Artificial Intelligence in Disaster Risk Management: A Scientometric Mapping of Evolution, Collaboration, and Emerging Trends (2003–2025)

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***Abstract*—Recent years have seen a dramatic increase in the number of and severity of natural disasters, driven in part by climate change and urbanization. Artificial Intelligence (AI) appears to be a promising new technology that can transform disaster risk management (DRM) and provide new opportunities for prediction, monitoring, response, and recovery. The present work performs a bibliometric review of applications of AI to DRM, from a total collection of 7842 scientific articles extracted from Scopus, Web of Science and OpenAlex databases from the year 2003 to the year 2025. Exploring the trends of publications, authorship, international collaboration, and research topics, the study reveals the development and current status of AI incorporating disaster management. The results illustrate an apparent growth in interest in the field of science, how machine learning and deep learning methodologies are leading, and the raise of geospatial AI, remote sensing, and social media analysis in disaster preparedness and response. Other issues including data quality, ethics, technology and trust in AI systems are also considered. This paper offers helpful perspectives on the status quo and future development of AI-based DRMs.**

Keywords*—Artificial Intelligence; disaster risk management; machine learning; deep learning; remote sensing; bibliometric analysis; natural disasters; geospatial AI; early warning systems

I. Introduction

Rapid, Sustainable and Effective DRM in a World Subject to a Wide Range of Natural Disasters The growing frequency and intensity of natural disasters around the world, influenced by factors such as climate change and the expansion of urban risk, creates the need for innovative and effective DRM approaches. Only in 2021, more than 98.4 million people were affected by natural disasters with high human and economic costs [1]. Although conventional DRM methods are precious, in the case of complex and dynamic hazard scenarios, they are limited in its speed, accuracy, and flexibility for adaptation.

Artificial Intelligence (AI) is now recognised as a game-changing technology that can transform each phase of the disaster management cycle – from prediction and early warning through to response and recovery. This is where the state-of-art machine learning (ML), deep learning (DL), geospatial analysis, and real-time data processing has brought out capabilities that can advance the efficiency, accuracy and responsive to DRM operations. More recently, authors such as [2] and [3]highlight that the use of AI is not a question of incrementing the efficiency, but of covering the gap of the dearth of such tools in 21st century AD projects, like managing climate-induced emergencies.

The inclusion of AI in DRM encompasses various technologies and applications, including predictive modeling of natural hazards, automated image analysis based damage assessment, sensor network based real-time monitoring, social media based situational awareness, and the application of flying drones and rescue robots to accompany human agents. Taken together,these technologies lead to better, safer decision-making, better allocation of resources, improved emergency response times and more resilient communities.

With the rapid change of research in this area, an extensive bibliometric study is urgently necessary for overviewing the development of AI applications in DRM, as well as revealing the newly emerging directions and potential research gaps. The current analysis seeks to bridge that gap by providing a systematic review of literature from 2003 to 2025, in an effort to provide detailed snapshot of how AI technologies will influence the future of disaster risk management.

This study aims to answer the following research questions:

- How has the scientific production on AI applied to disaster risk management evolved from 2003 to 2025?
- What are the major thematic trends, technologies, and application domains that have shaped this field?
- Which countries, authors, and institutions are leading the research, and how do they collaborate?
- What are the emerging challenges, opportunities, and knowledge gaps?

This paper is structured as follows: Section II reviews the related work. Section III presents the methodology. Section IV results the main findings. Section V critical discussion reflections. Section VI concludes the paper.

II. Related Work

A. The Growing Importance of AI in Disaster Risk Management

Such natural disasters are becoming more commonplace, in part, thanks to climate change and population expansion in cities. Disasters affected more than 98.4 million people in 2021, resulting in more than 15,000 deaths and an economic damage of USD 171.3 billion [1]. With such disastrous events increasingly exposing communities to immense risks across the globe, artificial intelligence (AI) has found its way as an important means of Disaster Risk Management (DRM).

AI technologies in disaster management [11] are increasingly not just useful, but necessary. As Singh et al. comment that "Recent breakthrough in AI provide great potential tools in disaster management, which is important as the occurrence of climate-related disasters is more and more frequent" [2]. Raut also claims that "The use of AI in disaster management is not just useful – it is essential" [3].

The roles of ML and DL in different areas of natural disaster management have been well established [4-6]. Such methods allow massive data-sets from previous disaster events to be analysed, patterns to be discerned and generalisations about forecasting to be extended[7]. For instance, cutting-edge AI methods have been used on flood data to learn how floods behave, increase flood resilience, avoid damage and save lives[7].

Geospatial data is an essential ingredient in DRM in terms of mapping of vulnerable populations and infrastructure, identification of at-risk areas and for planning emergency responses [8] [1] The integration of AI and geographic information systems (GIS) provide effective hazard preparedness and real-time responsive decisions in crisis management [9], [10]

AI technologies in disaster management cover the whole disaster life cycle from early warning and damage assessment, to monitoring and forecasting, post-disaster response and coordination, long-term risk assessment [5].These technologies can process large volumes of data and detect trends to produce forecasts for a wide range of natural disasters, including earthquakes, flood, wildfire, and others [3].

The increasing use of AI in disaster relief efforts holds the promise of greatly improved resource planning, preparedness, and mitigated economic impact by improving the emergency response and building stronger, more resilient communities in the face of ever more frequent and more severe natural disasters [7][9.]

