documents linked to each theme and the thickness of lines connecting the circles is proportional to the specified index of the themes.

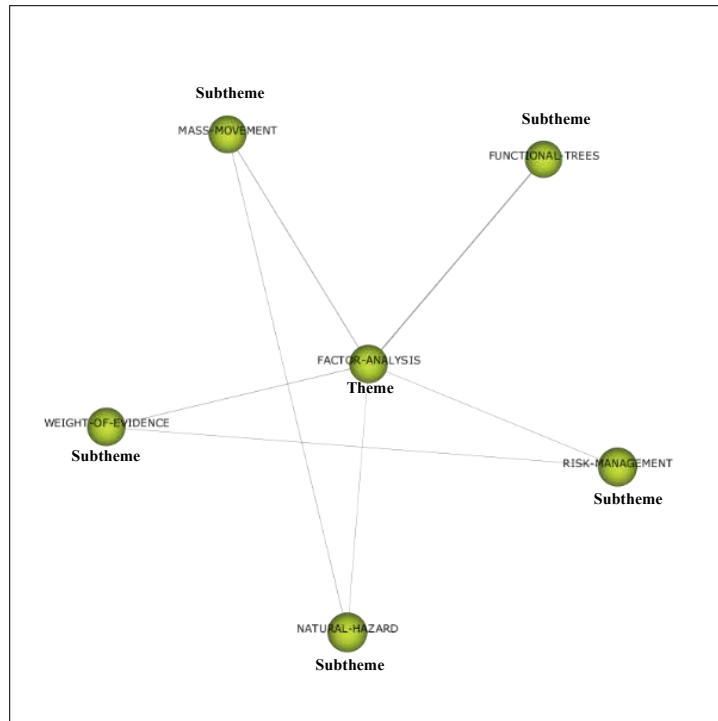


Figure 4. Cluster network map.

Also, the evolution map Figure 5 illustrates the relationships and developments that exist between various themes across different periods. This map presented a valuable diagram of how the themes maintain a conceptual design throughout a period and its subsequent subperiods. The size of each evolving circle is proportional to the number of linked documents for the theme within the circle, and the links indicate co-occurrence among the clusters. Continuous lines indicate that themes shared strong links among the clusters, which suggested a direct inheritance between themes. While dashed lines represented a weak link between cluster themes and indicated some levels of discrepancies between them. When themes have common elements, it is shown in the thickness of the lines that connect them which is also proportional to the inclusion index of connection.

Performance indicators including document count, h-index, and citation metrics were further employed to evaluate thematic influence and intellectual development across periods.

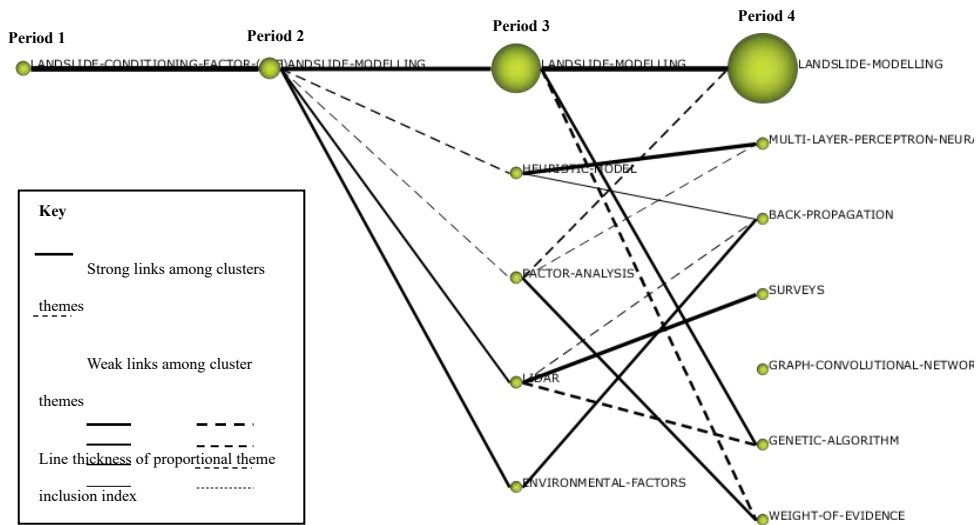


Figure 5. Thematic evolution map.

3. Publication Trends and Descriptive Bibliometric Analysis

3.1 Temporal Evolution of Publications

The temporal distribution of publications provides insight into the evolution of landslide susceptibility mapping research over the last two decades. Based on 795 peer-reviewed publications included in this study, substantial increase in research output was observed across the four predefined periods Figure 6. During the initial period (2006-2012), only 19 publications were identified, representing approximately 2.4% of the total dataset. This relatively low output reflects the early developmental stage of LSM research, where studies were largely focused on heuristic approaches, statistical analyses, and GIS-based susceptibility assessments.

Research productivity increased during the second period (2013-2018), with 67 publications accounting for 8.4% of the dataset. This growth coincided with advances in geospatial technologies, wider accessibility of digital elevation models, and increased adoption of statistical and machine-learning-based susceptibility modeling techniques. During this period, methods such

1 as FR, LR, ANNs, SVM, and AHP models gained widespread attention in susceptibility assessment
2 studies.

3 A pronounced increase in publication output occurred after 2018. The period 2019-2022 recorded
4 289 publications (36.4%), while 420 publications (52.8%) were published between 2023 and May
5 2026. Collectively, these two periods account for approximately 89.2% of all publications included
6 in the analysis. The rapid expansion of LSM research during this phase can be attributed to the
7 integration of machine learning, deep learning, LiDAR-derived terrain analysis, InSAR
8 monitoring techniques, cloud computing platforms, and emerging GeoAI frameworks. These
9 developments significantly enhanced the capability of researchers to model complex landslide
10 processes using large and heterogeneous geospatial datasets.

11 Unequivocally, the publication trajectory demonstrates a transition from traditional susceptibility
12 assessment approaches toward increasingly sophisticated data-driven and artificial intelligent-
13 based methodologies. The accelerating growth observed in recent years further indicates that
14 landslide susceptibility mapping remains an active and expanding research domain, driven by
15 increasing concerns regarding disaster risk reduction, infrastructure resilience, climate change
16 impacts, and advances in geospatial technologies.

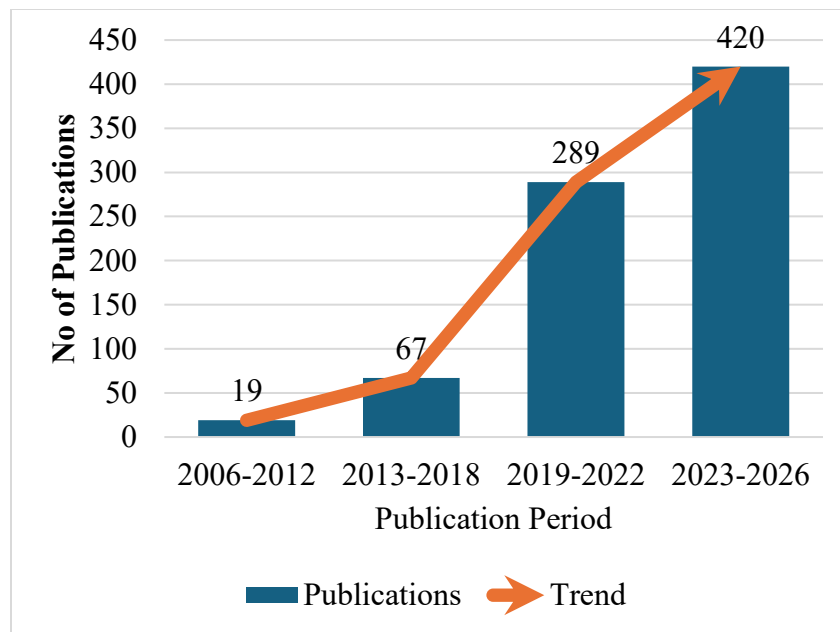


Figure 6. Publication trend of Landslide Susceptibility Mapping Research (2006-2026).

3.2 Author and Geographic Contributions

The rapid expansion of LSM research has been accompanied by the emergence of highly productive researchers and geographically concentrated research hubs. Analysis of the Web of Science records revealed that a relatively small group of authors has played a significant role in advancing methodological developments in susceptibility assessment, hazard mapping, machine learning applications, and geospatial modeling.

Among the most productive researchers, Wei Chen ranked first with 85 publications from the included studies, closely followed by Chong Xu with 84 publications and Biswajeet Pradhan with 78 publications Table 3. Other highly influential contributors include Binh Thai Pham, Qiang Xu, Haoyuan Hong, Tien Bui, Kunlong Yin, Luigi Lombardo, and Indra Prakash, each contributing more than 50 publications within the study period and based on their publications that falls within the scope of this work. The dominance of these authors reflects sustained scholarly efforts toward

improving landslide susceptibility modeling frameworks, integrating machine learning algorithms, enhancing geospatial data utilization, and developing robust validation procedures. Their collective contributions have significantly shaped the methodological progression of the field from conventional statistical approaches toward advanced artificial intelligence (AI) and GeoAI-driven models.

Table 3. *Top 10 Ranked Authors in LSM Research*

Author	Ranking	No of Publications
Chen, Wei	1	85
Xu, Chong	2	84
Pradhan, Biswajeet	3	78
Pham, Binh Thai	4	61
Xu, Qiang	5	56
Hong, Haoyuan	6	55
Dieu, Tien Bui	7	54
Yin, Kunlong	8	53
Lombardo, Luigi	9	52
Prakash, Indra	10	51

Geographically, LSM research exhibits a strong concentration in Asia, where rapid urbanization, mountainous terrain, infrastructure expansion, and recurrent landslide hazards have stimulated extensive scientific investigations. As shown in Table 4, China emerged as the most productive country with 234 publications, substantially exceeding all other nations in research output. India ranked second with 82 publications, followed by Vietnam with 41 publications. The United States

ranked fourth with 36 publications, while Iran, Australia, South Korea, Saudi Arabia, Turkey, and Malaysia completed the list of the top ten contributing countries.

