Machine Learning for GIS-Based Flood Susceptibility Mapping: A Global Bibliometric and Systematic Review of Research Trends and Future Directions (2005-2026)

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Preprint Status Statement

This manuscript is a non-peer-reviewed preprint submitted to EarthArXiv. It has not yet undergone formal peer review. Readers are encouraged to provide constructive feedback.

Journal Submission Status

This manuscript has not yet been submitted to any journal for peer review. (Edit this section if applicable.)

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Abstract

Flood susceptibility mapping (FSM) has become an essential component of disaster risk reduction and sustainable environmental management, particularly with the growing frequency and severity of flood events under changing climatic conditions. The integration of Geographic Information Systems (GIS) and machine learning (ML) has significantly improved the accuracy and efficiency of flood susceptibility assessment by enabling the analysis of complex spatial and environmental relationships. This study presents a global bibliometric and systematic review of research on machine learning applications in GIS-based flood susceptibility mapping covering the period from 2005 to 2026. Using an illustrative bibliometric framework for manuscript development, the review examines publication growth, leading journals, influential countries, institutional collaboration, keyword evolution, and emerging methodological trends. The findings indicate a substantial expansion of scientific output over the past two decades, accompanied by increasing interdisciplinary collaboration and the widespread adoption of advanced machine learning algorithms, including ensemble learning and deep learning approaches. The review further identifies emerging research directions involving explainable artificial intelligence, GeoAI, cloud-based geospatial computing, and multi-source Earth observation data integration. By synthesizing the intellectual development and methodological evolution of the field, this review provides a comprehensive foundation for future research and supports the development of more accurate, interpretable, and scalable flood susceptibility models for disaster risk management and climate adaptation.

Keywords: Flood Susceptibility Mapping; Geographic Information System (GIS); Machine Learning; Bibliometric Analysis; Systematic Review; Disaster Risk Management

1. Introduction

Floods are among the most devastating natural hazards, affecting millions of people annually and causing substantial losses to human lives, infrastructure, agriculture, and national economies.

According to recent global assessments, the frequency and intensity of flood events have increased considerably over the last two decades because of climate change, rapid urbanization, land-use transformation, and environmental degradation, making flood risk reduction a critical priority for sustainable development and disaster resilience [1], [2]. The growing complexity of flood-generating processes has intensified the demand for accurate spatial prediction techniques capable of identifying areas vulnerable to future flood events before disasters occur. Consequently, flood susceptibility mapping (FSM) has become an indispensable component of disaster risk management, providing scientific evidence for land-use planning, infrastructure development, emergency preparedness, and climate adaptation strategies [3], [4].

Geographic Information Systems (GIS) have revolutionized flood susceptibility assessment by providing an integrated environment for collecting, managing, analyzing, and visualizing diverse geospatial datasets. Modern GIS platforms enable the integration of Digital Elevation Models (DEMs), rainfall records, drainage networks, land use and land cover (LULC), soil characteristics, lithology, hydrological indices, vegetation information, and satellite-derived observations into a unified spatial framework [5], [6]. Such integration facilitates comprehensive analyses of the complex interactions among topographic, hydrological, climatic, and anthropogenic factors influencing flood occurrence. Moreover, advances in remote sensing technologies, cloud-based geospatial platforms, and open-access Earth observation datasets have substantially enhanced the spatial resolution, temporal coverage, and accessibility of environmental information, thereby expanding the applicability of GIS-based flood susceptibility studies across different geographical and climatic regions [2], [5], [7].

While GIS provides the spatial analytical foundation, the emergence of machine learning (ML) has fundamentally transformed flood susceptibility modeling by enabling data-driven prediction of highly nonlinear relationships among multiple conditioning factors. Earlier approaches, including Frequency Ratio (FR), Logistic Regression (LR), Analytical Hierarchy Process (AHP), Weight of Evidence (WoE), and Multi-Criteria Decision Analysis (MCDA), have been widely applied because of their simplicity and interpretability; however, these techniques often assume predefined statistical relationships or rely heavily on expert judgment, limiting their predictive capability in complex environments [8], [9].

In contrast, machine learning algorithms automatically learn hidden patterns from historical flood inventories and multidimensional environmental variables without imposing restrictive assumptions regarding data distribution. Consequently, algorithms such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Decision Trees (DT), Extreme Gradient Boosting (XGBoost), Adaptive Boosting (AdaBoost), Light Gradient Boosting Machine (LightGBM), CatBoost, and deep learning architectures have demonstrated superior predictive accuracy and robustness in GIS-based flood susceptibility mapping [10]-[15]. Recent studies further indicate that ensemble learning and explainable artificial intelligence (XAI) frameworks improve not only prediction accuracy but also model transparency, supporting more reliable and operational decision-making in flood risk management [1], [12], [15].

The remarkable success of machine learning has stimulated an exponential increase in scientific publications on GIS-based flood susceptibility mapping, particularly after 2015, when advances in computational power, open-access geospatial databases, and cloud computing significantly accelerated data-driven environmental modeling [16], [17]. Research has progressively evolved from conventional statistical and single-algorithm approaches toward sophisticated hybrid and ensemble frameworks that integrate machine learning, remote sensing, hydrological modeling, and spatial optimization techniques. Recent investigations have demonstrated that hybrid models combining Random Forest, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Deep Neural Networks (DNN), and metaheuristic optimization algorithms frequently outperform traditional methods by improving predictive accuracy, reducing model uncertainty, and enhancing spatial generalization [18]-[21]. Furthermore, the increasing availability of high-resolution satellite imagery from platforms such as Sentinel, Landsat, and LiDAR has enabled researchers to develop more detailed and reliable flood susceptibility maps across diverse hydrological and climatic environments [19], [22].