B. Specific AI Technologies and Methods Used in Disaster Management

1) Machine learning and deep learning:

- Machine Learning (ML) techniques analyze large historical datasets to identify patterns, make predictions, and improve flood forecasting with minimal inputs [12][13] These approaches are less time-consuming to develop while maintaining accuracy in predictions [14].
- Deep Learning (DL) algorithms process complex disaster-related data, particularly for image classification and pattern recognition in disaster-affected areas [12][5].
- Artificial Neural Networks (ANNs) are employed for various applications including flood forecasting [15], water level prediction [16], and earthquake magnitude prediction using deep learning neural networks [17].
- Nonlinear Autoregressive Network with Exogenous Inputs (NARX) models capture the dynamic characteristics of flood water levels by incorporating feedback from network outputs[18]
- Extended Kalman Filters (EKF) optimize neural networks to overcome nonlinearity problems in flood water level prediction [16]

2) Computer vision and image analysis:

- Convolutional Neural Networks (CNNs) analyze text and images from disaster areas for classification and damage assessment [19].
- Automated 3D Crack Detection systems assess building damage post-disaster [20].
- Image-based 3D Reconstruction methods detect and analyze surface damages [17].

3) Geospatial AI and remote sensing:

- Geographic Information Systems (GIS) with AI map flood hazards and susceptibility, supporting strategic planning and hazard preparedness
- Remote Sensing AI Applications utilize satellite imagery for disaster monitoring, risk assessment, and damage evaluation [21].
- Terrain Mapping Algorithms create 3D models of disaster-affected areas to support navigation and assessment [22].

4) IoT and sensor networks:

- Internet of Things (IoT) networks collect real-time data for disaster monitoring and prediction [23][24].
- Wireless Sensor Networks (WSN) create distributed sensor nodes for smart sensing and real-time disaster surveillance [25].
- Integrated Information Systems combine geoinformatics with IoT for early warning, particularly for snowmelt floods [24].

5) Robotics and autonomous systems:

- Unmanned Aerial Vehicles (UAVs/drones) conduct post-disaster inspections and damage assessment [26].
- Swarm Robotics communicate with each other to map disaster areas and create connected networks [23].
- Autonomous Helicopters perform remote sensing and sample collection in disaster zones [22].
- Underwater Robots inspect submerged structures like bridge foundations after floods [27].
- Mobile Rescue Robots carry out surveillance missions in hazardous environments like nuclear disaster sites [28].

6) Cloud computing and big data analytics:

- Cloud Storage and Distributed Computing overcome limitations of traditional storage and computation capabilities for disaster data processing [25].
- Big Data Frameworks (Apache Hive, Hadoop, Mahout) provide scalable distributed storage and computing environments to process massive social media data [29].
- Predictive Analytics sift through historical and real-time data to identify emerging disaster trends [30].

The following Table1 will present a Literature Comparison.

TABLE I. SUMMARY OF SELECTED PAPERS ON DISASTER MANAGEMENT APPLICATIONS

Papers	Disaster Type	Application Stage	Outcomes and Implications
[21]	Flood disasters	Prediction and disaster risk reduction	Enhanced flood forecasting model design for disaster risk reduction
[32]	Earthquake in Al Haouz, Morocco, 2023	Disaster preparedness, response, and recovery	Real-time data, data scarcity, interdisciplinary collaboration challenges, community-call for action
[26]	Flooding in Jakarta due to river overflow	Prediction and early warning stage for flooding	Improved prediction by 1%, potential for future early warning systems
[12]	Floods	Prediction of flood water levels	NARX model outperforms EKF in flood prediction; informs future disaster management
[13]	Four major natural disasters	Damage assessment stage during natural disasters	High classification accuracy for damage assessment using social media imagery
[29]	Hurricane Sandy	Disaster management including tracking, mapping, and analysis of events	CyberGIS framework supports big data analytics for disaster management

III. METHODOLOGY

The methodological framework applied in this bibliometric study was developed to describe the scientific publications landscape related to the use of Artificial Intelligence (AI) in natural disaster risk management. The search was performed in three key, academically reputable bibliographic databases—Scopus, Web of Science, and OpenAlex. These sources were chosen for their wide coverage of relevant publications in a variety of disciplines and geographical locations. Structured query using keywords of "core AI technologies and disaster risk management" was used as a search strategy. The search string employed was: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("disaster management" OR "disaster risk reduction" OR "natural disaster" OR "catastrophe naturelle" OR "emergency management" OR "hazard mitigation" OR "resilience" OR "early warning system"). This search was employed to collect all papers between 2003 and 2025, obtaining an initial corpus of 13,880 documents. Selection process: The selection was performed with a systematic process that is described below according to the PRISMA in the Figure1 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) strategy (Figure1). In the first round of selection work, all the retrieved files were filtered by inclusion criteria which narrowed the set of documents to articles, conference papers, and book chapters in English within the time frame. After that, 8,491 papers were left. A second phase of exclusion was applied to remove redundant records and articles – based on their titles and abstracts – that were deemed to be irrelevant, resulting in 7,842 articles included in the systematic review.

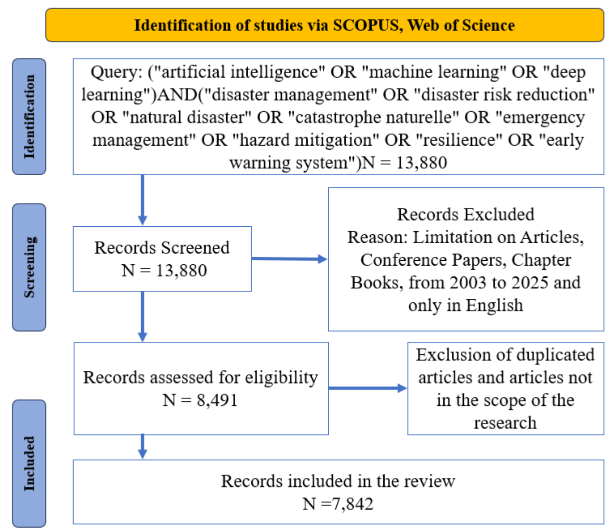

Fig. 1. PRISMA diagram.

