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Review

A Systematic Review of Disaster Management Systems: Approaches, Challenges, and Future Directions

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Abstract: Disaster management is a critical area that requires efficient methods and techniques to address various challenges. This comprehensive assessment offers an in-depth overview of disaster management systems, methods, obstacles, and potential future paths. Specifically, it focuses on flood control, a significant and recurrent category of natural disasters. The analysis begins by exploring various types of natural catastrophes, including earthquakes, wildfires, and floods. It then delves into the different domains that collectively contribute to effective flood management. These domains encompass cutting-edge technologies such as big data analysis and cloud computing, providing scalable and reliable infrastructure for data storage, processing, and analysis. The study investigates the potential of the Internet of Things and sensor networks to gather real-time data from flood-prone areas, enhancing situational awareness and enabling prompt actions. Model-driven engineering is examined for its utility in developing and modeling flood scenarios, aiding in preparation and response planning. This study includes the Google Earth engine (GEE) and examines previous studies involving GEE. Moreover, we discuss remote sensing; remote sensing is undoubtedly a valuable tool for disaster management, and offers geographical data in various situations. We explore the application of Geographical Information System (GIS) and Spatial Data Management for visualizing and analyzing spatial data and facilitating informed decision-making and resource allocation during floods. In the final section, the focus shifts to the utilization of machine learning and data analytics in flood management. These methodologies offer predictive models and data-driven insights, enhancing early warning systems, risk assessment, and mitigation strategies. Through this in-depth analysis, the significance of incorporating these spheres into flood control procedures is highlighted, with the aim of improving disaster management techniques and enhancing resilience in flood-prone regions. The paper addresses existing challenges and provides future research directions, ultimately striving for a clearer and more coherent representation of disaster management techniques.

Keywords: disaster management; natural disasters; floods; wildfire; earthquake; ecosystem

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1. Introduction

Natural catastrophes such as earthquakes, tsunamis, floods, forest fires, plane crashes, and viruses are becoming more common, posing major challenges not just for the public but for government organizations in charge of disaster management and preparedness. Recent failures to respond to natural disasters, such as the H1N1 pandemic (i.e., the management of the swine flu) which arrived on Australian shores through the cruise ship industry in 2009 [1] and the earthquake in Haiti have sparked concern. In Victoria, Australia, bushfires have been a recurring challenge, often exacerbated by a lack of timely availability of skilled resources and a failure to harness the potential for skill reuse. Such shortcomings in disaster management can lead to catastrophic outcomes [2]. Frequently, the potential for skill reuse is neglected with disastrous consequences. Therefore, utilizing the disaster management metamodel, in this work we suggest a method for integrating disaster management information to develop a flood and disaster support system that incorporates several disaster management (DM) operations tailored to a particular disaster. This strategy is inspired by method engineering, a knowledge management practice in software engineering.

DM manages disaster risks and effects. DM covers mitigation, readiness, response, and recovery [3]. DM involves organizing, directing, and using counter-disaster resources [4]. This domain's practitioners attempt to decrease or prevent natural disasters, assist disaster victims, and recover quickly. Operationalizing this domain involves many difficult activities. Risk evaluations, readiness, emergency responses, rescue, relief distribution, and reconstruction are all included. Data modeling and communication are difficult. Instead of attempting a comprehensive model, this work suggests a metamodel that can link various imperfect models that try to systematically convey DM knowledge. This approach allows us to set up a hypothesis of general notions that affect how we perceive reality [5]. Reality ought to be influenced by models [6]. They must be true or faithful representations to ensure that the model can be used to answer questions about the world or predictably change the world. A metamodel that explains what can be articulated in legitimate knowledge domain models is the result of metamodeling. The metamodel provides information about models. In this case, a model means the DM solution model, which shows how DM activities and their parts (such as people, resources, and plans) should be coordinated for a given disaster. Failures typically emerge from the accumulation of a complicated chain of events, and are frequently accompanied by changes in environmental factors [7].

A wildfire is an uncontrolled event that occurs in an area of combustible vegetation and is characterized based on the fuel consumed, such as a forest or grass fire, often known as a bush fire in different regions of the world. Such flora offer a carbon-rich fuel source which, when paired with seasonally dry conditions, can have severe effects on ecosystems and the human population in an area [8]. Lightning strikes, volcanic activity, arson, and the unintended consequences of agricultural land removal can all contribute to the occurrence of wildfires [9], which have existed for a long time and can be caused by both natural and artificial factors. For instance, it was determined that lightning was mostly responsible for the summertime fires which plagued the southeastern portions of the Australian continent in 2019–2020 [10]. About 21,000 hectares of agricultural land went up in flames due to additional fires in Australia during the same time period, and investigators have concluded that arson was likely to blame [11]. This conclusion is based on how much these fires were talked about in the news and on the idea that the arsonists were able to keep their secret because there were other bigger fires in the area [12].

Droughts, heat waves, seasonal weather, and El Nino's warming phase can increase wildfire risk. Furthermore, it is predicted that the effects of climate change could result in fire seasons that start sooner, terminate later, and cause more extreme fire weather conditions [13]. Fast-moving and difficult to control flames that result in widespread fire damage and health problems will undoubtedly be brought on by climate change [14]. Particulate matter (PM), polycyclic aromatic hydrocarbons (PAH), ozone, carbon monoxide, nitrogen dioxide, and volatile organic compounds are among the air contaminants that are typically present in wildfire smoke, and can all be harmful to human health [15]. Ophthalmic and psychological issues can arise, as can serious burns needing treatment in specialized burn centers, which frequently result in multiple organ failure as a complication of complex trauma. Respiratory and cardiovascular ailments are the primary health effects of air pollution, though they can cause ocular and psychiatric difficulties as well [16]. In addition to fire, throughout the world earthquakes continue to be the main cause of death and damage due to disaster [17]. In underdeveloped countries the death toll from earthquakes can reach shockingly large numbers; for instance, in Haiti 220,000 people lost their lives, and in Wenchuan 88,289 people died because of an earthquake.

According to historical records, the Sumatran fault and Sumatran subduction are the two fault zones that can impact Malaysia and Singapore [18]. Sabah, which is in Malaysia, is currently under threat from a series of earthquakes. The 30 s long 6.0-magnitude quake that hit Ranau, Sabah, Malaysia on 5 June 2015 was the biggest to strike Malaysia since the 1976 Sabah earthquake.

Because of this tragedy, there was substantial property damage and loss of life. A simple earthquake detector has proven to be beneficial in notifying individuals when an occurrence is about to occur. Existing seismic instrumentation and communication technologies necessitate the development of an automated earthquake early warning system. This method can alert users ranging from a few seconds to a few tens of seconds before an earthquake generates severe tremors in the earth [19]. New earthquake detectors have been used to find earthquakes and record their magnitude, with larger number indicating more severe earthquakes.

An increasing number of studies have elaborated on the importance and applications of remote sensing in disaster management [20–23]. A major reason for the adoption of remote sensing is that it is one of the fastest means of acquiring data for pre-disaster and post-disaster studies. It is used to provide data for damage assessment in a timely manner and to assist in evaluation and rehabilitation plans. During the pre-disaster phase, remote sensing can be applied to identify and develop adequate systems and resources before the occurrence of a disaster [24]. Adequate systems and resources can ensure that the response to a disaster is coordinated and efficient and that the recovery time is minimal [25].

Remotely sensed data such as MODIS, ASTER, Landsat, and Radarsat are used to produce maps of hazard and disaster risks. Digital terrain data derived from GTOPO30, SRTM DEM, and LiDAR are used for hydrological and flood modeling. For example, Li et al. [26] used GTOPO30 data to analyze the global impacts of potential inundation due to predicted sea level rise. Aleem and Aina [27] carried out a similar study on Yanbu Industrial City, Saudi Arabia using SRTM DEM data. Figure 1 shows the block diagram of the approach taken in the present research.

In this systematic review, we present a review of three types of disasters. First, we discuss earthquakes and previous relevant works, including the distribution of existing works concerning research areas, findings, and the impact of earthquakes on the environment. This is followed by wildfires, where key aspects, conclusions, validation approaches, and techniques used for wildfire detection are elaborated. Lastly, existing research on flood detection and management is discussed; this part covers the use of data analytics, machine learning, Geographical Information System (GIS), model-driven engineering, Internet of Things (IoT) networks, big data, and cloud computing for flood detection. In addition, we analyze the current challenges associated with fire, earthquake, and flood prediction and management as well as possible future research directions.

The rest of this survey is categorized into five sections. Our research methodology is explained in Section 2; earthquakes are covered in Section 3; Section 4 discusses works on wildfires; Section 5 elaborates flood-related works; applications based on remote sensing are elaborated in Section 6; and current challenges and future research directions are discussed in Section 7. Finally, Section 8 concludes the survey.

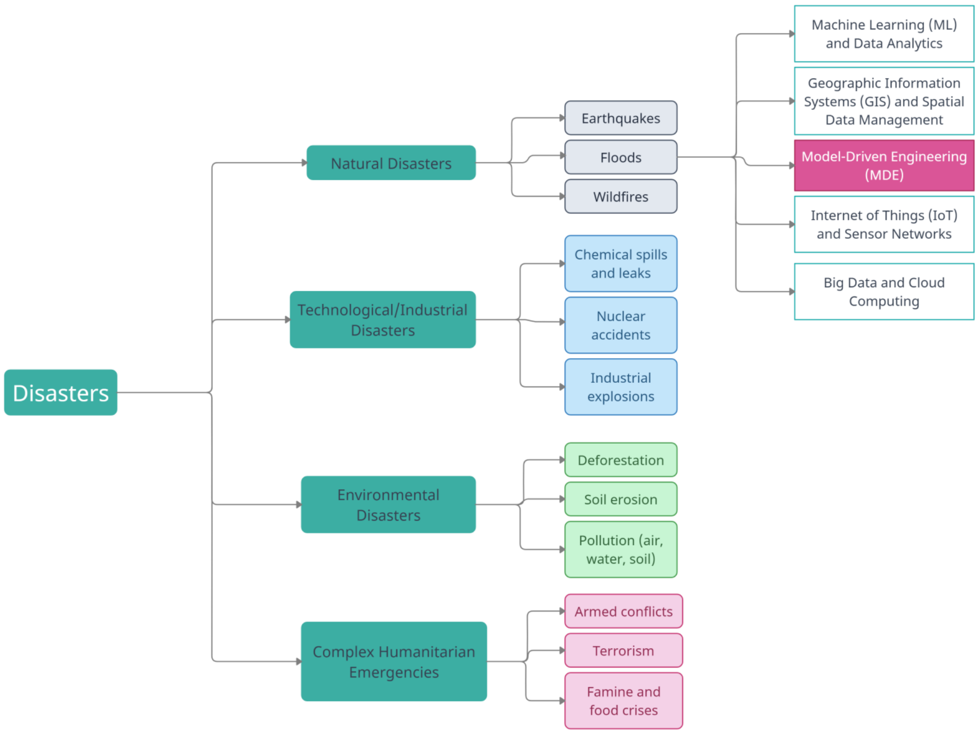

Figure 1. Block diagram showing the workflow followed in this review.