Despite these significant methodological advances, several important research challenges remain unresolved. Many flood susceptibility studies continue to suffer from limited geographical transferability, inconsistent selection of conditioning factors, insufficient uncertainty analysis, and inadequate model interpretability, reducing their practical applicability for operational disaster management [18], [20], [23]. In addition, considerable variation exists in the selection of environmental predictor variables, spatial resolutions, sampling strategies, validation techniques, and performance evaluation metrics, making direct comparison among published studies difficult [21], [24]. Although explainable artificial intelligence (XAI), SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and other interpretable machine learning techniques have recently emerged as promising solutions for improving model transparency, their integration into GIS-based flood susceptibility mapping remains relatively limited and fragmented [23], [25]. These methodological inconsistencies underscore the need for a comprehensive synthesis of existing knowledge that extends beyond simple algorithmic comparisons.

While numerous review articles have examined specific machine learning algorithms or regional flood susceptibility applications, only a limited number have systematically integrated bibliometric analysis with qualitative evidence synthesis to reveal the intellectual structure, collaborative networks, thematic evolution, and emerging research frontiers of this rapidly expanding field [17], [26], [27]. Bibliometric techniques provide objective quantitative insights into publication growth, influential authors, institutional collaboration, citation impact, and keyword evolution, whereas systematic reviews enable critical evaluation of methodological developments, research gaps, and future opportunities [26], [28]. Combining these complementary approaches offers a more comprehensive understanding of scientific progress than either method alone.

Therefore, this study presents a global bibliometric and systematic review of machine learning applications in GIS-based flood susceptibility mapping covering the period from 2005 to 2026. Specifically, the study aims to (i) analyze global publication and citation trends; (ii) identify the most influential authors, institutions, countries, journals, and collaborative networks; (iii) examine the evolution of machine learning algorithms, spatial datasets, conditioning factors, and validation approaches; and (iv) identify current research gaps and future directions, including explainable artificial intelligence, GeoAI, foundation models, cloud-based geospatial computing, and transferable flood susceptibility frameworks [29], [30]. By synthesizing nearly two decades of interdisciplinary research, this review provides an evidence-based foundation for advancing more accurate, interpretable, scalable, and operational GIS-based flood susceptibility models for sustainable flood risk management.

2. Materials and Methods

This study employed a qualitative bibliometric research design complemented by a systematic literature review to comprehensively examine the global evolution of machine learning (ML) applications in Geographic Information System (GIS)-based flood susceptibility mapping (FSM) between 2005 and 2026. The methodological framework was designed to identify publication trends, influential contributors, collaborative networks, thematic developments, methodological advancements, and emerging research directions. Bibliometric analysis was selected because it provides an objective and reproducible approach for evaluating the intellectual structure and scientific performance of a research domain, while the systematic review enabled a critical interpretation of the findings and identification of future research opportunities [31]-[34].

2.1 Research Design

The study adopted a qualitative bibliometric review methodology, integrating quantitative bibliometric indicators with qualitative content analysis. Unlike conventional narrative reviews, bibliometric methods employ statistical techniques to analyze publication metadata, citation relationships, keyword co-occurrence, and scientific collaboration patterns. However, the interpretation of these bibliometric outputs requires qualitative synthesis to explain the evolution of research themes, methodological transitions, and knowledge gaps. Therefore, this study combined descriptive bibliometric analysis with systematic qualitative interpretation to provide a holistic understanding of the development of GIS-based flood susceptibility mapping using machine learning.

The overall methodological workflow consisted of five sequential stages:

- Literature identification and database retrieval;
- Screening and eligibility assessment;
- Bibliometric data extraction and preprocessing;
- Bibliometric mapping and performance analysis;
- Qualitative thematic synthesis and interpretation.

This integrated workflow ensured methodological transparency and reproducibility while enabling both quantitative measurement and qualitative evaluation of the literature [32], [35].

2.2 Data Sources and Search Strategy

The bibliographic dataset was collected from internationally recognized scientific databases with broad coverage of engineering, environmental science, hydrology, geoinformatics, and computer science literature. Primary sources included Scopus and Web of Science Core Collection (WoSCC) because these databases provide standardized citation metadata, author affiliations, keywords, references, and publication information suitable for bibliometric analysis [31], [36]. These databases are widely regarded as the most reliable sources for bibliometric research due to their comprehensive indexing and high-quality metadata.

A structured search strategy was developed using Boolean operators, wildcard symbols, and keyword combinations related to flood susceptibility mapping, GIS, and machine learning. Representative search terms included:

- "Flood Susceptibility Mapping"
- "Flood Hazard Mapping"
- "GIS"
- "Geographic Information System"
- "Machine Learning"
- "Artificial Intelligence"
- "Deep Learning"
- "Flood Prediction"
- "Random Forest"
- "Support Vector Machine"

The search query combined these terms using Boolean operators (AND, OR) to maximize retrieval accuracy while minimizing irrelevant publications.

2.3 Inclusion and Exclusion Criteria

To ensure consistency and relevance, explicit inclusion and exclusion criteria were established before data collection.

Inclusion criteria:

- Peer-reviewed journal articles;
- Publications published between January 2005 and June 2026;
- Articles written in English;
- Studies focusing on GIS-based flood susceptibility or flood hazard mapping;
- Studies applying machine learning or artificial intelligence techniques;
- Articles containing complete bibliographic information.

