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REVIEW ARTICLE

Artificial intelligence-driven approaches for assessing social vulnerability to natural hazards: a comprehensive bibliometric review

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Abstract
Artificial intelligence (AI) applications in social vulnerability assessments have gained increasing attention in disaster management and risk reduction research. This study presents a comprehensive bibliometric analysis of AI applications in social vulnerability assessments from 1996 to 2024, analysing 26,717 publications from Scopus and Web of Science databases. The field has grown rapidly, with an annual publication growth rate of 19.94% and an average of 33.05 citations per document, reflecting both scale and scholarly impact. The analysis further highlights the collaborative nature of the field, with 63,778 contributing authors, an average of 4.94 co-authors per publication, and 27.69% of outputs featuring international co-authorship. Publication types are dominated by journal articles (25,910), supplemented by reviews (612) and conference papers (195). Leading publication venues include *Remote Sensing* and *IEEE Transactions on Geoscience and Remote Sensing*, while China, the United States, and India emerge as the most prolific contributors, alongside growing participation from developing economies. Keyword analysis across three distinct periods, Foundational (1996–2009), Developmental (2010–2019), and Transformative (2020–2024), shows a shift from traditional geospatial methodologies to advanced AI-driven analytics, with terms such as "machine learning," "deep learning," and "synthetic data" emerging as dominant themes. Remote sensing, GIS, and decision support systems have remained central, while recent years have focused more on convolutional neural networks and semantic segmentation. Overall, our review provides one of the largest, periodized mappings of this domain and surfaces critical gaps (e.g., under-integration of social science) while offering an actionable agenda centred on explainable AI, multimodal data fusion, participatory approaches, and responsible/ethical AI to enhance decision-making for disaster resilience.

Keywords Artificial intelligence · Disaster risk reduction · Geospatial analytics · Remote sensing · Social vulnerability · Natural hazard

Extended author information available on the last page of the article

1 Introduction

1.1 Background on social vulnerability

In the face of escalating climate change impacts, the frequency and severity of natural disasters have risen markedly, necessitating the development of sophisticated methodologies for assessing vulnerability (UNFCCC 2015, 2023; UNDRR 2022). *Natural hazard risk* is understood here as the probability of adverse impacts resulting from the interaction of three components: the occurrence of hazardous events, the exposure of populations or assets, and their underlying vulnerability (IPCC 2014, 2022; UNDRR 2015, 2019). *Social vulnerability* refers to the susceptibility of individuals and communities to the adverse impacts of natural hazards, shaped by social, economic, demographic, and environmental factors that influence their capacity to anticipate, cope with, and recover from disasters (Cutter et al. 2003, 2010; Wisner et al. 2004; Birkmann 2006; Wisner 2016). It emphasizes how dimensions such as age, gender, socioeconomic status, and access to resources determine resilience levels and highlight disparities in disaster impacts. Recognizing these dynamics is crucial for designing targeted interventions, as social vulnerability not only reflects exposure to hazards but also reveals underlying inequities that exacerbate risk (Cutter et al. 2010; Bergstrand et al. 2015).

1.2 Challenges in traditional assessments

Artificial intelligence (AI), defined here as computational approaches, including machine learning (ML), deep learning (DL), natural language processing, and computer vision, that enable systems to learn from data, detect patterns, and support predictive or prescriptive decision-making (Goodfellow et al. 2016; Russell and Norvig 2021), has transformative potential in assessing social vulnerability. Despite this potential of AI in assessing social vulnerability, several critical challenges remain underexplored. Foremost among these are issues of data availability, accessibility, quality, and reliability. Social vulnerability analysis inherently depends on high-quality, granular, and timely data, which are often scarce or unevenly distributed across regions, particularly in low-resource settings (Flanagan et al. 2011, 2018; Spielman et al. 2020; Rabiei-Dastjerdi et al. 2025). These data limitations can severely impact the effectiveness of AI models, which require comprehensive and diverse datasets for robust performance.

1.3 Role of AI and synthetic data

Emerging big data sources, such as satellite imagery, mobile phone usage, and social media activity, offer promising avenues to mitigate some of these technical challenges (Yuan et al. 2020; Goktas 2024; Panahandeh et al. 2025). Big data enables the integration of real-time, dynamic, and location-specific information, enhancing the responsiveness and granularity of vulnerability assessments. However, the quality and representativeness of these data sources must be rigorously evaluated, especially in socially and economically diverse contexts. The integration of AI into natural hazard risk frameworks, therefore, requires not only methodological innovation but also careful consideration of how social vulnerability is conceptualized and operationalized in diverse cultural, economic, and political settings

(UNDRR 2022). The concept of social vulnerability highlights the multifaceted nature of disaster impacts, where the interplay of social, economic, and demographic factors with environmental hazards shapes the differential capacities of communities to withstand, respond to, and recover from such events (Cutter 1996; Cutter et al., 2006). The emphasis on social vulnerability within the academic and practical realms of disaster management reflects a paradigm shift toward acknowledging and addressing the underlying conditions that exacerbate the adverse effects of natural disasters on specific populations (Cutter et al. 2003, 2010).

1.4 Opportunities in geographic information systems and synthetic data

Assessing social vulnerability is crucial for identifying populations that are most at risk during natural disasters and for implementing effective disaster preparedness and response strategies. Traditional approaches to assessing social vulnerability have primarily relied on demographic and socio-economic data collected through surveys and society reports. However, these methods often face limitations due to the static nature of the data, which may not accurately reflect the dynamic social and environmental conditions that influence vulnerability (Flanagan et al. 2011, 2018; Singh et al. 2014). Recent advancements in AI and the generation of synthetic data offer promising avenues for enhancing the accuracy and efficacy of these assessments. AI, with its capabilities in ML, predictive modelling, and data-driven decision support systems, enable a deeper exploration of complex datasets, including satellite imagery and social media interactions, thereby augmenting the depth of vulnerability assessments (Spielman et al. 2020; Goktas 2024). These technologies can identify patterns and correlations within data that are not immediately apparent, enabling more nuanced understandings of social vulnerability.

Moreover, remote sensing software and Geographic Information Systems (GIS) have become indispensable components in this domain. These platforms increasingly incorporate semi-automated or fully AI-driven techniques, such as image classification, semantic segmentation, and spatio-temporal modelling, to characterize hazard dynamics, exposure patterns, and vulnerability hotspots with greater precision. For instance, He et al. (2024) review AI applications in landslide risk assessment, demonstrating how GIS and remote sensing processing pipelines are enhanced by DL classification (e.g., landslide susceptibility mapping via satellite imagery). Similarly, Amatebelle (2025) conducts a systematic analysis of applications of remote sensing and GIS across various disaster management contexts (e.g., flood hazard prediction, vulnerability mapping), highlighting how AI-enhanced geospatial techniques support risk zoning and early warning systems. In addition, recent studies have demonstrated the strength of GIS-based analyses in hydrological and transportation contexts , for example, Valjarević (2024) applied GIS-based methods to identify river network types and changing river basins, while Yousefi et al. (2022) conducted a vulnerability assessment of road networks to landslide hazards in a dry-mountainous region. These works exemplify how GIS methodologies can be coupled with AI-driven frameworks to advance hazard mapping and vulnerability assessment (Mohammadi et al. 2025).

Similarly, synthetic data generated through simulations or AI models complements these AI-driven analyses by providing data where real-world data may be scarce or non-existent. This is particularly valuable in regions where data collection is challenging due to logistical, financial, or political constraints. Synthetic data can simulate hazard scenarios or create synthetic populations, offering insights into potential vulnerabilities and impacts without requiring extensive field data collection (Birkmann 2006; Rabiei-Dastjerdi et al. 2025). The integration of AI and synthetic data into social vulnerability assessments represents a significant shift toward more dynamic, real-time analysis. This approach enhances the accuracy of vulnerability models and provides a basis for developing more effective disaster risk reduction strategies. By utilising these technologies, researchers and practitioners can better understand how different groups within a society might be affected by natural hazards, thereby facilitating the development of targeted interventions to reduce risk and enhance community resilience (Spielman et al. 2020; Lovic Obradovic et al. 2022).

1.5 Ethical considerations and identified gap

Despite the potential of these emerging technologies, significant challenges remain, particularly concerning ethical considerations such as transparency, data privacy, and community engagement (UNDRR 2019, 2022). The responsible use of AI and synthetic data is crucial to maintaining public trust and ensuring that the outcomes of these assessments are equitable and just (Flanagan et al. 2011; Goktas 2024). Addressing algorithmic biases and ensuring inclusivity in AI-driven assessments are imperative to avoid reinforcing existing social disparities. While the practical applications of AI-driven social vulnerability assessments have demonstrated their potential in enhancing disaster response and recovery efforts, such as leveraging AI for post-disaster damage assessment through satellite imagery (Birkmann 2006; Sun et al. 2020). Yet, a critical gap remains in the systematic understanding of how AI and synthetic data contribute to social vulnerability assessments.