The prominence of China and several Asian countries reflect both the frequency of landslide occurrences and significant national investments in geospatial technologies, remote sensing infrastructure, and disaster risk reduction programs. Furthermore, the growing contribution of countries such as Vietnam, Iran, and Malaysia highlights increasing global interest in data-driven landslide assessment and the widespread adoption of machine learning techniques. The presence of the United States and Australia among the leading contributors demonstrates the expanding international nature of LSM research and the growing importance of interdisciplinary approaches involving geomorphology, engineering geology, GIS, remote sensing, and AI.

Table 4. *Top 10 Most Contributing Countries to LSM Research (Scopus)*

Country	Ranking	No of Publications
China	1	234
India	2	82
Vietnam	3	41
Unites States	4	36
Iran	5	35
Australia	6	24
South Korea	7	21
Saudi Arabia	8	19
Turkey	9	17
Malaysia	10	16

Thus far, the author and country distributions reveal a highly collaborative and internationally connected research landscape. The concentration of productive authors and leading countries has contributed meaningfully to methodological innovations that are further explored through the scientific mapping analyses presented in the subsequent section. Although, the descriptive bibliometric indicators provide a broad overview of publication growth, leading contributors, and geographic distribution. However, they do not reveal how research themes evolved, interacted, and metamorphosized over time. To address this limitation, a science mapping approach was implemented using SciMAT to examine thematic development, conceptual structures, and knowledge evolution across the four study periods (2006-2012, 2013-2018, 2019-2022, and 2023-2026).

4. Scientific Mapping and Analysis Based on SciMAT

4.1 Keyword Evolution and Conceptual Continuity Analysis

The overlapping map Figure 7 provides an overview of the conceptual development of landslide susceptibility mapping research by examining the evolution and continuity of keywords across successive periods. As shown in Figure 4, the number of keywords increased from 31 during the period 2006-2012 to 59 in 2013-2018, 80 in 2019-2022, and 84 in 2023-2026. This progressive increase indicates a continuous broadening of the thematic landscape and diversification of research interests within the field. The first period was characterized by a relatively limited conceptual structure, reflecting the early stages of susceptibility mapping research when investigations were primarily centered on hazard assessment, GIS-based spatial analysis, terrain factors, and heuristic modeling approaches. As research matured, the number of the thematic descriptors nearly doubled during the second period, suggesting the incorporation of additional analytical techniques, data sources, and modeling frameworks. The period coincided with

increasing use of statistical models, multi-criteria decision-making approaches, and growing availability of digital terrain datasets.

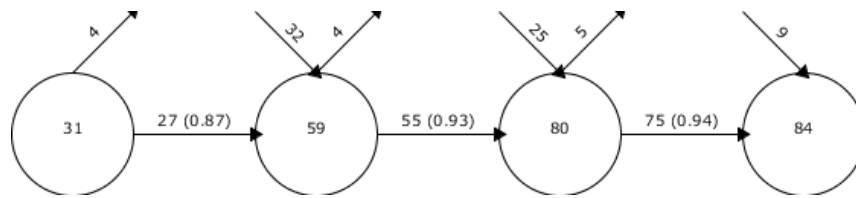


Figure 7. Overlapping map of thematic keywords across the four study periods generated using SciMAT.

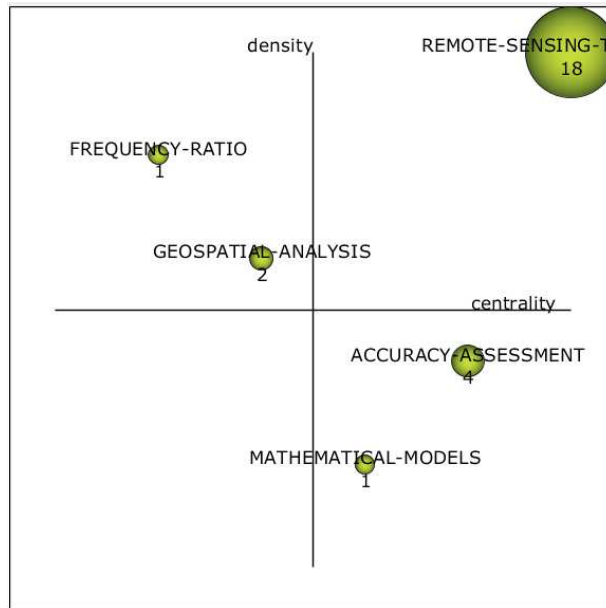
A more substantial expansion of thematic coverage occurred during 2019-2022, when the number of keywords increased to 80. The enlarged conceptual network reflects the integration of advanced computational methods, including SVM, random forests, ensemble learning techniques, neural networks, and high-resolution remote sensing datasets. The persistence of many keywords across consecutive periods further indicates that foundational concepts such as susceptibility modeling, hazard mapping, conditioning factors, geographic information systems, and spatial analysis continued to serve as central pillars of the research domain while accommodating emerging analytical innovations.

The final period (2023-2026) exhibited the highest level of conceptual diversity, with 84 identified keywords. Although the increase in keyword count relative to the preceding period was modest, the stability of keyword continuity suggests that the field has entered a stage of thematic consolidation. Rather than generating entirely new conceptual domains, recent studies have increasingly focused on refining existing methodologies through integration of multi-source datasets, explainable artificial intelligence techniques, advanced remote sensing technologies, and hybrid modeling frameworks. This pattern indicates the gradual maturation of discipline and the emergence of a more interconnected knowledge structure. In a nutshell, the overlapping map

demonstrates both thematic expansion and conceptual persistence throughout the study period. The coexistence of enduring foundational themes and newly emerging methodological concepts highlights the dynamic nature of landslide susceptibility mapping research and provides a basis for examining the strategic importance of individual themes in subsequent analyses.

4.2 Thematic Evolution of LSM Research (2006-2012)

Figure 8 presents the strategic diagram for the 2006-2012 period, revealing five principal research themes: remote sensing techniques, frequency ratio, geospatial analysis, mathematical models, and accuracy assessment. Among these, “remote sensing techniques” was the most influential and well-developed theme, exhibiting the highest centrality (99.30) and density (95.79). This indicates that remote sensing technologies served as the primary knowledge base for landslide studies during the period, supporting terrain characterization, inventory mapping, and susceptibility assessment. “Accuracy assessment” occupied a secondary position, reflecting increasing attention to model validation and reliability evaluation. Meanwhile, “geospatial analysis” and “mathematical models” represented developing analytical directions, whereas “frequency ratio” emerged as a specialized statistical approach that would later gain broader adoption in susceptibility modeling studies (Casagli et al., 2023; Zhong et al., 2020).



Theme	Centrality	Density
Remote-Sensing Techniques	99.30	95.79
Accuracy Assessment	32.82	31.02
Geospatial Analysis	21.81	50.00
Frequency Ratio	5.71	50.00
Mathematical Models	30.41	25.00

Figure 8. Strategic diagram of LSM research themes during 2006-2012.

The cluster networks shown in Figure 9 provide additional insight into the conceptual structure of the field during the period. The “remote sensing techniques” cluster was the largest and most interconnected, linking closely with themes such as “landslide modeling”, “hazard mapping”, “GIS”, “DEMs”, “landforms”, “landslide conditioning factors”, “SVM”, “fuzzy logic models”, and “machine learning.” This pattern demonstrates that early landslide research was already integrating geospatial technologies with emerging computational methods for susceptibility assessment and hazard evaluation (Lu et al., 2024).

The “accuracy assessment” cluster was associated with “heuristic models”, “statistical approaches”, “probabilistic methods”, “ANN”, and “databases”, indicating growing efforts to evaluate model performance and compare alternative prediction techniques. Smaller clusters reveal the emergence of more specialized topics. The “geospatial analysis” cluster was connected to “weight of evidence modeling” and transportation-related applications such as “road corridor analysis”. The “frequency ratio” cluster was linked with “LiDAR”, suggesting the initial adoption of higher-resolution topographic datasets for landslide investigations. Finally, the mathematical

models” cluster was associated with “neural network models”, reflecting the early exploration of data-driven predictive approaches that later evolved into more advanced machine learning and deep learning frameworks (Tordesillas et al., 2018; Ye et al., 2025).