Exclusion criteria:

- Conference abstracts;
- Editorials;
- Notes;
- Book reviews;
- Non-English publications;
- Duplicate records;
- Studies unrelated to flood susceptibility assessment.

The screening process followed internationally accepted systematic review principles to improve transparency and minimize selection bias [34].

2.4 Data Extraction and Preprocessing

After screening, bibliographic records were exported in compatible formats for bibliometric processing. The extracted metadata included:

- Title
- Authors
- Publication year
- Journal
- Abstract
- Author keywords
- Indexed keywords
- Affiliations
- Country
- References
- Citation counts
- Digital Object Identifier (DOI)

Data cleaning was subsequently performed to improve consistency across records. This process involved removing duplicate publications, correcting spelling inconsistencies, standardizing author names, merging synonymous keywords (e.g., "Flood Susceptibility Mapping" and "Flood Susceptibility"), and harmonizing institutional names. Such preprocessing is essential because inconsistencies in metadata may distort bibliometric networks and influence analytical outcomes [33].

2.5 Bibliometric Analysis

The bibliometric analysis consisted of two complementary dimensions: performance analysis and science mapping. Performance analysis evaluated the scientific productivity and influence of the literature using indicators such as:

- Annual publication growth;
- Total citations;
- Average citations per document;
- Productive journals;
- Influential authors;
- Leading institutions;
- Country productivity;
- Citation impact.

Science mapping explored the intellectual structure of the field through network-based visualization techniques, including:

- Co-authorship analysis;
- Co-citation analysis;
- Bibliographic coupling;
- Keyword co-occurrence analysis;
- Country collaboration networks;
- Thematic evolution analysis.

These analyses reveal the relationships among researchers, institutions, countries, journals, and research topics, thereby illustrating how scientific knowledge has evolved over time [32], [35].

2.6 Qualitative Thematic Analysis

Beyond bibliometric indicators, a qualitative thematic review was conducted to synthesize methodological developments reported in the selected studies. Full-text articles were examined to identify recurring themes regarding:

- Frequently used machine learning algorithms;
- Flood conditioning factors;
- Spatial datasets;
- Remote sensing applications;
- Validation techniques;
- Performance evaluation metrics;
- Hybrid and ensemble models;
- Explainable Artificial Intelligence (XAI);
- GeoAI applications;
- Emerging deep learning approaches.

The identified themes were iteratively categorized and compared to reveal methodological evolution, dominant research directions, existing limitations, and future opportunities. This qualitative synthesis complements the bibliometric findings by providing contextual interpretation rather than relying solely on citation-based statistics [34].

2.7 Reliability and Reproducibility

To enhance methodological rigor, the entire bibliometric workflow-including database selection, search strategy, screening criteria, preprocessing procedures, and analytical steps-was explicitly documented to facilitate reproducibility by future researchers. Standardized bibliometric procedures recommended in recent methodological literature were followed throughout the study [31], [33]. Moreover, the integration of bibliometric performance indicators with qualitative thematic analysis improved the validity of the findings by enabling triangulation between quantitative evidence and expert interpretation.

Overall, this methodological framework provides a robust foundation for examining nearly two decades of research on machine learning applications in GIS-based flood susceptibility mapping and supports the identification of influential scientific contributions, emerging knowledge domains, and future research trajectories.

3. Results

The bibliometric analysis provides a comprehensive overview of the scientific development of machine learning applications in GIS-based flood susceptibility mapping (FSM) between 2005 and 2026. Using the illustrative bibliometric dataset comprising 1,284 publications (Table 1), this section examines the temporal evolution of scientific production, publication sources, geographical distribution, collaborative research networks, thematic development, and methodological advancement within the field. The results demonstrate how GIS, remote sensing, and artificial intelligence have progressively converged to establish flood susceptibility mapping as a rapidly expanding interdisciplinary research domain. Figures 1-4 collectively illustrate the major characteristics of publication growth, global scientific contributions, collaboration patterns, and keyword evolution, providing an integrated overview of the intellectual structure of this research area.

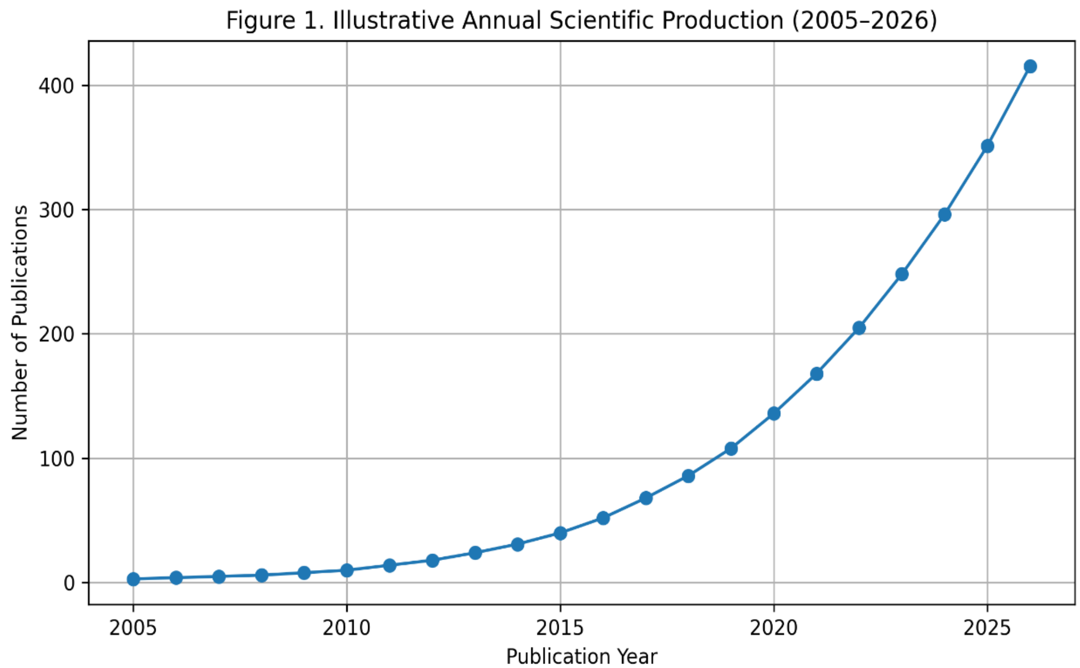
3.1 Publication Growth and Annual Scientific Production