2. Research Methodology

To carry out the study process known as a systematic review for the topic of disaster management systems, we used the methodology shown in Figure 2 for data collection and analysis.

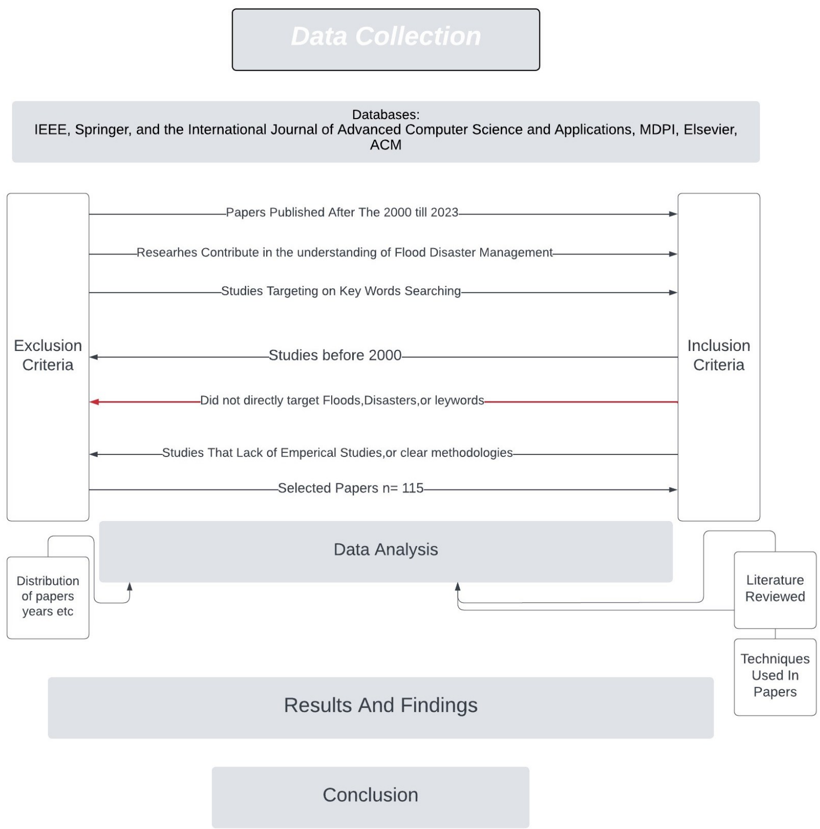

Figure 2. Methodology adopted for the literature review.

The primary objective of this scholarly investigation was to conduct a comprehensive and in-depth examination and analysis of the body of literature concerning disaster management systems. To attain a robust and impartial review of the subject matter, a methodical approach was adopted. In this regard, an extensive and thorough literature search was undertaken using a diverse array of online libraries and academic databases to curate the findings. Priority was given to studies that significantly contributed to the advancement of knowledge in the field of disaster management systems. To identify relevant studies, a set of specific keywords encompassing "disaster management systems", "Remote Sensing", "approaches", "challenges", and "future directions", along with disaster types such as "floods", "wildfires", and "earthquakes", was employed in the search process.

Third, high-quality databases, including IEEE, Springer, MDPI, and Elsevier were used for data collection. These databases were chosen for their dependability and wide coverage of research articles on disaster management systems.

Fourth, we employed inclusion and exclusion criteria to select the most relevant and important studies. The criteria considered a variety of issues involving disaster management systems, such as various relevant techniques, obstacles, and potential future orientations. Our initial search results were examined and refined to focus on the most relevant research.

Fifth, an extensive examination of the current studies and publications on disaster management systems was part of our research methodology. Approaches, problems, risk assessments, emergency response planning, and the resiliency of infrastructure are among the topics discussed n the literature. Finding knowledge gaps, new trends, and research possibilities in the field were goals of this literature review.

Sixth, collected data and analysis from relevant data sources, such as research papers, reports, case studies, and successful implementations of disaster management systems, were assembled to support the conclusions of the literature review. This included successful implementations of disaster management systems. The gathered information can provide insights into the efficacy of various techniques, tactics, and criteria for disaster management. A comparative analysis was carried out to highlight the benefits and the drawbacks of the various techniques.

Seventh, the study process took legal and ethical considerations into account to ensure that all works were properly cited and all authors acknowledged. Another aspect of this consideration was to ensure that objectivity was maintained throughout the process of assessing and understanding the material.

To summarize, the methodology used for this study included a literature review, data collection and analysis, use of evaluation metrics, comparative analysis, and an assessment of any ethical concerns. A thorough grasp of the state of disaster management systems, including different approaches, difficulties, and potential future directions, was made possible by this comprehensive methodology.

3. Earthquake

The data presented in this analysis were obtained from an examination of various journals, and are categorized into four sections: keyword, output, type of earthquake detector, and seismic effect. The conclusions of this analysis are examined in depth in order to ensure the study's quality and to meet the review paper's purpose [19].

3.1. Analysis of Earthquake Keywords

Figure 3 shows that there are five common ways to discuss earthquakes: vibration, seismology, tremor, seismic, and soil mechanism. Unjoh et al. [28] used the term "soil mechanism" in their study of earthquakes. Several authors, namely, Chakraborty et al. [29], Akhoondzadeh et al. [30], and Huayong et al. [31], have focused on seismology in their works. A group of two authors, including B.C. et al. [32] and Priyana et al. [33], have investigated the concept of vibration in earthquake studies. The term "tremors" was employed by Ahangar-asr et al. [34] in their investigations. Finally, the term "seismic" was the most used, appearing in works by eight authors: Zhu et al. [35], Sevilla et al. [36], Akhoondzadeh et al. [37], Foti et al. [38], Aczel et al. [39], Zhang et al. [40], Liu et al. [41], and Cakir et al. [42]. Table 1 shows terms used by the authors.

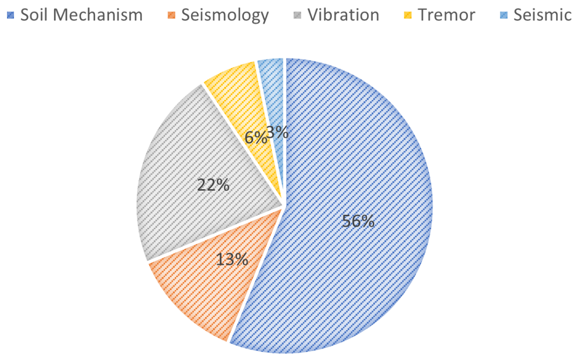

Figure 3. Earthquake keywords.

Table 1. Usage of earthquake-related terms listed by author.

Earthquake Terms	Authors
Soil Mechanism	Unjoh et al. [28]
Seismology	Akhoondzadeh et al. [30]; Huayong et al. [31], Chakraborty et al. [29]
Vibration	B. C. et al. [32]; Priyana et al. [33]
Tremor	Ahangar-asr et al. [34]
Seismic	Zhu et al. [35], Sevilla et al. [36], Akhoondzadeh et al. [37], Foti et al. [38], Aczel et al. [39], Zhang et al. [40], Liu et al. [41], Cakir et al. [42]

3.2. Analysis of Detector Keywords

Figure 4 demonstrates earthquake detection-related terms used in existing works. Table 2 shows earthquake terms used by the authors. Of the thirteen authors, several used varying terms instead of directly using the term "detector" in their studies, while the remaining authors used the term "detector". The term "sensor" was used by four authors: Mar et al. [43], Dutta et al. [44], Indiano et al. [45], and Huayong et al. [31]. Additionally, two authors investigated "alarms" in their research: T.S.D et al. [46] and Baser et al. [47].

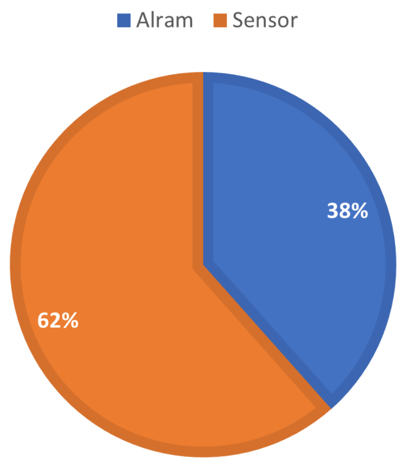

Figure 4. Ratio of the earthquake detector terms to number of authors.

Table 2. Earthquake detection-related terms listed by author.

Detector Term	Authors
Sensor	Mar et al. [43]; Huayong et al. [31]; Indiano et al. [45], Dutta et al. [44]
Alarm	T. S. D. et al. [46]; Baser et al. [47]

3.3. Findings on Different Earthquake Detectors

The findings on seismic detection are shown in Figure 5. Types of detection include S-wave, P-wave, detector, vibration, early warning, Arduino, alert, and level portions analysis. To reduce the damaging impacts of aftershocks, S-waves and P-waves are frequently used in the layout of quake detectors. The efficiency of an earthquake detector is significantly influenced by the selection of materials. The most effective way to gauge an earthquake's intensity and size while simultaneously avoiding false alarms is through vibration. Installing earthquake detectors improves human safety by providing early warning, allowing people to get ready beforehand and thereby minimizing fatalities.

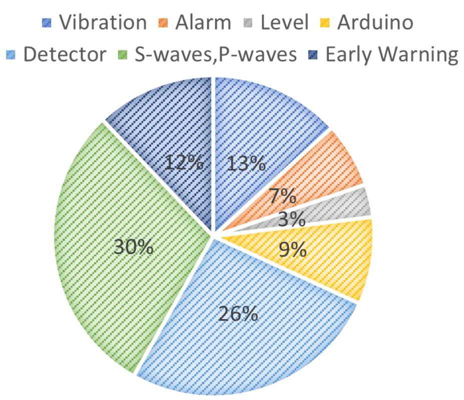

Figure 5. Types of earthquake detector.

The primary wave, called the P-wave, causes particles to move in the same direction as the wave's propagation, carrying the energy of the wave. Conversely, the secondary wave, or S-wave, moves particles perpendicular to the wave's direction, either up and down or side-to-side. P-waves are essential in separating real earthquake signals from false earthquake signals produced by sound waves that push and pull the air.

Researchers have developed electronic devices to detect initial tremors resulting from surface fractures and to identify the primary and surface waves in elastic rock mediums. This invention pertains to earthquake detection and focuses on filtering and detecting earthquakes with specific intensities over a wide area, allowing for early and accurate detection while minimizing false alarms [32,36,42,43,45,46,48].

This entails placing an earthquake detector inside a primary structural part of a building or other structure that shakes during a seismic event [45]. Patents et al. [49] reported that when vibrations occur, the detector generates a signal to trigger an alarm. An effective earthquake detector should be capable of detecting moderate earthquakes without generating false alarms.