1.6 Study aim and contributions

To address this gap, a bibliometric analysis provides a robust and evidence-based way of mapping the intellectual landscape of this interdisciplinary domain. By systematically tracing publication patterns, citation structures, and co-occurrence networks, bibliometrics enables us to capture how research on AI and social vulnerability has evolved over time, where collaborations are concentrated, and which thematic clusters are emerging. Such an approach not only situates current work within its historical development but also identifies underexplored areas and future research trajectories.

Thus, this bibliometric study aims to bridge this gap by comprehensively analysing the evolution of AI applications in social vulnerability assessments from 1996 to 2024. Through a systematic examination of publication trends, collaborative networks, and thematic developments, this study aims to illuminate the trajectory of research in this field, identify emerging trends, and offer strategic insights into future research directions. By offering a rigorous evaluation of existing methodologies, applications, challenges, and ethical considerations, this review contributes to the evolving discourse on disaster resilience. Ultimately, the findings presented herein aspire to guide policymakers, researchers, and practitioners in harnessing AI and synthetic data for more effective and equitable disaster risk reduction strategies, fostering resilient communities that are better prepared to confront the increasing threats posed by natural hazards (Cutter 1996; Cutter et al. 2003; Goktas et al. 2024).

2 Methodology

The methodology employed in this study utilises bibliometric methods to analyse the content and citations of scholarly articles, drawing insights from urban studies, information science, and disaster management. The focus is on understanding the role of advanced AI techniques and synthetic data generation in assessing social vulnerabilities to natural hazards. As defined by Ellegaard and Wallin (2015), bibliometric analysis involves examining scholarly literature to uncover trends across various domains. Unlike traditional literature reviews, bibliometric analysis offers a systematic and transparent framework (Donthu et al. 2021; Shi et al. 2021). The study employed a phased approach to conduct this bibliometric investigation, starting with the establishment of a comprehensive review database. Subsequent phases included thematic evolution analysis and science mapping to elucidate conceptual progressions and identify prevailing thematic groupings within the research domain.

2.1 Search strategy

This study employed a historical and analytical approach to identify and categorise key technological developments in the evolution of social vulnerability assessment for natural hazards, focusing on the application and advancements of the CDC/ATSDR Social Vulnerability Index (SVI) from Cutter (1996) to 2024. The timeline was divided into three distinct regimes: Foundational Era (1996–2009), Developmental Era (2010–2019), and Transformative Era (2020–2024), based on critical milestones, technological advancements, and public health applications (UNDRR 2015; UNFCCC 2015).

The categorisation of the three regimes was determined using a deductive thematic analysis, focusing on the following criteria (as detailed in Table 1):

- *Foundational era (1996–2009):* Identification of early discussions surrounding social determinants of health, the emergence of vulnerability-related frameworks, and limited integration of data-driven methodologies.

Table 1 Timeline of the evolution of social vulnerability index (SVI): Milestones and regimes from 1996 to 2024

Time period	Regime name	Key characteristics
1996–2009	Foundational Era	-Initial recognition of social determinants of health -Increasing awareness of public health inequities -Limited integration of data-driven tools -The groundwork for frameworks like SVI is laid
2010–2019	Developmental Era	-Introduction of the CDC/ATSDR SVI (2011) -Widespread adoption of geospatial data in health research -Increasing application of SVI in disaster response and community planning -Rapid advancements in GIS and big data analytics
2020–2024	Transformative Era	-Integrating AI, machine learning, and predictive analytics in social vulnerability assessment -Expanded use of SVI for climate resilience, COVID-19 response, and global health equity -Growing emphasis on real-time data and community engagement

Notes: For more information about the Social Vulnerability Index, refer to the official CDC/ATSDR website: https://www.atsdr.cdc.gov/place-health/php/svi/index.html

- *Developmental era (2010–2019):* Examination of advancements in geospatial data analytics and the formal launch of the SVI in 2011. This era also emphasized SVI's integration into disaster response and community planning.
- *Transformative era (2020–2024):* Analysis of recent developments, including the integration of AI, ML, and real-time data systems in SVI applications. Focus was placed on its expanded use during the COVID-19 pandemic and growing relevance in climate resilience efforts.

The three eras used in this review, Foundational (1996–2009), Developmental (2010–2019), and Transformative (2020–2024), are employed as an interpretative framework to organize longitudinal trends rather than as definitive historical periods. The boundaries were informed by observable inflection points in the dataset (e.g., acceleration of annual scientific production after ~ 2010) and thematic shifts in keyword co-occurrence (e.g., the rise of machine/deep learning and semantic segmentation after 2020), alongside major field milestones (e.g., operationalization and widespread use of SVI in the 2010s, pandemic-era data practices). A comprehensive search strategy was developed to investigate the applications of AI and synthetic data in social vulnerability assessments, utilizing the Scopus and Web of Science (WOS) Core Collection databases. The search covered key thematic areas, including AI technologies and synthetic data applications in assessing social vulnerabilities. The selected search terms included "Artificial Intelligence," "Machine Learning," "Synthetic Data," "Social Vulnerability," "Disaster Risk Assessment," and "Resilience Planning" (see Table 2).

Search queries targeted the TITLE-ABS-KEY field in Scopus and the Topic field in WOS to comprehensively cover article titles, abstracts, and keywords. Refinements were applied to ensure relevance to natural hazards and social vulnerability. The detailed search strategy for transparency and reproducibility is documented in Supplement S1.

2.2 Data extraction

Essential bibliometric information was systematically extracted from the datasets to facilitate comprehensive analysis. The extracted data encompassed:

- *Metadata:* Including article titles, author names, institutional affiliations, publication years, and source journals.
- *Citation metrics:* Covering total citation counts and average citations per year to assess research impact.
- *Thematic content:* Consisting of keywords, abstracts, and funding acknowledgements to identify core themes and research focus areas.

Python scripts were employed to clean and preprocess the dataset, ensuring consistency and accuracy. The data was standardised into a Scopus-compatible format to maintain uniformity across analytical tools and facilitate seamless bibliometric analysis. To ensure data quality, duplicate records retrieved from Scopus and Web of Science were removed automatically using Python scripts, followed by manual checks to consolidate entries with minor variations in metadata (e.g., journal abbreviations or author name formats). After automatic filtering, a manual screening of a subset of records was conducted to reduce false positives

Table 2 Summary of search commands and their descriptions for analysing the intersection of artificial intelligence, synthetic data, and social vulnerability assessments in the context of natural hazards

Search command category	Keywords	Description
For social vulnerability and artificial intelligence	("social vulnerability" OR "disaster risk assessment" OR "resilience planning" OR "vulnerability assessment" OR "synthetic populations" OR "risk reduction" OR "GIS" OR "geographic information system" OR "disaster preparedness" OR "community engagement") AND ("artificial intelligence" OR "machine learning" OR "predictive modelling" OR "decision support systems" OR "synthetic data" OR "data-driven approaches" OR "big data analytics" OR "neural networks")	Combines keywords related to social vulnerability and artificial intelligence (AI), including aspects like machine learning and predictive modelling, into a single search query to capture research at the intersection of these fields
For natural hazards and artificial intelligence	"natural hazards" OR "hazard impact" OR "environmental modelling" OR "hazard scenarios" OR "social media analytics" OR "satellite images" OR "remote sensing" OR "climate change adaptation" OR "emergency management") AND ("artificial intelligence" OR "machine learning" OR "predictive modelling" OR "decision support systems" OR "synthetic data" OR "data-driven approaches" OR "big data analytics" OR "neural networks")	Merges keywords related to natural hazards and artificial intelligence, emphasising the application of AI and machine learning to understand and mitigate the impacts of natural hazards
For social vulnerability, natural hazards, and artificial intelligence	("social vulnerability" OR "disaster risk assessment" OR "resilience planning" OR "vulnerability assessment" OR "synthetic populations" OR "risk reduction" OR "GIS" OR "geographic information system" OR "disaster preparedness" OR "natural hazards" OR "hazard impact" OR "community engagement" OR "environmental modelling" OR "hazard scenarios" OR "social media analytics" OR "satellite images" OR "remote sensing" OR "climate change adaptation" OR "emergency management") AND ("artificial intelligence" OR "machine learning" OR "predictive modelling" OR "decision support systems" OR "synthetic data" OR "data-driven approaches" OR "big data analytics" OR "neural networks")	Ensures a broad search scope, capturing documents that discuss any aspect of social vulnerability, natural hazards, and AI, including machine learning and its applications. It is designed to fetch a wide array of relevant research that intersects these critical areas, potentially useful for multidisciplinary studies

and exclude irrelevant documents. The search terms were also tested iteratively, with pilot queries adjusted to balance recall and specificity by incorporating commonly used terms (e.g., “machine learning” and “deep learning”) and excluding non-relevant usages of “vulnerability.” As this study employed bibliometric methods rather than qualitative coding, inter-coder validation/reliability was not required; however, both authors jointly reviewed and validated the final search strategy to ensure methodological robustness.

2.3 Bibliometric data analysis

The bibliometric analysis employed performance indicators and science mapping techniques to evaluate the research landscape on AI applications in social vulnerability assessments. Performance analysis focused on publication and citation metrics to evaluate research productivity and impact, while science mapping explored intellectual structures through co-authorship, co-citation, bibliographic coupling, and keyword co-occurrence. The study made use of VOSviewer and the Bibliometrix R package for data processing, visualization and mapping (van Eck and Waltman 2010, 2013; Aria and Cuccurullo 2017). These methos enabled identification of key contributors, leading countries, journals, influential institutions, and emerging thematic clusters in the field.