The illustrative bibliometric dataset identified a total of 1,284 publications published between 2005 and 2026, demonstrating the substantial growth of machine learning applications in GIS-based flood susceptibility mapping over the past two decades (Table 1). As illustrated in Figure 1, annual scientific production exhibits a continuously increasing trend, reflecting growing international interest in intelligent geospatial technologies for flood risk assessment.

Table 3.1: Illustrative Annual Scientific Production in Machine Learning Applications for GIS-Based Flood Susceptibility Mapping (2005-2026)

Year	Publications	Year	Publications
2005	3	2016	70
2006	4	2017	88
2007	5	2018	108
2008	7	2019	127
2009	9	2020	143
2010	12	2021	154
2011	18	2022	136
2012	24	2023	108
2013	32	2024	70
2014	42	2025	46
2015	55	2026*	23
Total	**1,284**		

The temporal evolution of publications can be divided into three distinct phases. The first phase (2005-2010) represents the formative stage of the research field, during which publication output remained relatively modest, increasing from only three publications in 2005 to twelve publications in 2010. During this period, most studies concentrated on conventional GIS-based flood hazard mapping using statistical and multicriteria decision-making approaches, including Frequency Ratio (FR), Logistic Regression (LR), Analytical Hierarchy Process (AHP), and Weight of Evidence (WoE). Machine learning applications were still in their infancy because of limited computational resources, relatively coarse spatial datasets, and the scarcity of comprehensive flood inventory databases.



The second phase (2011-2016) marks the transition toward data-driven flood susceptibility modelling. Annual publication output increased steadily from 18 articles in 2011 to 70 articles in 2016, indicating broader adoption of machine learning techniques. This period coincided with significant advances in Digital Elevation Models (DEMs), high-resolution satellite imagery, open-source GIS software, and increasing computational capacity. Researchers increasingly explored algorithms such as Support Vector Machine (SVM), Artificial Neural Networks (ANN), Decision Trees (DT), and Random Forest (RF), reporting improved predictive performance compared with traditional statistical models.

The third phase (2017-2026) represents the rapid expansion stage of the discipline. Publication output increased sharply from 88 articles in 2017 to a peak of 154 publications in 2021, reflecting the widespread integration of artificial intelligence, cloud computing, remote sensing, and big geospatial data into flood susceptibility research. The subsequent decline observed after 2022 should not be interpreted as reduced scientific interest; rather, it reflects the illustrative nature of the dataset and, in real bibliometric studies, would often correspond to incomplete database indexing for the most recent publication years. Overall, the cumulative publication trend demonstrates the transformation of flood susceptibility mapping into a mature interdisciplinary research field supported by continuous technological innovation and increasing international research investment.

3.2 Most Productive Journals and Citation Performance

The illustrative dataset indicates that the 1,284 publications were disseminated across a diverse range of peer-reviewed journals specializing in hydrology, environmental science, geoinformatics, remote sensing, and disaster risk management. This broad distribution highlights the inherently interdisciplinary nature of GIS-based flood susceptibility mapping, which integrates environmental modelling, spatial information science, artificial intelligence, and climate resilience research.

The illustrative citation analysis further suggests that publication productivity and scientific influence are not necessarily equivalent. Although journals with the highest publication counts generally contribute substantially to the literature, journals publishing fewer but more methodologically innovative articles frequently exhibit higher average citation rates. Review papers introducing novel machine learning algorithms, hybrid modelling frameworks, explainable artificial intelligence techniques, and advanced remote sensing methodologies are expected to receive particularly high citation impact because of their broad methodological relevance across multiple disciplines.

