Leveraging AI and Cloud Computing for Disaster Prediction and Management

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Abstract

Cloud Computing and Artificial Intelligence (AI) are two of the widely used technological domains in the present world. Clouds are considered as a base for Disaster Management Support Systems. In the cloud environment, people have enormous computing, storage, and communication capabilities at ease so that they could collect large amounts of data from different sources when disaster incidents occur, and later analyze these data and build knowledge. Data and information serve as the critical backbone of Disaster Management. AI techniques and systems are used in Disaster Management area for Disaster prediction and monitoring. AI is useful for searching damaged buildings and planning in dangerous environments of rescue with machine-to-machine or human-machine collaboration. Supported by cloud environment, Disaster Management Support Systems provide different real-time data analysis services.

In areas of the world that suffer from severe weather driven-hazards such as storm surges, flooding, or heavy snow and wind, a greater effort mediated by cooperatives and National Disaster Management Agencies is needed. There is an opportunity to develop Cloud Systems that bring together hydrological, meteorological, and impact models at high spatial resolution for forecast and early warning in these regions. Such a service will be essential not only for local, national, and regional receivers of the information but also for adjacent areas that may be indirectly affected by the potential trans-boundary effects of severe weather events.

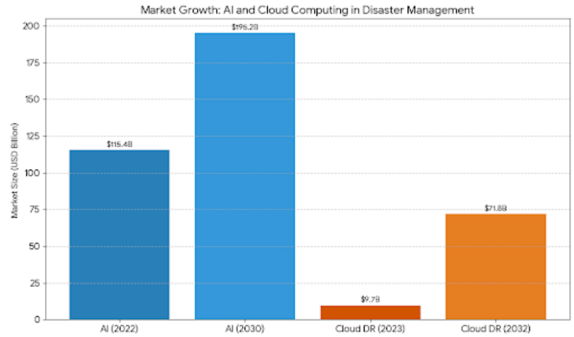
Keywords : Aim; cloud computing; computer science; computing; disaster management; information technology; information systems; machine learning; operational research; services; systems; technologies; artificial intelligence; big data; bioinformatics; cloud computing; data management; security; artificial intelligence; data processing; disaster prediction; disaster response; systems; services; technologies; warning; weather forecasting; cloud computing; machine learning; artificial intelligence; sensor networks; remote sensing; image processing; decision support system; object detection; deep learning; situational awareness; disaster management; science technology; education.

1. Introduction

Natural disasters claim the lives of hundreds of thousands of people every year, inflicting considerable financial losses and emotional pain. Climate change is exacerbating these problems, yet technologies offer new opportunities for improving disaster management and mitigation. Artificial-intelligence (AI) techniques can help avoid or alleviate crises, while cloud-computing resources facilitate smooth operations in a highly distributed environment in which a wide variety of actors continuously manage enormous amounts of data. In addition, the increasing ubiquity of advanced technologies in everyday life has made it easier for humanitarian organizations to gather and share real-time information about ongoing disasters. These new data sources can help sensor data and forecasts from dedicated systems. However, data gathered through social media and similar channels seldom offer the level of quality sufficient for direct use in practice; dedicated quality-assurance pipelines based on commonsense knowledge and new AI techniques are thus crucial. Finally, to ensure that these capabilities are fully leveraged in times of crises, disaster-management support systems must incorporate operations, communication, and collaboration models from a wide range of domains.

For decades, disaster risk management has relied on descriptive models, operating for example in flood, tsunamis, earthquakes, landslides or forest-fires, coupled with simulation systems that depend on a large amount of data, often collected during previous events. Researchers have explored how machine-learning algorithms could help support prediction and response in numerous disaster types.