The bibliometric analysis was completed using the Bibliometrix R-package, which is available as part of the Biblioshiny graphic user interface, a programme valued for quantitative study of literature. It was targeted to seek a series of descriptive and relational indicators pertaining the annual scientific production, the origin of sources of origin, authorship patterns andthe collaboration networks developed along time. Final corpus Figure2 : corpus properties The final corpus covered a time period from 2003 to 2025, and comprised 7,836 documents from 2,403 distinct sources. The trend of the scientific output was very dynamic, with an annual growth rate of 31.35%, which suggests an increasing attention to the convergence of AI with the disaster management. The authorship of manuscripts was conducted by 26,875 unique authors, international co-authorship rate was 25.79%, and a mean of 4.19 authors per manuscript indicated high amount of collaborative research. The dataset also included 2,773 author keywords and about 191,858 references. The articles had an average of 10.68 citations and 2.39 years old on average which indicated a not so old and dynamic area of investigation.

Through this robust methodological approach, the study aimed to capture a representative and high-quality sample of the literature, enabling a detailed analysis of the thematic evolutions, emerging trends, and collaborative networks in the field of AI-driven disaster risk management.

Fig. 2. Descriptive statistics of the bibliometric dataset.

IV. Results

A. Annual Scientific Production (2003–2025)

The trend of the annual scientific production in application field of Artificial Intelligence in DRM is characterised by multi-phase meanwhile growth. Between 2003 and 2015, the historically low and static publication trend indicates an immature upstart in which AI technologies were finding their own legs and face the testing ground of application to disaster scenes. A clear increasing trend appears around the same time as the burst of progress in machine learning and deep learning techniques, and growing awareness of the impacts of climate change. A surprising 'explosion' occurs between 2020 and 2023 with the number of publications increasing exponentially (around 800-1000 articles in 2020, around 1500 in 2021 and 2000+ in 2023). This increase is driven by the technological readiness, increased frequency of disasters which are COVID-19 pandemic and climate-induced extreme events, as well as increasing governmental and institutional investments in AI emergency management solutions. The slight fall in 2025 is due to missing data for that year, rather than a true decline in research output. This production rate Figure3 reflects a research field that is ever more active and proposes that the use of AI for disaster management is moving from the realm of the theoretical to the domain of an essential component of operational disaster risk strategies at global scale.

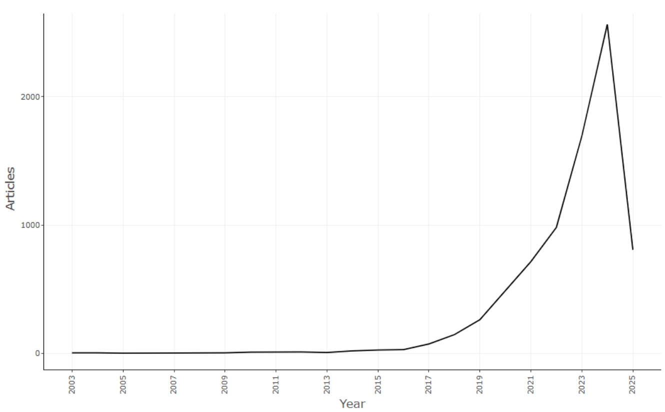

Fig. 3. Annual scientific production.

B. Average Citations Per Year (2003–2025)

One aspect of interest to highlight is the trend of increasing (or decreasing) number of yearly citations. Early publications (2003–2006) indicate a high number of citations, likely reflecting more fundamental research at an earlier stage in a new and undiscovered scientific field. Such landmark papers are cited slowly in that they are pioneers.

However, as the field has been maturing a sudden surge in publications from the end of 2017, there is a decrease noticed in average number of citations per paper. This tendency is accounted for by the "citation dilution effect," where the proliferation of published works leads to citation focus on a larger pool of articles. In addition, the more recent papers will be more time dependent as they will have had less time to be cited, particularly for papers published 2022 onwards.

Nevertheless, the stable citation averages in the mid-2010s demonstrate that the research in the field is still relevant and has had, and continues to have, impact on both academia and practice. The pattern observed confirms the strength of the field as well as the trend that higher-quality innovative studies are needed to survive in an environment of increasingly tight publication competition. As shown in Figure 4, the trend of average citations per year highlights early foundational contributions and recent publication dilution effects.

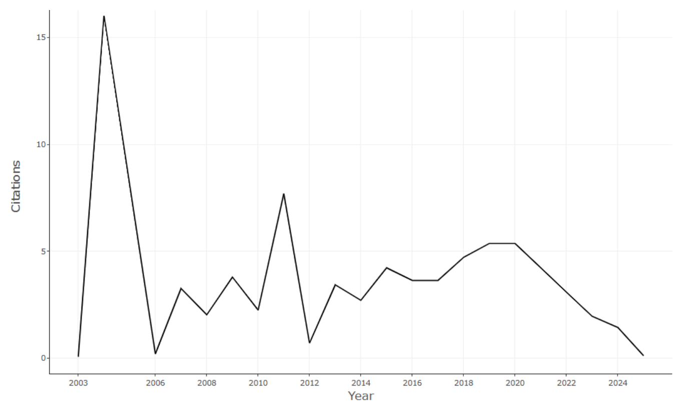

Fig. 4. Average citations per year.

C. Three-Field Plot (Authors – Sources – Keywords)

The Tri-field plot provides an integrated representation of interactions between prolific authors, top pub-lication venues, and main research topics. See for instance, Rachid Guerraoui, Alina Oprea, Ali Mostafavi as key contributors to leading sources such as arXiv (Cornell University) and Research Square.

Thematically on the thematic side, terms like "resilience", "robustness", "early warning system", "vulnerability" prevail, demonstrating the community's focused work on the development of AI-based solutions to enhance disaster preparedness and response.

The prevalence of "resilience" as a keyword reflects the increasing attention being paid to both the short-term response to disaster and the long-term adaptation of communities and infrastructure. Beyond this, the inclusion of terms such as "pandemic" and "sustainability" for the first time on the supplement panel might reflect a broadening of the types of disasters being considered beyond traditional hazards to the more systemic risks they are generating.