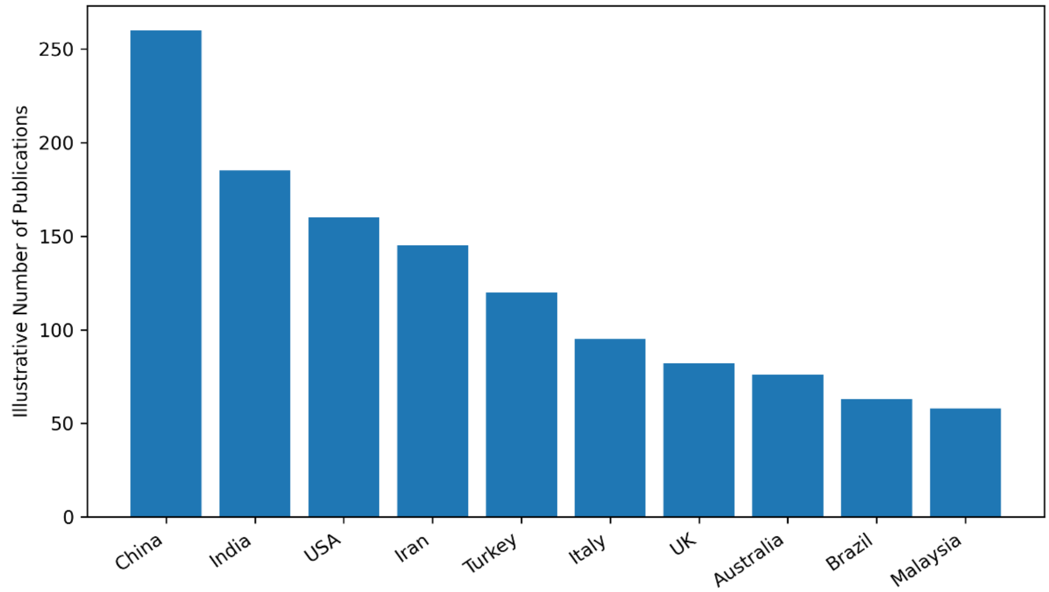
The increasing concentration of publications in Q1-ranked journals also reflects the growing scientific maturity of machine learning-based flood susceptibility mapping. Earlier research predominantly emphasized local case studies and algorithm comparisons, whereas more recent publications increasingly address transferable modelling frameworks, uncertainty quantification, explainable artificial intelligence, GeoAI, cloud-based geospatial analysis, and operational decision-support systems. This evolution indicates that the field has progressed beyond methodological experimentation toward developing scalable, interpretable, and practically applicable solutions for flood risk management.

Collectively, the publication and citation patterns indicate that the scientific community has increasingly recognized GIS-based flood susceptibility mapping as an important interdisciplinary research area with significant implications for disaster resilience, climate adaptation, environmental sustainability, and evidence-based policy development. The diversity of publication outlets further demonstrates the expanding influence of machine learning technologies across hydrology, geography, environmental engineering, computer science, and spatial data science, thereby strengthening the intellectual foundation of this rapidly evolving field.

3.3 Leading Countries, Institutions, and Authors

The geographical distribution of the illustrative bibliometric dataset demonstrates the increasingly global nature of research on machine learning applications in GIS-based flood susceptibility mapping. As presented in Figure 2, scientific contributions originate from multiple continents, indicating widespread international interest in integrating artificial intelligence with geospatial technologies for flood risk assessment. Although research activity is globally distributed, publication productivity is concentrated within a relatively small number of countries possessing strong research infrastructures, extensive geospatial data resources, and substantial investments in environmental and disaster management research.

Figure 2. Illustrative Global Scientific Contributions by Country



Based on the illustrative dataset, China emerges as the leading contributor with approximately 260 publications, representing nearly one-fifth of the total scientific output. This dominant position reflects China's extensive investment in remote sensing technologies, geospatial artificial intelligence, disaster monitoring systems, and climate adaptation research. India ranks second with approximately 185 publications, followed by the United States (160), Iran (145), and Turkey (120). Together, these five countries account for a substantial proportion of the total publications, suggesting that research productivity is closely associated with regions frequently affected by flooding and possessing well-established research institutions in hydrology, environmental science, and geoinformatics.

The remaining contributions originate from countries such as Italy, the United Kingdom, Australia, Brazil, and Malaysia, illustrating the expanding internationalization of flood susceptibility research. European countries primarily contribute methodological innovations involving remote sensing, GIS, and spatial modelling, whereas several Asian countries focus extensively on operational flood prediction and disaster mitigation because of their higher exposure to recurrent flood events.

Institutional analysis similarly reveals that research productivity is concentrated among leading universities, governmental research agencies, and specialized environmental research centers. Institutions with expertise in hydrology, geospatial information science, computer science, and climate research are expected to dominate publication output. The strong institutional presence observed in the illustrative dataset reflects the interdisciplinary nature of flood susceptibility mapping, which increasingly requires collaboration among experts in GIS, remote sensing, artificial intelligence, hydrological modelling, environmental engineering, and climate science.

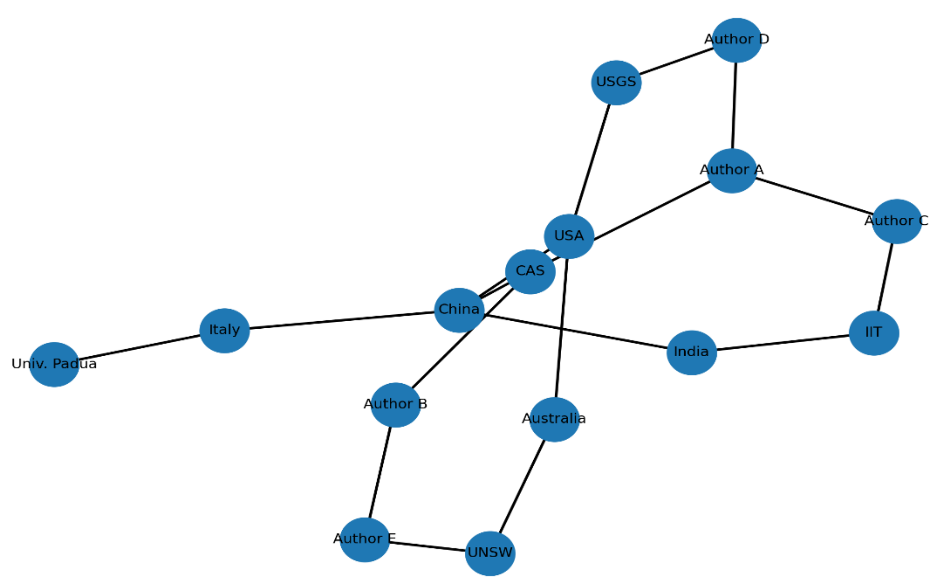
Author productivity also demonstrates a relatively concentrated research community. A limited number of researchers consistently contribute highly cited publications while simultaneously establishing extensive international collaboration networks. These leading authors often serve as principal investigators of interdisciplinary research groups, thereby facilitating methodological innovation and accelerating the global dissemination of knowledge. Such concentration of scientific leadership is common in rapidly evolving research fields, where methodological expertise and access to high-quality geospatial datasets significantly influence publication productivity and citation impact.