Fig 1: AI in Disaster Management



1.1. Background and Significance

Society expects governments to implement effective disaster management systems. Almost every country has a disaster management framework that is designed to prepare for foreseeable disaster scenarios. The advent of increasingly complex systems and climate change raises new concerns that can no longer be managed through traditional response systems. The need to integrate novel technologies within existing frameworks becomes obvious: in the face of extreme weather events, such as Hurricane Sandy that hit New Jersey in October 2012, new challenges overwhelm commonly used methods and technologies.

Research shows that flooding is the most common weather hazard, with ensuing losses surpassing those of all other weather-driven hazards combined. Stated in simple terms, rainwater that cannot be absorbed or drained away leads to flooding. Sophisticated physic-based approaches allow experts to assess these complex processes. During the last ten years, large amounts of past weather data, along with free-access satellite images, have become available. Improved computing power in the cloud makes it possible to use data-science-related methods on these data sets in near real time. Data-driven weather-hazard prediction for floods and other commonly known hazards is thus possible in combinatorial use with as little human intervention as possible. Crisis management authorities can then leverage existing models to maintain the old-fashioned beta testing of the weather-hazards prediction process while achieving effective and efficient results.

1.2. Research design

Disaster prediction and management is recognized as one of the main challenges of the twenty-first century. Various advanced technologies, such as ICT, remote sensing, social computing, and physical simulation, have been utilized to minimize loss of lives, property, and the environment. Recently, the further promising technologies of cloud computing and artificial intelligence have emerged. Cloud computing technology provides a computing model that is highly elastic, on-demand, cost-effective, and easily accessible through a network. Meanwhile, artificial intelligence can realize intelligent automatic processing of multi-source data in various forms. The combination of these two technologies is thus expected to promote many applications, including development of intelligent systems for weather-driven hazards, management and monitoring of floods and flood-prone areas, automated visual analysis and situational awareness tools for urban search and rescue, and the ArchiMob platform for crisis mapping.

Thirty-three real-world disaster case studies illustrate the developments made to date. For all weather-driven hazards in which cloud computing and artificial intelligence are applied, the combination of cloud computing technology and artificial intelligence is especially beneficial for prediction, management, support, and rescue, with a distinct ability to reduce time, labor, and costs in relatively short periods. For other types of disasters, including earthquakes and tsunamis, cloud computing provides a unified platform to facilitate data management, processing, and sharing among various organizations and systems from different countries. However, since disaster environments are very special and sensitive, a certain measure of data privacy, security, reliability, and human–machine cooperation should be ensured when applying artificial intelligence.

2. Theoretical Foundations of Disaster Management

Disasters are complex events that can affect individuals, communities, organizations, and states. As such, they are inherently interdisciplinary phenomena, and no single community of experts can supply an understanding of them. Better planning for, and reduction of, loss from disasters and their consequences requires collaboration by analysts and scientists familiar with the many aspects of these complex processes, including their political, socio-economic, cultural, and environmental characteristics. By understanding the scope of components and tasks involved in disaster management, practitioners can build their own integrated perspective more easily.

A disaster can be defined as an event that either causes such serious disruption to a community that its continued functioning is threatened, or exceeds the capabilities of the community to respond. A hazard is a phenomenon, substance, human activity or condition that has the potential to cause loss of life, injury or other health impacts, property damage, loss of services, social and economic disruption or environmental degradation. Comprehensive Disaster Management embraces the full range of risk-reduction activities, including both pre-disaster mitigation and preparedness as well as post-disaster emergency response, relief and recovery. Decision models at the strategic level of decision making, supporting emergency management agencies, scientific organizations and the military; at the operational level, for acute, short-term resource dispersion; and tactical-response-level models, for localized resource-allocation decisions during, or in the immediate aftermath of, damaging events.