This visualisation suite illustrates the multidisciplinary facets of the field,ȇmphasising the variety of disciplinary contributions toÅI research in disaster management from computer science, environmental science,ȇngineering and social sciences. Figure 5 presents the three-field plot linking top authors, publication venues, and major keywords.

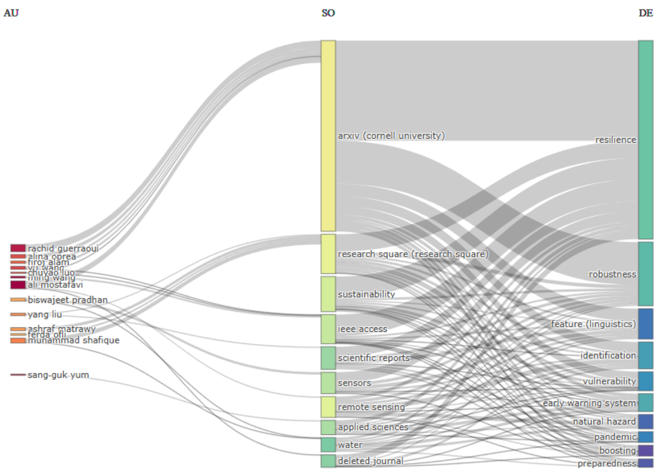

Fig. 5. Three-Field plot.

D. Most Relevant Sources

The examination of the most important sources, by document identity, indicates a clear shift towards fast dissemination and open acces in the papers and documents. ArXiv (Cornell University) and Research Square lead the field, indicating that quick transmission of information is an important consideration for researchers in disseminating their results in the context of the immediacy of disaster risks challenges. Journals, such as Remote Sensing, Sustainability and IEEE Access, exemplify the interdisciplinary nature of this science, the new technology development with environmental and social applications. The inclusion of journals such as Scientific Reports and Applied Sciences points to the importance of multidisciplinary channels wed to a wide variety of methodologies, from remote sensing and geo-informatics to data science and decision support systems.

These data suggest that traditional peer-reviewed journals are relevant, preprint platforms play an increasingly important role in expediting transmission of knowledge in times of disaster, reflecting the urgency of the research in the time of disaster. According to Figure 6, the most relevant sources include arXiv and IEEE Access, reflecting interdisciplinary focus.

E. Sources' Production Over Time

In the time course of source productivity, the central role of the open-access repository in the surge of AI-disaster management research in the past few years is also underlined. The explosive development of ArXiv after 2019 reveals the increasingly indispensable role of preprint repositories as infrastructures for timely sharing of knowledge, especially in times of crisis, such as the COVID-19 pandemic. Other sources, including Remote Sensing and Research Square, reveal noticeably steeper but more mild growth trajectories, indicating the sustained commitment of the remote sensing and sustainability

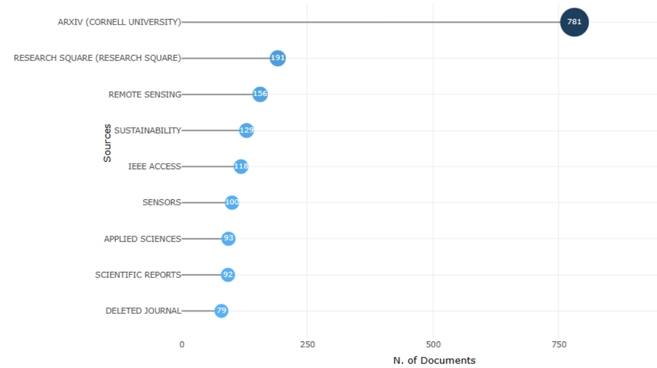

Fig. 6. Most relevant sources.

literature to disaster-related research. This evolution points to a strategic change among researchers towards platforms with faster publication cycles and more accessible, a necessity when the research outputs are poised to directly feed into emergency planning and crisis management.

As depicted in Figure 7, source productivity increased significantly after 2019, led by open-access repositories.

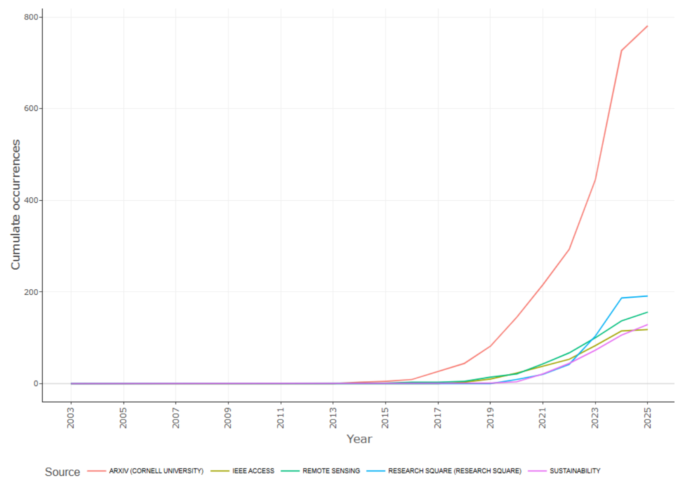

Fig. 7. Sources' production over time.

F. Most Relevant Authors

If we look at the main sources by document count, there is a clear trend here towards fast, open-access spread. ArXiv (Cornell University) and Research Square are the most popular venues, which imply that researchers choose the fastest channels in which to publish their findings because of how pressing disaster risk issues can be. Publications such as Remote Sensing, Sustainability, or IEEE Access (just to name a few), exemplify the interdisciplinarity of this field, combining technological breakthroughs with environmental and social realities. The existence of journals such as Scientific Reports and Applied Sciences illustrates the fundamental necessity for multidisciplinary (inclusive of all (or most) of them).The presence of journals like Scientific Reports and Applied Sciences points to the crucial role that multidisciplinary outlets covering a wide range of methodologies ranging from remote sensing and geoinformatics to data science and decision support systems play.