In a study by Sagarino et al. [47], a vibration sensor was connected to an Arduino to measure, display, and analyze earthquake acceleration, proximity, displacement, and linear velocity. When the magnitude reaches a level of 5 or above, the sensor sends electric impulses to a prototype earthquake-proof container, which instantly closes when the magnitude reaches this level. The vibration sensor senses earthquakes and displays the results on a screen. The authors used ADXL335 accelerometer-based seismic sensors and an Arduino minimum system. The P-wave data from the ADXL335 sensor was successfully buffered, calibrated, sent, and shown on a website [32,36,42,43,45,46,48].

A vibration sensor and power shut-off device [49] that integrates a pendulum switch made for universal movement is another item described in the literature. A pendulum switch closes and activates a solenoid in response to vibrations in any direction, turning off electricity at a particular switch in an electrical power line. A low-voltage circuit that was functioning before the power outage will continue to operating.

According to Dutta et al. [44], due to a lack of solid diagnostic antecedents for various geo-tectonic settings that has hampered earthquake prediction studies, an earthquake early warning system designed to mitigate seismic hazards in a region must have at least three sensors from distinct locations transmitting P-wave data on the same scale in order to prevent the transmission of false seismic waves. Through this technique, the validity of seismic waves can be guaranteed and erroneous signals minimized.

3.4. Analysis of Earthquake Effects on the Environment

Earthquakes have significant impacts on the environment; the selected articles provide a comprehensive overview of these effects. The articles discuss various impacts, and include topics such as the development of Arduino detectors, advanced apps for early warning systems, innovative designs of earthquake-resistant structures, and other relevant issues. This indicates growing public concern regarding earthquakes and their consequences. Professionals in the field are actively generating novel and innovative ideas to address the challenges associated with earthquakes and improve public safety. This research paper primarily focuses on earthquake detectors, aiming to gather knowledge from scientific articles to develop new detectors or enhance existing ones. Figure 6 provides a summary of the articles in terms of their findings on the environmental impacts of earthquakes.

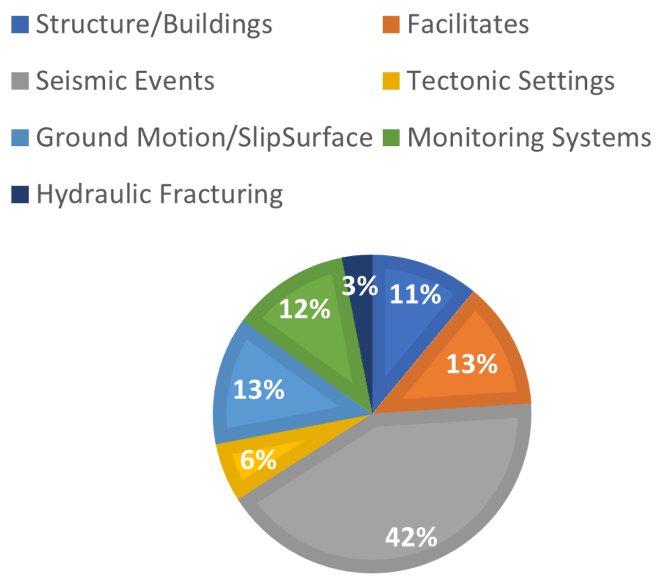

Figure 6. Earthquake effects on the environment.

When energy is released from the earth's crust during a seismic event, seismic waves are sent into space. These waves can vary in intensity, ranging from mild vibrations to significant earthquakes. Detecting and monitoring seismic events requires specialized equipment to accurately identify and analyze the seismic waves. One study implemented a compact earthquake alert system that utilizes light emitting diode (LED) displays to provide alert messages, helping people become aware of impending earthquakes and take necessary precautions to protect their lives [41]. The portability and versatility of such a system makes it suitable for installation in various areas, enhancing earthquake detection capabilities.

Buildings are particularly susceptible to structural harm and collapse during earthquakes. The rumbling that occurs during earthquakes is brought on by seismic waves moving through rock. Most seismic occurrences take place near geologic faults when rock masses shift in relation to one another. As a result, buildings can suffer severe structural damage during earthquakes, highlighting the importance of earthquake-resistant design and construction practices [40]. Researchers have investigated novel techniques to strengthen and retrofit reinforced concrete structures, such as the use of carbon fiber-reinforced plastic (CFRP). To improve structural integrity, CFRP offers benefits such as ease of handling, corrosion resistance, and high strength-to-weight ratio [40].

In addition to their immediate effects on buildings and other infrastructure, earthquakes can have an adverse effect on the environment and public safety. Earthquakes can impact on air quality, ground and surface water quality, and other environmental factors. Effective preparedness strategies are essential to reducing the threats that earthquakes pose to the environment. It is crucial to remember that seismicity can occur when waste water from processes such as hydraulic fracturing is disposed of. Waste water injection as a way to dispose of fluid waste has been linked to artificial seismic activity. This takes place when the waste water injection, which is frequently disposed of in underground injection pits, causes seismic activity due to elevated pressure and movement of underground fluids [38].

Therefore, a comprehensive understanding of seismic events, their effects on the environment, and the development of effective detection and monitoring systems is essential. By studying scientific articles and research, valuable insights can be gained to produce earthquake detectors, innovative solutions, and improved preparedness measures. These efforts contribute to a greater awareness of the impacts of earthquakes and help mitigate risks to both the environment and the public.

4. Wildfires

Based on the bibliometric study, Table 3 shows the top five publications referenced for modeling wild fires in order to provide insight into the most popular works. The two authors with the highest number of citations for their computational fluid dynamics (CFD)-based compositions were Linn in 2005 and Lopes in 2002. These two models have 118 and 100 citations, respectively. Both pieces serve as early models for detecting the growth of wildfires.

Table 3. Most cited papers about wildfires.

Ref.	Model	Key Aspects	Conclusion
[50]	CFD	Investigation of grassland fire behavior aspects	The size, shape, and ambient wind all affect ROS.
[51]	GIS/CFD	Putting in place a semi-empirical model to calculate the ROS.	Planning the control of fires using realistic simulations of wildfire progression.
[52]	CFD	A model's coefficients are optimized to replicate the impact of trees.	Successful comparison of various model tests to field measurements.
[53]	Mathematics	A description of the software architecture, numerical algorithms, and physical model.	Taking the level-set approach into consideration, the model might support real runs.
[54]	GIS	LANDFIRE's history and current applications are described.	LANDFIRE offers the tools necessary to create affordable fuel treatment options.

Table A1 in Appendix A provides a comprehensive overview of the evaluated research articles, concentrating on key aspects such as the authors, their specific work, validation/results, and employed techniques. The authors represent a wide variety of research works and professionals who have made contributions to the field of earthquake detection and related topics. Each article's conclusion summarizes the study's findings and outcomes while spotlighting the authors' specific contributions. The validation/results column presents the main results, outcomes, or validation methods utilized in each study, demonstrating the efficacy and dependability of the proposed methods. Finally, the techniques column describes the methodologies, techniques, or instruments used by the authors to conduct their research, providing insight into the scientific methods used to address fire-related challenges.

5. Floods

Floods are another common natural disaster that greatly influences the lives of humans along with the habitat, animal life, and atmosphere. A large range of tools and techniques have been deployed for flood detection in the existing literate; these are discussed under separate headings in the following subsections.

5.1. Data Analytics and Machine Learning for Floods

Machine learning and data analytics techniques can be incorporated into flood disaster management systems to improve flood forecasting, risk assessment, and response planning. These techniques can analyze large amounts of historical and real-time data, such as rainfall patterns, river levels, and meteorological conditions, to identify patterns, trends, and potential flood events. Machine learning algorithms can acquire knowledge from historical data to improve the accuracy of flood forecasting and facilitate proactive decision-making. Additionally, data analytics can be used to detect vulnerable populations, improve evacuation routes, and distribute resources effectively during flood events.

5.2. Geographical Information System and Spatial Data Management

By combining and analyzing spatial data related to flooding, the geographical information system (GIS) plays a significant role in flood disaster management systems. GIS facilitates the creation of accurate flood hazard maps by combining elevation models, hydrological data, and land use information, helping to identify flood-prone areas, infrastructure at risk, and high-risk zones. In addition, GIS facilitates spatial analysis and modeling in order to simulate flood scenarios, evaluate various flood management strategies, and support decision-making processes. GIS can help with real-time tracking and visualization of flood events, which makes it easier to respond quickly and use resources well.

5.3. Model-Driven Engineering

The model-driven approach or Model-Driven Engineering (MDE) is a systematic method that employs models to design, analyze, and simulate complex systems, including flood disaster management systems. Models that depict many components of the flood management procedure, such as flood forecasting, risk assessment, and emergency response planning, can be created using MDE. These models allow stakeholders to comprehend system behavior, evaluate various strategies, and maximize resource allocation. MDE facilitates the integration of various system components, promotes interoperability, and facilitates collaborative stakeholder decision-making.

5.4. Sensors Network and Internet of Things

Both sensor networks and IoT have the capability of real-time data collecting as well as monitoring for flood disaster management systems. By deploying sensors in flood-prone areas, such as riverbanks or municipal drainage systems, continuous data can be acquired on flood levels, the extent of rainfall, and infrastructural states. IoT and sensor networks facilitate the early detection of flood events, aid in the evaluation of flood impact, and provide vital data for decision-making. The data from these networks can be combined with data from other systems such as GIS to track and manage floods more completely.

5.5. Big Data Analysis and Cloud Computing

This analysis method provides adaptable and effective approaches for handling and processing the substantial amounts of data linked to floods. Cloud-based platforms can store and process data from a variety of sources, including sensor networks, satellite imagery, and historical records. Data mining, pattern identification, and predictive modeling can yield important insights from these data. Real-time data processing, stakeholder cooperation, and the creation of data-driven decision support systems for flood catastrophe management are made possible by cloud computing and large-scale data analysis. By utilizing historical data, these technologies can assist in enhancing flood forecasts and planning for resiliency.

Data analytics and machine learning, GIS, MDE, sensor networks and IoT, and big data analysis and cloud computing are the major areas that the existing literature on flood prediction and management has focused upon.

5.6. Google Earth Engine

Google Earth Engine is a cloud-based platform developed by Google that provides a powerful and scalable environment for analyzing and processing geospatial data from satellite imagery and other Earth observation sources. It was launched in 2010, and is primarily used for conducting large-scale geospatial analysis, monitoring environmental changes, and supporting scientific research related to Earth sciences.

Google Earth Engine hosts an extensive archive of satellite imagery and geospatial datasets, including Landsat, Sentinel-2, MODIS, and others, dating back several decades. The platform allows users to access and analyze this vast collection of data using Google's computing infrastructure, which includes thousands of servers, enabling quick and efficient processing of large-scale datasets. Table 4 provides an overview of the advantages and disadvantages of each of these approaches.

Table 4. Advantages and disadvantages of techniques/domains used for flood disaster management.