2.1. Definitions and Dimensions of Disasters

A disaster may be defined as a serious disruption of the functioning of a community or a society involving widespread human, material, economic, or environmental losses which exceeds the ability of the affected community or society to cope using its own resources. The underlying concept of disasters highlights the importance of the human dimension; i.e. the people who experience the event, their vulnerabilities, the coping capabilities of the individuals, households, or societies, and the related local production systems, infrastructure, institutional frameworks, and the physical and socio-cultural environment. The distribution of the affected population also plays an important role, especially in large-scale disasters. Indeed, small-scale events may disrupt the functioning of local communities, while larger events may affect the functioning of wider social geographic units.

The previous definition is very broad and aims as being universally acceptable. It is essential to note that not all serious disruptions are considered disasters. Disasters are not seconds or reasons for being one. Some hazards may cause a national impact disaster while others may cause a global incident. Small-scale hazards can also appear without being a disaster or with an insignificant national impact. The psychological aspect of matters should never be underestimated. Disasters have always been part of the history of communities and families. People were not prepared to cope, explain, or make safety provision. The term disaster in current usage denotes a calamity, an event in which a serious illness or injury has occurred, or in the case of a major calamity, many casualties have occurred, making it a major disaster.

Equation 1: Probabilistic hazard forecasting with Bayes' rule

Let:

- $Y \in \{0,1\}$be event (e.g., flood tomorrow),
- Xbe observed features (rain forecast, soil moisture, river level, etc.).

We want:

$$P(Y = 1 \mid X)$$

Bayes derivation (step-by-step):

1. Joint probability identity:

$$P(Y, X) = P(Y \mid X)P(X)$$

2. Also:

$$P(Y, X) = P(X \mid Y)P(Y)$$

3. Equate and solve for $P(Y \mid X)$:

$$P(Y \mid X)P(X) = P(X \mid Y)P(Y)$$
$$\boxed{P(Y \mid X) = \frac{P(X \mid Y)P(Y)}{P(X)}}$$

2.2. The Role of Data, Models, and Decision Support

Disaster management relies on data-based models and decision support to inform and guide timely action before, during, and after crises. During the preparedness phase, predictive models support risk assessments, hazard forecasts, impact estimates, and resource planning, while information for the response phase is often disseminated via web maps and mobile applications. An integrated architecture for disaster management systems serves as a blueprint for organizing data sources, analytical tools, and information delivery systems in a scalable manner that supports real-time operational requirements and broader learning by the community.

The architecture is based on an extended version of the data processing pyramid, supplemented with a row that captures decision support services and three additional planes that address data acquisition and fusion, real-time analytics, and cross-organizational collaboration. Data from satellite-based remote sensing systems provide a near-real-time overview of surface conditions at a global scale with invaluable information for several weather-driven hazards. New streaming analytics and open-source technologies address big data problems and exploit advances in data quality and interorganizational interoperability to enhance situational awareness and support resource-constrained humanitarian organizations.

3. Cloud Computing as an Enabler for Disaster Management

Cloud Computing provides a scalable on-demand infrastructure and a range of value-adding services for Disaster Management. Cloud Data Centers hosted at geophysical stable locations and at a significant distance from weather-driven hazards, augment Disaster Management through secure, reliable, and cost-effective storage of large volumes of historical Data. The economics of Cloud Computing further enable allocation of sufficient computational resources for computationally intensive Data acquisition, Modeling, Simulation, and Monitoring tasks that cannot be internally performed by an individual organization having limited resources. The essential functionality of Cloud Computing presents low threshold participation and consequently enhances operational cooperation.

The integration of Cloud Computing with Disaster Management greatly enhances the Scalability, Availability, and Resilience of the Disaster Management and Support Systems. Disaster Management Systems commonly attract high-level participation and engagement only during Crisis Situations. Private Clouds provide contained environments for Disaster Management Organizations that require continuous Data Processing, secure Data storing, Development, and Testing. Security, Compliance, and Regulations defined in the context of data transfer and use of Clouds set the guidelines for Disaster Management in the Cloud. The availability of Resources, Procedures, and precursors to across-Geographic Region-or-Organization-Cross-Clouds in Cloud Computing provides a valid and Robust support for Disaster Management.