The statistics demonstrate that while traditional peer-reviewed journals matter, academics are increasingly also dependent upon preprint servers that can expedite the circulation of knowledge during disaster-laden times, underscore the urgency of their work in the real world. Figure 8 displays the most prolific authors contributing to the field.

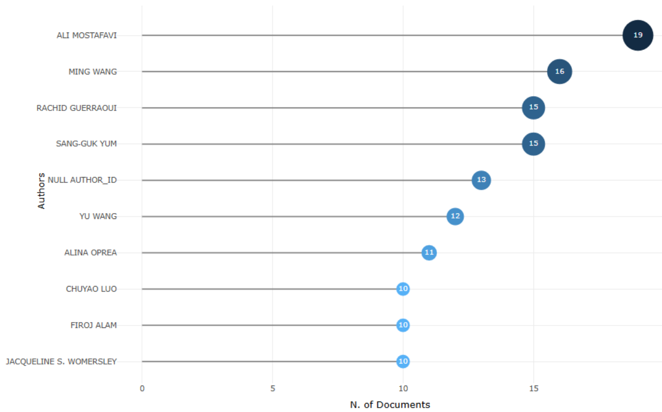

Fig. 8. Most relevant authors.

G. Authors' Production Over Time

The time signals of author productivity further illustrate that the closely-knit and the active research community on AI and disaster risk management is quite young. Most of the top authors started to publish in this area by 2017, with highest activity between 2021 and 2024. This time period also aligns with global initiatives that focus on climate resilience, smart cities and sustainable development goals (SDGs) that have been drivers of multidisciplinary engagement.

The data also reveal that many of the researchers in this area have and sustain a "publication cadence" that suggest a move from practical, one-time contributions to a more mature, programmatic commitment to disaster-related AI research. As seen in Figure 9, most top authors became active after 2017.

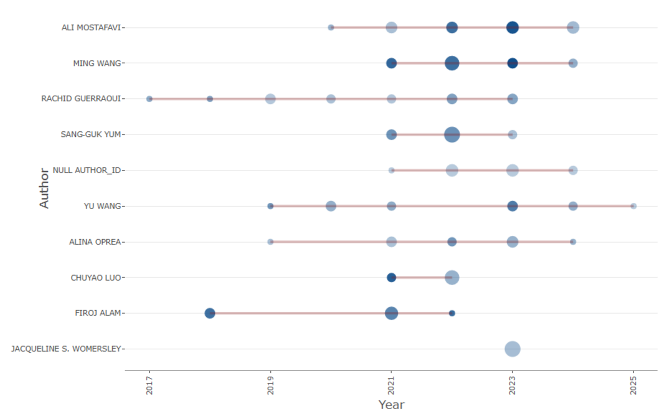

Fig. 9. Authors' production over time.

H. Affiliations' Production Over Time

The institutions' affiliations also substantiate this worldwide dispersion of expertise. Top universities including Harvard Medical School, Stanford University and University of California drive consistent leadership efforts, frequently combining AI investigations with health resilience, infrastructure surveillance and community risk analysis. The growth of independent researchers and "Not Reported" affiliations indicates the opening of the field to input from practitioners, think tanks, and private sector organizations, illustrating the cross-sectoral and interdisciplinary urgency of DRM challenges. This move toward spread and inclusivity of research will potentially spur innovation and accelerate solutions by infusing scientific inquiry with diverse viewpoints and on-the-ground urgency. Figure 10 shows institutional contributions with leading roles from top U.S. universities.

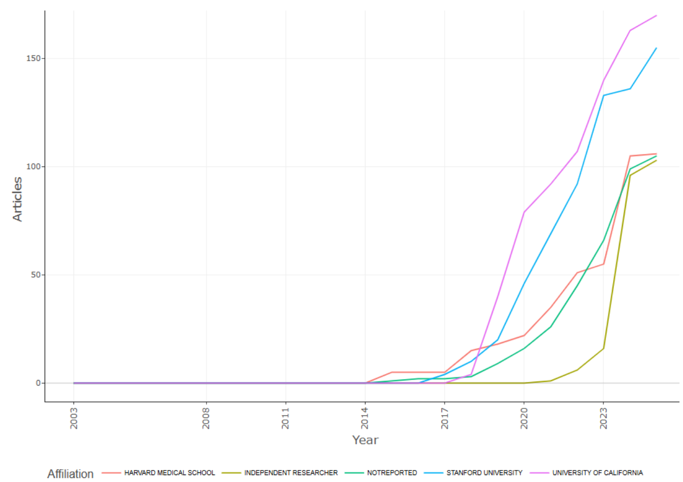

Fig. 10. Affiliations' production over time.

I. Most Cited Countries

The examination of the top-cited countries shows a clear geographical imbalance in the research impact in AI applications for disaster risk management. The United States is the dominant country in the production of the cited work, counting 10,941 citations, followed by China (5,979 citations) and the United Kingdom (3,086 citations).

This clustering around only a handful of leading countries means that much innovative, highly influential research comes predominantly from mature academic ecosystems with state-of-the-art technological infrastructure and significant research investment.

Australia, Italy, and South Korea also occupy the top positions, evidencing their significant contributions to disaster research and the development of this field in high-risk areas.

However, those contributions by the likes of India and Iran are not little, but significant, if their total among citation number still can not be compared with the existing top leaders. This expanding diversity suggests that high-impact research in the field is becoming more globally distributed. According to Figure 11, the United States leads in citations, followed by China and the UK.