Domain	Advantages	Disadvantages
Machine Learning and Data Analytics for floods	• Improved accuracy of flood predictions • Proactive decision-making based on data patterns and trends. • Identification of vulnerable areas and populations • Optimization of evacuation routes • Effective resource allocation	• Dependency on large volumes of historical and real-time data • Need for continuous updating and maintenance of models. • Interpretability challenges in complex machine learning algorithms
GIS and Spatial Data Management	• Accurate flood hazard mapping and identification of flood-prone areas • Spatial analysis and modeling for flood scenarios • Real-time monitoring and visualization of flood events • Integration of various data sources for comprehensive analysis • Support for decision-making processes	• Initial setup and data collection may be time-consuming. • Reliance on accurate and up-to-date spatial data • Cost of acquiring and maintaining GIS software and infrastructure
Model Driven Engineering	• Systematic approach for designing and analyzing flood disaster management systems. • Improved understanding of system behavior • Optimization of resource allocation and decision-making • Interoperability and collaboration among stakeholders	• Initial investment of time and resources in developing models and frameworks • Complexity in model development and integration

Table 4. *Cont.*

Domain	Advantages	Disadvantages
IoT and Sensor Networks	• Real-time data collection and monitoring of flood-related parameters. • Early detection and assessment of flood events • Data-driven decision-making based on accurate and timely information. • Integration with other systems for comprehensive flood monitoring	• Deployment and maintenance of sensor networks can be costly and challenging. • Data quality and reliability issues in sensor measurements • Security and privacy concerns related to data transmission
Big Data Analysis with Cloud Computing	• Scalable and efficient data storage and processing • Real-time data processing and analysis • Collaboration and data sharing among stakeholders • Development of data-driven decision support systems • Leveraging historical data for improved flood forecasting	• Dependence on reliable internet connectivity for data transfer and access • Cost considerations for cloud infrastructure and storage
Google Earth Engine	• Access to a vast repository of satellite imagery and environmental datasets without the need for extensive data storage or downloading. • Efficient processing of large-scale geospatial data using Google's cloud infrastructure. • Suite of advanced tools and APIs for complex analyses like time-series analysis and land cover classification. • Easy collaboration with others and sharing of analyses, code, and results.	• Requires programming and remote sensing knowledge, which may pose a learning curve for new users. • Not all types of geospatial data may be available, limiting the scope of analyses for certain research needs. • Some latency in acquiring the most recent satellite imagery due to data processing and availability. • Requires a stable internet connection for effective usage, which may limit accessibility in regions with unreliable internet • Commercial use may be subject to licensing fees and restrictions, making it less ideal for certain business applications.

In this review, we found around 45 papers on flood prediction and management, with each paper using different techniques. Table A2 in Appendix A provides a comprehensive overview of the evaluated research articles, concentrating on key aspects such as the authors, their specific work, validation/results, and employed techniques. Table A2 presents a wide variety of researchers and professionals who made contributions to the field of flood disaster and related topics. Each article's conclusion summarizes the study's findings and outcomes while spotlighting the authors' specific contributions. The validation/results column presents the main results, outcomes, or validation methods utilized in each study, demonstrating the efficacy and dependability of the proposed methods. Finally, the techniques column describes the methodologies, techniques, or instruments used by the authors to conduct their research, providing insight into the scientific methods used to address flood-related challenges.

6. Applications Based on Remote Sensing for Disasters

The complexity of disaster management arises from the unpredictable and diverse nature of disasters, making it impossible to find a single comprehensive solution. Instead, a wide range of remote sensing platforms and sensors can and should be utilized for image acquisition [24]. In the following section, we explore specific instances in which remote sensing has been applied in disaster management contexts. Furthermore, readers interested in delving deeper into this topic can find additional studies in the existing literature.

6.1. Wildfires

Wildfires, like other disasters, pose threats to life and property; moreover, they contribute to carbon emissions. Remote sensing data can prove valuable in fire detection, monitoring, modeling, and burnt area mapping. Satellite sensors with high temporal resolution, such as GOES (Geostationary Operational Environmental Satellite) and SEVIRI (approximately 30 min), have been utilized for fire monitoring [55]. Sensors with thermal and infrared capabilities, such as MODIS and AVHRR, can be employed as well. Burnt area mapping is accomplished through a multi-temporal comparison of NDVI using visible and near-infrared sensors [55,56]. In Europe, the European Forest Fire Information System (EFFIS) established by the Joint Research Centre and European Commission provides current and historical forest fire information using remote sensing data. Furthermore, remote sensing data have been employed to quantify forest fire contributions to carbon emissions [57].

6.2. Earthquakes

Earthquakes are natural disasters associated with earth movements, while landslides result from mass movements. Predicting earthquakes and volcanic eruptions remains challenging, limiting earthquake disaster management to preparedness and relief. Remote sensing has proven highly valuable across all phases of volcanic eruption disaster management, while its usefulness for earthquakes and landslides is somewhat limited [58]. Tralli et al. [59] suggested that high-resolution digital elevation models (DEMs) such as InSAR and LIDAR combined with in situ data and imaging spectroscopy, e.g., ASTER, MODIS, and Hyperion, can aid in assessing and monitoring volcanic and landslide hazards. Sensors such as ASTER can be utilized to monitor earthquake-induced landslide dams for hazard mitigation in case of dam breach [60]. Satellite remote sensing imagery was successfully employed for deployment, data collection, and dissemination during disaster management operations following the Haiti earthquake [61].

6.3. Floods

Flooding comprises various types, such as river floods, flash floods, coastal floods, and dam breaks, each exhibiting distinct characteristics with respect to occurrence time, magnitude frequency, duration, flow velocity, and areal extent. Satellite data have been effectively utilized throughout the multiple stages of flood disaster management [62]. The GOES satellite's multi-channel and multi-sensor data sources are employed for meteorological evaluation, interpretation, validation, and the development of numerical weather prediction models. Additionally, they can aid in assessing hydrological and hydro-geological risks [63]. Nonetheless, the use of optical sensors for flood mapping is constrained by the substantial cloud cover prevalent during flood events. To overcome this limitation, Synthetic Aperture Radar (SAR) and RADARSAT have demonstrated significant utility in flood mapping [64]. It is essential, however, to integrate remote sensing data and GIS data during flood management, particularly in disaster relief operations. In summary, remote sensing data find application in flood management for hazard assessment map preparation, hydrological model generation, quantitative soil assessment, flood risk mapping, and early warning [65].

6.4. Interconnections Between Techniques

Our review of 29 research papers on how fires behave, how to predict them, and how to find them shows important insights and links in the field, as shown in Table A3 in Appendix A. These papers show how important historical data and fire maps are for determining how fires spread in different weather situations and on different types of land. These data can help to improve fire prediction models by considering variables such as weather, fuel moisture, and fuel load, and can be used with machine learning methods. The goal is to ensure that there are good tools for finding fires, predicting their spread, and determining the flammability of materials. High-resolution fuel information is important for capturing fire behavior accurately. The papers explain how fire behavior is related to different factors, testing methods, and statistical models for predicting fires on a small scale. This review provides important information that can help us to learn more about fires and how to control them, in turn leading to better safety measures for communities and ecosystems. The other publications on floods shown in Table A4 in Appendix A concentrate on employing cutting-edge technology and approaches such as machine learning, decision support systems, and IoT to enhance flood risk management. The goal is to develop new ways to prevent flood tragedies and make it easier to prepare for and respond to them. Integration of these technologies, along with data-driven models and teamwork between stakeholders, is a key part of reducing flood risk and making predictions accurate. More study and real-world usage are needed to fully use the potential of these approaches in real-world disaster situations in order to advance disaster management and risk reduction across different fields.

6.5. Impacts of Disaster Management System on Human Beings

People's social, cultural, and economic lives can be greatly affected by technical problems in emergency management systems; these effects can include:

i. **Loss of Life and Injury:** Technical problems in crisis management systems can slow down response and rescue efforts. This may cause delays in reaching affected areas, resulting in a larger number of casualties and injuries.
ii. **Psychological Distress:** When emergency management systems do not work well, people may feel alone and overwhelmed. This can make them feel more stressed, anxious, and traumatized.
iii. **Disruption of Social Networks:** When a disaster strikes, people often band together to help each other. Technical problems with crisis management systems can make it hard for people and communities to talk to each other and coordinate their relief efforts.
iv. **Loss of Culture:** Sometimes, disasters can damage or destroy culturally important locations and artifacts. Technical problems could make it harder to maintain and protect these important parts of cultural identity.
v. **Economic Loss:** Technical flaws can stymie disaster response and recovery efforts, resulting in protracted downtime for businesses and key infrastructure. People, companies, and governments may lose money because of such disruptions.
vi. **Inequality and Vulnerability:** Vulnerable individuals, such as the elderly, disabled, or disadvantaged communities, may experience additional difficulties obtaining resources during catastrophes. Technical problems can make these differences worse, placing groups even more at risk.
vii. **Migration and Displacement:** If emergency management systems do not provide people with the right information or help, they may have to move or be moved in order to obtain help and resources.
viii. **Lack of Information:** During disasters, timely and accurate information is critical. Technical problems with communication systems can cause people to receive the wrong information, resulting in confusion and fear.
ix. **Interconnected Disasters:** In complex disasters with multiple events, technical problems can make it hard to obtain a full picture of events, in turn making it difficult to coordinate reactions.
x. **Loss of Trust in Institutions:** Persistent technological failures in disaster management systems can erode public trust in government agencies and other institutions responsible for disaster response and management.
xi. **Long-Term Recovery Challenges:** It might be difficult to plan for effective recovery and mitigation plans when technical issues that hamper data collection and analysis make it impossible to estimate the long-term effects of catastrophes.

To lessen these effects, it is important to invest in strong and effective disaster management systems, test and update them regularly, and make sure that communities are well-informed and involved in efforts to prepare for disasters. In addition, supporting a disaster management strategy that considers the different needs of all people and communities can help make people less vulnerable and strengthen their ability to deal with technical problems.

7. Challenges and Future Directions

Different disasters such as earthquakes, fire, and flooding have their own challenges and problems, in addition to the general challenges that are associated with natural disasters.

7.1. General Challenges

In this section, we first discuss general challenges in disaster management systems, then highlight challenges related to each category through short descriptions.

i. Effectively allocating limited resources such as personnel, equipment, and funding poses a challenge in disaster management, especially during simultaneous or resource-scarce events.
ii. Ensuring effective communication and coordination among stakeholders is needed to overcome issues such as complex networks, language barriers, and coordination problems between agencies and organizations.
iii. Gathering, analyzing, and disseminating timely and accurate information can be challenging during rapidly evolving disasters due to obstacles such as limited data, misinformation, and communication breakdowns.
iv. Engaging local communities and promoting their resilience presents challenges due to cultural differences, distrust, limited awareness, and resource constraints.
v. It is necessary to adapt disaster management systems to cope with the changing characteristics and impacts of disasters, including climate change and urbanization.
vi. Overcoming challenges in collaboration across disciplines such as emergency management, engineering, social sciences, and public health, which have differing terminologies, approaches, and priorities, can be difficult.
vii. Ensuring sustainable and equitable recovery, addressing vulnerabilities, and integrating disaster risk reduction into development planning pose challenges beyond the immediate response phase.