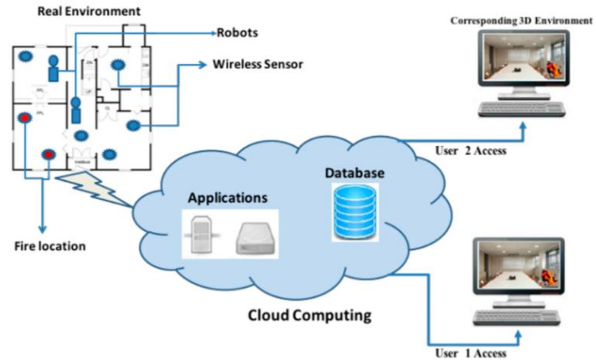


Fig 2: A Cloud Based Disaster Management System

3.1. Cloud Infrastructure and Service Models

Cloud computing has found a niche in disaster management, offering a novel business model with an enhanced ability to manage peak loads and improve user service quality. The cloud service model is a distributed model that shifts the acceptance of cloud application resources from client service procurement to on-demand service consumption and integrates data storage with business applications through secure channels to provide various services. The cloud infrastructure is built on professional service platforms for processing and transforming peak loads via the data hosting center of the ICT.

The types of clouds include public clouds, created by service providers to supply services primarily on an on-demand basis, partially open through a shared interface to allow users to build and create services; community clouds for organizations with shared concerns or requirements; hybrid clouds as a composition of several clouds; and private clouds offering an environment dedicated to a service client but running on distributed facilities owned by a different organization and kept secure from other users. In addition, three basic cloud service models exist: Software as a Service (SaaS), with various software applications stored in the cloud; Platform as a Service (PaaS), enabling users to develop business applications without the need to build the infrastructure behind it; and Infrastructure as a Service (IaaS), offering backend infrastructure services through the cloud.

3.2. Data Management, Security, and Compliance in the Cloud

The data-driven nature of modern organizations creates considerable risks and challenges for data management in the cloud, particularly in crisis environments. Cloud providers must ensure strong data governance practices addressing data classification, protection, privacy, residency, and retention. These considerations are challenging in crisis environments. As a highly dynamic and unpredictable cloud environment, the security of the IaaS cloud is the responsibility of both the provider and the customers. Cloud tenants are primarily responsible for securing their virtual servers and data against cybersecurity threats and incidents, while the IaaS cloud provider is responsible for assuring tenants that the IaaS infrastructure is security-hardened and properly configured.

Security and privacy concerns must be carefully examined before utilizing any public cloud service for data analysis or storage. For storing private and confidential data such as personal health information (PHI), organizations need to choose a cloud service provider that complies with specific security standards. Data stored on third-party cloud services might not continue to have the same level of privacy as it had before. Assuring data integrity is another key aspect within the realm of cloud security. There is a risk that data and files get corrupted while being uploaded or downloaded, or that they are altered by unauthorized individuals during data storage.

3.3. Scalability, Availability, and Resilience in Disaster Contexts

Cloud computing technologies are highly scalable, and their inherent elasticity facilitates scaling resources up or down by orders of magnitude in response to demand. This is particularly advantageous when space-related suppliers need to operate within and around long-term, low-use projects. For natural disasters, scalability is highlighted during predictive and real-time decision-support phases. The available local and national resources for predictive modeling and early warning system deployment are typically small compared to the scale of the region affected. Resources are quickly scaled up in peak use periods during such extreme weather events. The model runs and forecasts stream for consuming applications that issue alerts, or deploy response force teams.

Similarly, for consumer-oriented applications, such as crisis maps, sensors, crowd-sourced data, and images are acquired in real-time at unknown peak demand levels. These systems continuously monitor the status, adjust resource scaling, and guarantee adequate service levels. Utilization records around operation peak periods become a reference model for technology scaling for subsequent hazard events. Local and regional operations are downsized and switched off for long stages between crises. Enterprises, businesses, and social networking cloud resources operate within multi-tenancy models, scaling resources naturally as applications demand. Organizations, such as Google, Microsoft, and Amazon, regroup labor and computing at these times to explore the engine-optimizing characteristics of the cloud.