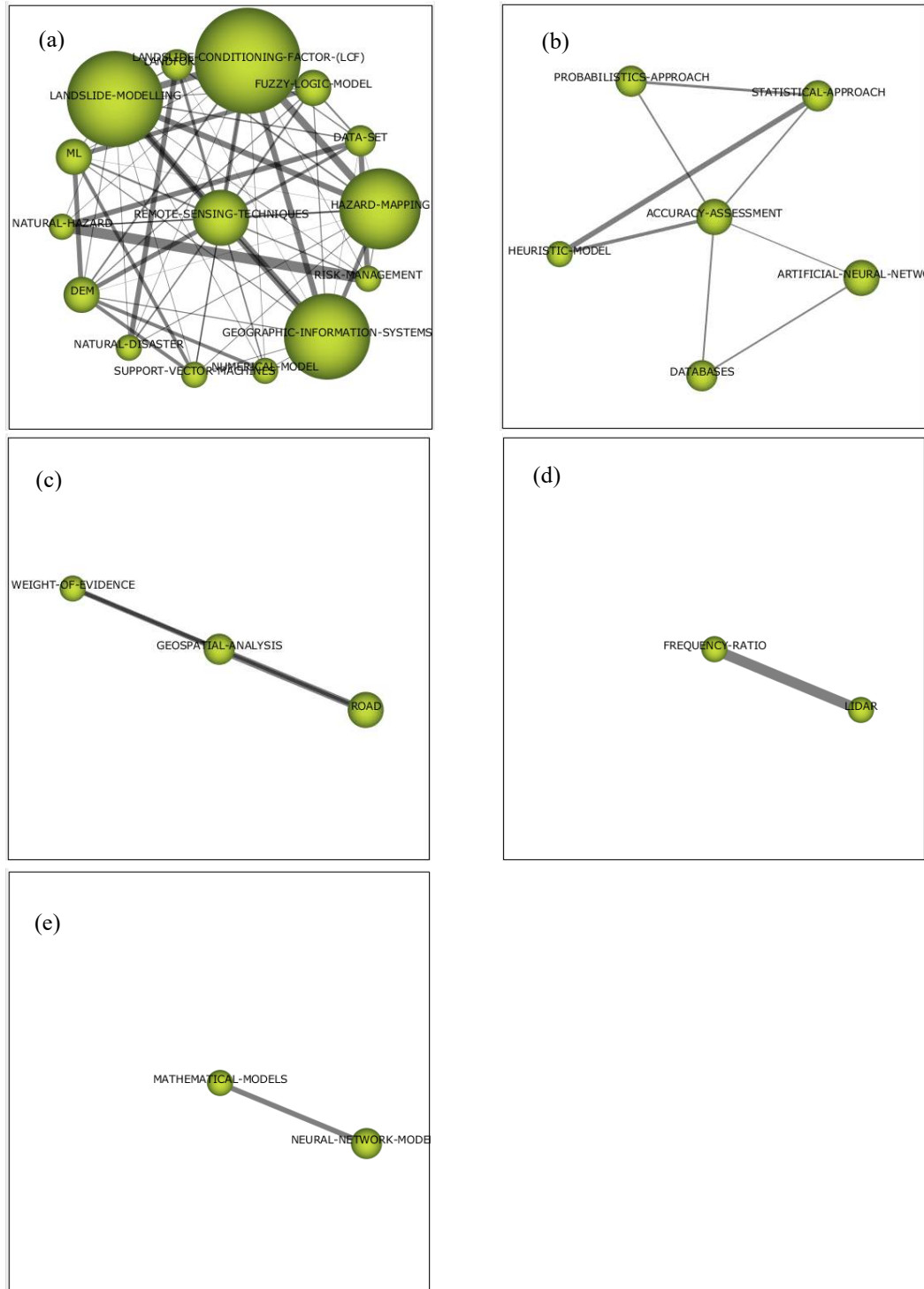


Figure 9. Cluster network map showing thematic relationships in LSM research during 2006-2012. Themes include (a) remote sensing techniques (b) accuracy assessment (c) geospatial analysis (d) frequency ratio (e) mathematical models.

4.3 Thematic Evolution of LSM Research (2013-2018)

This period marks a transition from foundational susceptibility assessment toward more advanced and quantitatively driven modeling approaches. Figure 10 illustrates the strategic diagram for the 2013-2018 period. Compared with the previous period, the thematic structure became more diversified and methodologically mature. “Landslide modeling” emerged as the dominant motor theme, exhibiting the highest centrality (224.28) and density (102.49), indicating its strong influence and internal development within the research field. The prominence of the theme reflects the growing emphasis on developing reliable susceptibility and hazard prediction frameworks. “Decision support systems” also occupied a strategic position with high centrality and density, demonstrating increasing efforts to translate susceptibility assessments into practical tools for planning and risk management. Other notable themes included “databases”, DEMs”, and “LR”, highlighting the growing importance of geospatial data infrastructure and statistical modeling techniques. Emerging but less central themes such as “frequency ratio”, “wavelet transform”, and “mathematical models” indicate continued exploration of specialized analytical approaches for landslide prediction and hazard assessment (Zhang et al., 2021).

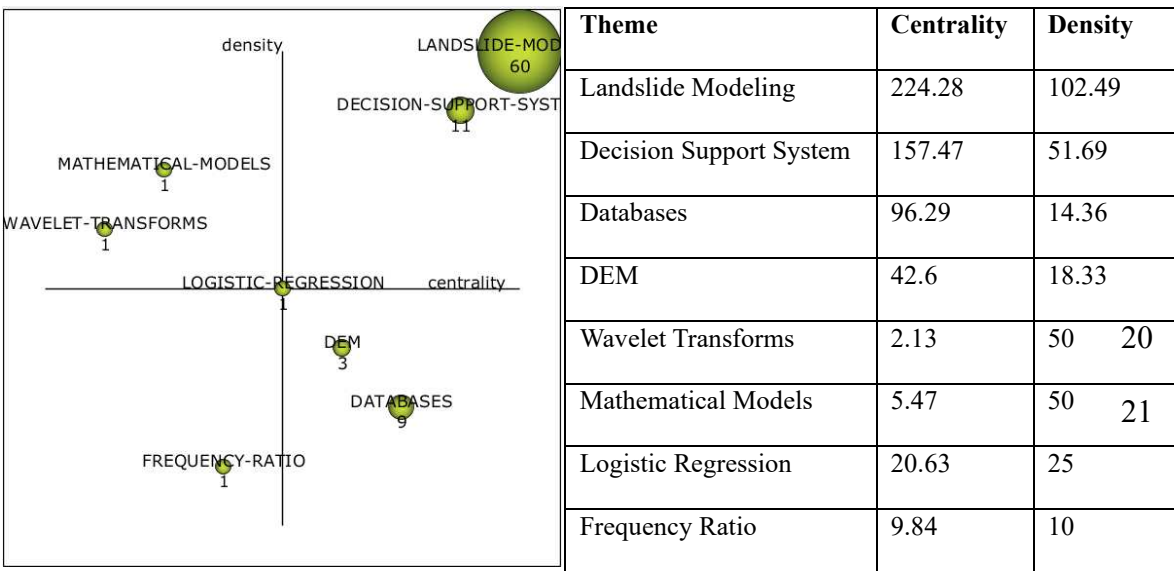
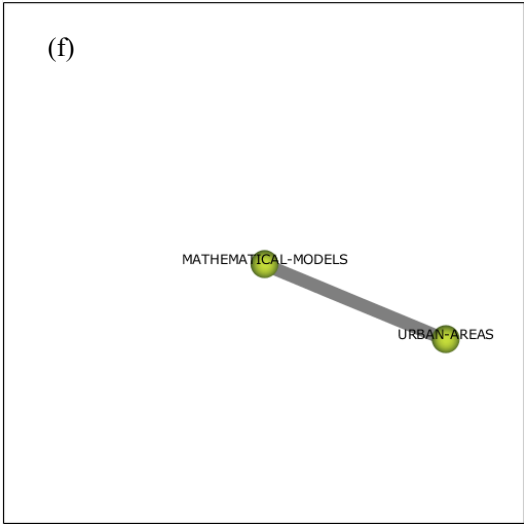
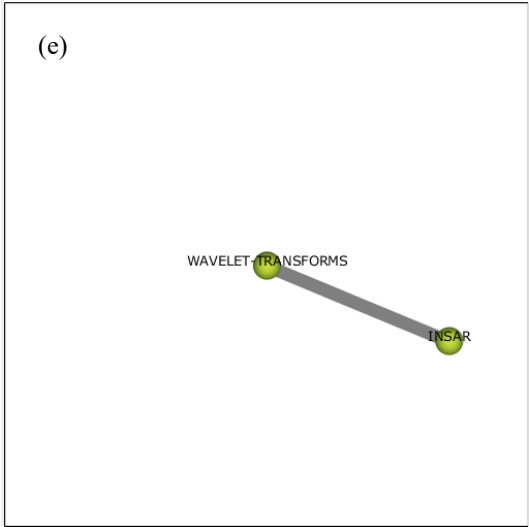
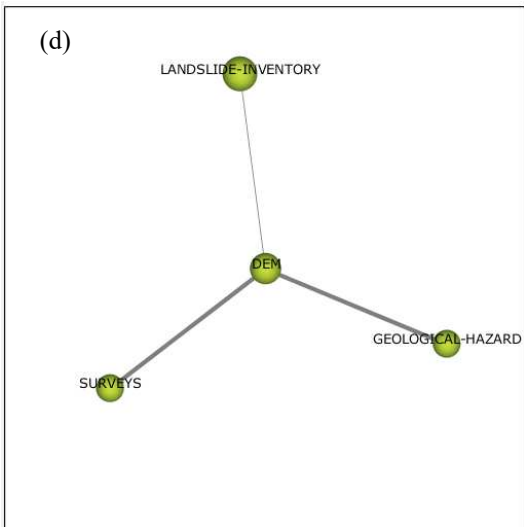
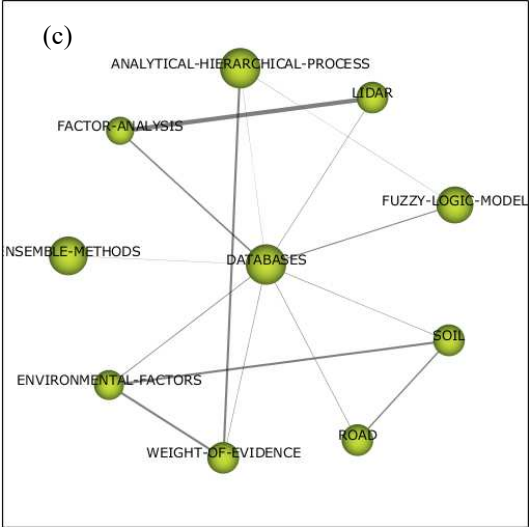
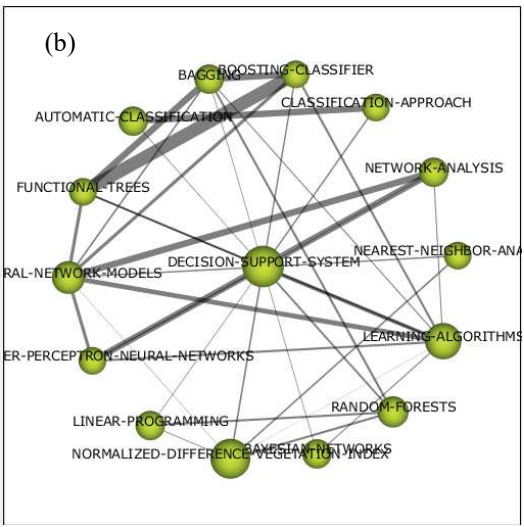
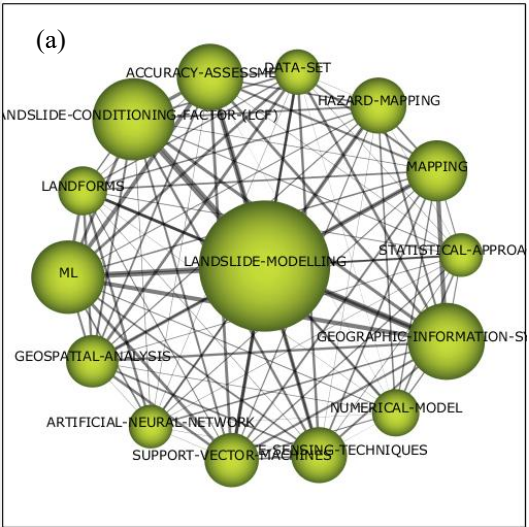


Figure 10. Strategic diagram of LSM research themes during 2013–2018.