7.2. Challenges Related to Floods

The following challenges are faced by flood management systems:

i. The need for constant improvement in domains related to floods (model-driven, machine learning, GIS, etc.) to enhance the speed and interpretability of flood-related models.
ii. Lack of information on the computational time associated with flood modeling, hindering the evaluation of model applicability in disaster management.
iii. Limited development of feature selection techniques needed to increase the efficiency of decision support in flood management.
iv. Scarcity of studies comparing the computational efficiency of different simulation platforms for flood management.

7.3. Challenges Related to Earthquakes

In addition to general challenges, earthquake management systems have the following specific challenges:

i. Insufficient exploration of global models that can be applied to different regions and datasets in earthquake prediction along with limited assessment of their potential for generalization.

ii. Limited integration of earthquake protection concerns in multi-functional landscape management planning considering multiple ecosystem services.
iii. Inadequate analysis of the minimum amount of data required for useful earthquake modeling, particularly during the active disaster stage.
iv. Challenges in dealing with uncertainties in earthquake forecasting models and their impact on management decisions.

7.4. Wildfire Challenges

Challenges in the context of wildfire management include:

i. Lack of extensive wildfire datasets for training models; most models are developed using smaller wildfire events, and may not adequately represent extreme wildfire contexts.
ii. Need for advances in acquiring landscape dynamics data to quantify spatial patterns and changes in wildfire management.
iii. Addressing issues of model overfitting in wildfire prediction and management.
iv. Bridging the gaps between monitoring, learning, and decision-making in wildfire management.
v. Developing broader models that can integrate different stages of wildfire management effectively.

7.5. Limitations and Challenges in Using Remote Sensing for Disaster Management

Limitations and challenges when using remote sensing data in disaster management contexts include:

i. Finding the most applicable remote sensing system for a given type of disasters.
ii. The need to evaluate the nature of the disaster and select appropriate sensors while considering spectral and temporal resolution as well as cloud coverage limitations; notably, the synergistic approach suggested by Joyce et al. [23] and Leblon et al. [55], involves combining visible sensors with microwave sensors to overcome cloud coverage effects.
iii. Available frameworks for using remote sensing in disaster management are limited [23]; moreover, there is a need to develop new frameworks or templates for applications in remote sensing for disaster management without “reinventing the wheel”.
iv. Challenges around timely provision of data mean that developing countries in particularly face limited access to certain data (e.g., high-resolution images) and may lack the technical expertise to handle it.
v. Lack of research funding for application of remote sensing data in hazard management contexts limits the effective use of satellite data [21].

Based on the above, it is important that new research studies investigate the application of new algorithms and frameworks for remote sensing in disaster management.

7.6. Future Directions

Future research should prioritize the development of new and improved approaches to detection, warning, prevention, mitigation, and response across all disaster types by considering the above issues with the overarching goal of advancing more effective and integrated disaster management systems that prioritize the protection of lives and property. By uniting these future directions, we anticipate a safer and more resilient world better equipped to face the challenges posed by natural disasters. In the realm of disaster management, remote sensing holds in particular holds immense potential to revolutionize response efforts in the event of earthquakes, wildfires, and floods. Advances in integrated remote sensing systems offer versatile solutions to address a range of disaster types, addressing challenges such as cloud coverage and temporal resolution limitations. Standardized frameworks and templates can streamline numerous processes, promoting efficient and effective responses in different disaster scenarios. Timely data provision remains a priority, particularly in developing countries where access to high-resolution images and technical expertise may be limited. By investing in capacity building, research funding, and international collaboration, the future of remote sensing in disaster management promises enhanced preparedness and resilience, paving the way for more effective earthquake detection and warning methods, improved coordination between agencies, better fire suppression techniques in wildfire management, and a comprehensive approach encompassing forecasting, early warning systems, and infrastructure floodproofing in flood management.

8. Conclusions

This systematic review concludes with a comprehensive evaluation of current disaster management systems, with an emphasis on earthquakes, wildfires, and flooding. We have reported promising strategies and identified challenges that must be addressed in order to improve preparedness, response, and mitigation. For earthquake management, seismic monitoring and early warning systems show promise, although data collection and communication strategies must be improved. Prescribed burning and fireproofing are two strategies that are becoming more popular in wildfire control, although coordination and fire suppression methods remain an issue. Likewise, flood management necessitates a comprehensive approach involving flood forecasting, early warning systems, and flood-proofing of infrastructure, necessitating new developments in data collection, analysis, and evacuation strategies. This review highlights the importance of remote sensing technology, particularly in those phases of disaster management that involve preparation, warning, response, and monitoring. Combining remote sensing and GIS techniques can greatly improve efficiency; however, there are obstacles and limitations to using satellite data for disaster management that necessitate additional research. Future research should concentrate on developing innovative and enhanced detection, warning, prevention, mitigation, and response strategies. Using remote sensing data in conjunction with other surveying and monitoring techniques can improve disaster management with the objective of developing more efficient systems that safeguard lives and property during disasters. The findings of this review can serve as a basis for future research and innovation in disaster management, as natural disasters continue to pose significant global challenges. Adopting these insights will result in a safer and more resilient future for everyone, enabling communities to be better prepared for natural disasters. Constantly striving for development can help to mitigate the effects of these catastrophic events and place the well-being of affected populations at the forefront.

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Appendix A

Table A1. GIS, mathematical, CFG and ML-based techniques for wildfire management.

Ref.	Key Aspects	Conclusions with Specific Work	Validation/Results	Technique
[66]	Based on past data, create a monthly fire spread probability model.	Historical data and the likelihood of fire spread are significantly correlated.	Historical data	GIS
[67]	Analysis of wildfire exposure and risk transfer in Sardinia using wildfire simulation modeling	The major conclusions can be applied to further assess the likelihood of transmission or anticipated wildfire behavior.	Historical data	GIS

Table A1. *Cont.*

Ref.	Key Aspects	Conclusions with Specific Work	Validation/Results	Technique
[68]	Introduction of Fire Map, a web platform for geospatial data services and fire prediction, including its architecture and main components.	Fire map has proven valuable in the firefighting community, providing automatic fire perimeter detection and reliable future forecasts.	-	GIS
[69]	Presentation of a methodology that combines automated wildfire monitoring with accurate fire spread forecasting.	The backward time method is a simple and effective approach for solving fire prediction.	Experiments	GIS
[70]	Proposal of various algorithms for fire behavior analysis using the final perimeter as input.	The developed tool is efficient and fully functional.	-	GIS
[71]	Discussion on integrating two models into a GIS-based interface	The tool developed is efficient and fully operational.	Historical data	GIS
[72]	Introduction of a model that evaluates the impact of five landscape factors on fire spread performance.	Categorizing fires based on synoptic weather conditions can enhance fire modeling in landscape fire models.	Historical data	GIS
[73]	Exploration of multi-fidelity approaches to fire spread prediction.	Fuel moisture, fuel load, and wind speed are the main uncertainties affecting fire spread rates.	Experiments	CFD
[74]	Investigation of how fuel density and heterogeneity affect fire behavior in relation to wind characteristics.	Increasing canopy fuel structure detail and implementing turbulent boundary conditions have minimal impact	Experiments	CFD
[75]	How fuel density and heterogeneity affect fire behavior in relation to wind characteristics.	Incorporating high-resolution fuel fidelity and heterogeneity information is crucial to capture effective wind conditions.	-	CFD
[76]	Considers the effect of vegetation characteristics on the flame tilt angle and the radiative heat transfer.	High-resolution fuel fidelity and heterogeneity information are vital for accurately capturing wind conditions.	Simulations	CFD
[77]	Investigate fire regime transition and its associated heat transfer mechanisms.	The model predicts both free and non-free fires, introducing new models for tilt angle and radiative heat power reaching vegetation.	Simulations	CFD
[78]	a fresh simulation tool for quick resolution, atmosphere fire reaction.	The ability to record fundamental patterns in fire behavior, the relationship between fire spread and fire size, and the use of canopy fuels.	Compared With other models	CFD
[79]	The multiphase model is created and added to PHOENICS.	The anticipated ROS and experimental values measured at varied wind speeds were in good agreement.	Experiments	CFD
[80]	Outlines a method for creating a burned area probabilistic forecast	The calibrated ensembles improve accuracy overall.	Simulations	Mathematical
[81]	Creation of a computer model to forecast soil organic matter loss	The amount of water in the soil regulated the amount of heat used during vaporization and stopped soil deterioration.	Simulations	Mathematical
[82]	Creating a fire spread model using a heterogeneous cellular automata model.	The model can anticipate the spread of a fire with a respectable level of accuracy and efficiency.	Simulations	Mathematical
[83]	Prediction of the spread of a surface fire with an emphasis on uncertainty.	Based on probabilistic fire simulations, maps of the potential for fire can be created.	Simulations	Mathematical

Table A1. *Cont.*

Ref.	Key Aspects	Conclusions with Specific Work	Validation/Results	Technique
[84]	In an upslope fire spread model, parametric uncertainty analysis is developed.	The projected values of ROS under lower slopes are significantly impacted by the values of ignition and flame temperatures.	Simulations	Mathematical
[85]	Creation of two empirical ROS functions in a windless environment.	Both models demonstrate that independent variables serve as suitable ROS descriptors.	Simulations	Mathematical
[86]	Creation of an empirical model for ROS assisted by wind.	A laboratory examination of the Rothaermel model revealed improved predictions.	Simulations	Mathematical
[87]	Support Vector Machines, K-Nearest Neighbors, Random Forest, and Extreme Gradient Boosting.	Improvement techniques for the Fuel Management Zone	F1 scores between 90.0% and 94.0%, and a Kappa between 0.80 and 0.89.	Machine Learning
[88]	Gradient boosted regression, multiple linear regression, random forests, and neural networks	Determining fuel moisture content	Errors between 25.0–33.0%	Machine Learning
[89]	Support Vector Machine, Random Forest, and Multiple Linear Regression	Calculating the fine dead fuel load and comprehending the factors that affect it	(Random Forest, RMSE 0.09, MSE 0.01, r 0.71, R-2 0.50)	Machine Learning
[90]	Support vector machines and random forests	Estimating fuel moisture content for 10 h	R^2 is between 0.77 and 0.82, while the RMSE ranges between 2.0 and 2.8%.	Machine Learning
[91]	Mask-Based Convolutional Neural Network	Network-based Dead Tree Detection from Aerial Images	54.0% is the mean average precision score.	Machine Learning
[92]	Neural Network	Identification of flammable liquids on actual fire debris	0.07 percent false positives and 0.59 percent real positives	Machine Learning
[93]	Support Vector Machines with Radial and Linear Kernels, K-Nearest Neighbors, and Linear and Quadratic Discriminant Analysis	Finding flammable liquid residue on fire debris	Equal error rates (17.0–22.0%), area under the receiver operating characteristic curve (0.86–0.92)	Machine Learning
[94]	Classification Trees, Random Forests, Neural Networks, Logistic Regression Models, and Logistic Generalized Additive Models are a few examples of the types of models.	Methods for fine-scale, spatially explicit daily fire occurrence prediction using statistical and machine learning models that have been correctly calibrated	-	Machine Learning

Table A2. Flood management techniques related to machine learning, GIS, MDE, IoT and GEE.