Cloud-operated systems must also provide operational resilience and reliability. Multiple geographically dispersed data centers operating under cloud service models counteract natural disasters within a metropolitan area while releasing load from long-distance, latency-sensitive apps. These centers must also implement deployment procedures—such as replication, backup on remote data centers, and real-time data flow to nursery data centers in different metropolitan areas—that ensure data integrity throughout operational delivery. Organizations, such as Facebook, employ real-time replication of service in data engineering functions to implement such operations around the globe.

4. Artificial Intelligence in Disaster Prediction and Response

Artificial intelligence (AI) enables the modeling, analysis, and simulation of complex systems, making it invaluable for large-scale disaster data analysis. The different approaches employed in disaster prediction and response include AI-driven machine learning for hazard forecasts, deep learning applied to high volumes of image and sensor data, and AI for situational awareness and decision support. In disaster contexts, these methods are often deployed as intelligent services that integrate data from heterogeneous sources in cloud environments, accommodating multi-organizational decision-making based on real-time and large-scale data.

Weather-driven hazards such as heatwaves, droughts, floods, cyclones, and wildfires play a leading role in global disaster frequencies and intensities. Weather forecasts provided by national meteorological services are available at different time scales and resolutions. Atmospheric variables are also tailored to different applications by regional agencies. Probabilistic weather forecasts indicating the likelihood of weather conditions being exceeded are increasingly used by agencies dealing with potential disasters to develop their operational responses and mitigation actions. For example, disaster management agencies can make decisions at different time scales: industrial managers can take immediate actions depending on heat stress probabilities, while the railway and aviation sectors react based on 2–5 day forecasts, and the tourism industry takes long-term decisions based on seasonal forecasts.

Equation 2: Logistic regression (a common probabilistic classifier)

Start from odds → log-odds:

1. Let $p = P(Y = 1 \mid x)$. Then odds:

$$\text{odds} = \frac{p}{1-p}$$

2. Assume log-odds is linear in features:

$$\log \frac{p}{1-p} = w^{\top}x + b$$

3. Exponentiate:

$$\frac{p}{1-p} = e^{w^{\top}x+b}$$

4. Solve for p:

$$p = (1-p)e^{w^{\top}x+b}$$
$$p = e^{w^{\top}x+b} - pe^{w^{\top}x+b}$$
$$p\left(1+e^{w^{\top}x+b}\right) = e^{w^{\top}x+b}$$
$$\boxed{p = \frac{e^{w^{\top}x+b}}{1+e^{w^{\top}x+b}} = \frac{1}{1+e^{-(w^{\top}x+b)}}}$$

4.1. Machine Learning for Hazard Forecasting

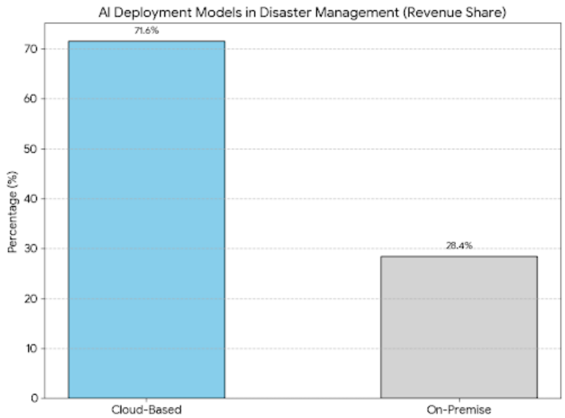
A wide variety of extreme events can be classified as weather-driven hazards, with temperature and precipitation being the most relevant drivers. Many of these events are forecasted operationally by meteorological services at national and regional levels, such as hurricanes, typhoons, tropical storms, extra-tropical storms, droughts, severe convective storms, heat waves, and forest fires. Consequently, machine learning is seldom involved in the final stage of disaster prediction. Nevertheless, it plays an increasingly prominent role at earlier stages of the monitoring and modeling processes, improving the accuracy of observations and simulations by assimilating weather and climate data from multiple sources, that is, ground-based sensors, satellites, and climate and weather models.