2.4 Data analysis

Building on the methods outlined in Sect. 2.3, the analysis proceeded in four stages:

Publication Trends: Annual publication counts, leading journals, and keyword frequencies were examined to capture shifts in research focus over time.
Collaborative Networks: Patterns of co-authorship and institutional/international collaboration were mapped to identify influential researchers, institutions, and geographic clusters.
Thematic Evolution: Keyword co-occurrence and thematic mapping provided insights into conceptual progressions and the emergence of new research themes.
Citation Analysis: Highly cited publications, authors, and institutions were evaluated to highlight the most impactful contributions shaping this domain.

This structured approach ensured a comprehensive exploration of both the quantitative dimensions of research performance and the qualitative evolution of research themes, while avoiding redundancy between methodological description and analytical outcomes.

3 Results

3.1 Descriptive insights into research on AI applications in social vulnerability assessments

The bibliometric analysis provides a comprehensive overview of the research landscape concerning AI applications in social vulnerability assessments from 1996 to 2024. The dataset comprises 26,717 documents published across 4,633 sources, reflecting the growing interest and multidisciplinary engagement in this field. The annual growth rate of 19.94% highlights the increasing research activity in leveraging AI and synthetic data for disaster risk reduction. Table 3 summarises key bibliometric indicators, offering insights into the scope and impact of this evolving research domain.

The analysis indicates a high degree of collaboration, with 63,778 authors contributing to the field and an average of 4.94 co-authors per document, emphasising the interdisciplinary nature of the research. Single-authored publications are relatively scarce, comprising only 680 documents, while international co-authorships appear in 27.69% of the works, highlighting the global relevance of AI-driven social vulnerability assessments. The majority of published works comprises 25,910 journal articles, supplemented by 612 conference papers and 195 book chapters, reflecting a diverse mix of empirical research, theoretical advancements, and practical applications. Additionally, the bibliometric analysis identifies 85,879 Keywords Plus and 52,478 author-supplied keywords, illustrating the thematic diversity and interdisciplinary nature of the research. The documents exhibit substantial influence, with an average citation count of 33.05 citations per publication, signifying the field's growing impact and relevance. The average document age of 9.87 years suggests foundational studies continue to inform contemporary research efforts.

Table 3 Summary of bibliometric data on AI applications in social vulnerability assessments (1996–2024)

Indicator	Description
Timespan	1996 − 2024
Sources (Journals, Books, etc.)	4,633
Documents	26,717
Annual Growth Rate (%)	19.94
Average Document Age (years)	9.87
Average Citations per Document	33.05
Keywords Plus (ID)	85,879
Author's Keywords (DE)	52,478
Authors	63,778
Single−authored Documents	680
Co−Authors per Document	4.94
International Co−authorships (%)	27.69
Document Types	Article: 25,910, Review: 612, Conference Paper: 195

Notes: Timespan indicates the years during which the documented research has been published, highlighting the duration covered by the study. **Sources** reflect the diversity and distribution of publication outlets that have featured the documents included in the analysis. **Documents** represent the volume of research on the topic, encompassing articles, proceedings papers, and reviews. **Annual Growth Rate** shows the rate at which the field is expanding, indicated by the percentage increase in the number of published documents per year. **Average Document Age** helps gauge the recency and ongoing relevance of the research within the field. **Average Citations per Document** measure the impact or influence of the research in the domain, based on citation counts. **Keywords Plus** and **Author's Keywords** represent the scope of topics and themes explored across the documents, with counts indicating the range of discourse. **Authors** and **Authors of Single-authored Documents** reveal the size of the research community and the level of individual contributions to the field, respectively. **Co-authors per Document** and **International Co-authorships** provide insight into the degree of collaboration and the extent of international partnerships among researchers. **Document Types** categorise the forms of research output found in the dataset, highlighting the predominance of articles

3.1.1 Annual scientific production

The annual scientific production from 1996 to 2024 shows a consistent upward trajectory in research output, with significant increases observed after 2010. A total of 26,717 documents were published during this period. The early years (1996–2005) witnessed relatively modest research activity, averaging fewer than 10 publications per year. A notable surge occurred post-2008, with 294 articles published in 2008 and 293 in 2009, marking the initial adoption of AI techniques in social vulnerability research.

From 2010 onwards, research output accelerated, with annual publication counts increasing from 348 in 2010 to a peak of 5,200 in 2023. The most significant growth occurred between 2015 and 2020, reflecting increased interest in AI-driven methodologies and their applications in disaster management. The peak publication year of 2023, with 5,200 documents, highlights the field's critical role in contemporary disaster preparedness and response efforts. The sustained increase in publication output aligns with global efforts to harness AI to improve resilience and adaptive capacity in vulnerable communities (UNDRR 2022; UNFCCC 2023).

3.1.2 Average citations per year

The average number of citations per document provides valuable insights into the impact and influence of research outputs over time. Across the entire dataset, the average citation rate is 33.05 citations per publication, indicating that works in this field have been widely referenced and have had notable scholarly visibility. Early publications (1996–2005) had relatively low citation counts, indicating the field's nascent stage. However, citation rates increased significantly post-2010, with peaks in 2017 (120.74 citations per document) and 2019 (80.49 citations per document), reflecting the emergence of seminal contributions that have shaped the research landscape.

Between 2020 and 2024, the number of publications grew substantially, with citation averages stabilising. The highest average citations per document were recorded in 2020 (34.7 citations), followed by 2021 (21.74 citations) and 2022 (13.1 citations), highlighting the increasing recognition and utilisation of AI in addressing social vulnerability. The most recent works (2023–2024) exhibit lower citation averages, which can be attributed to the shorter time frame since their publication. This measure highlights not only the growth in publication volume but also the evolving scholarly impact of the field over time.

3.2 Author keyword analysis

This section presents an analysis of the most frequently occurring keywords identified through bibliometric analysis, providing insights into the dominant research themes and emerging priorities in AI applications for social vulnerability assessment.

3.2.1 Prominent keywords across different time periods

The keyword analysis across three distinct periods, 1996–2009, 2010–2019, and 2020–2024, reveals a dynamic evolution in research focus and thematic priorities.

Foundational Era (1996–2009)

During this early period, research largely centered around geospatial technologies and the foundational applications of AI. Remote sensing, with 74 occurrences, emerged as a critical tool for environmental monitoring and vulnerability assessment. Similarly, GIS appeared 73 times, highlighting the importance of spatial analysis in the study of social vulnerability. Early adoption of ML techniques was evident through the frequent appearance of terms like "neural network" (30 occurrences) and "artificial neural networks" (24 occurrences), which highlighted the initial exploration of AI-driven pattern recognition. The concept of decision support systems also featured prominently, with 21 occurrences, reflecting efforts to develop tools that could facilitate informed decision-making in the context of risk management.

Developmental Era (2010–2019)

The period from 2010 to 2019 witnessed a rapid expansion in the application of AI and a shift toward data-driven methodologies. Remote sensing continued to dominate, with 972 keyword occurrences, affirming its sustained relevance in vulnerability assessments. ML gained substantial traction, appearing 532 times, indicating a growing dependence on AI for predictive analytics. DL also emerged strongly, with 322 occurrences, highlighting advancements in data processing and feature extraction. Keywords such as "classification" (184 occurrences) and "random forest" (166 occurrences) illustrated the increasing importance of categorizing vulnerability indicators and the adoption of ensemble methods to enhance predictive accuracy. Decision support systems, mentioned 149 times, reflected ongoing developments in tools designed to support decision-making processes.

Transformative Era (2020–2024)

The most recent period, 2020 to 2024, showcases a transformative shift toward more sophisticated AI-driven analytics. Remote sensing surged to 3,687 occurrences, marking its expanded application in high-resolution and real-time environmental monitoring. ML, with 3,357 occurrences, solidified its position as a fundamental component of AI-driven social vulnerability analysis. DL gained further prominence, appearing 2,605 times, indicative of its critical role in handling big data analytics. The rise of convolutional neural networks (CNNs), with 754 occurrences, pointed to the growing utilization of DL architectures for image processing tasks. Semantic segmentation, cited 629 times, reflected notable progress in automated feature extraction from spatial data. Finally, the term "artificial intelligence" appeared 502 times, highlighting the broader and more integrated adoption of AI frameworks across a range of applications.

3.2.2 Thematic representation of keywords

The thematic structure of the literature is visually represented in Fig. 1 and Supplementary Figs. 1 and 2, which depict the distribution of the most frequently occurring keywords across the three time periods.

- **Foundational era (1996–2009)**.

Foundational themes such as "remote sensing," "GIS," and "decision support systems" dominate this period, reflecting the early exploration of spatial technologies in vulnerability assessments (Supplementary Fig. 1).

Fig. 1 Treemap visualization of the most frequently occurring keywords during 2020–2024. Each rectangle represents a keyword, with its size reflecting frequency of occurrence and colour illustrating thematic grouping for visualization clarity

- **Developmental era (2010–2019)**.