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[95]	• Novel approach using machine learning to map flood risk. • Primarily requires DTM and known flooded locations. • Identifies flood risk hotspots for further hydrodynamic modeling. • Reduces computational cost	• Cannot replace traditional hydraulic-hydrodynamic modeling. • Can be used for local-scale flood risk identification. • Reduces computational cost	N/A	Machine learning, DTM, known flooded locations
[96]	• Review of amphibious construction strategies for flood resilience • Introduction to self-floating house design • Use of fiber molding technology • Load calculations and stability checks	• Assurance of sustainability in flood damage reduction • Design of self-floating house for flood resilience	N/A	Fiber molding technology, load calculations, stability checks
[97]	• Creation of a long-term disaster risk planning decision-making model • Application of game theory and stratification theory • Creation of interactive web application • Application to flooding risk strategy evaluation	• The most effective mitigation techniques are flood forecasting and raising awareness. • Restrictions and difficulties with applying the model.	Monte Carlo simulation	Decision-making model, game theory, stratification, interactive web application, Monte Carlo simulation
[98]	• Change the focus from flood protection to flood risk reduction. • Model-driven decision support system (MDSS) development • Combining data from many sources, multidisciplinary models, and GIS technologies. • Implementation in the Jingjiang flood diversion area of flood risk management	• Model-driven approach offers efficiency, adaptability, and flexibility. • Promising solution for comprehensive flood risk management	N/A	GIS tools, multi-source data, transdisciplinary models, and model-driven decision support systems
[99]	• Review of flood disaster management in Malaysia • Emphasis on prevention/mitigation and preparedness • Identification of responsible agencies • Role of technology and community awareness	• Education and community awareness crucial for effective flood mitigation • Importance of prevention/mitigation and preparedness strategies	N/A	Review Paper
[100]	• Creation of Disaster Management (DM) metamodel • A system for DM decision assistance that combines several DM activities. • Proof of concept in bushfire domain	• Unification, facilitation, and expedited access to DM expertise • Refinement of metamodel concepts in bushfire domain	N/A	Disaster Management metamodel, DM decision support system

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[101]	• Utilization of deep learning models for flooded building detection using UAV images • Accurate detection of flooded buildings and vegetation • Estimation of inundation area based on UAV images. • Timely visualization of the spatial distribution of inundation	• Accurate and timely detection of flooded buildings and vegetation • Benefits flood emergency response sector	Achieved 88% accuracy for flooded buildings and 85% accuracy for vegetation	Deep learning models, UAV imag
[102]	• Disaster Management and IoT • Evaluation of IoT-based catastrophe management programs • Challenges in disaster management with IoT • Future areas of improvement	• Stakeholders can use IoT technology for smart cities' infrastructure security and disaster management. • Improvement needed in cost-effectiveness, fault tolerance, standardization, context awareness, knowledge discovery, real-time analysis, security, and social media utilization. • Future areas of improvement include low-cost devices, user-friendly interfaces, clean energy sources, interoperability, and maintenance efficiency	Not mentioned	Literature review, analysis of challenges, identification of areas for improvement
[103]	• Development of a visualization and animation system for storm surge flooding • Real-time and offline animation • Parallel computing • Selective visualization • Use of geo-referenced data • Extensibility of the system	• Realistic 3D visualizations and animations for educating coastal residents, assisting emergency managers, and aiding in urban planning and flood damage mitigation. • Differentiation between real-time and offline animation for a quick assessment and detailed analysis • Utilization of georeferenced data and user input for personalized impact visualization • Extensibility to visualize other phenomena and repurpose for different applications	Not mentioned	Real-time visualization and animation, parallel computing, selective visualization, georeferenced data usage
[104]	• Use of Agent-based Modeling (ABM) in flood risk assessment • Creation of FDMACS, a flood disaster multi-agent complex system Challenges in internal design, collaboration, and communication within FDMACS • Need for interdisciplinary collaboration. • Micro-level understanding and macro-level insights into flood disaster systems	• ABM offers valuable insights into flood risk assessment. • Improvement needed in internal design, collaboration, and communication within FDMACS. • Interdisciplinary collaboration required for leveraging ABM's potential. • Micro-level understanding and macro-level insights can be achieved with ABM	Not mentioned	Agent-based Modeling, development of FDMACS

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[105]	• Use of remotely sensed data for monitoring natural hazards and flood index insurance • Challenges in validation and utilization of satellite data • A framework for remote sensing application validation in contexts with limited data. Evaluation of validation metrics • Development of a high-resolution and high-temporal flood inundation time series using Sentinel-1 data • Importance of combining and cross-referencing data sources for a comprehensive understanding	• Potential of remotely sensed data for flood index insurance • Criteria for validating remote sensing algorithms. • Development of a high-resolution flood inundation time series using Sentinel-1 data • Importance of combining data sources for a comprehensive understanding • Applicability of validation criteria beyond Bangladesh	Results demonstrate the improved performance of the adapted Sentinel-1 algorithm	Validation criteria, development of flood inundation time series, combination and cross-referencing of data sources
[106]	• A framework for describing and capturing disaster management systems (DMS) using model-based systems engineering (MBSE) using SysML Holistic approach and traceability between subsystems • Importance of systems engineering principles in disaster management • Areas for future research in DMS requirements, behavior, and adoption of MBSE in non-traditional domains	-	-	-
[107]	Importance of flood prediction and prevention systems, technologies for flood prediction and prevention, drawbacks of existing systems, proposed flood alert system	Existing flood alert systems have limitations, proposed model is protective and reliable, economical in terms of cost, assures self-defense from flash floods	Not specified in the given text	Grid-based monitoring, Warning based on User mobility, Early flood warning, Flood alarming, ShonaBondhu, Zigbee technology
[108]	Application of semantic computing models in IoT early warning systems, benefits, and challenges, proposed IoT EWS system framework	Semantic EWSs offer easier integration, improved analysis, and service interoperability, challenges include data exchange, heterogeneous data sources, and resource constraints	Validation through system-related metrics and a case study	Lightweight and heavyweight semantics, metadata-driven data analysis, semantic decision support, workflow orchestration
[109]	Using case-based reasoning in a multi-agent intelligent system, flood disaster forecasting	Proposed framework accurately predicts water levels and forecasts flood disasters with a lower error rate compared to neuro-fuzzy network-based method	Validation using "Active Archive of Large Floods, 1985-Present" dataset	Case-based reasoning, multiple agents, flood disaster forecasting algorithm
[110]	Risk-based flood management, flood management measures and approaches, risk assessment	Risk-based approaches gaining prominence globally, need for understanding risk dynamics and key parameters, consideration of socio-economic and environmental constraints	Not specified in the given text	Risk-based flood management, risk parameters, floodplain characteristics analysis
[111]	Implementation of a Smart IoT Flood Monitoring System using IoT technology	Proposed system enables real-time monitoring of water levels, remote access, and prediction capabilities, enhances public awareness, preparedness, and resilience	Not specified in the given text	Smart IoT Flood Monitoring System, IoT technology, web servers, wireless control

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[112]	Emergency fleet management for preventing urban flooding, dependable fleet management approach	Data-driven resilient fleet management platform, dynamic management mechanism, and dispatching algorithm improve emergency fleet management resilience	Not specified in the given text	Optimization techniques, data-driven robust fleet management, cloud asset-enabled systems, and greedy-based dispatching algorithms
[113]	• Efficient and accurate early flood warning systems • Convolutional neural networks and long short-term memory networks are combined • Development of ConvLSTM model • Superior performance in flood forecasting • Validation using rainfall datasets from Fiji • Evaluation metrics: RMSE, LME	• ConvLSTM model demonstrates superior performance in flood forecasting. • Usefulness in reducing risk and managing disasters Potential for forecasting floods at shorter timescales	• Validation of nine rainfall datasets from Fiji's flood-prone areas • Evaluation metrics: RMSE, LME • ConvLSTM model outperformed benchmark methods	Long-Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and ConvLSTM model
[6]	• Efforts towards achieving a comprehensive flood management system in Jakarta. • Challenges in implementation • Sensor-based monitoring systems • Data analysis for enhanced understanding • Decision support dashboard • Importance of data management and stakeholder collaboration	• Importance of disaster management as a Sustainable Development Goal • Challenges related to data management and governance. • Future applications for minimizing flood risks in Jakarta	• Sensor-based monitoring systems deployed. • Data analysis conducted. • Decision support dashboard utilized	Sensor-based monitoring systems, data analysis, decision support dashboard
[114]	• China's vulnerability to natural disasters • Quick Service and Integrated Disaster Reduction Platform • Planning a satellite mission, gathering data, producing it, and using it for remote sensing • Effectiveness of the platform • Case study of the Yunnan Cangyuan earthquake	• China's Integrated Disaster Reduction and Quick Service Platform for disaster prevention and mitigation • Rapid and integrated services for disaster response • Swift dissemination of satellite data products and information	• Case study of the Yunnan Cangyuan earthquake • The Integrated Disaster Reduction and Quick Service Platform's effectiveness	Satellite data, Integrated Disaster Reduction and Quick Service Platform, and remote sensing
[115]	• The multiplicative seasonal ARIMA (SARIMA) model's usefulness in predicting flood catastrophes in the Tarim River Basin • SARIMA model development and adjustment • Satisfactory prediction performance • Criteria for testing the model. • Future trends prediction	• Predicting flood disasters using the SARIMA model in the Tarim River Basin • Satisfactory prediction performance • Criteria for testing the model. • Importance of continuous data updates and local environmental factors	• Analysis of flood data from 1980 to 2019 SARIMA model development and adjustment • Flood catastrophe forecasting for the Tarim River Basin	Multiplicative seasonal ARIMA (SARIMA)
[116]	Importance of response phase in Disaster Management System life cycle.	• Need for integrated routing application specifically designed for emergency response (ER) units. • Limitations of commercial navigation systems for ER units. • Underutilization of location information in disaster management and potential of GIS technology.	N/A	Spatial DBMS, spatial schema, indexing techniques, operations