Machine learning techniques are also being applied to historical data in order to develop classifiers capable of distinguishing between past events and non-events, often using remotely sensed variables as predictors. These classifiers are particularly attractive in contexts where very few past disaster cases are available, such as forecasting the occurrence of very intense extra-tropical storms over Central Europe or predicting the large-scale pattern conducive to the development of severe thunderstorms in southeastern Brazil. In both studies, the potential of using sub-seasons of large datasets as additional training sets was demonstrated; the developed classifiers can therefore be applied to future seasons without any bias in the external data distribution. Finally, the application of similarity search methods to past events is another useful approach in DATA-DRIVEN research.

4.2. Deep Learning for Image and Sensor Data Analysis

The analysis of remote sensing images, social media data, and various sensor data is becoming a significant area of AI research for disaster management. Remotely sensed data has recently been collected at ever-increasing temporal frequencies from many sensors on the Earth's orbit. Deep learning methods have been developed to automatically classify, detect, segment, and extract them with the potential to quickly convert data into important situational information. For example, Chen et al. reviewed scene classification approaches using regional and global convolutional neural networks and visual vocabulary built with deep features, respectively. Meanwhile, Wang et al. proposed a CNN-based approach for urban land-use classification, where the CNN model acts as a feature extraction model and its feature extraction ability is first trained on ImageNet. More specifically for disaster prediction and response, Chen et al. presented visual synthesis for virtual disaster training, Buck et al. proposed the semiautomated detection and text classification of water-related disasters in Twitter using a random forest approach, and Xu et al. presented a geovisualization tool for social media photos during various events.

Apart from remotely sensed images from satellites and UAVs, the progress of edge computing has enabled many sensor devices to access the Internet directly without the help of a cloud. With the development of low-cost embedded platforms, various sensors, such as RGBD cameras, LiDARs, thermal imagers, and UWB transceivers, can now be connected to the Internet as end devices. Wang et al. introduced a robot system with multi-UWB sensors to detect a large number of fire sources simultaneously. Sun et al. proposed using depth images captured by a GoPro Hero3 RGBD camera for urban flood modeling. Meyer et al. presented a new real-time thermal-object-detection approach to identify and localize fire spots for firefighting assistance and damage prevention during fireworks. Sensor data fusion has also been applied, such as Yang et al. detecting and predicting potential waterlogging hazards based on the fusion data from weather stations, gas stations, and 3G/4G mobile network data. In another field, Hu et al. integrated RGB, depth, and thermal images for urban human detection and tracking. Monocular depth cameras, for example, are also becoming an alternative choice for many researchers instead of RGBD cameras.



4.3. AI for Situational Awareness and Decision Support
During and after hazardous events, situational awareness relies on rapidly evolving information streams provided by people, sensors, satellite imagery, and other data sources. Important progress has been achieved in integrating, fusing, and filtering such information streams. Advanced visualization instruments help analysts and users alike to identify trends, make sense of the information, and discover relationships among disparate datasets. Machine learning techniques are increasingly adopted in these contexts. Spatiotemporal models for information fusion can consider the uniqueness of different sources while integrating and processing the information provided by them through event-driven designs. Deep learning techniques for image, video, and text processing can strengthen media-based runtimes for both data generation and stream analysis.