The thematic focus shifts toward the integration of AI methodologies, with keywords such as "machine learning," "deep learning," and "decision support system" gaining prominence. The presence of terms like "image classification" and "learning systems" emphasizes the adoption of sophisticated analytical methods (Supplementary Fig. 2).

- **Transformative era (2020–2024)**.

This period marks a shift toward advanced AI techniques, as evidenced by terms such as "artificial neural network," "convolutional neural networks," and "semantics," which highlight the growing emphasis on high-resolution data and AI-driven insights (Fig. 1).

These keyword trends and thematic representations provide a comprehensive understanding of the evolving landscape of AI applications in social vulnerability assessments, offering valuable insights into research trajectories and future directions.

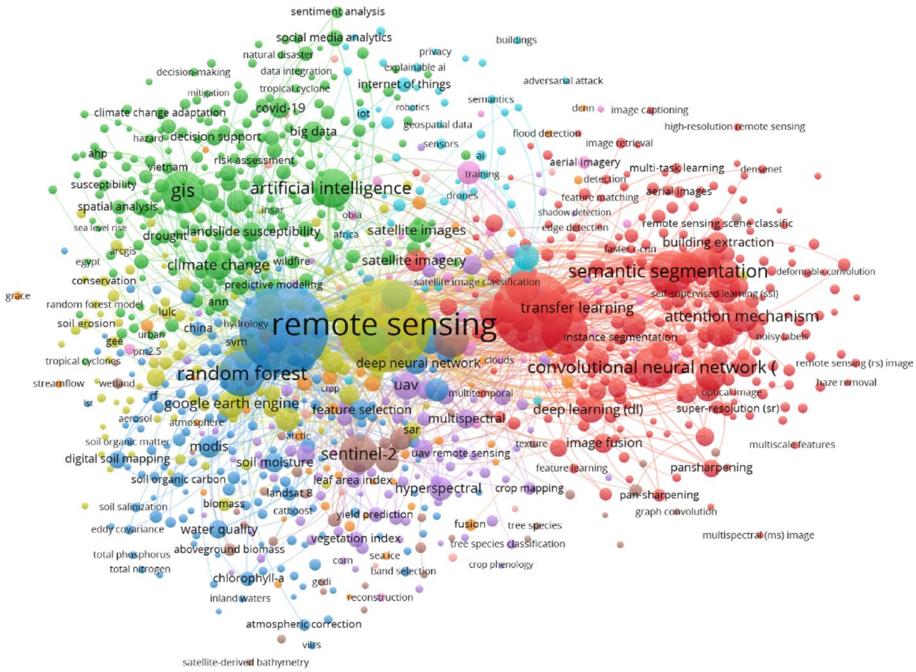

Fig. 2 Keyword co-occurrence network (2020–2024) generated with VOSviewer. The most recent period shows significant complexity and density, with *remote sensing* continuing as the dominant hub, surrounded by expanding clusters on *semantic segmentation*, *convolutional neural networks*, *transfer learning*, and *Sentinel data*

3.3 Co-occurrence network of research themes on AI applications in social vulnerability assessments

3.3.1 Thematic clusters and connections

The co-occurrence network visualizations in Fig. 2, Supplementary Figs. 3 and 4, generated using VOSviewer, depict the evolving relationships among key research themes in AI-based social vulnerability assessments across three periods: 1996–2009 (Supplementary Fig. 3), 2010–2019 (Supplementary Fig. 4), and 2020–2024 (Fig. 2). Color-coded clusters illustrate dominant areas, with node size reflecting keyword frequency and link thickness indicating the strength of their co-occurrence. These clusters illustrate how foundational methods in geospatial technologies and early AI applications gradually expanded into advanced ML techniques, decision support systems, and sustainability-oriented approaches. Across the three analyzed periods, the connections between these clusters became increasingly integrated, reflecting technological advancements, methodological diversification, and a stronger emphasis on real-time, data-driven decision-making in environmental and risk management contexts.

- Cluster 1: Remote Sensing and Geospatial Technologies (Red Cluster).

Across all three periods, remote sensing consistently emerges as the central thematic node, underscoring its pivotal role in vulnerability assessment studies. Associated keywords such as GIS, land cover, and classification reflect the early reliance on geospatial technologies for data collection, mapping, and spatial analysis. As research advanced, the focus expanded to more sophisticated applications, including multispectral image analysis, multiscale features, and multitask learning. These developments highlight a significant enhancement in data processing capabilities and the ability to extract richer, more detailed insights from geospatial datasets, as visualized in Fig. 2.

- Cluster 2: AI and Machine Learning Techniques (Yellow/Blue/Red Cluster).

The second major thematic area centres on the application of AI and ML techniques. During the foundational era, terms such as neural networks and decision support indicated an initial experimentation with AI-based approaches, as shown in Supplementary Fig. 3. In the developmental era (2010–2019), keywords like ML, DL, and random forest gained prominence, signalling a broader adoption of data-driven methodologies for predictive analytics. By the transformative era (2020–2024), the emergence of CNNs and semantic segmentation points to the growing sophistication and specialization of AI applications, particularly in the areas of predictive modelling and automated feature extraction from complex datasets (Fig. 2).

- Cluster 3: Decision Support Systems and Risk Assessment (Blue Cluster).

Decision support systems and risk assessment frameworks form another crucial thematic cluster. Throughout the periods analyzed, keywords such as decision support system and vulnerability consistently appear, reflecting the field's commitment to integrating AI into decision-making processes. The evolution from traditional decision frameworks observed in Supplementary Fig. 3 to AI-enhanced, real-time decision support systems depicted in Fig. 2 illustrates a clear shift toward more dynamic, data-driven, and adaptive approaches in vulnerability assessment and disaster risk management.

- Cluster 4: Environmental Monitoring and Sustainability (Cyan Cluster).

Environmental monitoring and sustainability concerns emerge as an increasingly prominent thematic cluster. Early research focused on modelling, predictive modelling, and hazard-specific studies such as landslide assessment (Supplementary Fig. 3). Moving into the developmental era, there is a noticeable inclusion of climate change adaptation, precipitation modelling, and flood risk assessment, reflecting a growing awareness of climate resilience strategies (Supplementary Fig. 4). In the transformative era (Fig. 2), new topics such as buildings, Internet of Things (IoT), and sensors surface, showcasing the trend toward integrating AI, IoT, and smart technologies to enhance environmental monitoring capabilities and advance sustainable development planning.

4 Research priorities and future directions

The co-occurrence network analysis emphasizes key research priorities and provides insights into future directions, including:

- *Integration of AI into disaster risk reduction:* There is a growing emphasis on using AI methodologies, such as DL and remote sensing data fusion, to enhance disaster preparedness and response capabilities.
- *Advancement of decision support systems:* Efforts are focused on developing AI-powered decision-making frameworks that facilitate evidence-based policy planning and emergency response.
- *Expansion of remote sensing applications:* With the increasing availability of high-resolution satellite data, researchers are exploring more efficient methods for monitoring environmental changes and predicting vulnerabilities.
- *Sustainability and ethical considerations:* As AI becomes more embedded in social vulnerability assessments, attention is being directed toward ethical concerns related to data privacy, bias mitigation, and community involvement.
- *Interdisciplinary collaborations:* The future of the field lies in fostering collaborations across disciplines, integrating insights from environmental science, data analytics, social sciences, and public policy.

The co-occurrence analysis provides a strategic overview of the research landscape, identifying major thematic areas and knowledge gaps. The progression from basic geospatial analysis in Supplementary Figs. 3 and 4 to advanced AI-driven insights in Fig. 2 demonstrates the field's continuous evolution and alignment with emerging technological trends.

4.1 Most relevant sources publishing on AI applications in social vulnerability assessments

This subsection identifies the most influential sources contributing to the discourse on AI applications in social vulnerability assessments. Understanding the key publishing venues is essential for tracking foundational research and identifying journals at the forefront of this field.

4.1.1 Prominent journals in the field

The bibliometric analysis highlights *Remote Sensing* as the leading journal, having published a total of 2,375 articles by 2024, thereby establishing it as the primary source for research in this domain. Other significant contributors include *IEEE Transactions on Geoscience and Remote Sensing*, with 1,432 articles, and IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, with 1,052 articles, both of which emphasise multidisciplinary approaches involving geospatial technologies and AI-driven assessments.