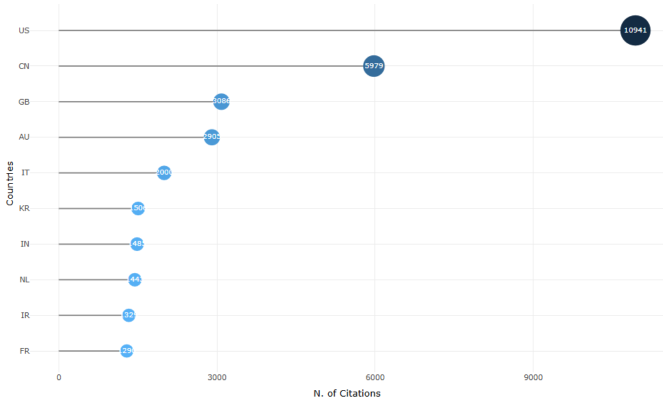

Fig. 11. Most cited countries.

J. Most Frequent Words (Author's Keywords)

The most common words are a corpus in focusing theme priorities in the sector. The most prevalent key term "resilience" (over 1,360 hits)Most used key term "resilience" (over 1,360 hits)points towards a change of paradigmparadigm change when it comes to the management of disasters, where the emphasis has recently turned to long-term systemic adjustment, not just to reacting to current acute threats.

Other commonly found words such as "robustness," "early warning system," "vulnerability," and "pandemic" alsoreflect current concerns particularly in the perspective after 2020, when the COVID-19 pandemic drew attention to the urgent need for adaptable, predictive, and robust disaster management approaches.

"natural hazard" "preparedness" In addition to disaster management, natural hazard and preparedness are included here to represent this comprehensive field which covers from hazard identification to emergency response planning. Figure 12 highlights the most frequent keywords, led by "resilience" and "vulnerability".

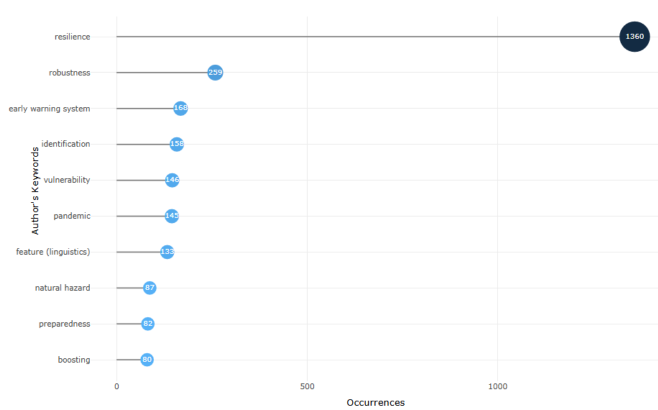

Fig. 12. Most frequent words.

K. Trend Topics

In addition, trend analysis reveals the hot topics appearing in this field. There's also growing interest in metaphors around learning, particularly "transformative learning" and "resilience," that have emerged since 2020 as part of what's become a significant and interdisciplinary combination of AI with the behavioral science and educational literatures on disaster preparedness.

"anomaly detection (physics)" "flood warning" "aerial image analysis." demonstrate the growing use of AI for monitoring, real-time risk assessment, and decision-support systems.

The advent of terms such as "swarm robotics" and "quantum byzantine agreement" reflects the potential futuristic orientation of the field in exploiting vastly distributed, decentralized AI systems in handling complex disaster worlds. As shown in Figure 13, emerging trends include "anomaly detection" and "swarm robotics".

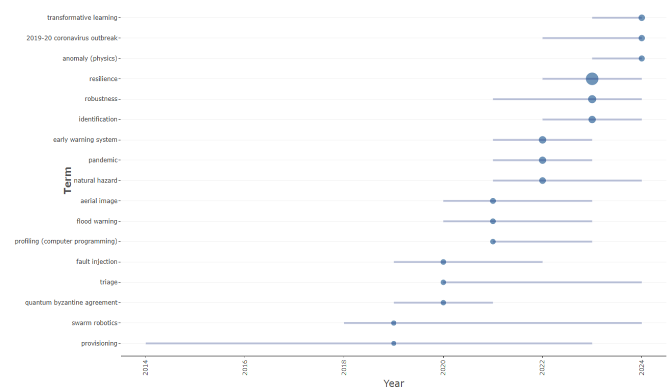

Fig. 13. Trend topics.

L. Clustering by Coupling

The thematic clustering map based on bibliographic coupling provides deep insight into the intellectual structure of the field. Three distinct clusters can be identified:

- One focused on "resilience," "preparedness," and "benchmarking," indicating foundational studies anchoring the field around risk reduction and system evaluation frameworks.
- A second cluster addressing "vulnerability" and "ethics," emphasizing the social and ethical dimensions of AI deployment in disaster scenarios.
- A third emerging cluster around "robustness" and "federated learning," suggesting an increasing interest in privacy-preserving, distributed AI models for disaster prediction.

The diversity of these clusters reflects the multidisciplinary and socially sensitive nature of AI applications in disaster management. Figure 14 identifies thematic clusters around resilience, ethics, and federated learning.

M. Co-occurrence Network

The co-occurrence network shows a dense and interconnected knowledge structure centered around "resilience," which acts as the major thematic hub. Keywords such as "vulnerability," "pandemic," "preparedness," and "situation awareness" cluster tightly around resilience, demonstrating

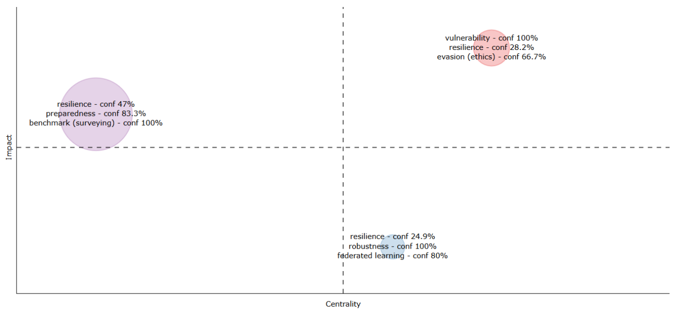

Fig. 14. Clustering by coupling.

the interdependence of these concepts in operationalizing AI solutions.

