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Review

Toward an Integrated Disaster Management Approach: How Artificial Intelligence Can Boost Disaster Management

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Abstract: Technical and methodological enhancement of hazards and disaster research is identified as a critical question in disaster management. Artificial intelligence (AI) applications, such as tracking and mapping, geospatial analysis, remote sensing techniques, robotics, drone technology, machine learning, telecom and network services, accident and hot spot analysis, smart city urban planning, transportation planning, and environmental impact analysis, are the technological components of societal change, having significant implications for research on the societal response to hazards and disasters. Social science researchers have used various technologies and methods to examine hazards and disasters through disciplinary, multidisciplinary, and interdisciplinary lenses. They have employed both quantitative and qualitative data collection and data analysis strategies. This study provides an overview of the current applications of AI in disaster management during its four phases and how AI is vital to all disaster management phases, leading to a faster, more concise, equipped response. Integrating a geographic information system (GIS) and remote sensing (RS) into disaster management enables higher planning, analysis, situational awareness, and recovery operations. GIS and RS are commonly recognized as key support tools for disaster management. Visualization capabilities, satellite images, and artificial intelligence analysis can assist governments in making quick decisions after natural disasters.

Keywords: disaster management; artificial intelligence; geographic information system

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1. Introduction

A disaster is a phenomenon that may inflict harm on a community through loss of human life, damage to the environment, or economic loss. It is beyond the community's capacity to react [1]. According to the Center for Research on the Epidemiology of Disasters, disaster-affected countries lost $2.9 trillion in economic value between 1998 and 2017 [2]. With approximately $1 trillion in losses, the United States leads the pack, followed by China, Japan, and India. According to the UN Refugee Agency, the rate of calamities has nearly doubled throughout the last 20 years. Since 1995, the Asia–Pacific region has been the most vulnerable [3]. As highlighted in Figure 1, global disaster losses are a share of GDP from 1990 to 2017.

Disaster management is a strategic and multi-faceted procedure for mitigation, preparedness, response, and recovery to protect the vulnerable community and critical intrastate from any disaster. Researchers, decision-makers, and government officials working in the area of disaster risk reduction share a common perception of the disaster and take proactive actions before a disaster occurs. However, all disasters are linked to humans coping with their consequences. Therefore, success and failure depend on the planning and implementation of effective disaster management practices. Furthermore, a hazard also causes a secondary hazard, which has an enormous impact, such as a tsunami, which triggers coastal flooding. Thus, in disaster management, AI is a significant force multiplier in the ability to protect people and property in the face of disaster and is undoubtedly the future of disaster management.

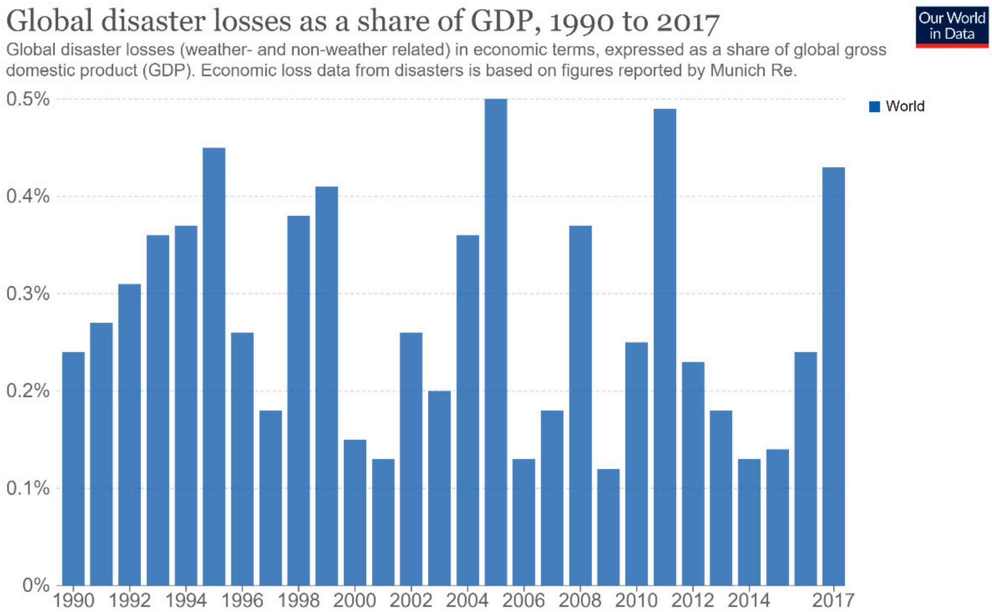

Figure 1. Global flood losses, 1990 to 2017 [4].

Today's artificial intelligence systems and geospatial technology are highly developed, and they have the potential to be highly effective in crisis scenarios [5]. Disaster response planning is significantly influenced by the area's morphology, weather conditions, ecology, other factors, and the machinery's available resources. It is recommended to use operations research and management science criteria to enhance resilience in emergency relief while considering the impact of relief resource allocation on the population [6]. However, several papers in the literature evaluate the utility of artificial intelligence in disaster management [7]. The crisis response situation in other countries is vastly different from that in India. As a result, there is a need to identify and prioritize the data needed for compelling crises in natural disasters [8]. The proper ways to minimize the impact of a catastrophe are preventive and minimization, vulnerability, readiness, and resilience in disaster management [9–11].

Artificial intelligence and geographic information systems are vital tools used by many scholars to plot the spatial dispersal of flood hazards and susceptibility to flooding [12,13]. A geographical information system acts as a facilitator that inputs, stores, integrates, manages, and delivers spatial data for strategic planning and real-time decisionmaking for timely and effective hazard preparedness and flood crisis management [10]. These systems are capable and comprehensive in flood crisis management issues. With quick and more accurate decisions, it is necessary to adopt a systematic approach in the planning process. This paper reviews the advantages of artificial intelligence and its applications in disaster management and mitigating disaster damage.