Additional noteworthy journals include the *International Journal of Remote Sensing* (with 737 articles) and *IEEE Geoscience and Remote Sensing Letters* (with 362 articles). These sources focus on the technological advancements and applications of remote sensing and AI in disaster management and social vulnerability assessment (Fig. 3, Supplementary

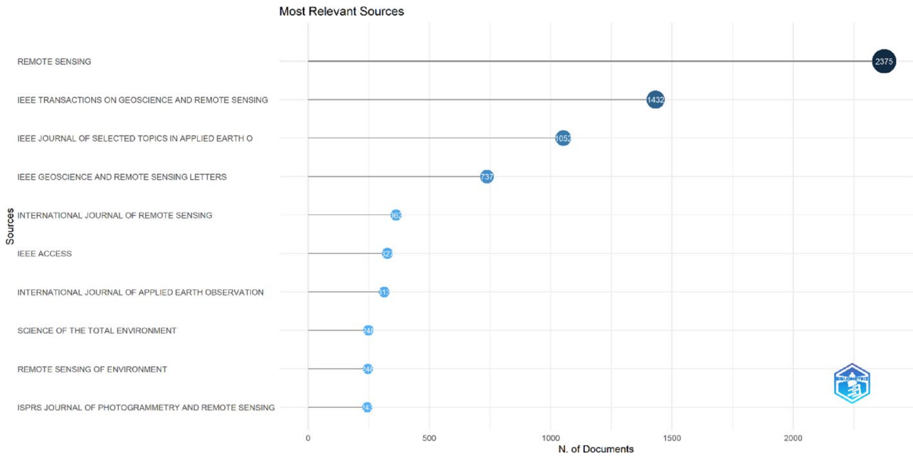

Fig. 3 Most relevant sources (2020–2024). The most recent period shows exponential growth, with *Remote Sensing* far outpacing all other journals, followed by *IEEE Transactions on Geoscience and Remote Sensing* and *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*

Figs. 5 and 6). The collective contributions of these journals highlight their critical role in advancing knowledge on geospatial analytics, predictive modelling, and decision support systems for vulnerability assessments.

4.1.2 Sources' production over time

Analysing source production over time reveals trends in journal contributions to the field. From 1996 to 2009, *Remote Sensing of Environment* demonstrated a gradual increase in publications, rising from 1 article in 2006 to 20 articles by 2009. Other early contributors included *IEEE Transactions on Geoscience and Remote Sensing* and *Photogrammetric Engineering and Remote Sensing*, with 17 articles each by 2009. Between 2010 and 2019, there was significant growth in publication outputs. *Remote Sensing* emerged as the dominant source with 536 articles by 2019, followed by *IEEE Transactions on Geoscience and Remote Sensing* (225 articles) and the *International Journal of Remote Sensing* (189 articles). The increase in contributions reflects the growing recognition of AI and remote sensing technologies in vulnerability assessments.

From 2020 to 2024, publication activity further accelerated, with *Remote Sensing* leading the field, publishing 2,375 articles by 2024. Notable contributors such as *IEEE Transactions on Geoscience and Remote Sensing* (1,432 articles), *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* (1,052 articles), and *IEEE Access* (327) solidified their positions as key venues for research dissemination. These trends emphasise the growing recognition of AI applications in social vulnerability assessments as an essential research area, driving innovation and practical applications in disaster risk reduction and resilience planning.

4.2 Global impact and collaboration in remote sensing and GIS research

4.2.1 Key contributing countries

In the 1996–2009 period (Supplementary Fig. 7), the United States led global research efforts with 6,426 citations, demonstrating its pivotal role in advancing remote sensing applications and geospatial technologies. Italy and China followed, reflecting their early investment in environmental monitoring and decision-making support using GIS technologies. Between 2010 and 2019 (Supplementary Fig. 8), China emerged as the dominant player, accumulating 98,688 citations and surpassing the USA to establish itself as the leading contributor in the field. The USA maintained a strong presence, while Germany, Iran, and Italy also gained traction, emphasising the diversification of research leadership across different regions. In the most recent period, from 2020 to 2024 (Fig. 4), China further strengthened its position, accumulating 112,968 citations, which emphasizes its sustained growth and influence in remote sensing research. The USA remained a key player with 22,672 citations, while India, Germany, and Korea showed significant advancements, signalling an expanding global research network.

4.2.2 Trends in global collaboration

The analysis reveals a clear shift towards increased global collaboration over time. While a few leading countries predominantly drove early research efforts, recent years have witnessed a substantial expansion in international cooperation, particularly among emerging economies. Countries such as India, Australia, and Brazil have demonstrated rising research engagement, reflecting their growing focus on leveraging remote sensing technologies for environmental sustainability and disaster management. The data further indicate that research partnerships are becoming more interdisciplinary and geographically diverse, with

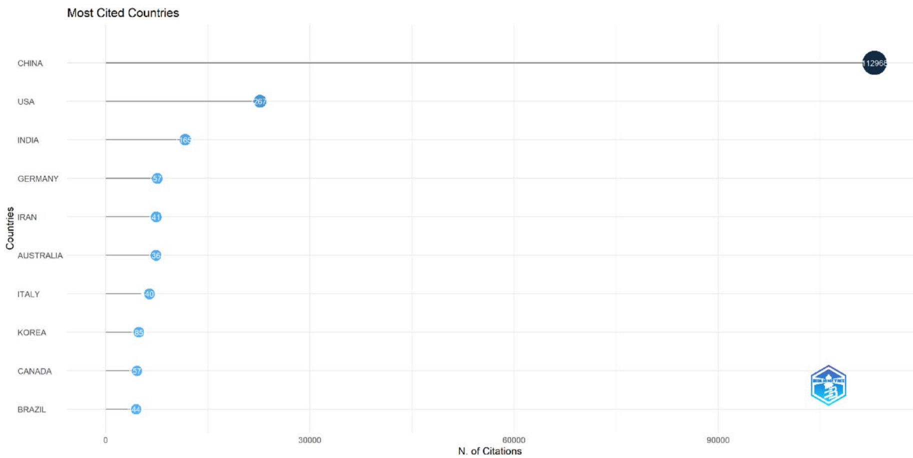

Fig. 4 Most cited countries (2020–2024). China consolidated its dominance with citation counts far exceeding other countries, followed by the United States and India. Germany, Iran, Australia, and South Korea also played increasingly prominent roles, alongside contributions from Italy, Canada, and Brazil. This reflects the globalization of the research landscape, with significant growth in Asia and the Global South

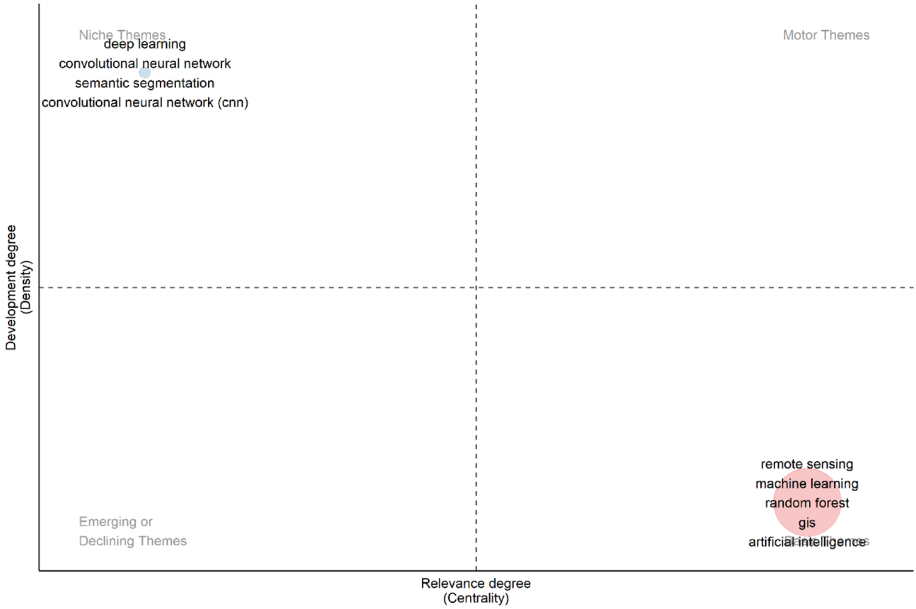

Fig. 5 Thematic evolution of remote sensing and GIS research (2020–2024). The thematic maps categorize clusters into four quadrants: motor themes (upper-right: high relevance, high development), basic themes (lower-right: high relevance, low development), niche themes (upper-left: low relevance, high development), and emerging/declining themes (lower-left: low relevance, low development). The bubble size represents the density of publications within each theme

collaborations bridging gaps between technologically advanced regions and developing economies. This trend highlights the growing recognition of remote sensing as a crucial tool for addressing global challenges, including climate change, urbanization, and sustainable management of natural resources.

4.3 Strategic thematic evolution in remote sensing and GIS research

The evolution of research themes in remote sensing and GIS has undergone significant transformations over the years, highlighting key areas of focus and emerging trends. The thematic maps illustrate the thematic development across three distinct periods: 1996–2009 (Supplementary Fig. 9), 2010–2019 (Supplementary Fig. 10), and 2020–2024 (Fig. 5). These figures categorise research themes into four quadrants: *motor themes, basic themes, niche themes,* and *emerging or declining themes*, based on their degree of centrality (relevance) and density (development).

4.3.1 Motor themes

Motor themes are well-developed and highly relevant, driving innovation and application in the field. In the earlier period (Supplementary Fig. 9), themes such as "GIS" and "artificial neural networks" played a pivotal role in advancing spatial data analysis and modelling. In the subsequent years (Supplementary Fig. 9), "remote sensing," "machine learning," and “classification” emerged as dominant themes, reflecting the increasing integration of AI-driven techniques in geospatial analysis. In the most recent period (Fig. 5), the focus shifted to advanced methodologies, such as “random forest” and “artificial intelligence,” indicating a growing emphasis on precision, automation, and large-scale data processing.