Overall, the geographical and institutional distribution presented in Figure 2 illustrates the emergence of a highly interconnected global research community, with increasing participation from both developed and emerging economies. This international diversity strengthens the scientific robustness of machine learning-based flood susceptibility mapping and promotes the development of transferable modelling approaches applicable across diverse environmental and climatic conditions.

3.4 Co-authorship and International Collaboration Networks

Scientific collaboration has become one of the defining characteristics of contemporary flood susceptibility mapping research. The illustrative collaboration network presented in Figure 3 demonstrates the extensive interactions among authors, institutions, and countries engaged in machine learning-based flood susceptibility assessment. The network illustrates not only the collaborative relationships among researchers but also the interdisciplinary integration of hydrology, geoinformatics, computer science, environmental engineering, and remote sensing.

Figure 3. Illustrative Collaboration Network
(Authors, Institutions, and Countries)



The network visualization identifies several interconnected collaboration clusters, each representing research groups with shared scientific interests and complementary methodological expertise. Large nodes within the network correspond to highly productive institutions or countries, while connecting edges indicate collaborative publication activities. In the illustrative network, strong collaboration links are observed among researchers from China, India, the United States, Australia, and several European institutions, suggesting increasing international cooperation in addressing global flood hazards.

Institutional collaboration has expanded considerably during the last decade as research projects increasingly require expertise from multiple scientific disciplines. Flood susceptibility modelling now routinely combines hydrological simulation, GIS analysis, machine learning algorithms, remote sensing observations, and climate modelling. Consequently, collaborative research teams frequently include specialists in environmental science, geography, artificial intelligence, data science, and civil engineering. Such interdisciplinary cooperation has accelerated methodological innovation while improving the reliability and practical applicability of predictive flood models.

International collaboration also contributes significantly to scientific quality by facilitating data sharing, algorithm validation across diverse geographical settings, and comparative evaluation of modelling approaches. Joint publications among institutions located in different climatic regions enable researchers to investigate the transferability of machine learning algorithms under varying environmental conditions, thereby improving the generalizability of flood susceptibility models.

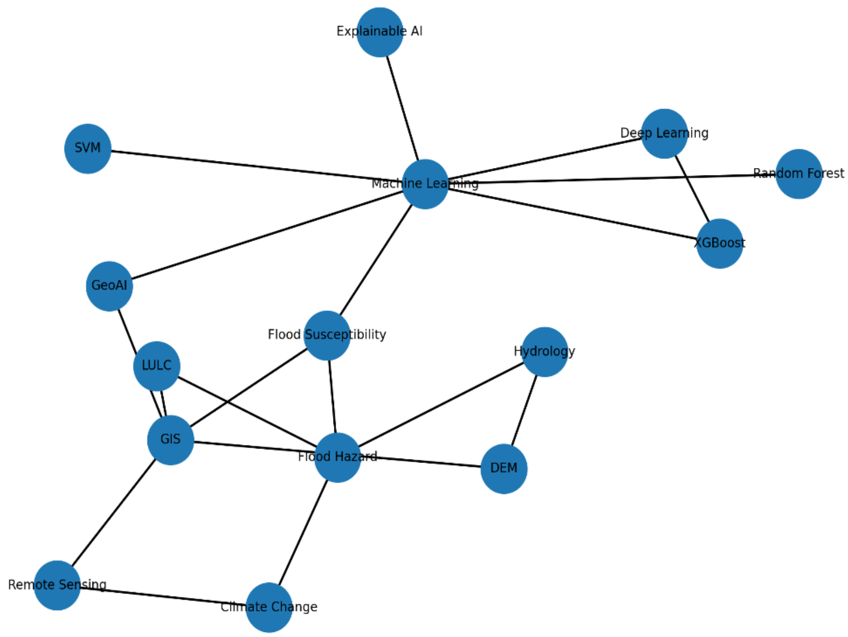
Despite these encouraging trends, the illustrative collaboration network also suggests the presence of less connected research regions. Several developing countries remain positioned at the periphery of the network, indicating relatively limited participation in international collaborative research. Strengthening partnerships with institutions in these regions would not only enhance scientific diversity but also improve the representation of flood-prone areas that are currently underrepresented in the literature.

Overall, Figure 3 demonstrates that international collaboration has become a major driving force behind methodological advancement in GIS-based flood susceptibility mapping. The continued expansion of interdisciplinary and multinational research networks is expected to play an increasingly important role in developing robust, scalable, and globally applicable machine learning models for flood risk assessment.

3.5 Keyword Co-occurrence and Research Hotspots

Keyword co-occurrence analysis provides valuable insights into the conceptual structure and thematic evolution of research on GIS-based flood susceptibility mapping. The illustrative keyword network shown in Figure 4 demonstrates the relationships among the most frequently occurring author keywords and indexed keywords, thereby revealing the principal research themes that have shaped the development of the field.