2. Methodology

This paper aimed to provide a literature review to examine the role of AI and see how AI can boost disaster management and develop pragmatic information to achieve the study objective. A keywords search string was used to review the previous studies published from 2015 to 2020. These keywords are associated with the application of artificial intelligence and disaster management aspects. In addition, science citation index journals were used for selecting the studies and identifying diverse ways to address AI in disaster management.

A list of keywords used in various journals indexed in the Scopus, Web of Science, and Science Direct databases was prepared to evaluate AI's role in disaster management. In addition, several studies around the world were selected for the review (Table 1 and Figure 2).

Table 1. Search string (keyword analysis in international journals, 2015–2020).

Source	String
Science Direct Web of Science	("Disaster Management", OR "Artificial Intelligence", OR "Flood", "GIS", "Remote Sensing", "machine learning", deep learning)
Scopus	TITLE-ABS-KEY (Disaster Management & Artificial Intelligence) AND (LIMIT-TO (PUBYEAR, 2020, 2019, 2018, 2017, 2016, 2015) AND "Disasters", "Human", "Disaster Management", "Disaster Planning", "Disaster Prevention", "Risk Management", "Natural Disasters", "Floods", "Remote Sensing", "Flooding", "GIS", "Flood Control", "Hazard Assessment", "Artificial intelligence", "Geographic Information Systems", "Natural Hazard", "Disaster Relief", "Disaster Response", "Disaster Preparedness", "Deep Learning", "Forecasting", "Artificial Intelligence", "Mapping", "Disaster Risk Reduction", "Disaster Recovery", "Machine Learning"

Figure 2. Keywords assessed within different international journals (2015–2020).

Figure 2 shows a graphical representation of identified keywords and methods in the search database from 2015 to 2020. *Natural Hazards* has the greatest number of studies, followed by *Sustainability*, *Disasters*, and *Journal of Natural Disasters*.

This study was based on a review process to determine the role of AI and GIS in disaster management. During the review process, the Scopus database was utilized to identify previous studies. The Scopus database provided sufficient literature in the target domain. Therefore, studies were extracted from the Scopus, Science Direct, and Web of Science databases, covering the latest and most reliable literature for AI and its applications.

This research was conducted in the middle of May 2021, using the advanced search option (Figure 3). The initial search yielded 2460 publications; 1178 were duplicates among the three databases and thus excluded. After carefully reviewing the studies' title and abstract, 1089 studies were excluded. The remaining articles went through another round of screening, and 93 studies were again excluded by judging their nature and scope. Finally, 100 studies met all of the criteria and were selected in this review. Furthermore, the critical demographic statistical findings from the articles are presented in the journal database used and countries.