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[117]	• Proposal of a flood forecasting model using federated learning. • Integration of locally trained models from eighteen clients. • Identification of flood-prone stations with five-day lead time alert.	• Successful prediction of previous floods with 84 • Making use of information about rivers, barricades, snowmelt, rainfall-runoff, flow paths, and hydrodynamics. • Training of global model for flood analysis. - Estimation of water level increase using a feed-forward neural network model. • Issuing flood alerts to the flood mitigation department. • Potential expansion of the model to other regions.	Successful prediction of previous floods with 84% accuracy.	Federated learning, local models, flood forecasting, feed-forward neural network
[118]	• Evaluations of a developed flood forecasting system that are both subjective and objective. • High accuracy in predicting flood incidents. • Benchmarking experiments with MLP ANN configuration.	• High level of accuracy in predicting flood incidents. - Effective use of MLP ANN configuration. • Integration of meteorological, hydrological, geospatial, and crowdsource data. • User experience enhancements through responsive graphical interfaces. • Distributed architecture for widespread implementation.	Correct percentage: 97.93, Kappa coefficient: 0.89, MAE: 0.01, RMSE: 0.10.	Decision trees, Naive Bayes, MLP ANN, Random Forest (RF), Support Vector Machines (SVM), fuzzy logic, meteorological data, hydrological data, geospatial data, crowdsource data
[119]	• Climate-proofing framework for flood risk management planning in Finland. • Incorporation of regional data and consideration of climate scenarios.	• Useful information for flood risk managers and water resource planners. • Identification of robust measures and adaptation options. • Improved decision-making processes. • Challenges in dealing with uncertainties and resource limitations. • Framework's flexibility and applicability.	Ongoing evaluation required.	Regional data, climate scenarios, flood risk management planning
[120]	• DPSIR framework to analyze flood risk factors. • RF algorithm to identify important risk indicators. • RBF neural network to build a model of flood risk. • Using GIS to display a risk map.	• Flood risk is increasing due to urbanization. • Economic development is positively correlated with flood risk. • Variations in flood risk and current status among provinces	• Model results validated against actual situation. • RF algorithm and RBF neural network show applicability in flood risk assessment	• DPSIR framework • RF algorithm • RBF neural network • GIS

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[121]	• Standards for judging the use of geographical data in DRM. • Comparison of the National Disaster Management Frameworks of Bulgaria and India	• Criteria can be effectively used for general comparisons of geospatial data utilization in national DRM frameworks. • Geospatial technologies are important in disaster prevention - Various aspects of geospatial data activities are crucial elements in DRM frameworks	Criteria validated through comparative analysis	Criteria for evaluating the incorporation of geospatial data in DRM
[122]	• Inconsistencies and problems with Egypt's integration of spatial planning and flood risk assessment. • Recommendations for improving integration	• A lack of understanding of how spatial design might reduce the risk of flooding • Poor communication between officials • Limited availability and accessibility of necessary data • Subjective nature of conducted flood analyses	• Analysis based on input from a small group of experts. • Language barrier between English and Arabic	Literature review - Recommendations for improving integration
[123]	• Correlation between disastrous events and unstoppable force of nature • Inadequacy of human resistance mechanisms in controlling calamities • Promise of IoT technology in mitigating disaster challenges	• IoT-enabled disaster management systems offer promising solutions. • Simultaneous interventions with IoT can mitigate disaster challenges. • Modern examples of using IoT to manage catastrophic situations. • Supported protocols and goods that are ready for sale.	IoT-enabled disaster management systems' current research directions and open problems	Literature review - State-of-the-art scenarios - Open challenges and research trends
[124]	• The Namibia Sensor Web Pilot Project, which will serve as a testing ground for important flood monitoring and management technology. • Combining data from ground-based and space-based sensors to create flood maps and estimate risk. • Benefits of integrating grid and cloud computing technologies with sensor webs. • Emphasis on interoperability and utilization of OGC-compliant standards. • Potential for improving flood forecasting, risk assessment, and disaster management strategies.	• Quickly obtaining and disseminating data products for decision support systems. • Effective decision-support tools for flood control • Further research and advancements in the field can enhance flood management globally.	• Products that may be accessed in real-time through the system, including forecasts for probable flooding, rainfall estimates, and alarms. • Generation of flood maps within 24–48 h using computational and storage services. Demonstrates the advantages of combining sensor webs with emerging technologies. Potential for improving flood management and decision support systems.	• Sensor Webs, Grids, Computation Clouds. • OGC-compliant standards. • Workflow orchestration, parallel data processing. • Integration of space-based and ground sensor data.

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[125]	• The idea of a comprehensive decision-support system (DSS) for managing flood disasters. • Integration of observation, forecasting of rain with flooding, modeling of past floods, response plans, and ICT/IoT technologies. • Using the Metaverse, augmented reality, or virtual reality (VR) technologies for training. • Determining research gaps and making suggestions for future lines of inquiry.	• Better emergency services, community-based disaster risk management, and response methods. • Through the integration of many components, increased public crisis awareness and informed decision-making. • Need for data accuracy and reliability, interoperability, and advanced visualization techniques. • Practical application, training, and evaluation of the DSS in real-world scenarios.	• Incorporation of real-time observation data, rainfall forecasting, and fast flood simulation. • Integration of historical events, response strategies, and measures • Utilization of ICT and IoT technologies for data communication and sharing. • Training using VR, AR, and Metaverse technology. • Comprehensive evaluation and validation of the DSS.	• Real-time observational data and models for predicting rainfall. models for quick flood simulation. • IoT & ICT innovations. • Metaverse technology, augmented reality (AR), and virtual reality (VR).
[126]	• Recognition of flash floods as a leading cause of high casualties and infrastructure loss. • Challenges in accurate flash flood prediction due to sensor efficiency and data transmission issues. • Categorization of flash flood identification approaches into engineering-based and non-engineering-based methods. • Swarm intelligence weights optimization as the most effective forecasting approach.	• Efforts to improve accuracy and reliability of flash flood prediction. • Engineering and non-engineering approaches for flash flood identification. • Evaluation of several flash flood analysis techniques. • Recommendations for further research in the field. • Promising outcomes from the optimization of swarm intelligence weights for neural networks.	• Flash flood identification using engineering-based and non-engineering-based methods. • Swarm intelligence optimizes neural network weights. • Using nowcasting, modeling, and observation techniques based on radar and satellite data.	radar, sensor fusion, or artificial intelligence
[127]	• Using imagery from UAVs to collect data on vegetation, channel geometry, and river shorelines. • Using data from UAVs, calibrate and validate distributed flood routing models. • Online update and verification of flood risk maps. • Resolving issues in obtaining current data on the depth of the flood. • Importance of accuracy in UAV-based observations and data processing techniques.	• UAV-based observations improve flood risk assessment and model updating. • Challenges related to the accuracy of UAV-based observations need to be addressed. • Spatial observations and data processing methods require refinement. • Application of UAV-based observations for improving low flow maps and assessing drought impacts on riverine ecology.	• Limited measurement networks in small catchments. • Highlighted significance of UAV-based observations for model calibration and validation.	• Utilization of UAV-based imagery. • Development of new techniques for data acquisition and processing.

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[128]	• The use of ontology-based semantic modeling to control river flow and reduce flooding. • The creation of the ORFFM, or Ontology for River Flow and Flood Mitigation. • Using semantic modeling to deal with the different types of data, their ability to work together, and their complexity. • Big data analytics and natural language processing are crucial.	• Semantic modeling facilitates effective coordination and disaster management. • ORFFM as a methodology for developing a knowledge base. • Addressing challenges in data extraction, processing, and comprehension across multiple domains.	N/A	• Ontology-based semantic modeling. • Big data analytics. • Natural language processing.
[129]	• The combination of satellite imagery and social media for post-disaster management. • Making use of cutting-edge tools and current data to speed up rescue efforts. • Locating passable routes in flooded areas. • Classifying locations according to the severity of the damage. • Analyzing social media data for identifying stranded individuals and essential items.	• Integrated approach enhances post-disaster management. • Limitations of relying solely on satellite imagery. • Importance of road detection techniques within satellite imagery. • Addressing the challenge of cloud cover during analysis.	N/A	• Integration of social media and satellite imagery. Maximum number of connected pixels for road detection. • Comparison of pre-and post-disaster satellite images for damage analysis.
[130]	• Advancements in AI-based techniques for flash flood prediction. • Investigation of flash floods using multimodal sensing. • Satellite-based X-band pictures and radar images for forecasting flash floods. • Artificial intelligence techniques for improving prediction accuracy and minimizing false alarm rates. • Particle swarm optimization (PSO) for optimizing neural networks	• AI-based techniques enhance flash flood prediction accuracy. • Multi-modal sensing provides comprehensive environmental data. • Radar and satellite-based images contribute to early warning systems. • PSO optimization improves classification and forecasting capabilities. • Practical applications extend beyond flash flood prediction.	• Evaluation of AI algorithms using simulated results. • Comparative analyses against other existing strategies.	• Multi-modal sensing. • Radar images and satellite-based X-band images. • Artificial intelligence techniques (neural networks). • Particle swarm optimization.
[131]	• Resilience framework for power systems • Categorization of strategies to enhance power system resilience. • Microgrids as one of the most effective enhancement strategies	• Resilience is a dynamic and ongoing process of adapting frameworks and operations to better prepare for unexpected external shocks. • A resilient power system must be robust and flexible, capable of functioning under normal conditions and adapting to schedule, encourage planning, and execute strategies to prepare for recurring or novel events in the future.	• System resilience framework is introduced. • Categorization of strategies to enhance power system resilience is presented. • Microgrids as one of the most effective enhancement strategies is introduced.	• Literature review • System resilience framework • Categorization of strategies • Microgrids

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[132]	• Big Data Analysis and IoT used to detect disasters. • Z-score normalization used to evaluate threshold capacity. • Fog computing and cloud computing compared. • Fully automated evacuation concept discussed	• Collaboration of IoT and Big Data Analysis in disaster management is found to be effective and efficient. • Fog computing is found to be advantageous in sudden disaster situations. • Fully automated evacuation considering humanitarian aspects is a feasible concept.	• Real-time data is collected through IoT devices. - Big Data Analysis is used to process and aggregate the data. • Z-score normalization is used to evaluate threshold capacity. • Fog computing and cloud computing are compared. • Fully automated evacuation concept is discussed.	• Literature review • Big Data Analysis • IoT • Z-score normalization • Fog computing • Cloud computing • Fully automated evacuation
[133]	• The first in-depth study on the use of USVs in DM • Existing research on USVs for DM is scattered and lacks focus. • Most research emphasizes technical aspects of USV hardware and software rather than practical significance in DM	• USVs have promising potential in DM, but current deployments in disaster scenarios are limited. • USVs can be used for search and rescue, extreme weather forecasting, structural inspection, and environmental impact assessments. • A development in DM is the use of different deployments of autonomous systems. • Integration of these systems is still evolving, and regulatory and legal concerns need to be addressed.	• Various applications of USVs in DM are listed. • The challenges in conducting research on USVs are highlighted. • The multidisciplinary nature of DM research and the high cost of field trials are identified as challenges. • The deployment of diverse fleets of unmanned devices is recognized as a trend in DM.	• Literature review • USVs • DM • Search and rescue • Extreme weather forecasting • Structural inspection • Environmental impact assessments • Heterogeneous fleets of unmanned systems
[134]	• Assessment of droughts and floods impact on croplands and crop production in Southeast Asia • Use of Palmer Drought Severity Index (PDSI) to determine drought and flood levels. • Assessment over 40 years from 1980 to 2019	• Rainfed crops in Thailand, Cambodia, and Myanmar were severely affected by droughts. • Rainfed crops in Indonesia, the Philippines, and Malaysia are more affected by floods. • Four levels of policy interventions are prioritized based on geolocated crop damage levels.	• 20.64 million tons of crop production loss estimated between 2015 and 2019. • 9.42 million ha and 3.72 million ha of cropland damaged by droughts and floods, respectively	• Google Earth Engine (Sentinel-1 SAR satellites, Geospatial analysis tools)
[135]	• Development of an algorithm to map surface inundation during flood events. • Exploitation of Sentinel-1 SAR images in combination with historical Landsat data. • Rapid flood mapping using cloud computing platforms like GEE	• Area-normalized accuracy of 89.8% achieved over Houston, Texas following Hurricane Harvey. • Significant improvement in flood mapping accuracy compared to simple backscatter threshold	• Overall agreement rates of 98.5% in Thessaly, Greece, and Eastern Madagascar following floods in January and March 2018. • Rapid processing of hundreds of SAR and optical images within minutes	• Google Earth Engine (Multi-temporal SAR statistics, Surface water class probabilities, very high spatial resolution imagery)