Robust and tested simulation models play a vital role in decision support. These simulation models are essential for estimating the possible impact of a response measure, e.g., deploying search and rescue resources in a given area, and for evaluating alternative plans and strategies. A cloud or platform-as-a-service implementation can offer actors on the ground the ability to run such simulation models in a sandbox mode: i.e., without actual execution of the recommended actions, and but to generate an assessment of their possible effectiveness. Cloud computing can provide the essential combination of space, capacity, and speed of execution for these simulation models, especially when large numbers of agents are present and the demand for execution grows immediately.

5. Integrated Architectures for Disaster Management Systems

A functioning disaster management system integrates data from different sources, processes it to detect signals or threats in real time, and generates results for decision support. Each component involved in such a system can be sophisticated, offering advanced functionalities. However, it is not sufficient to rely solely on the best available individual modules; they must also be well connected to ensure seamless communication, data exchange, and a low-latency flow. An integrated architecture enables the comprehensive system to achieve better performance than the sum of its parts.

Real-time detection of catastrophic events requires a reliable and timely supply of data from different sources. On the one hand, specific types of measurement data (e.g., weather data, water levels, remote sensing images, and seismographic data) need to be collected and made accessible as rapidly as possible. On the other hand, information from the social sphere, such as social media posts and www-based reports, should be constantly surveyed in order to identify de facto events. The acquisition process can benefit from data fusion approaches that combine multiple sources into a single consolidated view. Such integration may include automatic quality assessment to control the level of trust that can be placed on specific sources, and even in the data received from a specific source.

The use of streaming analytics is critical in a disaster context, as warning decisions must be made within a very limited time frame. In cases with significant uncertainty about the nature and actual location of the event, various types of sources can supply hints and cues pointing to the same incident. Progressive accumulation of corroborating pieces of evidence can boost confidence levels. Furthermore, a well-structured and standardized data-sharing architecture can facilitate information exchange among different organizations with complementary operational profiles and response capabilities.

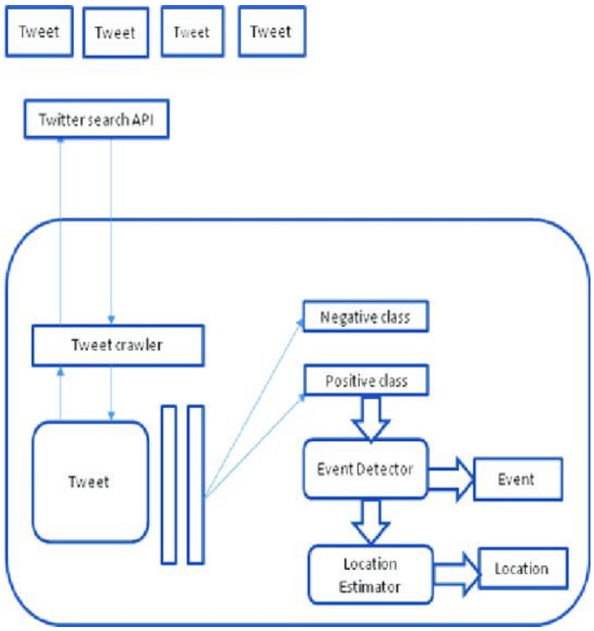


Fig 3: Architecture of disaster management system

5.1. Data Acquisition, Fusion, and Quality Assurance
Temperature, humidity, circulation, and other parameters within the atmosphere condition the pressure exerted on the earth's surface. Consequently, these fluctuations produce meteorological, climatological, and hydrological phenomena like storms, blizzards, landslides, floods, and droughts—geological events that arise from natural processes taking place within the earth's asthenosphere, so-called geological hazards. Urbanization, industrialization, and structural development influence the region's hydrological cycle, thus increasing the region's hydro-logical response to extreme climatic events and its vulnerability and exposure to hydrological disasters, amongst others. Over time, the need to monitor disaster annual responses, while minimizing the loss of lives and property, has become significant. Such tasks involve not only the Natural Disaster Management Authority (NDMA) but also the State Disaster Management Authority (SDMA), District Disaster Management Authority (DDMA), and various stakeholders, such as search and rescue teams, satellite mapping agencies, research institutions, and related organizations.