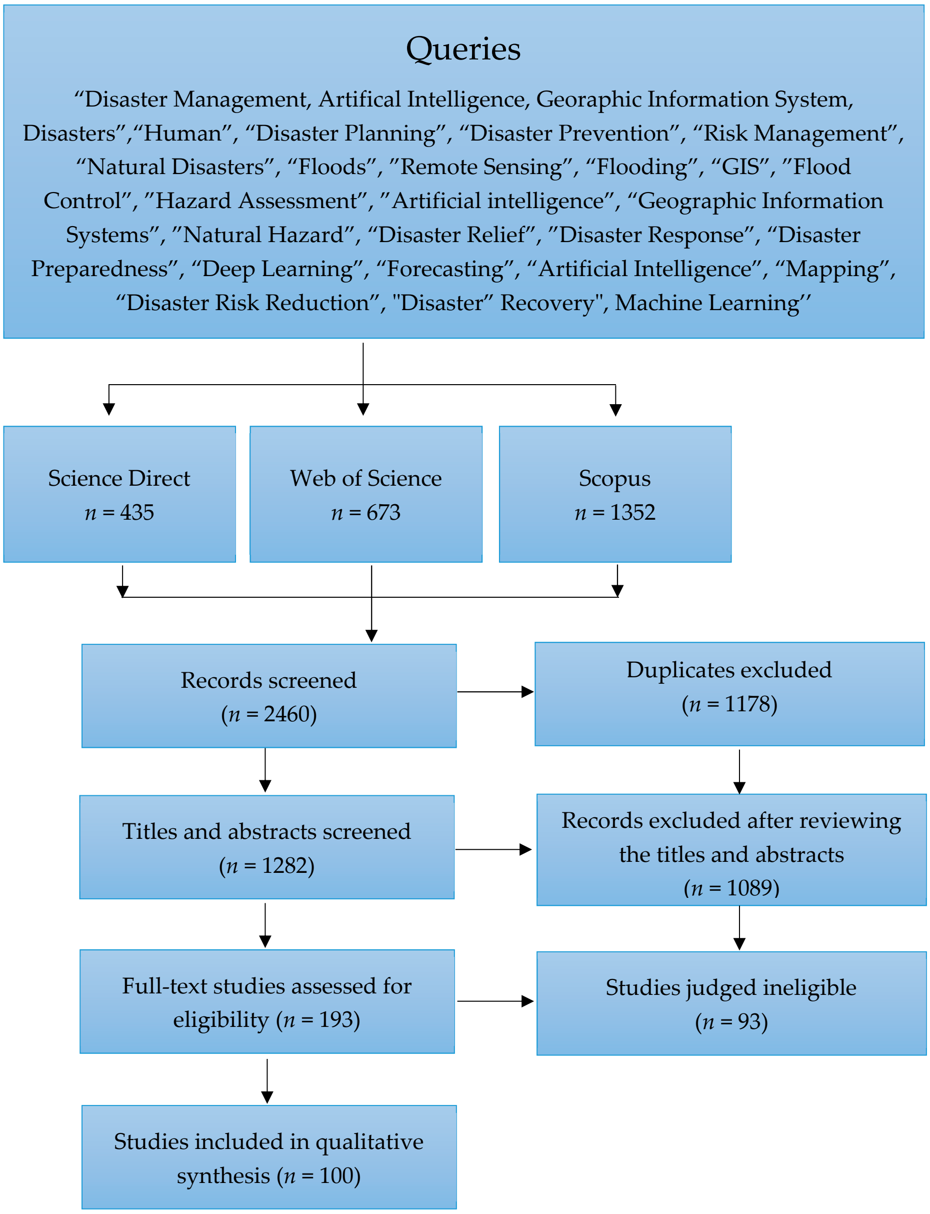

Figure 3. The detailed screening process of the latest articles for AI and disaster management.

An expanded list of various peer-reviewed journals and their studies was selected to overview different works on artificial intelligence and disaster management (Figures 2, 4 and 5). Most studies were published by China, the U.S., South Korea, Iran, Australia, and Italy from January 2015 to December 2020.

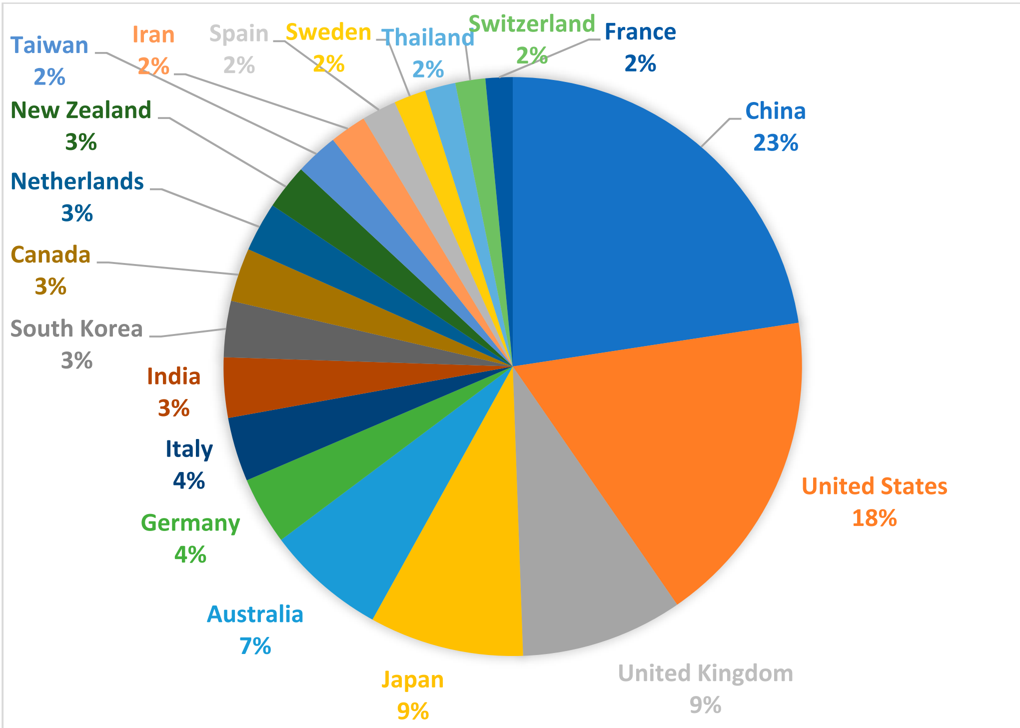

Figure 4. Distribution of the studies published by country (2015–2020).

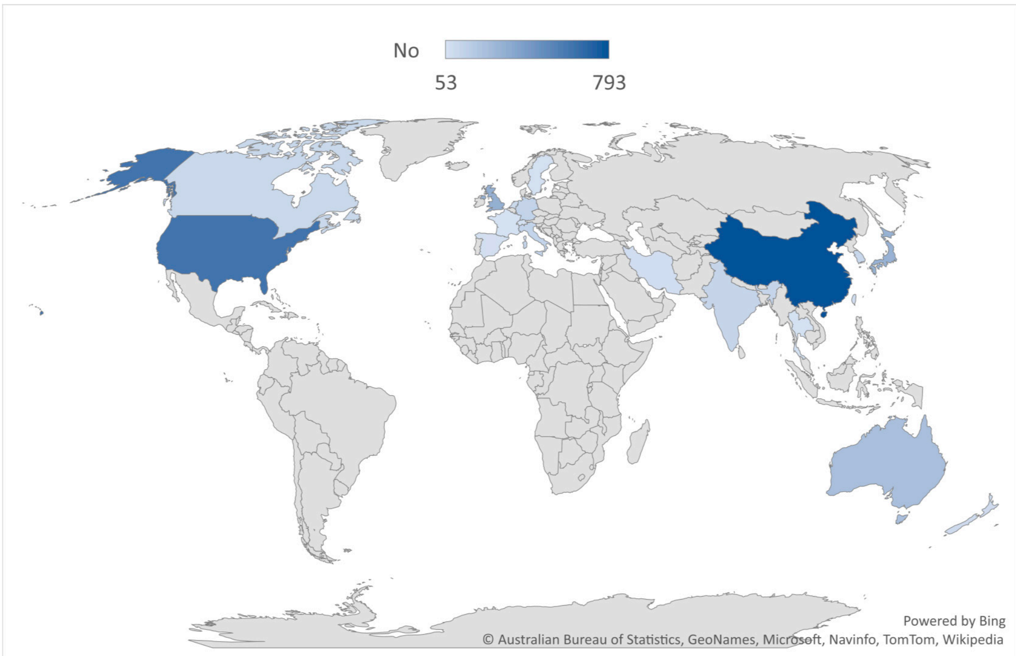

Figure 5. Identified studies on artificial intelligence and disaster management.