Figure 11 represents the cluster networks associated with the major themes identified during the 2013-2018 period. The “landslide modeling” cluster formed the intellectual core of the field and was strongly connected with “landslide conditioning factors”, “hazard mapping”, “mapping”, “GIS”, “remote sensing techniques”, “spatial analysis”, “ML”, “ANN”, “SVM”, “numerical models”, and “accuracy assessment.” These relationships indicate a transition from traditional inventory-based investigations toward integrated geospatial and predictive modeling frameworks (Guo et al., 2025; Wei et al., 2023).

The “decision support systems” cluster was linked to concepts such as “decision trees”, “classification methods”, “forecasting”, “network analysis”, and “training algorithms”, reflecting increasing interest in operational tools capable of supporting hazard mitigation and land-use planning. The “databases” cluster was associated with “LiDAR”, “ensemble methods”, “soil characteristics”, “roads”, “environmental factors”, “weight of evidence models”, and “hierarchical approaches”, emphasizing the growing role of structured geospatial datasets and high-resolution terrain information in susceptibility modeling. Meanwhile, the “DEM” cluster was closely connected with “landslide inventories”, “surveys”, and “geological hazard”, underscoring the importance of elevation-derived terrain parameters for landslide detection and prediction. The smaller “frequency ratio” cluster exhibited a direct connection with “hazard assessment”, while the “wavelet transform” cluster was associated with “InSAR” suggesting early efforts to integrate advanced signal-processing and deformation-monitoring techniques into landslide studies (Fontes et al., 2025; Thirugnanam et al., 2022).



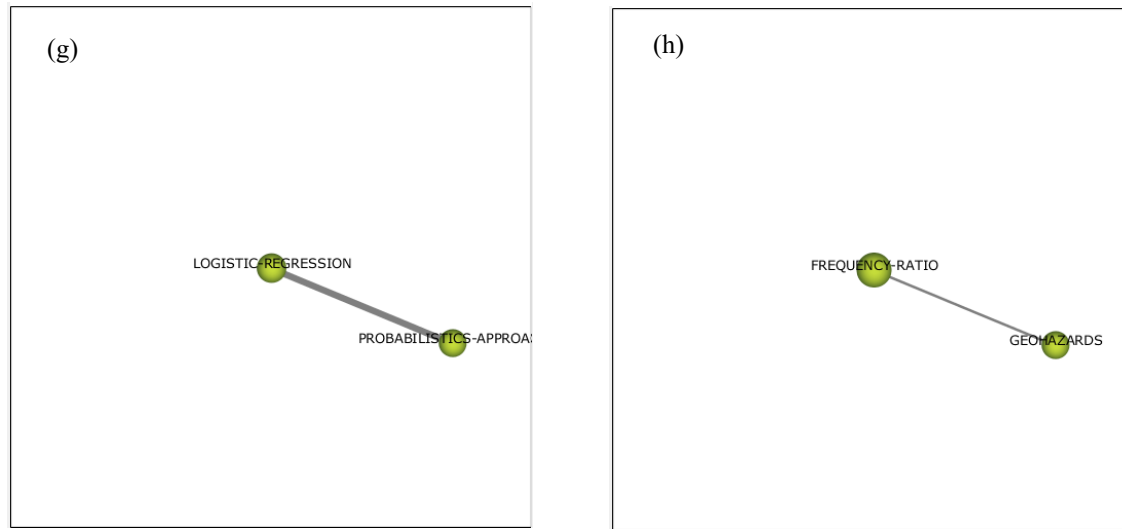
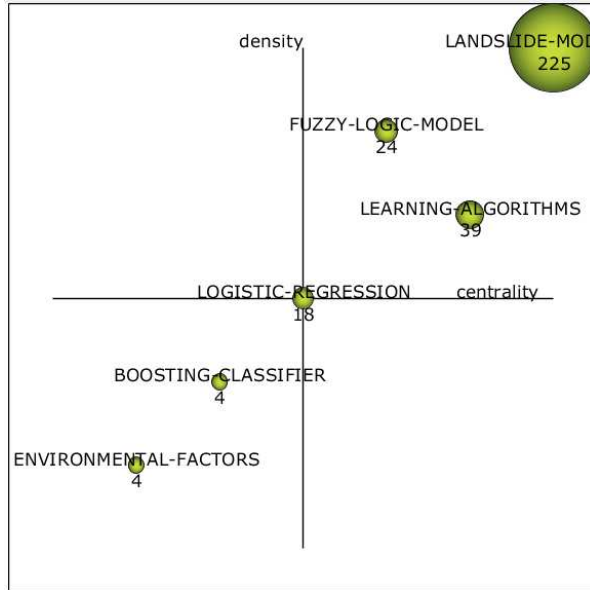


Figure 11. Cluster network map showing thematic relationships in LSM research during 2013–2018. Themes include (a) landslide modeling (b) decision support systems (c) databases (d) DEM (e) wavelet transforms (f) mathematical models (g) logistic regression (h) frequency ratio.

4.4 Thematic Evolution of LSM Research (2019-2022)

Figure 12 shows the strategic diagram for the 2019-2022 period, highlighting a clear shift toward advanced computational and data-driven approaches in landslide research. “Landslide modeling” remained the dominant theme, exhibiting the highest centrality (168.03) and density (73.97), confirming its continued role as the core research focus. Unlike the previous period transition, however, several ML-oriented themes emerged as major research directions. “Learning algorithms” demonstrated high centrality (119.56), reflecting the increasing integration of AI techniques into susceptibility assessment and hazard prediction. Similarly, “Fuzzy logic models” maintained a strong position within the thematic structure, indicating their continued relevance for handling uncertainty in geospatial decision-making. Additional themes such as “logic regression”, “boosting classifier”, and “environmental factors” reveal a growing emphasis on predictive

modeling, ensemble learning techniques, and the incorporation of environmental variables into landslide susceptibility frameworks (Sreelakshmi & Chandra, 2026).



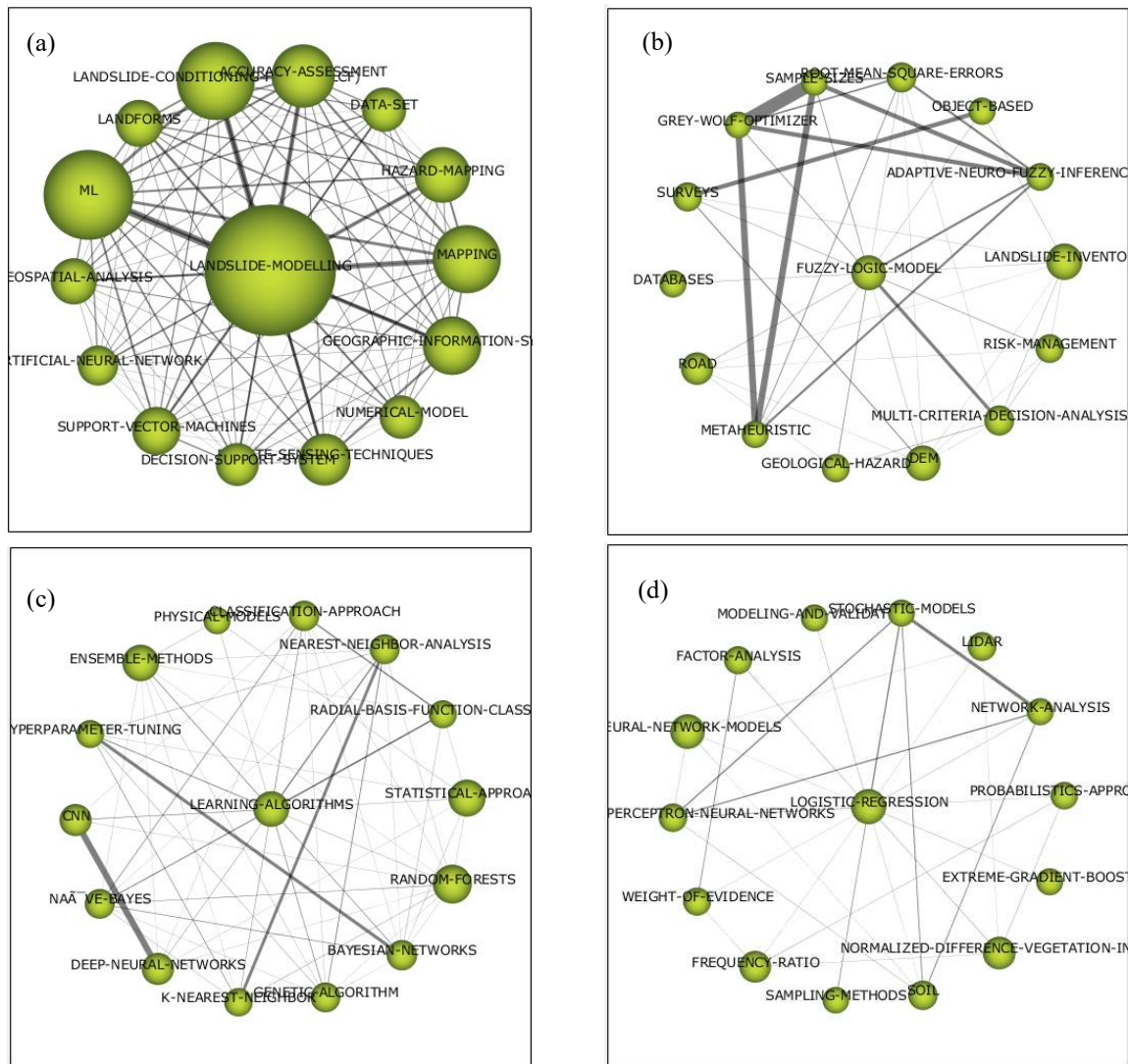
Theme	Centrality	Density
Landslide Modeling	168.03	73.97
Fuzzy Logic Model	88.91	32.04
Learning Algorithms	119.56	17.28
Logistic Regression	83.63	8.14
Boosting Classifier	55.29	7.9
Environmental Factors	22.19	3.63

Figure 12. Strategic diagram of LSM research themes during 2019–2022.