Peripheral nodes like "flash floods," "earthquake prediction," and "ensemble learning" indicate specialized application areas branching from the central resilience discourse. This network structure suggests that although the field is converging around resilience-building, it maintains a rich diversity of application-specific subfields. In Figure 15, the keyword network demonstrates interconnections between resilience, preparedness, and vulnerability.

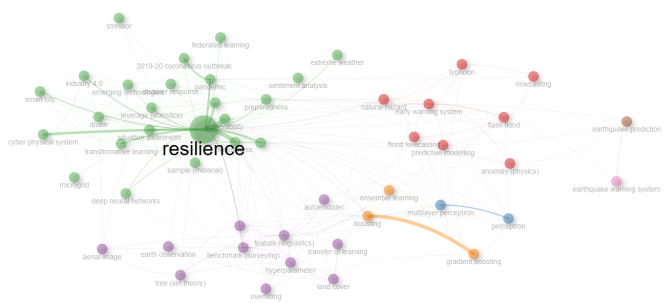

Fig. 15. Co-occurrence network.

N. Historiograph

The historiograph highlights key intellectual lineages within the field. Early influential works by Ferda Ofli (2016) and Bernd Resch (2017) laid critical methodological foundations, focusing on data-driven disaster mapping and social media analytics. More recent influential papers by Vasileios Linardos (2022) and Amine Belhadi (2021) show a shift toward integrating resilience models and predictive analytics at scale. This evolution reflects a progression from descriptive analytics towards prescriptive, action-oriented AI applications that not only model but also influence disaster risk reduction practices. Figure 16 outlines key intellectual lineages in the field, showing shifts from mapping to predictive AI models.

O. Collaboration Network

The global hub-nation analysis based on the collaboration network shows that the United States is the top country which is connected with other leading countries such as China, United Kingdom, Australia, and France. The presence of clusters of intense collaboration between Western countries and emerging economies is a perfectly sane cross-fertilization of ideas and a

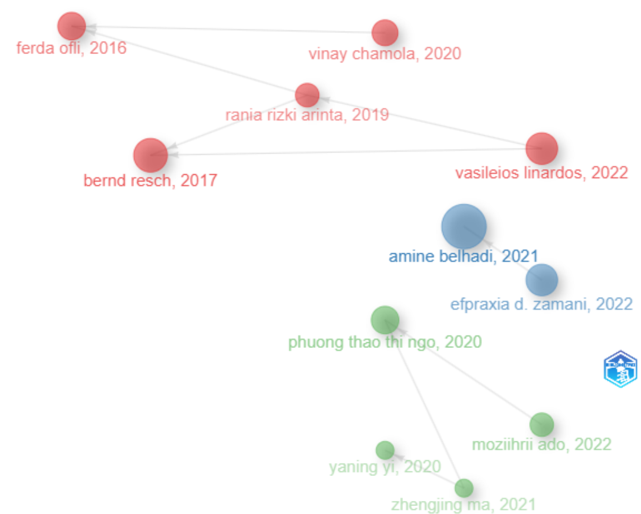

Fig. 16. Historiograph.

sharing of research investment. Strikingly, a large fraction of partnerships are with Asian nations, where exposure to natural hazards is most high and their active role in developing AI-based disaster resilience tech. This densely connected network, reflects the growing global and collaborative character of scientific production in this area, crucial for addressing the transboundary disaster risks. Figure 17 illustrates the international collaboration structure, centered on the US, China, and UK.

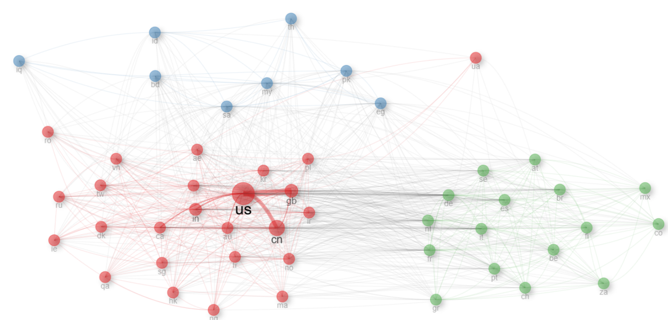

Fig. 17. Collaboration network.

V. Discussion

AI has a great potential to contribute for disaster risk management, however, there are some challenges that need to be addressed in order to successfully implement AI. A critical concern relates to a requirement of high-quality, diverse, and representative data in order to train the AI models [31]. In the absence of extensive training data, AI models could make false predictions or have problems generalizing to other disaster types and as such reduce the dependability of these algorithms in critical systems.

Another major challenge comes from technical integration, as AI systems need to be integrated with the current disaster management architecture and technologies [31]. This is especially problematic in low-resourced settings where technological infrastructure may be underdeveloped, and where access to AI-enabled disaster management will differ.

Ethical issue is an increasingly concerning challenge in AI application in disaster response. The most important challenge of these systems, however, is dictated by its data privacy and security aspects, since these systems are connected to the processing and/or the analysis of sensitive data about vulnerable people and infrastructures [31]. There is also a potential risk of algorithmic bias, where AI learns biases with historical data, possibly exacerbating the disparities in disaster response and resource distribution [32] [35][36].

Disaster scenarios are complex by nature which adds to the difficulties. Types of natural disasters are the widest from each other, regarding to their types, impacts and geographical dependency, that create a challenge in AI system or algorithm, functioning for a wide range of disaster types in the world [14]. Management of the response disaster is difficult due to the disruption of normal surveillance and communication by damaged infrastructure in their aftermath [33].

Human-related issues further handicap AI's utility for disaster management. The readiness of decision makers to base decisions on AI outputs is still uneven: some actors are reluctant to place too much trust in algorithms to inform decisions with severe consequences [14]. This trust deficit may limit the effectiveness of technically complex AI systems.