3. Four Phases of Disaster Management

The disaster management cycle (DMC) is the process for planning to reduce the impact of a disaster (Figure 6). The DMC also guides government, agency organizations, civil society, and businesses to execute and build resilience in the community.

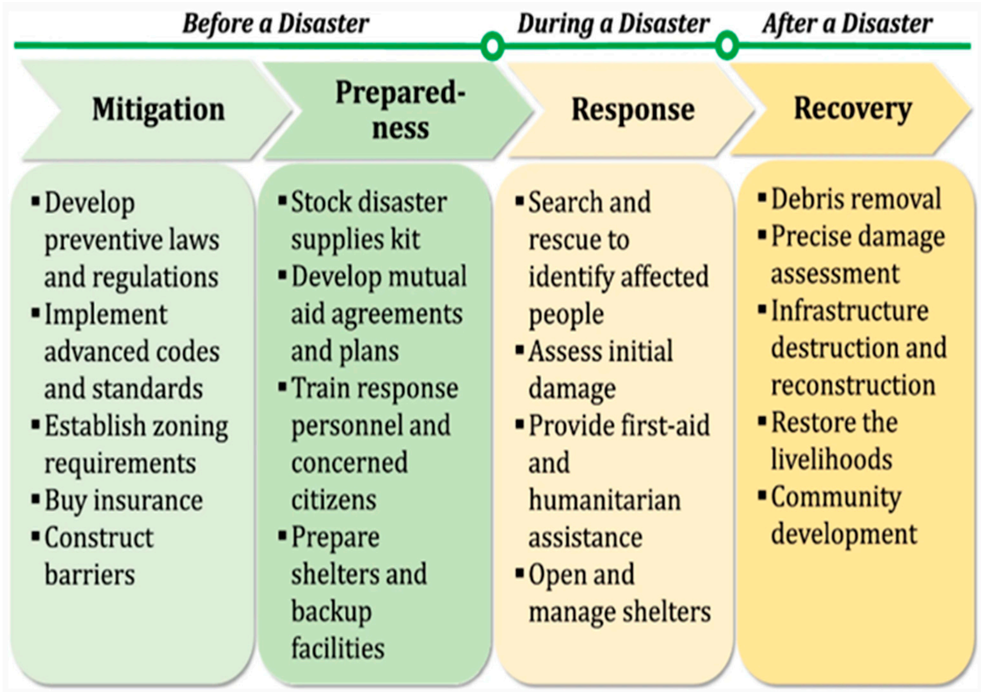

Figure 6. Phases of disaster management (before, during, and after a disaster) [14].

The process illustrates four stages of disaster management, which implies interlinked activities further classified into three activities: Pre-disaster activities, current, and post-disaster activities.

In the DMC, the activities are combined to reduce the risk of human and physical losses. Before a disaster, the planning referring to mitigation includes developing prevention laws and implementing standards to battle any catastrophe or emergency. It also suggests preparing well and in accordance with the available resources—preparedness is considered one of the most significant phases in the DMC to minimize the damage of a disaster. During a disaster, response and rescue activities are performed. The aim is to provide first aid and humanitarian assistance and assess the initial damage. After the disaster, recovery activities, including the overall community development assistance program, are started, restoring the livelihood of the community, and precise damage assessments are implemented.

4. Artificial Intelligence and Disaster Management

Artificial intelligence is the intellect expressed by computer systems as opposed to human intelligence [15]. AI is the process of different connected machines simulating human behavior. AI deals with computer-related activities concerned with building-related intelligent machines. Over the last decade, AI breakthroughs have considerably increased our capacity to forecast disasters and provide support throughout catastrophes [16–18]. AI development can be evident in disaster preparedness, crowdsourced information systems, rescue, and humanitarian distribution [15,19]. Although AI has many forms, this report concentrates on using AI such as robotics, drones, machine learning, deep learning, sensors, and algorithms utilized in the context of catastrophe prediction and facilitating speedier rescue and relief delivery activities [20–23]. Robotics and robots have been around for decades, but due to the recent increasing trend in sensor and compute technology, robots have evolved from close to zero decision-making devices to truly automated and artificially intelligent machines [24].

Machine learning, unlike robotics, which has been around for years, is a comparatively modern aspect of artificial intelligence. Machine learning algorithms can accomplish a particular job without any given directions, instead of learning from patterns and conclusions in the data input, and are thus categorized as AI [25]. A model can be developed for change detection on satellite images using CNN networks, locating areas most affected by disasters and helping coordinate relief efforts.

Airborne robots travel deep into disaster zones to inspect destruction and bring help [26]. Machine learning is a category of complicated software capable of learning. It interprets patterns from numbers, words, photos, videos, and other data collection methods and then uses that data to predict outcomes in previously unknown circumstances [27,28].

Artificial intelligence attempts to improve and increase the efficiency of the disaster management process. AI equipment, such as sensors, aid in emergencies by improving the exchange of information through ontologies, supplying information to disaster factors, and offering multi-agent platforms for real-time support and simulated scenarios. The effectiveness of emergency management is dependent on obtaining information from disparate sources, combining it, and making sound decisions [29].

Artificial intelligence is a substantial force multiplier in our power to defend civilian populations in the face of disasters, and it is unquestionably the future of disaster management. However, to adopt AI in disaster management, governmental agencies must accomplish a development plan of basic requirements to guarantee that the deployment is productive and convenient.