The cluster networks presented in Figure 13 provide further insight into the thematic composition of the field during this period. The “landslide modeling” cluster remained highly interconnected, linking with “ML”, “landslide conditioning factors”, “hazard mapping”, “mapping”, “GIS”, “remote sensing techniques”, “spatial analysis”, “SVM”, “ANN”, “numerical models”, “accuracy assessment”, and “geospatial information systems.” The breadth of these connections demonstrates the growing integration of geospatial technologies and AI into LSM (Akbari et al., 2026; Ali et al., 2022; Pradhan, 2010).

The “fuzzy logic models” cluster was associated with “fuzzy systems”, “decision-making approaches”, “DEMs”, “roads”, “heuristic methods”, “landslide inventories”, and “risk management applications”, reflecting the continued use of knowledge-driven and hybrid modeling techniques. The “learning algorithms” cluster was characterized by strong links to “CNNs”,

“recurrent neural networks (RNNs)”, “RF”, gradient boosting methods”, naïve Bayes classifiers”, “NN”, and “ensemble learning approaches”, illustrating the rapid expansion of ML applications in landslide prediction. Meanwhile, the “logistic regression” cluster remained closely connected with “environmental variables”, “LiDAR”, “statistical methods”, “frequency ratio”, “SVMs”, and “soil-related factors”, highlighting its role as a benchmark statistical approach for susceptibility assessment. Smaller clusters associated with “boosting classifier”, “environmental factors” further demonstrate increasing interest in ensemble-based prediction techniques and the influence of environmental controls on slope instability (Abdo, 2025; Joyce et al., 2014; Turner, 2018).



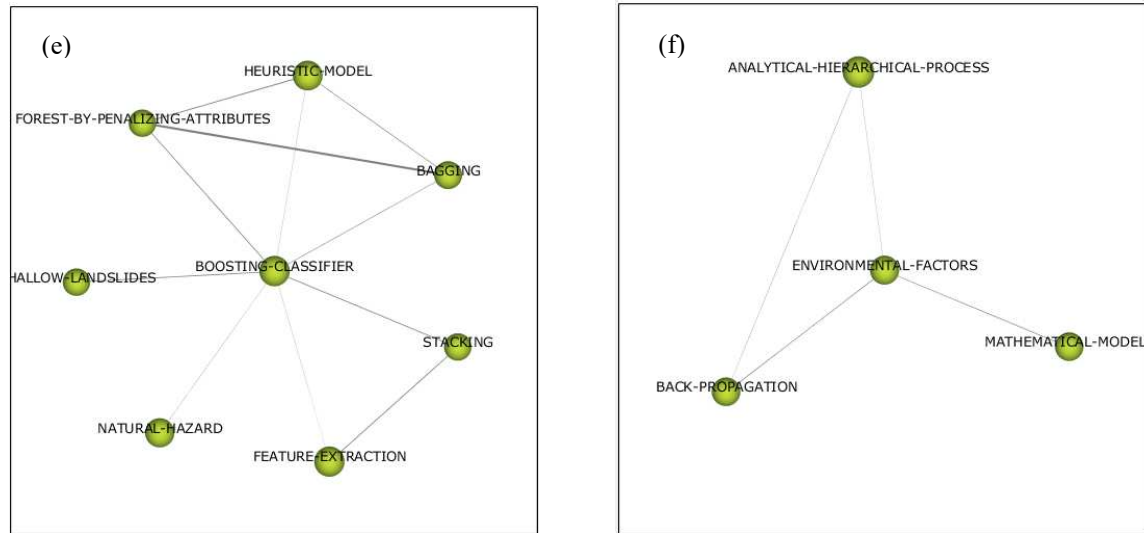


Figure 6. Cluster network maps showing thematic relationships in LSM research during 2019-2022. Themes include (a) landslide modeling (b) fuzzy logic model (c) learning algorithms (d) logistic regression (e) boosting classifier (f) environmental factors.

4.5 Thematic Evolution of LSM Research (2023-2026)

The strategic diagram for the 2023-2026 period Figure 14 reveals a mature and highly specialized research landscape dominated by AI-driven approaches. Although “landslide modeling” remained the principal motor theme, it exhibited lower centrality and density values than in previous periods, suggesting that the field has transitioned from methodological development toward model refinement and application. The most influential accompanying themes were “logistic regression” (centrality = 57.87), “learning algorithms” (centrality = 47.82), and “classification approaches” (centrality = 44.72), indicating the continued importance of predictive analytics and ML frameworks in LSM. Additional themes such as “road”, “back propagation”, “feature extraction”, “buffer zone”, and “multiple linear regression” illustrate increasing attention to transportation infrastructure vulnerability, deep learning architectures, feature engineering, and spatial contextual analysis. Collectively, the thematic structure reflects a shift toward explainable, data-intensive, and

infrastructure-oriented landslide prediction systems supported by advanced ML and geospatial analytics techniques (Agrawal et al., 2017; Alqadhi et al., 2024; Alshayeb et al., 2024; Y. Chen et al., 2021).