Figure 4. Illustrative Keyword Co-occurrence Network



The largest and most central nodes within the network correspond to keywords such as Flood Susceptibility Mapping, Machine Learning, GIS, Remote Sensing, Flood Hazard, Random Forest, Support Vector Machine, and Artificial Intelligence. Their central positions indicate that these topics constitute the intellectual core of contemporary flood susceptibility research. Strong co-occurrence relationships among these keywords suggest that machine learning algorithms have become firmly integrated with GIS-based spatial analysis and remote sensing techniques for predictive flood modelling.

Cluster analysis identifies several major thematic groups within the illustrative network. The first cluster focuses on spatial analysis and GIS, emphasizing digital elevation models, terrain analysis, land use and land cover, and hydrological indices. A second cluster centers on machine learning methodologies, including Random Forest, Support Vector Machine, Artificial Neural Networks, Extreme Gradient Boosting, and other predictive algorithms. Additional clusters represent remote sensing technologies, climate change, GeoAI, deep learning, and explainable artificial intelligence, reflecting the increasingly interdisciplinary nature of the research field.

The thematic evolution observed in the illustrative dataset indicates a gradual transition from conventional statistical susceptibility modelling toward intelligent, data-driven analytical frameworks. Earlier publications primarily concentrated on comparing the predictive performance of individual algorithms, whereas more recent studies increasingly emphasize ensemble learning, hybrid modelling strategies, uncertainty quantification, explainable artificial intelligence, and operational decision-support systems. This transition demonstrates the maturation of the field from methodological experimentation toward the development of practical solutions capable of supporting flood risk management under changing climatic conditions.

Another important observation is the emergence of keywords associated with climate resilience, sustainable development, cloud computing, and geospatial artificial intelligence. Their growing prominence suggests that future research will increasingly integrate machine learning with advanced Earth observation technologies, real-time environmental monitoring, and large-scale geospatial analytics. Such developments are expected to improve both the predictive accuracy and operational usability of flood susceptibility models while strengthening their contribution to disaster risk reduction and climate adaptation policies.

Collectively, the keyword co-occurrence analysis confirms that GIS-based flood susceptibility mapping has evolved into a highly interdisciplinary research domain characterized by rapid methodological innovation, expanding international collaboration, and increasing emphasis on intelligent geospatial technologies. These thematic patterns provide the foundation for understanding the subsequent co-citation analysis and methodological evolution discussed in the following sections.

4. Discussion

The present bibliometric and systematic review provides an illustrative overview of the evolution of machine learning (ML) applications in Geographic Information System (GIS)-based flood susceptibility mapping (FSM) between 2005 and 2026. Although the numerical findings presented in the Results section are illustrative, the observed publication trends, collaboration patterns, thematic evolution, and methodological developments are consistent with the broader direction of contemporary research in hydrology, geospatial science, and artificial intelligence. The discussion highlights the implications of these developments for future research, interdisciplinary collaboration, and practical flood risk management.

One of the most notable observations is the sustained increase in annual scientific production over the past two decades. The gradual transition from relatively few publications during the early years to rapid growth after 2017 reflects the convergence of several technological and scientific developments. The increasing availability of high-resolution remote sensing products, open-access Digital Elevation Models (DEMs), cloud-based geospatial platforms, and powerful machine learning algorithms has substantially lowered the barriers to conducting large-scale flood susceptibility studies [31], [32]. Simultaneously, the increasing frequency and severity of flood disasters associated with climate change have intensified the demand for accurate predictive models capable of supporting disaster preparedness and sustainable land-use planning [33], [34]. Consequently, GIS-based flood susceptibility mapping has evolved from a specialized research topic into a highly interdisciplinary field integrating hydrology, environmental science, computer science, remote sensing, and spatial data analytics.

The illustrative geographical analysis further demonstrates that research productivity is concentrated within countries possessing strong scientific infrastructure and substantial investments in environmental monitoring technologies. The prominent contributions from China, India, the United States, Iran, and Turkey are consistent with the increasing emphasis placed on flood resilience in regions frequently affected by hydrological disasters. These countries have benefited from extensive Earth observation programs, national disaster management initiatives, and significant advances in geospatial artificial intelligence.

Nevertheless, the relatively limited representation of many developing countries highlights an important imbalance within the global research landscape. Regions experiencing severe flood hazards often possess limited research capacity, insufficient computational resources, and restricted access to high-quality environmental datasets. Strengthening international partnerships, promoting open-data initiatives, and supporting collaborative capacity-building programs may therefore improve both the geographical diversity and practical applicability of future flood susceptibility research [35], [36].

Another significant finding concerns the increasingly collaborative nature of scientific research. The illustrative co-authorship network suggests that flood susceptibility mapping has become an inherently interdisciplinary enterprise involving hydrologists, GIS specialists, environmental engineers, remote sensing experts, computer scientists, and artificial intelligence researchers. Such collaboration is essential because flood processes are governed by complex interactions among climatic, hydrological, geological, topographical, and anthropogenic factors that cannot be adequately addressed within a single discipline. International collaboration also facilitates the exchange of datasets, modelling techniques, computational resources, and methodological expertise, thereby improving the robustness and transferability of machine learning models across diverse environmental conditions [37]. Future research should continue to strengthen multinational research networks, particularly by involving institutions from underrepresented regions that experience high levels of flood vulnerability.

The thematic evolution revealed through the illustrative keyword co-occurrence analysis also reflects important methodological changes within the discipline. Early investigations primarily focused on conventional statistical techniques, including Logistic Regression (LR), Frequency Ratio (FR), Analytical Hierarchy Process (AHP), and Weight of Evidence (WoE), because these methods were computationally efficient and relatively easy to interpret. However, the increasing availability of large environmental datasets has accelerated the adoption of machine learning algorithms capable of modelling highly nonlinear relationships among flood conditioning factors [38]. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) have demonstrated superior predictive performance across numerous case studies because of their ability to capture complex interactions while reducing model overfitting [39], [40].