Usage of social networking sites and digital technologies provides the general population with appropriate and effective means of disseminating and consuming information [30]. Throughout natural or man-made disasters, millions of people are rapidly turning to social media to disclose information [31,32]. In addition, the utility of social media activity for a range of philanthropic responsibilities to raise “situational awareness” has been established in previous research [33]. However, whereas details on social media may be beneficial to response organizations, a clear understanding of it in a time-sensitive crisis is complex. Manual analysis of dozens of messages, for example, is very tricky because of the enormous volume and high speed of social media data streams [32].

People have recently enhanced their use of social media sites and others to broadcast a range of data such as stylistic messages, photographs, and films online during the outbreak of any natural or man-made calamity in the current era [34]. In previous natural and social crisis scenarios, such as flooding, social media data have shown to be a vital source of information, earthquakes, wildfires, nuclear disasters, and civil wars [35]. For example, in the aftermath of the 2011 Japan quake, 177 million tweets on the tragedy were posted in one day alone [36].

Figure 7 refers to the publications from 1991 to 2018 in the WorldCat database concerning the role of AI in disaster management. Among the disaster management phases, disaster response has the greatest number of publications in this particular period. AI has been widely applied in the response phase compared to the other phases. AI applications and techniques rapidly analyze the big data in disaster response, provide effective decision making, and improve overall disaster management. The increasing trends of disaster response shown in Figure 7, highlighting the importance of AI by analyzing publications, namely, books, articles, and other downloadable material.

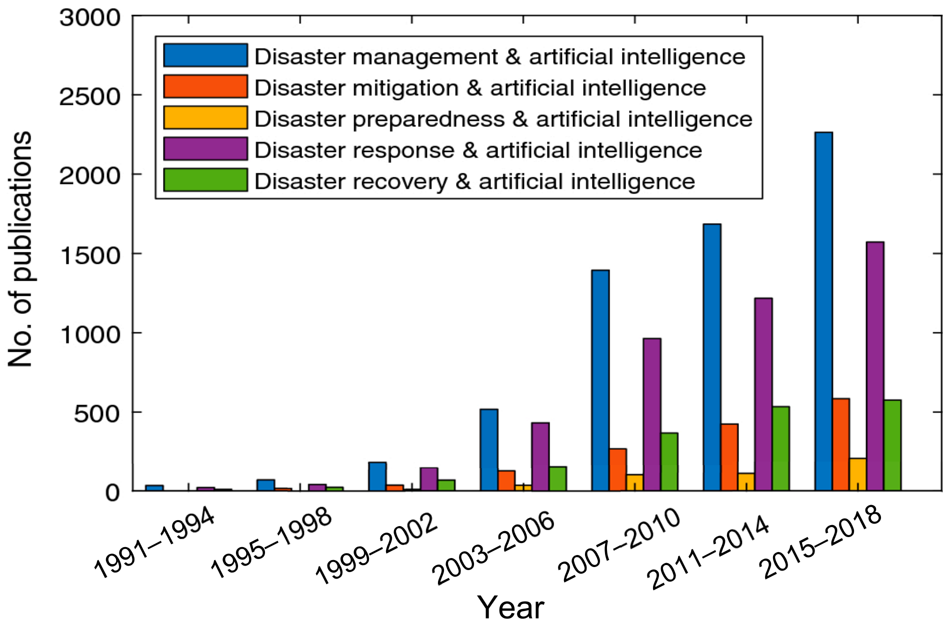

Figure 7. Number of publications from 1991 to 2018 [14].

Timely disaster responses are a matter of life and death. Decision-makers need to make their best effort to understand the situation and improve the efficiency of response efforts. This naturally requires situational awareness for effective decision making and user-friendly disaster information systems for effective coordination to ensure disaster relief and address people's urgent needs and concerns. AI methods can be applied to facilitate relief and response efforts.

Artificial intelligence, specifically machine learning (ML), plays a vital role in analyzing enormous amounts of social media data and turning the volume of social media data throughout catastrophes into comprehensible, credible data. AI applications can emulate human-like intellect in given duration concepts in big data, significantly improving the efficiency of various jobs, processes, and pattern discovery in massive amounts of data [37]. While there has been much study on catastrophes in terms of evaluating social media data using multiple ML techniques, only a few research studies have systematically studied recent advancements, none with a particular emphasis on AI for social media disaster management with big data analytics [38]. One of the most prominent methodologies for prediction systems is deep learning [39], such as time series analysis, which is used in emergency management to limit the threat of disasters. Combining hierarchy time series with a deep learning algorithm is another method used to solve forecasting problems [40–42].

Kumar and Sud [15] established a flood-supported mobile application called "DHARA", where they used long short-term memory AI application CNN (LSTM). It was created to anticipate the likelihood of flooding so that early warning preparedness and restoration techniques can be implemented before an incident. The research proposed by [43] employed a rainfall prediction model, which provided projected data by assessing environmental characteristics linked with rainfall.

Artificial intelligence methods such as regression, including linear, nonlinear, and logistic regression, are used to forecast hazards and risks and evaluate the possible impact of hazards. Support vector machines also provide timely forecasting and risk assessment. Neural networks, hierarchical clustering, k means clustering, fuzzy clustering, and principal component analysis have been used to develop and compare mitigation strategies, training systems, and disaster evacuation procedures [44–46]. However, deep learning techniques include convolutional neural networks, deep neural networks, and multilayer perception, used for disaster mapping. While damage assessment, disaster information systems, and interagency collaboration are used in emergencies [47,48], Deep Q-networks and genetic algorithms are the latest AI techniques used to evaluate loss and repair costs [14,49].

Another option is to employ numerous or blended deep learning algorithms to find the fastest and most accurate forecast [50]. However, vast amounts of data are needed to anticipate future outcomes, particularly for natural catastrophes, and high-performance techniques are very often essential due to their large dense datasets and nonlinear features [51]. Table 2 mentions the previous studies focused on disaster management and the role of AI in successful disaster management practices.