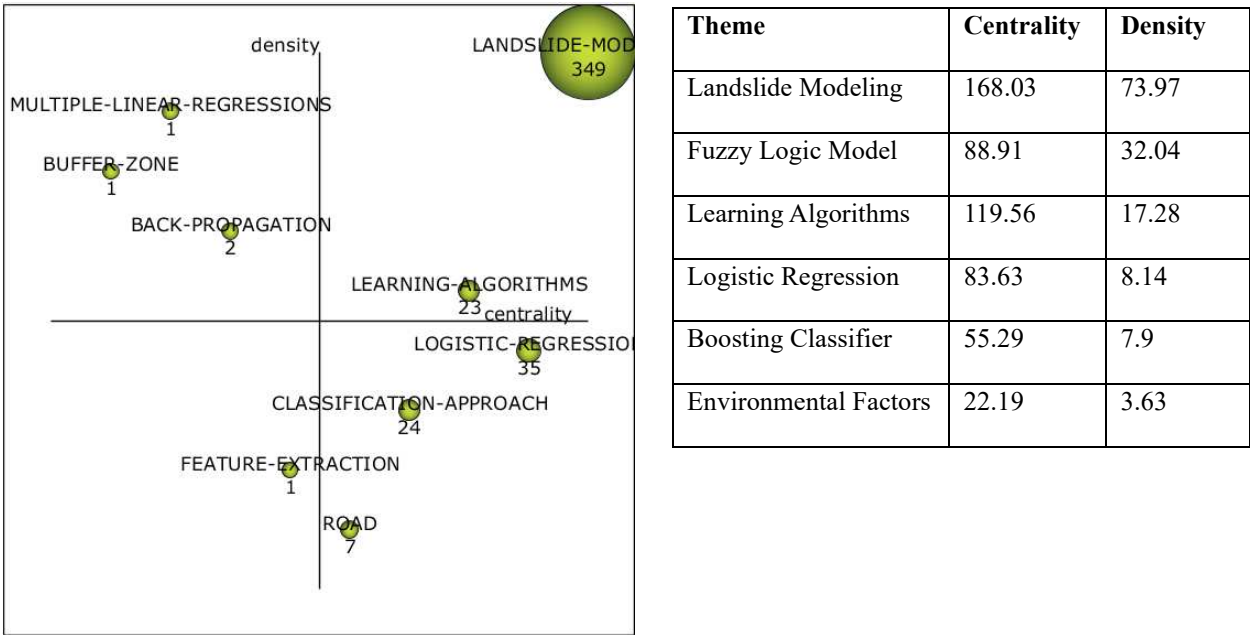
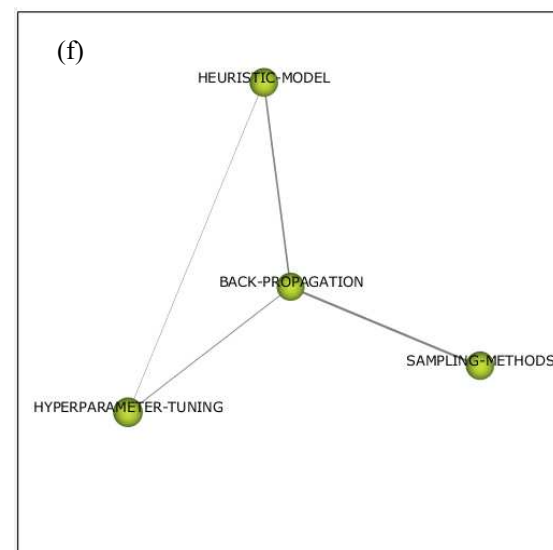
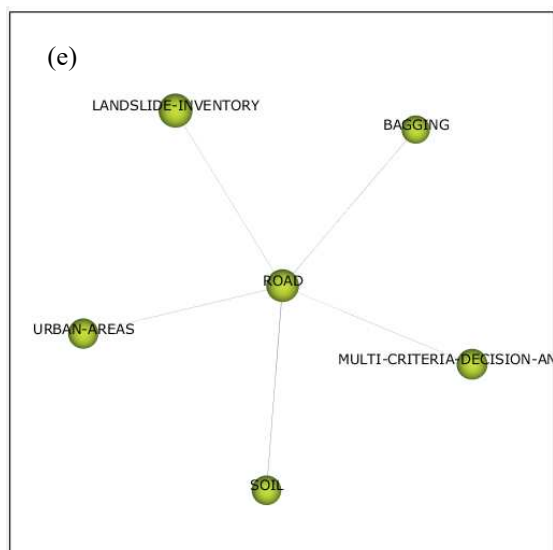
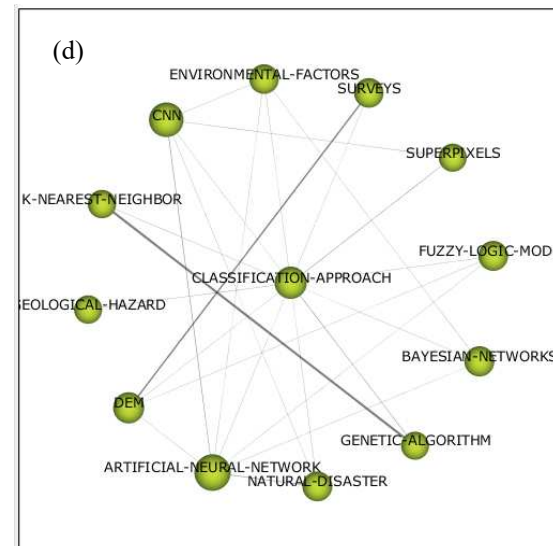
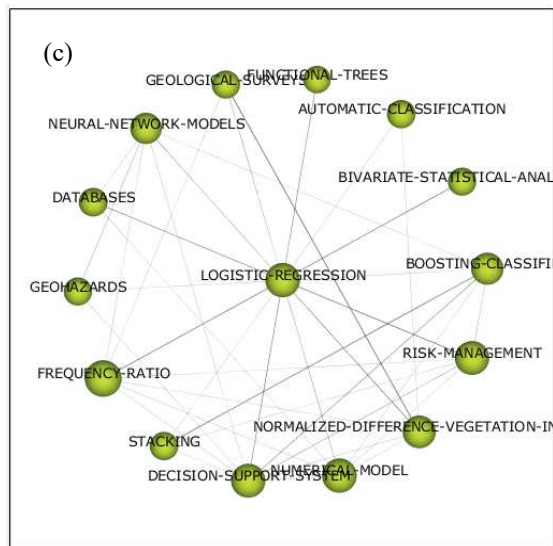
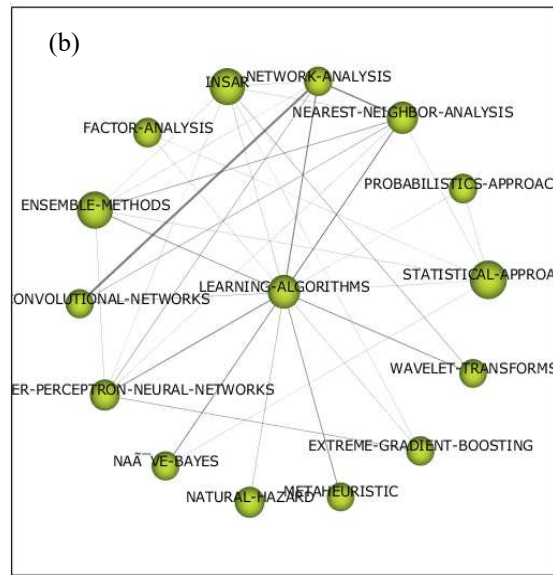
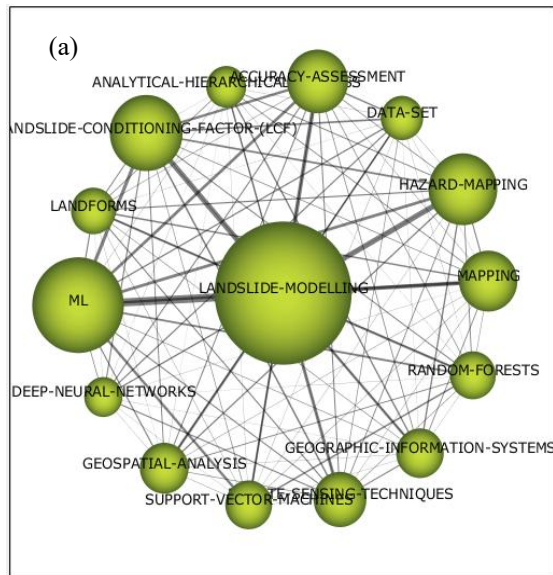


Figure 14. Strategic diagram of LSM research themes during 2023-2026.

The cluster networks shown in Figure 15 demonstrate the increasing sophistication of landslide research during the most recent period. The “landslide modeling” cluster remained the largest and most interconnected theme, linking strongly with “machine learning”, “ANNs”, SVMs”, “hazard mapping”, “remote sensing techniques”, “GIS”, “spatial analysis”, “landslide conditioning factors”, “DEMs”, “accuracy assessment”, and “geospatial information systems.” Compared with earlier periods, the network shows stronger integration between predictive algorithms and geospatial data sources, reflecting the emergence of GeoAI-based susceptibility mapping frameworks (Das et al., 2022; Mora et al., 2018; Naveen & Sahoo, 2024).

1 The “learning algorithms” cluster highlights the growing adoption of advanced ML methods,
2 including ensemble methods, hyper perceptron neural networks, XGBoost, naïve Bayes, CNs,
3 classification approaches, heuristic methods, nearest neighbor analysis, and InSAR-based
4 applications. The appearance of “InSAR” as a connected theme is particularly significant because
5 it demonstrates the growing integration of deformation monitoring technologies with predictive
6 modeling. Likewise, the “logistic regression” cluster remained an important methodological
7 benchmark, maintaining links with frequency ratio, hazard management, statistical approaches,
8 databases, automatic factor classification, boosting, and stacking models, confirming its continued
9 use for comparison and validation of more advanced models (Ahmad et al., 2024; Bravo-López et
10 al., 2025; Pradhan, 2010; Shang et al., 2024)

11 Emerging clusters further illustrate the diversification of contemporary landslide studies. The
12 “classification approaches” cluster incorporates themes such as ANN, CNN”, “environmental
13 factors”, “genetic algorithm”, “k-nearest neighbor (KNN)”, and tracking methods, emphasizing
14 automated classification and pattern recognition. The “road” cluster reflects increasing concern for
15 transportation infrastructure resilience, connecting road networks with soil conditions, landslide
16 inventories, decision-making frameworks, and hazard analysis. Smaller but strategically relevant
17 themes such as “back propagation”, “feature extraction”, “buffer zone”, and “multiple linear
18 regression” indicate growing interest in deep-learning optimization, feature selection strategies,
19 spatial influence modeling, and hybrid statistical-ML frameworks. These developments
20 collectively demonstrate the movement of the field toward operational prediction systems capable
21 of integrating remote sensing, geospatial analytics, and AI for hazard mitigation and infrastructure
22 risk management (Abdo, 2025, 2025; Ali et al., 2022; D & Manjula, 2025; Xia et al., 2024).



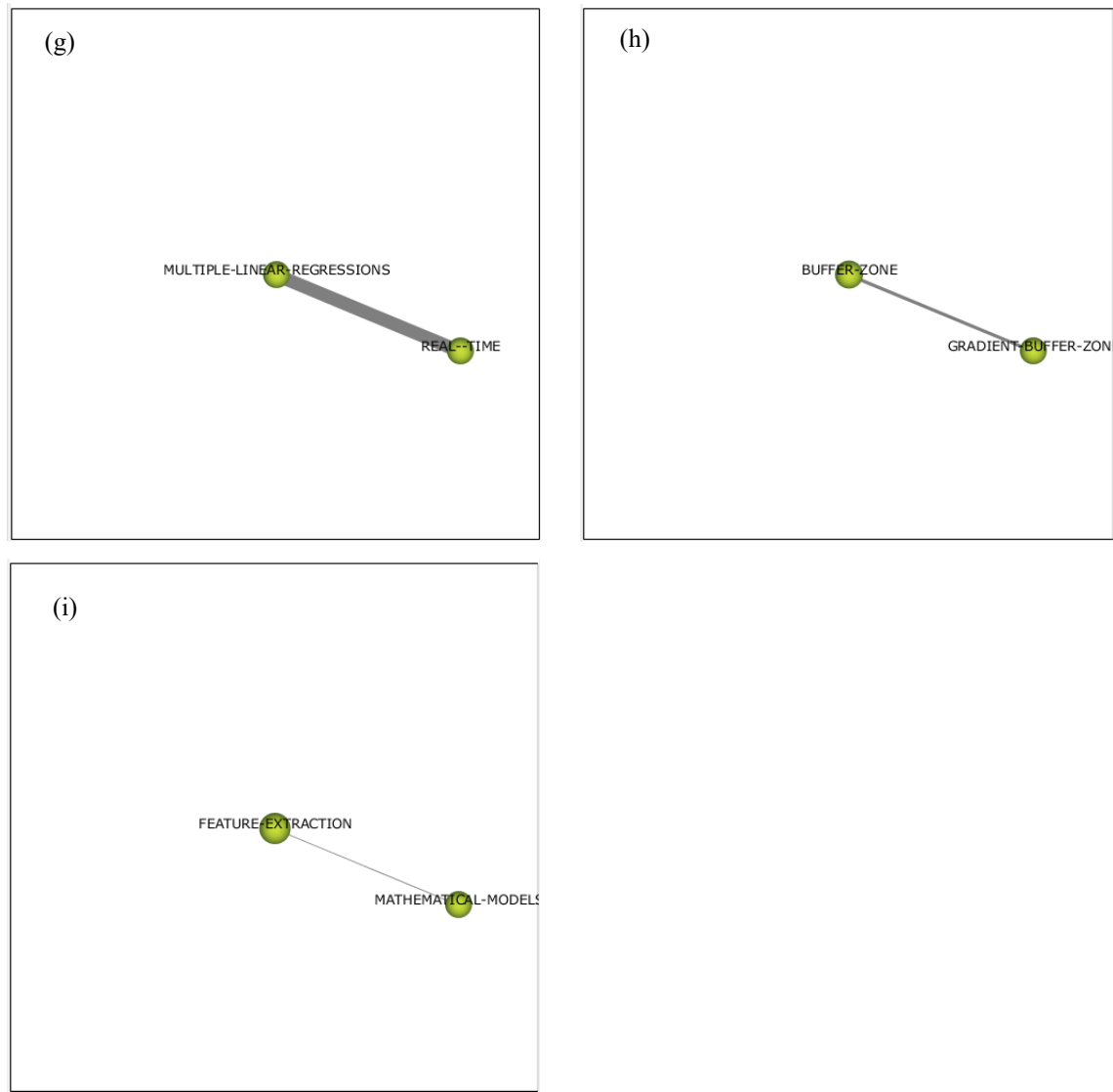


Figure 7. Cluster network maps showing thematic relationships in LSM research during 2023-2026. Themes include (a) landslide modeling (b) learning algorithms (c) logistic regression (d) classification approach (e) road (f) back propagation (g) multiple-linear regressions (h) buffer zone (i) feature extraction.