4.3.2 Basic themes

Basic themes form the foundation of the field but exhibit lower density in terms of ongoing development. Between 1996 and 2009 (Supplementary Fig. 9), “remote sensing” and “neural networks” were core areas of research, providing essential insights into geospatial analysis techniques. Over the following decade (Supplementary Fig. 10), these topics expanded to include “machine learning” and “classification,” underlying their critical role in supporting data interpretation and analysis. In recent years (Fig. 5), the integration of “GIS,” “artificial intelligence,” and “big data” into remote sensing applications has reinforced their significance as fundamental elements of geospatial studies.

4.3.3 Niche themes

Niche themes represent highly specialised research areas with focused applications. Between 1996 and 2009 (Supplementary Fig. 9), the terms “decision support system” and “geographic information system” emerged as specialized topics addressing spatial decision-making and environmental modeling. The 2010–2019 period (Supplementary Fig. 10) witnessed the rise of “deep learning,” a rapidly evolving area with applications in image analysis and automated classification. In the most recent timeframe (Fig. 5), topics such as “semantic segmentation” and “convolutional neural networks” reflect the cutting-edge advancements in DL applications for remote sensing data analysis.

4.3.4 Emerging or declining themes

Emerging or declining themes represent areas that are either gaining traction or becoming less relevant over time. Between 1996 and 2009 (Supplementary Fig. 9), themes such as “neural networks” emerged as key research trends. However, in the following decade (Supplementary Fig. 10), traditional GIS approaches began to decline in prominence as AI-based methodologies gained momentum. In the most recent period (Fig. 5), themes such as “convolutional neural network” and “feature extraction” suggest new directions for future research, reflecting a shift toward more sophisticated data analysis techniques and automation.

4.3.5 Insights and future directions

The thematic evolution of remote sensing and GIS research highlights several key trends and insights:

- *Motor themes* drive practical applications and innovation, with an increasing reliance on AI and ML.
- *Basic themes* provide foundational knowledge supporting new developments in geo-

spatial science.

- *Niche themes* highlight specialised research areas with targeted environmental monitoring and data analysis applications.
- *Emerging themes* suggest potential areas for future exploration, including automation and advanced pattern recognition.

Figure 5 provides a strategic overview of the evolving landscape in remote sensing and GIS research, offering valuable insights into current trends and future directions.

5 Discussion

The evolution of AI applications in social vulnerability assessments has been significant over the past two decades, highlighting both opportunities and challenges in disaster risk reduction and resilience planning (UNDRR 2022). This study provides a comprehensive bibliometric analysis of AI-driven research in social vulnerability assessments from 1996 to 2024, offering insights into the field's growth, thematic evolution, and interdisciplinary collaborations. The notable annual growth rate of 19.94% in publications underlines the increasing research interest and the growing importance of AI in addressing social vulnerabilities. The findings reveal a substantial collaborative effort, with an average of 4.94 co-authors per document and a global co-authorship rate of 27.69%, emphasising the interdisciplinary nature of the research landscape. The prominence of journals such as *Remote Sensing*, *IEEE Transactions on Geoscience and Remote Sensing*, *International Journal of Remote Sensing* and *IEEE Access* further illustrates the field's expansion and the critical role of remote sensing and AI technologies in social vulnerability studies.

The thematic analysis indicates a shift from geospatial technologies and foundational AI applications in the early years (1996–2009) to sophisticated AI-driven analytics in recent years (2020–2024). The growing prominence of keywords such as "deep learning," "convolutional neural networks," and "semantic segmentation" highlights the increasing reliance on AI techniques to enhance vulnerability assessments. Notably, most applications are image-based, leveraging CNNs for satellite imagery, land-use mapping, and damage detection, whereas sequential data approaches such as RNNs and LSTMs have been used more selectively in analyzing time-series data, including rainfall prediction, climate variability, and socio-economic dynamics. This distinction highlights the predominance of geospatial imagery but also signals opportunities for expanding sequential and multimodal methods in future studies. This evolution aligns with broader trends in AI research, where advanced methodologies are being employed to improve the precision and efficiency of social vulnerability assessments (Roy et al. 2020; Hong et al. 2021). A critical observation from the analysis is the impact of AI on decision support systems. Early studies focused on traditional frameworks for informed decision-making, while recent research has increasingly integrated AI-powered tools to provide real-time, data-driven insights. The increasing prevalence of AI methods such as ML and DL highlights the field's transition toward predictive analytics and automated decision-making processes (Li et al. 2020; Weiss et al. 2020). However, one notable concern revealed through this bibliometric analysis is that many researchers deploying AI in this domain may come from technical fields, such as data science, physical geography, and engineering. It may not have formal training in the social sciences. As a result, social vulnerability is sometimes operationalised through proxy indicators without sufficient engagement with its socio-behavioral complexities or community-based contextual understanding. This disciplinary gap risks limiting the interpretability, validity, and equity of AI-generated insights (Cutter et al. 2003; Wisner 2016; Goktas 2024; Rabiei-Dastjerdi et al. 2025). Moreover, vulnerability is not only a matter of exposure but is also deeply rooted in inequality, marginalization, and policy failures. If AI systems overlook these structural drivers and rely solely on technical proxies, they risk reproducing existing inequities rather than addressing them. Integrating socio-political determinants and participatory approaches is therefore critical to ensuring that AI-based vulnerability assessments are socially just and contextually grounded.

In addition to thematic trends, our analysis also reveals the status of intellectual interaction between prominent researchers and institutions. Co-authorship and institutional collaboration networks highlight the presence of several influential hubs, such as leading universities in China, the United States, and Europe, that foster connections across geography, data science, geospatial analytics, and disaster management. These hubs often serve as bridges between technical and applied disciplines, enabling cross-fertilization of methods (e.g., machine learning and GIS) with social and policy-oriented perspectives. The clustering of collaborations indicates that intellectual interaction in this field is not confined to disciplinary silos but is instead increasingly interdisciplinary, reflecting the complex and multifaceted nature of disaster research. In addition, by incorporating world map visualization as Fig. 6, our study highlights where AI-driven social vulnerability research is most active and where significant gaps remain. The countries' collaboration world map (2020–2024) illustrates that the United States, China, and several European nations dominate international partnerships, while collaborations involving low- and middle-income countries remain sparse. This finding indicates that while the field is advancing globally, the distribution of intellectual networks is uneven, potentially limiting inclusivity and knowledge diversity. Similar to prior bibliometric works (Mora et al. 2017, 2019), the use of spatially related findings enables a clearer identification of global research hubs and underrepresented regions. This perspective adds a geographic layer to the intellectual and thematic

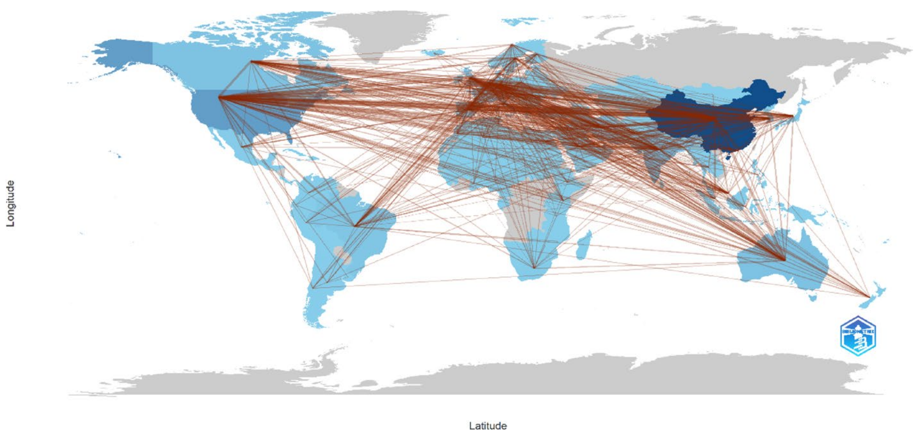

Fig. 6 Countries' collaboration world map (2020–2024). Node size corresponds to the number of publications from each country, while line thickness indicates the intensity of collaboration links (co-authorships). Darker shades of blue highlight higher research productivity

analyses, pointing to opportunities for future collaboration and more balanced knowledge production worldwide. Our bibliometric findings further suggest that author collaborations are becoming more centralized around these publication hubs, reinforcing the role of specific journals and institutions as incubators for niche and interdisciplinary themes.

Furthermore, synthesizing across journals, countries, and themes reveals several important interaction patterns. Specifically, the interaction between authors and journals has developed notably in recent years, with *Remote Sensing* and *IEEE Transactions on Geoscience and Remote Sensing* serving as central venues that foster international collaboration. Between 2020 and 2024, niche themes such as semantic segmentation, CNNs, and feature extraction have emerged strongly in outputs originating from China, India, and Korea, reflecting their rapid advancement in DL-based disaster studies. In contrast, researchers from the USA and some European countries, though still contributing significantly to foundational frameworks, appear less represented in these rapidly evolving AI-driven niches, indicating a relative lag. Journals such as *International Journal of Remote Sensing* and *IEEE Access* have recently published a growing share of these niche studies, reinforcing their positions as leading outlets for innovative disaster-related AI applications. It is important to recognize that bibliometric patterns not only illustrate scientific growth but also indicate practical priorities in disaster risk management. For instance, the growing prominence of CNNs and semantic segmentation corresponds with the operational demand for automated damage detection, hazard monitoring, and predictive modelling in real-world disaster contexts (Agrawal and Goktas 2025). Similarly, the increasing role of international co-authorship highlights a global recognition that vulnerability assessment is not merely a technical issue but one that requires cross-disciplinary collaboration across geography, computer science, sociology, and policy. These insights highlight that bibliometric trends must be interpreted not only as scholarly evolution but also as reflections of shifting needs in disaster preparedness and resilience implementation.