Table 2. Previous studies that implemented artificial intelligence in disaster management.

Studies	Purpose of the Analysis	AI Algorithm	Input Data
[52]	Flood vulnerability mapping and plotting	Artificial neural network	Rainfall data, slope, elevation data, flow accumulation, soil, land use, and geology data layers from the remote sensing technique
[53]	Landslide disaster exposure mapping	RFEs and NBT classifiers	Satellite spatial images and field survey data
[54]	Landslide and flood disaster risk reduction	CNN	Satellite spatial images
[55]	Disaster risk reduction through social media and flood prediction by satellite images	CNN, SVM, RFS, and GVN networks	Social media application and satellite images
[52]	Disaster assessment in coordinating relief (flood and fire management)	CNN and semantic segmentation models of satellite images	Satellite images
[56]	Earthquake prediction detection	CNN networks	3D point cloud
[57]	Classification of building damages (earthquake)	CNN networks	Satellite and UAV images
[58]	Near real-time damage mapping	CNN networks	UAV images
[59]	Post-earthquake damage mapping	ANN (the backpropagation algorithm) and support vector machines (radial basis function, RBF)	Satellite images

A new AI platform called MOBILISE was developed for building resilient communities to employ multi-agency collaboration. MOBILISE provides real-time intelligence to disaster management agencies to work under one umbrella for disaster mitigation [60].

The MOBILIZE platform is a user-friendly API, allowing agencies to upload and explore hazards, exposure, and vulnerability data interactively to establish a common understanding of their local risks and implement disaster risk reduction actions. The underlying risk information server runs on an Azure cloud service.

MOBILIZE also offers VR technology-based interface. This VR novel VR interface allows the user to visualize 3D representations as textured point clouds or meshes captured from airborne sensing devices such as drones. The MOBILISE web platform visualizes the hazards and models the effect of disasters. MOBILIZE 3D visualization of real-time data supports disaster response, information such as flood-prone areas, rainfall predication, and drainage lines in the form of layers (Figures 8 and 9).

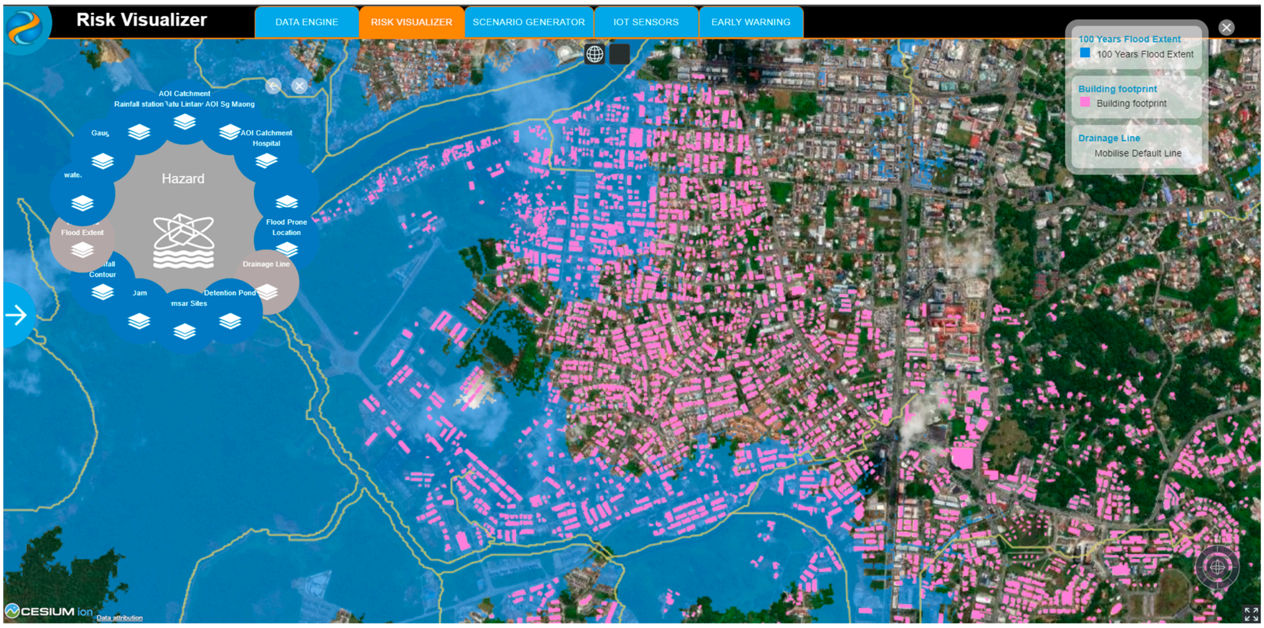

Figure 8. Visualization of risk hazard exposure mapping using MOBILISE platform in one of Malaysian state [60].