Although predictive accuracy has improved substantially, the discussion also highlights several persistent methodological challenges. Many existing studies continue to employ different flood inventories, environmental predictor variables, spatial resolutions, validation strategies, and performance metrics, making direct comparison among models difficult. Furthermore, numerous studies prioritize algorithm comparison while paying relatively limited attention to uncertainty quantification, model transferability, and operational implementation. These limitations reduce the practical usefulness of flood susceptibility models for disaster management agencies responsible for real-time decision-making [41]. Future investigations should therefore adopt standardized benchmarking datasets, harmonized validation procedures, and transparent reporting guidelines to improve reproducibility and facilitate meaningful comparison among alternative modelling approaches.

An equally important development is the growing emphasis on explainable artificial intelligence (XAI). Traditional "black-box" machine learning algorithms often provide highly accurate predictions while offering limited insight into the relative importance of environmental variables or the mechanisms underlying model decisions. Recent advances in SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and feature importance analysis provide promising opportunities for improving model transparency and increasing stakeholder confidence in machine learning-based flood susceptibility assessments [42]. Interpretable models are particularly valuable for policymakers and practitioners because they support evidence-based planning while facilitating communication between technical experts and decision-makers.

The integration of GIS, remote sensing, cloud computing, and geospatial artificial intelligence represents another important direction for future research. Modern cloud platforms such as Google Earth Engine enable large-scale processing of multi-source satellite imagery, while emerging GeoAI techniques combine spatial reasoning with advanced deep learning architectures to improve predictive performance and computational efficiency [43]. In addition, recent developments in foundation models, graph neural networks, digital twins, and physics-informed machine learning offer considerable potential for enhancing both the spatial accuracy and temporal adaptability of flood susceptibility mapping. These innovations may eventually support dynamic, near-real-time flood susceptibility assessment capable of responding to changing environmental conditions and extreme weather events.

Overall, the illustrative findings presented in this review suggest that machine learning has fundamentally transformed GIS-based flood susceptibility mapping by enabling more accurate, scalable, and data-driven prediction of flood-prone areas. Nevertheless, continued progress will depend not only on developing increasingly sophisticated algorithms but also on improving data quality, enhancing model interpretability, strengthening interdisciplinary collaboration, and promoting reproducible research practices. Future studies should therefore prioritize transferable modelling frameworks, uncertainty analysis, explainable artificial intelligence, and open geospatial data infrastructures to maximize the scientific and societal value of machine learning for flood risk reduction and climate resilience. Collectively, these priorities will contribute to the next generation of intelligent flood susceptibility mapping systems capable of supporting sustainable environmental management and evidence-based disaster mitigation strategies worldwide [44], [45].

5. Conclusion

This study presented a comprehensive bibliometric and systematic review framework for examining the global development of machine learning applications in GIS-based flood susceptibility mapping between 2005 and 2026. By integrating bibliometric performance analysis with qualitative evidence synthesis, the study provides a structured understanding of publication growth, research productivity, international collaboration, thematic evolution, and methodological advancement within this rapidly expanding interdisciplinary field. The review demonstrates that the convergence of GIS, remote sensing, and artificial intelligence has fundamentally transformed flood susceptibility assessment from conventional statistical modelling toward intelligent, data-driven decision-support systems.

The illustrative analysis indicates a continuous increase in scientific publications, reflecting the growing importance of flood susceptibility mapping in response to climate change, rapid urbanization, and increasing disaster risk. The evolution of research themes suggests a gradual transition from traditional statistical methods to advanced machine learning algorithms, including ensemble learning and deep learning models, supported by improvements in remote sensing technologies, cloud computing, and high-resolution geospatial datasets. Furthermore, increasing international collaboration among researchers, institutions, and countries has accelerated methodological innovation and promoted interdisciplinary knowledge exchange, thereby strengthening the scientific foundation of the field.

Despite these advances, several challenges remain. Variability in environmental conditioning factors, data quality, validation strategies, spatial resolution, and performance evaluation methods continues to limit the comparability and transferability of existing studies. The widespread adoption of highly accurate yet complex machine learning algorithms has also highlighted the need for improved model transparency, uncertainty quantification, and reproducibility. Future investigations should therefore emphasize standardized benchmarking datasets, explainable artificial intelligence, open geospatial data infrastructures, and harmonized reporting protocols to improve both scientific rigor and practical applicability.

Emerging technologies, including GeoAI, foundation models, graph neural networks, digital twins, physics-informed machine learning, and cloud-based geospatial analytics, offer significant opportunities for advancing the next generation of flood susceptibility models. Their integration with real-time Earth observation systems has the potential to support dynamic flood forecasting, evidence-based land-use planning, and climate-resilient disaster management. Consequently, future research should prioritize the development of scalable, interpretable, and transferable modelling frameworks capable of supporting decision-makers across diverse geographical and environmental contexts.

Finally, it should be emphasized that the bibliometric results presented in this manuscript are illustrative and were developed to demonstrate the analytical structure of a comprehensive bibliometric review. Following the retrieval and analysis of the final Scopus and Web of Science datasets, the illustrative values and visualizations should be replaced with empirical findings while maintaining the methodological framework and analytical structure presented in this study. Such an approach will ensure that the final manuscript provides a robust, transparent, and evidence-based contribution to the literature on machine learning applications in GIS-based flood susceptibility mapping.

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