4.6 Thematic Evolution and Methodological Transition

The thematic evolution map Figure 16 illustrates the progression of landslide susceptibility research from remote sensing-based investigations during 2006-2012 to increasingly sophisticated predictive modeling frameworks in later periods. While remote sensing techniques dominated the

1 earliest stage, landslide modeling emerged as the central research theme during 2013-2018 and
2 remained the dominant focus through 2023-2026. The evolution pathways indicate strong
3 continuity among periods, suggesting that advances in susceptibility assessment were driven by
4 gradual integration of geospatial technologies, statistical methods, and machine learning
5 approaches rather than abrupt methodological shifts (Abbas et al., 2024; Khadka et al., 2025;
6 Naveen & Sahoo, 2024).

7 The overlapping map presented earlier in Figure 7 further confirms the expansion of the field, with
8 the number of identified themes increasing from 31 in period 1 to 84 in period 4. This growth
9 reflects the incorporation of new analytical techniques while maintaining a stable foundation of
10 core research concepts. Across the four periods, the field evolved from descriptive mapping and
11 inventory-based studies toward data-driven susceptibility modeling supported by machine
12 learning, deep learning, LiDAR, InSAR, and advanced geospatial analytics. These developments
13 highlight an emerging research frontier centered on GeoAI-enabled landslide prediction and
14 decision-support systems for hazard mitigation and infrastructure resilience (L. Chen et al., 2023;
15 Hosseini et al., 2023; Mora et al., 2018).

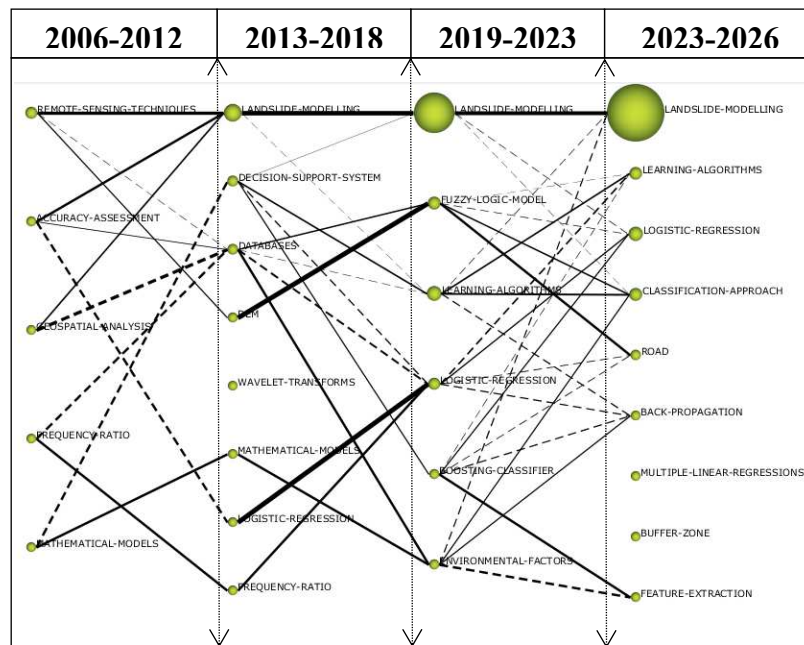


Figure 8. Thematic evolution map showing the development and continuity of research themes from 2006-2026.

5. Collaboration Network Mapping Based on VOSviewer

To complement the thematic evolution analysis, collaboration network mapping was performed using VOSviewer. The software was used to visualize co-authorship structures, country collaborations, institutional linkages, and keyword co-occurrence networks within the global LSM research landscape. The collaboration analysis provided additional insight into the geographic distribution of scientific productivity, institutional partnerships, and emerging research communities contributing to the advancement of LSM research.

5.1 Author Collaboration Network

The author collaboration network reveals a highly interconnected research community dominated by several influential scholars who serve as central nodes within the global LSM knowledge network. As shown in Figure 17, authors such as Chen Wei, Xu Chong, Pradhan Biswajeet, Binh

Thai Pham, Xu Qiang, Hong Haoyuan, Dieu Tien Bui, and Yin Kunlong occupy prominent positions within the collaboration structure, indicating substantial research productivity and extensive co-authorship relationships. Several clustered groups are evident, reflecting established research teams and long-term collaborative partnerships that contribute significantly to methodological advancements in landslide susceptibility assessment.

The network also demonstrates strong interconnections among Asian, European, and Middle Eastern researchers, highlighting the increasingly international nature of LSM research. The presence of multiple densely connected clusters suggests that scientific progress in the field is being driven by collaborative efforts rather than isolated contributions, facilitating the exchange of expertise in GIS, remote sensing, ML, and landslide hazard assessment.

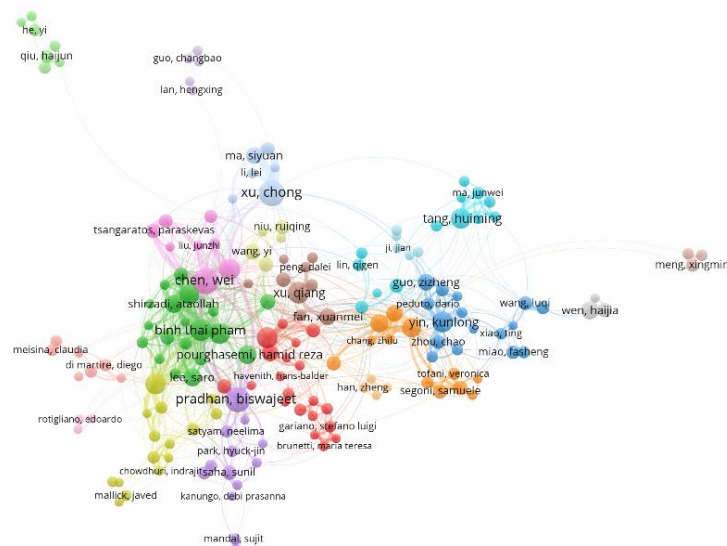
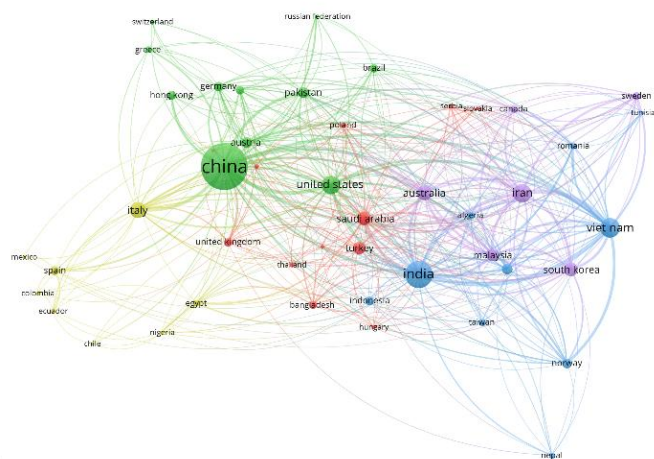


Figure 17. Author collaboration network in LSM research.

5.2 Country Collaboration Network

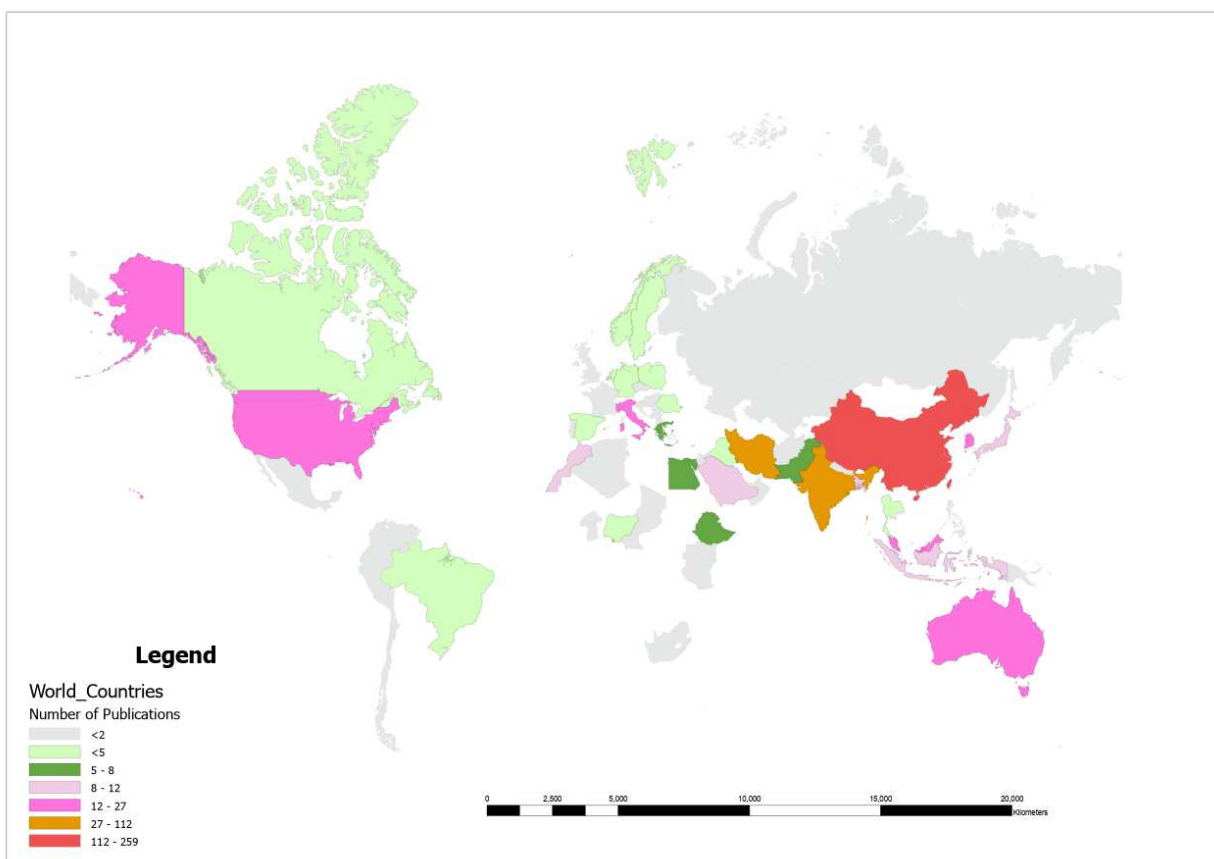
The country collaboration network illustrates the global distribution of LSM research and highlights the countries serving as major international research hubs. As shown in Figure 18, China, India, Vietnam, United States, and Iran occupy central positions within the network and exhibit extensive collaborative links with numerous countries. China forms the largest collaboration node, reflecting its dominant contribution to LSM publications and its extensive partnerships across Europe, Asia, and North America.