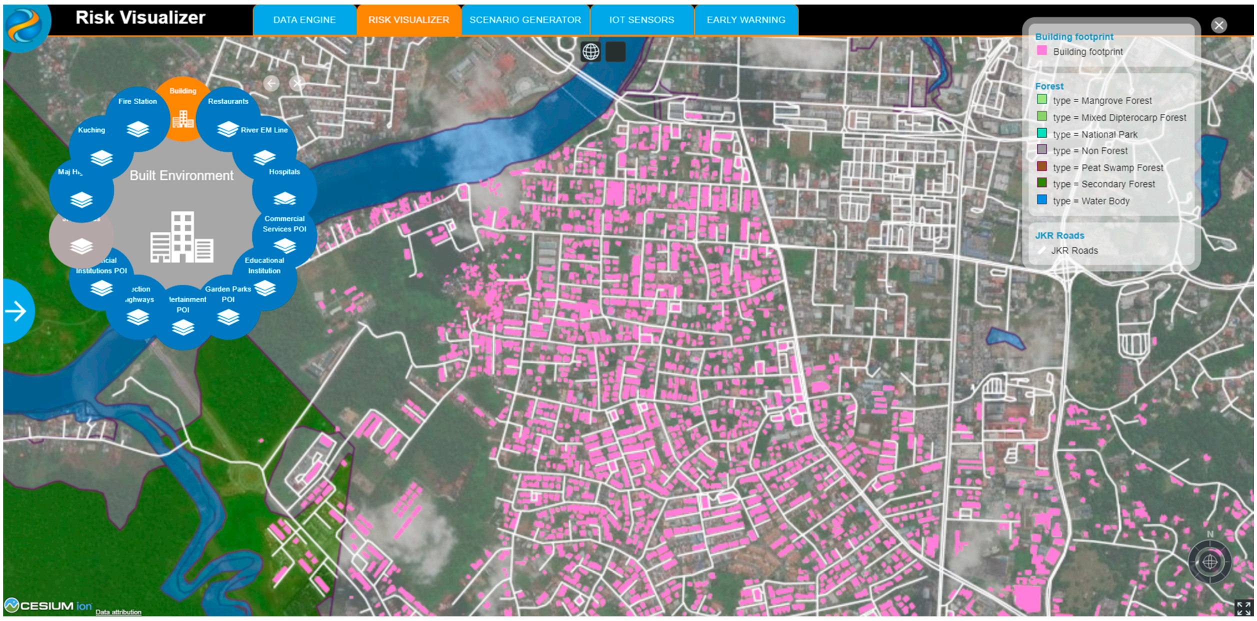

Figure 9. Risk visualization of built environment GIS data using MOBILISE platform in one of Malaysian state [60].

5. Geographic Information Systems and Disaster Management

Data from several sources are used in all forms of disaster management. The required data must be acquired, processed, and shown rationally [57]. In a disaster, having the relevant data at the right moment presented logically is essential for responding and taking necessary action. Disasters might affect the entire government or just a few sectors. Emergency workers frequently require the drainage system, electrical distribution, and other details. All sectors can communicate information via databases on computer-generated mapping in one area by using a GIS [61,62]. Because without that functionality, emergency responders will have to access a wide range of department managers and their map data. Most disasters do not allow enough time to obtain these supplies. As a result, emergency personnel are forced to assume, anticipate, or make decisions based on incomplete data.

Effort, resources, and, in some cases, lives are lost as a result of this. During calamities, GIS provides a way to organize and graphically show crucial information [3].

To mitigate the impact of disaster requires timely, precise, and reliable information. First, the local authority and municipal officer collect data from the hazard area. This information includes a description of the location before and after the disaster. These data guide the rescue personals by integrating the data into GIS to plan their activities in an emergency state [63].

Geospatial analysis provides a graphical and visual output that consists of maps, graphs, and tables for further research and forecasting to evaluate flood warnings. These maps offer a wide range of prediction and mitigation strategies before a disaster occurs, further strengthening disaster agencies' ability to take emergency measures before the catastrophe strikes under favorable environmental conditions [64]. Early warning systems, a technique of remote sensing and satellite imagery, also provide tools to monitor effective disaster preparedness operations. Aerial surveys are used to determine the disaster zone by marking the area and identifying the flood-prone location for action to minimize the damage [65]. Usage of the above tools reduces the impact of flood disasters and minimizes the damage to flooded land and the community. Malaysian institutes for remote sensing have accentuated flood risk mapping by integrating AI and GIS applications [66].

GIS is considered the most effective tool for data analysis and environmental planning [67]. This is because the spatial analysis of GIS can provide better viewing and advanced features that interpret the relationship of ecological conditions and physical factors such as the steepness of slopes, vulnerability and risk analysis, crisis mapping, and various environmental parameters and impact analysis [68].

GIS is a conceptualized framework that captures geospatial data and analyzes them. GIS is the combination of different parts, and these interconnected parts are composed of software and hardware programs and equipment, methods, people, and data information. Other types of GIS software are available on the market for different operations—including commercial, open-source, and individually licensed programs. The most commonly used program is Esri ArcGIS. However, customized programs also use Google Earth Pro, Mapinfo Pro, Google Maps API, and BatchGeo [69].

Disaster management has three primary objectives: To protect life, infrastructure, and a sustainable environment. GIS is a valuable resource for meeting these prerequisites for the disaster management cycle, including the mitigation, preparedness, response, and recovery phases. Each phase links with others and uses GIS to analyze data and develop a framework for disaster management [64]. In every stage of disaster management, the GIS process contains three steps. The first step includes the acquisition of data from reliable resources, while the second step is to measure the spatial data and to provide these data in readable forms, such as numbers, figures, charts, and graphs; this process is converted through the geographic database (GDB) [70]. The last step is to finalize the data and provide them to the end-user. Finally, the data are disseminated via statistical distribution. These geospatial skills are appropriate and robust for spatial analysis and valuable tools for boosting disaster management [3].

Another characteristic of GIS is to provide the data in a layer format. Thus, in any hazard zone, GIS offers a wide range of visuals of different layers such as flood-prone areas, buildings, land, roads, hospitals, schools, and the vulnerable community. At the same time, the satellite imagery technique of remote sensing monitors flood activity and assesses the damage before and after the flood through high-resolution cameras, helping researchers and scientists to "sense" Earth [71–73].

The GIS lens has the capacity and capability to conduct geometric and arithmetic analysis in each phase of disaster management. These analyses of past flood events help to predict future trends. Different layers are used to perform damage analysis [74].