Table A2. *Cont.*

Ref.	Key Aspects	Conclusions	Validation/Res	Technique
[136]	• Examination of spatiotemporal flood patterns in Bangladesh. • Identification of flood-affected paddy rice fields.	• Frequent flooding in northeastern Bangladesh and along major rivers (Ganges, Brahmaputra, and Meghna). • Important for adaptation and mitigation strategies to address annual flooding impact on agriculture and food security in Bangladesh.	• Flood-affected paddy rice areas accounted for 1.61–18.17% of total paddy rice area between 2014 and 2018.	• Sentinel-1 Synthetic Aperture Radar (SAR) images, Google Earth Engine.
[137]	• Algorithm to generate reliable inundation maps using different polarization combinations. • Flood depth estimation to address overestimation of urban flooded areas. • Rapid assessment of flooding disasters and making accurate decisions	• Good results were achieved using squared addition of polarizations for flood extent mapping. • All four methods implemented on GEE are effective for identifying flooded areas.	• Flood depth estimation approach improved overall accuracy on average by 7% for all methods. • Change detection method requires little user involvement and can be applied to new study areas without flood depth estimation.	• Sentinel-1 SAR imagery, Google Earth Engine.
[138]	• Development and application of the Flood Prevention and Emergency Response System (FPERS) • Application of FPERS at different stages of floods • Switching among different topographic models and managing data through a geospatial database.	• FPERS integrated various remote sensing imageries to detect and monitor barrier lakes, derive inundation maps, and evaluate the damage. • Example of Typhoon Soudelor in August 2015 demonstrates FPERS application in flood prevention and emergency response.	• Capable of supporting flood prevention and emergency response work using different topographic models. • Utilization of geospatial database for managing and searching data	• Formosat-2 optical imagery, Synthetic aperture radar imagery.

Table A3. Interconnections and synergies among techniques for wildfires.

Ref.	Interconnection and Synergies
[66]	Historical Data and Fire Maps for Fire Spread Prediction; Enhancing Fire Prediction Models; Factors Influencing Fire Behavior
[67]	Enhancing Fire Prediction Models; Calibration and Ensemble Methods for Improved Predictions
[68]	Historical Data and Fire Maps for Fire Spread Prediction; Enhancing Fire Prediction Models; Efficient Tools for Fire Detection and Spread Prediction
[69]	Factors Influencing Fire Behavior; Calibration and Ensemble Methods for Improved Predictions
[70]	Efficient Tools for Fire Detection and Spread Prediction; Efficient Tools for Non-Free Fires and Radiative Heat Power
[71]	Enhancing Fire Prediction Models; Efficient Tools for Fire Detection and Spread Prediction
[72]	Historical Data and Fire Maps for Fire Spread Prediction; Factors Influencing Fire Behavior
[73]	Enhancing Fire Prediction Models; Factors Influencing Fire Behavior; Importance of High-Resolution Fuel Information
[74]	Efficient Tools for Fire Detection and Spread Prediction; Importance of High-Resolution Fuel Information
[75]	Importance of High-Resolution Fuel Information
[76]	Enhancing Fire Prediction Models; Factors Influencing Fire Behavior; Importance of High-Resolution Fuel Information
[77]	Enhancing Fire Prediction Models; Efficient Tools for Fire Detection and Spread Prediction; Efficient Tools for Non-Free Fires and Radiative Heat Power

Table A3. *Cont.*

Ref.	Interconnection and Synergies
[78]	Factors Influencing Fire Behavior; Statistical and Machine Learning Models for Fire Occurrence Prediction
[79]	Enhancing Fire Prediction Models; Calibration and Ensemble Methods for Improved Predictions; Factors Influencing Fire Behavior; Statistical and Machine Learning Models for Fire Occurrence Prediction
[80]	Enhancing Fire Prediction Models; Efficient Tools for Fire Detection and Spread Prediction; Factors Influencing Fire Behavior; Calibration and Ensemble Methods for Improved Predictions
[81]	Efficient Tools for Fire Detection and Spread Prediction; Techniques for Detecting Flammable Substances
[82]	Enhancing Fire Prediction Models; Efficient Tools for Fire Detection and Spread Prediction; Calibration and Ensemble Methods for Improved Predictions; Factors Influencing Fire Behavior
[83]	Historical Data and Fire Maps for Fire Spread Prediction; Enhancing Fire Prediction Models; Calibration and Ensemble Methods for Improved Predictions
[84]	Importance of High-Resolution Fuel Information; Statistical and Machine Learning Models for Fire Occurrence Prediction
[85]	Enhancing Fire Prediction Models; Efficient Tools for Fire Detection and Spread Prediction; Factors Influencing Fire Behavior; Efficient Tools for Non-Free Fires and Radiative Heat Power
[86]	Enhancing Fire Prediction Models; Techniques for Estimating Fuel Moisture Content and Load
[87]	Statistical and Machine Learning Models for Fire Occurrence Prediction; Techniques for Estimating Fuel Moisture Content and Load
[88]	Enhancing Fire Prediction Models; Importance of High-Resolution Fuel Information
[89]	Enhancing Fire Prediction Models; Importance of High-Resolution Fuel Information; Techniques for Estimating Fuel Moisture Content and Load
[90]	Techniques for Estimating Fuel Moisture Content and Load
[91]	Techniques for Detecting Flammable Substances
[92]	Efficient Tools for Fire Detection and Spread Prediction; Techniques for Detecting Flammable Substances
[93]	Factors Influencing Fire Behavior
[94]	Enhancing Fire Prediction Models; Statistical and Machine Learning Models for Fire Occurrence Prediction

Table A4. Interconnections and synergies among techniques for flooding.

Ref.	Interconnection and Synergies
[95]	Machine Learning and Flood Risk Mapping
[96]	Machine Learning and Flood Risk Mapping
[97]	Amphibious Construction Strategies for Flood-Resilient Housing
[98]	Decision-Making Models for Flood Risk Management
[99]	Model-Driven Decision Support Systems (MDSS)
[100]	Flood Disaster Management in Malaysia
[101]	Disaster Management Metamodel; UAV-based Flood Detection; Agent-based Modeling for Flood Risk Assessment; Storm Surge Visualization and Animation
[102]	Disaster Management Metamodel; Semantic Computing in IoT Early Warning Systems; Agent-Based Flood Disaster Forecasting
[103]	IoT-based Disaster Management Challenges
[104]	Storm Surge Visualization and Animation; Data-Driven Resilient Fleet Management; Flood Risk Assessment and Prediction
[105]	Agent-based Modeling for Flood Risk Assessment
[106]	Remote Sensing for Flood Index Insurance; Flood Prediction and Prevention Systems

Table A4. *Cont.*

Ref.	Interconnection and Synergies
[107]	Model-Based Systems Engineering (MBSE) for Disaster Management Systems
[108]	Remote Sensing for Flood Index Insurance; Flood Prediction and Prevention Systems
[109]	Semantic Computing in IoT Early Warning Systems; Smart IoT Flood Monitoring System
[110]	Model-Based Systems Engineering (MBSE) for Disaster Management Systems; Agent-Based Flood Disaster Forecasting
[111]	Risk-Based Flood Management; ConvLSTM-based Flood Forecasting Model; Comprehensive Flood Management System in Jakarta
[112]	Smart IoT Flood Monitoring System; Data-Driven Resilient Fleet Management; Risk-Based Flood Management; ConvLSTM-based Flood Forecasting Model
[113]	Data-Driven Resilient Fleet Management
[6]	Risk-Based Flood Management; Smart IoT Flood Monitoring System; ConvLSTM-based Flood Forecasting Model; Flood Risk Assessment and Prediction
[114]	Risk-Based Flood Management; ConvLSTM-based Flood Forecasting Model; Comprehensive Flood Management System in Jakarta
[115]	Disaster Management System in China; Flood Prediction Models
[116]	Semantic Computing in IoT Early Warning Systems; Flood Prediction Models; GIS and Spatial Data Management; Data Privacy and Security
[117]	GIS and Spatial Data Management; Data Privacy and Security
[118]	Disaster Management System in China; Flood Prediction Models; GIS and Spatial Data Management; Data Privacy and Security
[119]	Disaster Management System in China; Flood Prediction Models; GIS and Spatial Data Management; Data Privacy and Security; Utilization of Geospatial Data; Communication and Collaboration
[120]	Data Privacy and Security; Utilization of Geospatial Data; Communication and Collaboration
[121]	Data Privacy and Security; Utilization of Geospatial Data; Communication and Collaboration
[122]	Utilization of Geospatial Data; Communication and Collaboration
[123]	Data Privacy and Security; Utilization of Geospatial Data; Communication and Collaboration
[124]	Future Research and Improvements; Flood Risk Assessment and Prediction
[125]	Integrated Decision Support Systems (DSS); Data Acquisition and Processing; Use of Artificial Intelligence; Focus on Specific Regions; Data Sharing and Interoperability; Integration of Advanced Technologies
[126]	Integrated Decision Support Systems (DSS); Data Acquisition and Processing
[127]	Use of Artificial Intelligence; Focus on Specific Regions
[128]	Data Acquisition and Processing
[129]	Technology Integration, Use of Artificial Intelligence, Focus on Specific Regions
[130]	Future Research and Improvements, Integration of Advanced Technologies, Real-Time Information and Decision-Making
[131]	Future Research and Improvements, Integration of Advanced Technologies, Real-Time Information and Decision-Making
[132]	Integration of Advanced Technologies
[133]	Integration of Advanced Technologies, Real-Time Information and Decision-Making
[134]	Assessment of droughts and floods impact on croplands and crop production in Southeast Asia, Google Earth Engine.
[135]	Development of an algorithm to map surface inundation during flood events, GEE.
[136]	Examination of spatiotemporal flood patterns in Bangladesh, GEE.
[137]	GEE, Algorithm to generate reliable inundation maps using different polarization combinations.
[138]	Google Earth Engine, Development and application of the Flood Prevention and Emergency Response System (FPERS)

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