Several regional collaboration clusters are also evident. India maintains strong collaborative relationships with Vietnam, Malaysia, South Korea, and other Asian countries, while Iran serves as an important bridge linking researchers across the middle East, Asia, and Europe. European countries, including Italy, Germany, Austria, and the United Kingdom, form an interconnected network that contributes substantially to international research activities. These findings demonstrate that contemporary LSM research is increasingly characterized by multinational collaborations aimed at addressing landslide hazards across diverse geographic and environmental settings.



VOSviewer

(a)



(b)

Figure 9. (a) Country collaboration network in LSM research generated using VOSviewer (b) global research publications across countries generated using ArcGIS Pro.

5.3 Institution Collaboration Network

The institution collaboration network further demonstrates the concentration of research activities within several leading academic and governmental organizations. As illustrated in Figure 19, the China University of Geosciences, Chinese Academy of Sciences, Ministry of Natural Resources (China), and China Geological Survey constitute the most influential institutional cluster within the network. These organizations maintain extensive collaborative links with universities and research institutes worldwide, underscoring China's leading role in LSM research.

Strong institutional collaborations are also observed among European organizations, including the University of Padua, University of Florence, University of Twente, and Consiglio Nazionale delle Ricerche, as well as Asian institutions such as Duy Tan University, Ton Duc Thang University, Sejong University, and the Indian Institute of Technology. The dense connectivity among these organizations suggests that institutional partnerships play a critical role in advancing methodological innovation, data sharing, and interdisciplinary research within the LSM community.

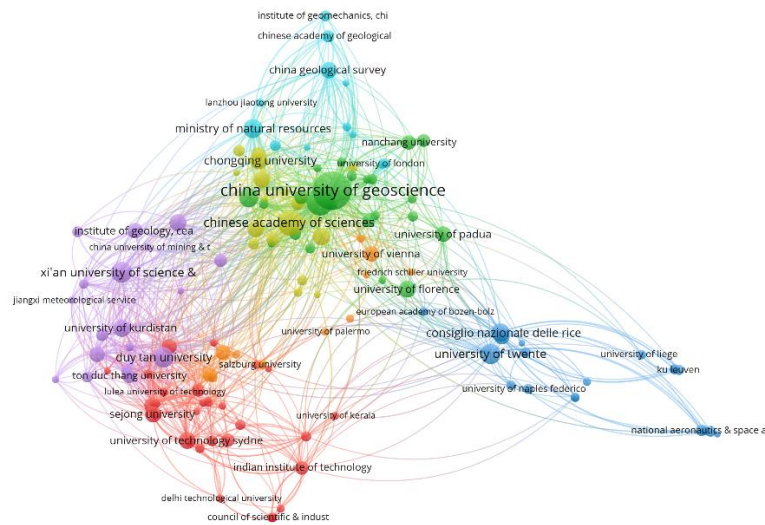


Figure 19. Institutional collaboration network in LSM research.

6. Discussion and Future Research Directions

The scientometric and collaboration analyses collectively reveal a research field that has undergone substantial methodological transformation over the last two decades. The thematic evolution analysis demonstrated progression from remote sensing and statistical susceptibility assessment approaches toward increasingly advanced ML, AI-driven frameworks. Throughout this evolution, landslide modeling remained the dominant research theme, serving as the primary knowledge stream connecting early susceptibility studies with recent advances in predictive analytics. The persistence of this theme across all periods highlights its central role in the development of LSM research and reflects continued efforts to improve prediction accuracy, model robustness, and decision-support capabilities.

The increasing prominence of ML, learning algorithms, classification approaches, neural networks, and ensemble techniques indicate that contemporary LSM research is transitioning toward data-intensive predictive frameworks. These developments have been supported by parallel

1 advances in geospatial technologies, including LiDAR, InSAR, high-resolution DEMs, and multi-
2 source remote sensing datasets. The integration of these technologies has improved the
3 representation of terrain characteristics and environmental controls while enabling more detailed
4 analyses of landslide-prone environments. However, despite notable improvements in predictive
5 performance, challenges remain regarding model transferability, uncertainty quantification, and
6 the interpretability of complex ML models (C. Chen & Fan, 2023; Lu et al., 2024; Ye et al., 2025).

7 The collaboration networks further demonstrate that LSM research has become increasingly
8 international and interdisciplinary. Strong collaborative relationships among researchers,
9 institutions and countries have facilitated methodological innovation and accelerated the adoption
10 of emerging technologies. Nevertheless, research activities remain concentrated within a limited
11 number of countries and institutions, particularly in Asia and Europe. Expanding collaboration
12 with underrepresented regions may improve the geographic diversity of landslide inventories and
13 contribute to the development of more transferable susceptibility models capable of addressing
14 diverse environmental and geological settings.

15 Several research directions emerge from the findings of this review. First, future studies should
16 emphasize the integration of multi-source geospatial datasets, including LiDAR, InSAR, UAV
17 observations, and satellite-derived environmental and hydrographic variables, within unified
18 susceptibility modeling frameworks. Second, greater attention should be devoted to explainable
19 artificial intelligence and uncertainty analysis to improve model transparency and facilitate
20 practical adoption by decision-makers. Third, the growing appearance transportation and
21 infrastructure-related themes suggest increasing opportunities to develop susceptibility assessment
22 frameworks specifically tailored for highway corridors, critical infrastructure, and resilience
23 planning. Additionally, advances in GeoAI, digital twins, and real-time monitoring systems may

support the development of next-generation landslide prediction platforms capable of providing dynamic and operational hazard information.

7. Limitations

This research notes some limitations. First the analysis was restricted to publications indexed in Scopus, Web of Science, IEEE Xplore, and Springer, and therefore may not capture all relevant studies available in other databases or gray literature sources. Second, although extensive screening and duplicate removal procedures were implemented, the results remain dependent on the selected search terms, inclusion criteria, and database coverage. Third, the scientometric findings are inherently influenced by the characteristics of the retrieved dataset and the analytical parameters used in SciMAT and VOSviewer. Variations in keyword standardization, thematic clustering, and citation patterns may affect the resulting thematic structures and network relationships. Finally, the literature search was concluded on May 8, 2026; consequently, studies published after this date were not included in the analysis. Given the rapid growth of ML and GeoAI applications in landslide research, emerging developments beyond the study period may further influence future thematic and methodology trends.

8. Conclusions

This study presented a comprehensive bibliometric and scientometric review of landslide susceptibility mapping research published between 2006 and May 2026 using a combination of PRISMA-based literature screening, SciMAT scientific mapping, and VOSviewer collaboration analysis. A total of 795 publications were analyzed to examine publication trends, thematic evolution, methodological development, and global collaboration patterns within the field. The findings reveal sustained growth in LSM research over the past two decades, accompanied by increasing thematic diversification and methodological sophistication. Thematic evolution

analysis identified remote sensing techniques as the dominant theme during the earliest period, followed by the emergence of landslide modeling as the central and most persistent research theme across subsequent periods. The field evolved from primarily statistical and GIS-based susceptibility assessment approaches toward machine learning, deep learning, and hybrid intelligence-based frameworks supported by advanced geospatial technologies.

Collaboration network analysis demonstrated strong contributions from researchers, institutions, and countries in ASIA, Europe, and North America, with China emerging as the leading contributor to LSM research. Increasing international collaboration has facilitated methodological innovation and accelerated the adoption of advanced analytical techniques across the field. The results indicate that future developments in LSM will likely be driven by the integration of GeoAI, multi-source remote sensing datasets, explainable ML, and infrastructure-focused decision-support systems. By providing a comprehensive assessment of research trends, thematic evolution, and collaborative structures, this study contributes a valuable reference for researchers and practitioners seeking to advance landslide hazard assessment and risk mitigation strategies.

CRedit authorship contribution statement

Micheal Oketunde Okegbola: Study conception, design and methodology, data collection/literature search. **Micheal Oketunde Okegbola, Oludare Owolabi:** Formal analysis and interpretation. **All authors:** Writing - original draft manuscript preparation, writing - review and editing. **Oludare Owolabi, Zhuping Sheng, Yi Liu:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

1 **Achnowledgements**

2 Not applicable.

3 **Funding sources**

4 Not applicable.

5 **Data availability**

6 The datasets used in this study are from the public domain online, and all other data analyzed in
7 this study are included in this publication. Further data is available based on reasonable requests
8 from the corresponding author.

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