Despite these advancements, challenges persist in ensuring the ethical deployment and transparency of AI systems. As AI becomes more embedded in social vulnerability assessments, addressing concerns related to data privacy, bias mitigation, and explainability becomes paramount. The misapplication of AI in vulnerable settings often arises when biased algorithms or incomplete datasets disproportionately represent certain geographies or demographics. This can result in inaccurate vulnerability maps, misallocation of emergency resources, or the systematic neglect of marginalized communities, thereby exacerbating inequality rather than reducing it (UNDRR 2022). Ensuring fairness, transparency, and inclusivity in model design is therefore essential to prevent AI from reinforcing structural inequities in disaster risk management. Real-world case studies provide evidence of both successful and problematic applications of AI in vulnerability assessments. For instance, deep learning models, particularly CNNs, were effectively applied for rapid structural damage detection following the 2017 Pohang earthquake in South Korea, where transfer learning approaches enabled accurate and timely mapping of building damage (Ogunjinmi et al. 2022). Conversely, in wildfire management, Convolutional LSTM models have been employed to simulate fire spread; however, many of these approaches rely on simplified or simulated datasets, which limits their generalizability across complex and diverse real-world terrains (Burge et al. 2020). These examples highlight the dual trajectory of AI in practice: it can greatly enhance disaster response capabilities when supported by robust data, but it also risks misapplication when models lack contextual adaptation. In addition, the literature emphasises the need for regulatory frameworks and guidelines that promote responsible AI development and application (Cheng et al. 2020; Diakogiannis et al. 2020). The surge in publications and citations from 2023 to 2024 further indicates the urgency of these discussions, particularly as AI-driven methodologies are increasingly applied in high-stakes environments such as disaster response and resilience planning. Addressing these shortcomings requires deliberate efforts to foster multidisciplinary collaboration and knowledge exchange. Involving social scientists in model design and evaluation, training a new generation of computational social scientists, and promoting hybrid methodologies that combine AI with participatory approaches can ensure more socially grounded and ethically sound outcomes (Panahandeh et al. 2025; Rabiei-Dastjerdi et al. 2025).

Key emerging trends identified in this study include:

- *Integrating AI into disaster risk reduction:* The increasing use of AI methodologies such as DL and remote sensing data fusion enhances disaster preparedness and response capabilities.
- *Advancement of decision support systems:* AI-powered decision-making frameworks are evolving to facilitate evidence-based policy planning and emergency response.
- *Expansion of remote sensing applications:* The availability of high-resolution satellite data drives innovative approaches to monitoring environmental changes and predicting vulnerabilities.
- *Sustainability and ethical considerations:* There is a growing emphasis on addressing ethical challenges related to the deployment of AI in social vulnerability assessments.

The co-occurrence network analysis further emphasises the thematic evolution in AI applications, illustrating how foundational concepts such as “remote sensing” and “GIS” have been complemented by cutting-edge AI techniques over time. The transition from foundational to advanced themes highlights the field’s continuous adaptation to technological advancements and emerging societal needs. It should be noted that both the abbreviated form “GIS” and the full term “Geographic Information System” appear separately in the thematic map. This distinction arises because the bibliometric algorithm treats them as independent keywords, although they conceptually represent the same domain. Their presence in different clusters (basic vs. niche themes) reflects variations in author preference and disciplinary context rather than conceptual differences. Future research directions should focus on bridging the gap between technical AI capabilities and ethical considerations. Developing comprehensive AI Trust, Risk, and Security Management (AI TriSM) frameworks is essential to establishing trustworthy AI applications in social vulnerability assessments (Yuan et al. 2020; Hong et al., 2021; Habbal et al. 2024). Moreover, initiatives such as ecological and hotspot analyses of social vulnerability provide empirical evidence that can be integrated into AI models to enhance geographic and contextual relevance (Lovic Obradovic et al. 2022). Additionally, fostering interdisciplinary collaborations and global partnerships could be crucial in addressing complex social vulnerability and disaster resilience challenges (Goktas et al. 2024).

Table 4 Comparative strengths and limitations of AI approaches in social vulnerability assessments

Approach	Strengths	Limitations	References
Traditional statistical models	Interpretability; ease of use; well-established	Limited in handling nonlinear and high-dimensional data	Flanagan et al. 2011
Machine learning (RF, SVM, Logistic Regression)	Works well with structured/tabular data; more interpretable; effective with limited datasets	Struggles with high-dimensional unstructured data; feature engineering often required	Kalaycıoğlu et al. 2023; Zhang et al. (2023)
Deep learning (CNNs, RNNs, transformers)	High accuracy with large-scale and unstructured data; strong feature extraction from imagery/text	Data-hungry; less interpretable ("black box"); high computational cost	Goodfellow et al. (2016); He et al. (2024); Amatebelle, 2025
Supervised learning	High predictive accuracy with labelled data; effective for classification and regression	Requires labelled training data; may not generalize well	Yuan et al. (2020); Panahandeh et al. (2025)
Unsupervised learning	Identifies hidden patterns without labels; useful for clustering/anomaly detection	Validation is challenging; results may lack interpretability	Yuan et al. (2020); Rabiei-Dastjerdi et al. (2025)

5.1 Comparative discussion of AI techniques

While both ML and DL approaches have been widely adopted in disaster risk management and social vulnerability assessment, their methodological orientations differ significantly. Traditional ML techniques, such as Random Forests, Support Vector Machines, and logistic regression, are advantageous for structured data (e.g., census indicators, socioeconomic indices), offering interpretability and requiring smaller datasets (Kalaycıoğlu et al. 2023; Zhang et al. 2023). In contrast, DL methods, particularly CNNs and recurrent neural networks (RNNs), excel at extracting features from unstructured data, including satellite imagery, text streams, and social media signals, though they demand large datasets and are often less transparent (Goodfellow et al. 2016; He et al. 2024).

Similarly, a distinction arises between supervised and unsupervised learning approaches. Supervised methods are effective for predictive accuracy when labelled training data are available (e.g., post-disaster damage classification, flood exposure modeling), while unsupervised methods are valuable in contexts where labelled datasets are scarce, as they can uncover hidden patterns, clusters, or anomalies in vulnerability profiles (Yuan et al. 2020; Panahandeh et al. 2025). However, unsupervised methods often face validation challenges and may require expert interpretation to ensure meaningful outputs (Rabiei-Dastjerdi et al. 2025).

This comparative perspective highlights that no single technique is universally superior; instead, the choice of method depends on data availability, interpretability requirements, and the scale of the disaster context under investigation, as detailed in Table 4.

5.2 Limitations and strengths

In conducting this study, several limitations must be acknowledged, which are inherent to bibliometric analyses. First, database coverage was limited to Scopus and Web of Science. Although these databases are widely regarded as comprehensive and authoritative, they may exclude relevant articles from Google Scholar, PubMed, regional indexing services, and grey literature sources such as government reports and NGO documents. This limitation may have led to the underrepresentation of community-based studies or localized disaster management practices. Second, author and affiliation disambiguation remain a persistent challenge in bibliometric research. Despite applying standardized cleaning methods using Python and bibliometric software tools, variations in institutional names and inconsistent author spellings may have introduced minor attribution errors in our analysis of co-authorship and institutional productivity. Third, as a bibliometric study, this work does not provide an in-depth qualitative evaluation of individual methodologies, assumptions, or contextual frameworks. Unlike systematic reviews, bibliometric mapping emphasizes structural and quantitative patterns, meaning interpretive depth regarding the robustness of particular studies is inherently limited. Recognizing these constraints is essential in framing the scope and intended contribution of our work. Additionally, our three-era periodization is necessarily interpretative. The principal patterns we report, including growth rates, leading venues, collaboration structures, and thematic transitions, remained substantively unchanged. We therefore retain the proposed eras for clarity of presentation, while acknowledging that other equally defensible boundary choices are possible.

Beyond bibliometric constraints, conceptual and structural limitations should be acknowledged. First, vulnerability itself is a multidimensional and context-dependent construct that resists straightforward quantification; reliance on numerical proxies may obscure social, cultural, and political dynamics that critically shape exposure and resilience. Second, the increasing reliance on remote sensing and AI-derived indicators introduces the risk of misinterpreting proxies such as nighttime lights or building footprints, which may not uniformly reflect socioeconomic conditions across regions. Third, cultural and political biases may influence both the design of vulnerability indices and the interpretation of AI models, potentially privileging data-rich regions while overlooking localized knowledge systems or marginalized communities. These challenges highlight that while bibliometric analysis maps the intellectual structure of the field, the ontological complexity of vulnerability imposes interpretive constraints that must be carefully acknowledged in any research synthesis.