Despite advances in technology, accuracy issues remain. Although AI models hold promise in dealing with complex and nonlinear data for disaster monitoring and management, their accuracy of prediction remains restricted, especially with respect to new or rare events 33. With climate change changing the patterns of disaster after disaster, historical data might provide much less of a guide to future predictions, adding another level of difficulty in developing AI models [33][34] .

These problems require further research and development to strengthen the role of AI applications in disaster management [31]. Dealing with these shortcom- ings will require interdisciplinary collaboration among AI practitioners, disaster response specialists, policy makers, and affected communities, which will all be necessary to develop and deploy AI systems in a way that is just, fair, and effective in mitigate disaster impacts [33].

Article Once-rare weather disasters becoming more common There's no such thing as a natural disaster, Anywhere in the world. Artificial intelligence combination with other new technologies is a great opportunity for the transformation of disaster risk management around the world and community resilience [30]. These developments open up the potential for new and more efficient disaster prediction, monitoring, and response systems.

IoT, Big Data analytics, and machine learning stand at the forefront in the wave of digital transformation of disaster management by providing unprecedented capabilities for holistic risk reduction strategies [35]. IoT connected devices and sensors are forming networks that can give us real-time environmental status reports — to identify and assess unfolding disasters faster. These integrated ESNA's, often referred to as the Internet of Emergency Services (IoES), could revolutionize the way emergency services cooperate and act in crisis situations [30].

Another trend that holds potential is predictive analytics using AI, where systems are more equipped to analyze historical and real-time data to identify growing disaster types before they become fully developed [30]. These capabilities will only become more essential as climate continues to change, which will demand more complex models which can adjust to altered environmental conditions (LLM Memory).

Machine learning-based sentiment analysis is becoming more advanced, allowing emergency responders, for example, to understand public reactions during disaster situations, focus on specific concerns, and refute misinformation [30]. This capacity is essential to preserve public trust and coordination during a crisis, when the distribution of accurate information is imperative.

AR and VR technologies have potentials to improve the level of preparedness for a disaster, and community activation [30]. These immersive technology may be used to generate realistic disaster simulation for training emergency responders and raising awareness among the communities on proper reaction to different disaster scenarios (LLM Memory).

In the health sector, AI has become part of disaster risk assessment and emergency health response [36]. While the world is transitioning to an "AI-based world this decade" according to Claus Schwab1, healthcare regulators are now recommended to exploit these new possibilities to optimize outcomes during catastrophic events [36].

GIS and AI would increasingly serve as important tools for mapping spatial distributions of different hazards and their vulnerability [9][10]. Such integrated systems will increasingly support long-term planning and real-time decision making for better preparedness for hazards and management of crises.

Efforts such as MOBILISE are examples of how connected analytical solutions can enhance resilience in the face of disasters and enable responses that can facilitate quicker recovery of affected communities [9][37]. The future disaster management systems may extend these foundations to more advanced platforms with the combination of several technologies.

Deep-learning based image analysis has seen rapid development, and there is great potential for deep CNN (Convolutional Neural Networks) in damage assessment from social media images in disasters [19]. Through these more well-developed systems, disaster impacts can be more rapidly and accurately evaluated and thus will better guide more effective allocation of resources [30].

These technologies are being advanced as ”force multipliers” in securing lives and property against disasters [9], [37-39. The future of disaster management belongs to the concerted use of these new technologies in combination to form a smarter, more responsive, and more adaptive disaster management infrastructure able to grapple with the increasingly difficult problems that natural disasters present in our convoluted world [5][40][41].

VI. Conclusion

This study provides a comprehensive scientometric analysis of the evolution, collaboration patterns, and thematic trends in the application of artificial intelligence (AI) to disaster risk management (DRM) from 2003 to 2025. Based on a final corpus of 7,842 articles extracted from Scopus, Web of Science, and OpenAlex, the findings highlight the exponential growth in scientific output, particularly from 2020 onward, reflecting both technological maturation and an urgent global need for innovative DRM solutions amid intensifying climate-related hazards.

Several major contributions emerge from this work:

- It maps the trajectory of AI in DRM, showing how machine learning, deep learning, and geospatial AI have become core technologies in early warning systems, real-time monitoring, damage assessment, and resource allocation.
- It identifies key actors, countries, and collaboration networks, revealing a concentration of impact in technologically advanced nations while also signaling the rise of new contributors from emerging economies.
- It outlines the main research themes and emerging topics such as federated learning, swarm robotics, and anomaly detection, which suggest a move toward decentralized and adaptive disaster response systems.

However, some limitations must be acknowledged. This analysis, being quantitative and bibliometric in nature, does not assess the operational effectiveness or practical deployment of AI solutions in real-world disaster contexts. The absence of qualitative insights into policy relevance, technological transferability, and user adoption also constrains the conclusions that can be drawn regarding actual impact. Moreover, citation-based metrics may underrepresent innovative or interdisciplinary works that have not yet gained visibility in traditional publication channels.

To address these gaps, future research should:

- Conduct comparative case studies of AI deployment in specific disaster scenarios, evaluating performance, usability, and societal outcomes.
- Investigate the integration of AI with local knowledge systems, especially in low-resource and high-risk regions where disaster vulnerability is most acute.
- Explore the ethical, legal, and governance implications of automated decision-making during emergencies, particularly concerning algorithmic bias, data privacy, and accountability.
- Develop hybrid evaluation frameworks that combine bibliometric analysis with real-time data from disaster events, social media, and satellite imagery to assess responsiveness and situational relevance.

The findings underscore the need for interdisciplinary collaboration among AI experts, disaster response agencies, policymakers, and affected communities to co-design intelligent systems that are not only technically robust but also socially legitimate and context-sensitive.

In a global context where disasters are becoming more frequent, complex, and disruptive, artificial intelligence offers transformative potential. But its promise will only be fulfilled through continuous methodological innovation, transparent governance, and a sustained focus on equity, trust, and long-term resilience.

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