6. Geographic Information Systems and Flood Management

Several methods and techniques have been developed to investigate flood hazards and risk assessment. These techniques include the AHP method, logistics regression, the analytic network method, statistical index, random forest, and flood zoning. Hydraulic science techniques are rich in geometric and flood damage assessment through flood zoning maps. These maps identify the location of a flood and help to assess the damage incurred [75]. Flood zoning has become vital and emerged as a crucial source of safety and security for humankind. It is also strengthen flood reduction strategies and reduces flood-related damage [76]. GIS combined with hydrologic engineering models (HEC-RAS) is customized to provide river maps. These models have been successfully applied in Warsaw, Columbia, and Dhaka, as well as many other flood-prone states [77,78]. In South Asia, Malaysia, Indonesia, and Thailand also use HEC-RAS models for flood zoning and to successfully mitigate flood hazards [79,80].

GIS has also been proven to identify areas suitable for developing flood mitigation systems and evaluate the effectiveness of the available flood mitigation systems [81]. The research by Puttinaovarat and Horkaew [82] addressed assisting flood disaster mitigation via an internetworking system using remote sensing, GIS, and deep learning (DL) (Figure 10). Such approaches enable flood notifications and verification in real-time, thus significantly reducing the time spent on investigations [39]. Darabi et al. [83] applied ML algorithms to calculate the flood-related region in Amol city, Iran, using geospatial predictor variables. The distance to channel, land use, and run-off generation were identified as the primary causes of flood hazards [84]. The obtained vulnerability map indicates the need for flood mitigation planning in high-risk areas [85].

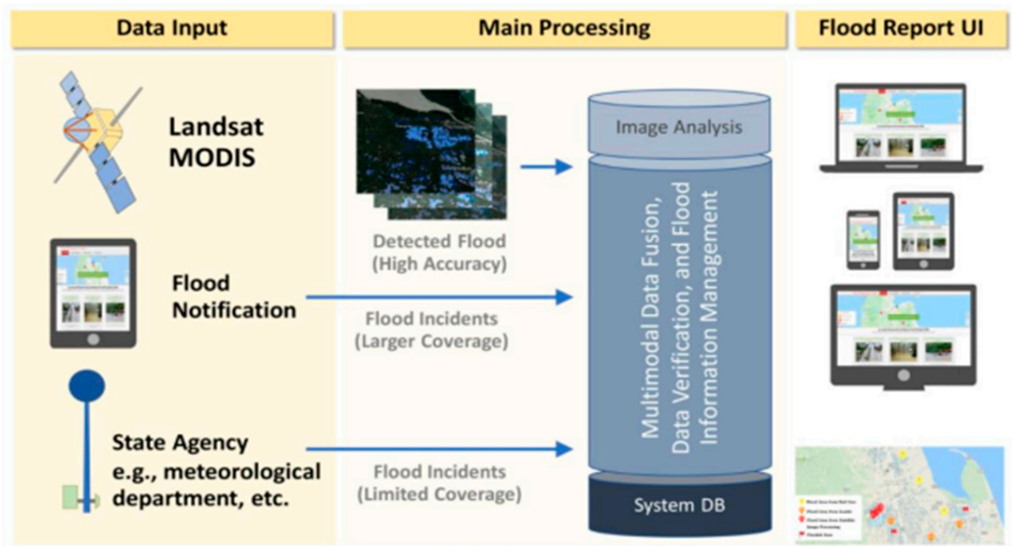

Figure 10. Design of the online flood information management system [82].

Puttinaovarat and Horkaew [82] presented a system for flood mitigation. The design was based on two contributions. First, the plans included data input and central processing, and output a final flood report UI; data intelligence was then used to analyze the flood report through remotely sensed images. The second phase involved verifying the reported information by ensuring two-factor authentication by applying deep learning techniques and authoritative investigations, as shown in Figure 10.

7. Application of a Geographic Information System in Managing Diseases in Crisis Areas

After a disaster, especially flood disasters, several other problems occur for devasted communities. Floods can cause different infection diseases, which result in virus infection and other contagious skin allergies. GIS provides indispensable support in any outbreak and provides timely information to monitor and mitigate the impact of a crisis [86,87]. In December 2019, a new virus emerged called coronavirus disease 2019 (COVID-19), which is a respiratory disease and spread rapidly across the world. The COVID-19 crisis was officially called a pandemic and forced countries to impose a lockdown to stop the spreading of this disease. GIS has offered accurate information to fight the previous virus, such as Ebola and avian influenza; perhaps mapping and plotting techniques could help track and identify COVID-19 hotspots by integrating the population. We are still fighting COVID-19, but these tools play a vital role in health disaster management and health planning to fight this deadly pandemic [87].

8. Conclusions

This research focused on the role of artificial intelligence in disaster management, and how these applications can boost disaster management. In particular, this study reviewed the different applications of AI to identify the methods and approaches implemented in disaster management phases. This review supports that AI models are valuable in boosting disaster management. We also concluded that the current trends focus on how to respond and mitigate a disaster. Geospatial technology continues to expand and provide a timely solution and provides a rich agenda for GI Science. Therefore, it is imperative to develop and think about the geographical implication. Nowadays, GIS and RS are powerful tools, providing a new capability to understand emergencies.

In the future, we assume that Al technology with a more complex and multispectral dataset will soon be available, which will surely help to mitigate the impact of disasters. However, remotely sensed data and spatial analyses with geographic information systems have led to a new iconic informatics science. Therefore, artificial intelligence has immense potential to deal with natural and man-made disasters. Of course, the success of any AI platform is directly tied to proprietary data management and analytical capabilities engineered into the underlying algorithms. However, effectiveness also hinges on other key technology components for enhancing effective management team success.

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