Despite these limitations, this study presents several strengths that contribute to the growing body of knowledge in AI-driven social vulnerability research. The large dataset of 26,717 documents spanning nearly three decades provides a robust foundation for understanding the evolution of research in this interdisciplinary domain. The high degree of collaboration observed, with 63,778 contributing authors and an average of 4.94 co-authors per document, highlights the global and interdisciplinary nature of this research landscape. The study employs advanced bibliometric techniques, including co-occurrence network analysis, thematic mapping, and citation analysis, to offer valuable insights into the intellectual structure and emerging research trends in AI applications for addressing social vulnerability. Identifying key thematic clusters across different time periods, foundational, developmental, and transformative, provides a nuanced understanding of how AI methodologies have evolved to address social vulnerabilities in disaster risk reduction and resilience planning.

Additionally, this study's emphasis on visual analytics, such as VOSviewer-generated maps, enhances the interpretability of complex bibliometric data, facilitating a more comprehensive exploration of research trajectories. The findings provide policymakers, researchers, and practitioners with actionable insights by highlighting emerging themes and strategic directions for future research. Ultimately, while this study acknowledges its methodological constraints, it makes a meaningful contribution to the discourse on AI and social vulnerability assessment by providing a systematic, large-scale mapping of thematic trends, disciplinary gaps, and collaboration patterns spanning nearly three decades. These insights help clarify not only where the field stands but also how future interdisciplinary and policy-oriented research can better integrate AI with socially grounded approaches to disaster resilience. The results highlight the growing influence of AI in addressing societal challenges and emphasise the need for continued ethical considerations, transparency, and explainability in AI-driven decision-making processes.

5.3 Future recommendations

Based on our findings, several promising avenues for future research can be identified to enhance the understanding and application of AI in social vulnerability assessment. Future work should aim to integrate hybrid approaches that combine bibliometric analysis with systematic or scoping review methodologies, thereby achieving both breadth and interpretive depth. An especially promising frontier lies in the development of large land-use models integrated with generative AI to advance the SVI. Such an approach could enhance the ability to capture spatial heterogeneity, simulate scenario-based vulnerabilities, and fuse environmental with socio-economic dimensions in a dynamic and scalable manner. By embedding generative frameworks into SVI design, future research can provide more nuanced, context-aware, and adaptable measures of vulnerability that better inform disaster risk reduction policies. Researchers could also broaden the evidence base by incorporating grey literature and region-specific datasets, particularly those from developing economies where vulnerability assessments are critical but often underrepresented in global bibliometric studies. Another direction involves developing standardized benchmarking frameworks for AI-based vulnerability assessment, including guidelines for reproducibility, bias auditing, and explainability. The integration of multimodal data sources, such as remote sensing, IoT sensor data, and demographic statistics, offers another frontier for improved predictive accuracy. Finally, participatory AI models that involve affected communities directly in the data-gathering and decision-making processes can ensure more equitable and context-sensitive outcomes. In addition, future research should conduct a more granular breakdown of research outputs by disaster type (e.g., floods, earthquakes, hurricanes, wildfires) and by geographical location. Such an approach would allow researchers and policymakers to identify underrepresented hazards and regions, prioritize context-specific interventions, and evaluate the global distribution of AI-driven vulnerability studies with greater precision. Providing openly accessible, filtered datasets organized by hazard type and region could also serve as a valuable resource for the research community, increasing both the practical usability and the long-term citation impact of subsequent studies. The key areas for future investigation can therefore be summarized as follows:

- *Multidisciplinary and interdisciplinary research integration*: A core solution lies in fostering collaborative teams that combine expertise from computer science, physical geography, and social sciences. Involving social scientists, particularly those specializing in vulnerability theory, community studies, and human behaviour, can ensure that AI models reflect socio-cultural contexts and ground realities. Moreover, training a new generation of computational social scientists who can bridge data science with qualitative insight is essential to developing ethical, inclusive, and context-aware AI systems.
- *Integration of advanced AI techniques:* Future studies should explore the potential of integrating advanced AI models, such as slow feature analysis (SFA), to enhance temporal feature extraction in social vulnerability assessments (Song et al. 2024). Leveraging SFA's ability to capture slowly varying features could provide deeper insights into long-term social and environmental changes.
- *Multimodal data fusion for enhanced predictive accuracy*: The fusion of multimodal data sources, including remote sensing and socioeconomic datasets, can provide a more comprehensive understanding of social vulnerabilities. Techniques such as code-aligned autoencoders have demonstrated effectiveness in multimodal remote sensing applications and could be adapted to vulnerability assessments (Luppino et al. 2024).
- *Adoption of Explainable AI (XAI) models:* Given the complex nature of social vulnerability, adopting XAI frameworks could enhance transparency and interpretability in decision-making processes. Methods such as fractional Fourier image transformers have shown promise in remote sensing classification and could contribute to making AI-driven vulnerability models more interpretable (Zhao et al. 2024).
- *Circular economy and AI synergies*: Exploring the intersection of AI and circular economy principles could lead to sustainable solutions for resource management in vulnerable communities. Industry 4.0 and 5.0 technologies at the design stage have shown potential to reduce construction waste and promote sustainability, which can be applied to urban planning for vulnerable populations (Talla and McIlwaine 2024).
- *Human-AI collaboration for community resilience*: Future research should focus on developing AI-driven tools that empower communities to take proactive measures against social vulnerabilities. Studies have highlighted the effectiveness of dual-channel neural networks in real-time applications, which could facilitate human–machine collaboration for resilience-building initiatives (Sahu et al. 2024).
- *Benchmarking and standardization efforts*: Establishing standardised evaluation frameworks for AI applications in social vulnerability assessments could enhance the reliability and comparability of results across studies. Efforts to benchmark algorithms using publicly available datasets and multi-label classification frameworks could be crucial (Aksoy et al. 2024).
- *Ethical and policy considerations:* As AI continues to influence social vulnerability research, it is essential to address ethical considerations and policy implications (UNDRR 2015, 2022; UNFCCC 2015, 2023). Transparent AI frameworks that align with existing regulatory frameworks, such as those proposed in recent studies on AI ethics (Chen et al. 2024; Goktas 2024), should be further investigated.

Finally, given the rapid advancements in AI and ML, future efforts should prioritise the development of hybrid models that combine knowledge-guided frameworks with traditional process-based models. This approach, as highlighted by Liu et al. (2024), can significantly improve predictive accuracy and decision-making capabilities across various sectors. By addressing these future directions, researchers can build on the current findings and further advance the field, ensuring the continuous development of innovative solutions that align with evolving technological and societal needs.

6 Conclusion

This bibliometric analysis provides a comprehensive overview of the evolving role of AI and synthetic data in social vulnerability assessments from 1996 to 2024. By mapping research output, collaboration networks, thematic clusters, and methodological trends, the study traces the intellectual and practical evolution of this interdisciplinary field across three distinct eras *Foundational, Developmental,* and *Transformative*. The analysis was conducted on 26,717 documents published between 1996 and 2024 across 4,633 sources (primarily journal articles, reviews, and conference papers) retrieved from Scopus and Web of Science, with an observed annual growth rate of nearly 20% and an average of 33 citations per document. The findings highlight a rapid acceleration of scholarly output, with a high international collaboration rate, reflecting the maturity and global significance of this domain. The thematic evolution highlights a transition from traditional geospatial methodologies to advanced AI-driven analytics, including ML, DL, CNNs, and semantic segmentation. Journals such as *Remote Sensing* and *IEEE Transactions on Geoscience and Remote Sensing* have served as core platforms for disseminating this research, while China, the United States, and India emerged as leading contributors alongside growing participation from developing economies. Beyond documenting growth patterns, this review surfaces critical gaps. The dominance of technical disciplines has often overshadowed the engagement of social science perspectives, resulting in limited integration of socio-behavioral complexity into AI-driven vulnerability models. Ethical issues, including transparency, algorithmic bias, and data privacy, remain pressing challenges that must be addressed to ensure socially equitable and trustworthy outcomes. Building on these insights, this study offers a strategic research agenda for advancing the field. Future directions should prioritize the integration of XAI to enhance interpretability, multimodal data fusion to capture the complexity of vulnerability contexts, participatory AI models that involve communities in co-designing solutions, and frameworks aligned with sustainability principles such as the circular economy. The adoption of such approaches will not only strengthen methodological rigor but also ensure that AI applications remain ethically responsible and practically impactful. Ultimately, this study contributes a robust evidence base for researchers, practitioners, and policymakers by illuminating how AI and geospatial analytics are reshaping social vulnerability assessment. The results emphasize the dual imperative of advancing technical innovation while embedding ethical, social, and interdisciplinary considerations. As climate change intensifies the scale and frequency of natural hazards, the integration of responsible AI into disaster risk reduction frameworks represents both a scientific necessity and a societal obligation.

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Data availability Data is provided upon request from the corresponding author.

Declarations

Conflict of Interests The authors declare that they have no conflicts of interest.

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