Effective data acquisition, collection, and management are crucial because the information derived from weather-driv-en meteorological, climatological, past flood, and flood hazard-event datasets must be reliable. Such data must be genuine and free from bias so that hidden patterns can help predict hazard conditions before their onset. Integrating their responses enables the NDMA to proactively plan for various disasters. Moreover, during times of crisis, an environment conducive to the free flow of data, information, and knowledge among agencies and NGOs involved in providing and supporting disaster relief must be maintained. Information and knowledge from various sources, such as proximate/near real-time news and social media, should be effectively and efficiently integrated to support risk mitigation and management efforts.

5.2. Real-time Analytics and Streaming Platforms
Disaster events create critical needs for trustworthy and timely information. This is often provided by models undertaking real-time simulation and forecasting. Increasing frequency and scale of such demand is leading to a move away from traditional batch-mode processing towards a paradigm based on continuous, real-time data streams and short-lived computation. Technologies such as sensor networks, GPS-enabled mobile devices, RFID tags, and digital cameras create an abundance of data that must often be processed in situ and displayed on interactive maps for time-critical decision-making. With the burgeoning reliance on real-time data streams, major IT vendors have introduced streaming systems suitable for commercial applications.

Data-centric applications are usually implemented within the Data-as-a-Service (DaaS) paradigm offered as public cloud. DaaS providers aggregate data from numerous public and semi-public sources, perform model-driven data fusion to ensure data quality and correctness, and offer the enriched data through a convenient DaaS interface. Data from the DaaS can then be augmented with proprietary data from application stakeholders and employed for data-intensive operations within the framework of Cloud BI/BA.

5.3. Interoperability and Standards for Cross-Organizational Collaboration
Semantics and ontologies provide a basis for enabling interoperability for data management and analysis between different applications. These play a crucial role in the preparation of data for machine learning, along with data quality. An efficient approach for the fusion of heterogeneous data sources provides a solution for disaster management services, especially in disaster recovery phases.

Organizational interoperability reflects a high level of alliance and trust among involved agencies, leading to effective and efficient resource utilization during a disaster. Approaches based on semantically annotated content allow for cross-organizational Cloud Disaster Management as a Service. These enable users from different organizations to share information in order to support CSP operations. As organizations become accustomed to these techniques, additional services should be considered. Such services may encompass both the rescue phase, involving the search for survivors, and recovery aspects, such as damage assessment and infrastructure restoration. Support for the creation and management of teams offers the potential for a further extension to these Semantically-Aware CSPs. A formal model supporting these themes has also been proposed.

6. Case Studies and Applications

Weather-driven hazards typically receive the greatest attention in research and interventions. Floods, for example, affect more people than any other disaster; hydrological models providing river discharges, inundation projections, and flood risks are seen as fundamental prerequisites for an effective flood management cycle; and location- and time-specific flood-danger information forms the basis for public safety measures. Urban search and rescue (USAR) operations deal with a wide range of disasters, including earthquakes, hurricanes, and terrorist attacks involving collapsed structures. USAR has recently been recognized as a data-driven application enabled by Earth observation (EO) sensors that can detect both damage and people in distress. Human-placed assets (e.g., cameras, microphones, etc.) have been deployed in search-and-collaboration platforms, improving awareness, resource coordination, and rendering. Enhanced situational awareness allows for better prioritization of search areas and rescue techniques. Analysis of social-media activity in disaster zones can yield crisis maps that provide a solid basis for decision making. Recognition of the distinction between crowd-sensed information and geo-referenced information form the basis for a viable architecture capable of supporting online crisis mapping.

Flooding, earthquakes, and oil spills represent different types of floods and resultant data from various sensors. Data acquisition, fusion, and quality-assurance models have been applied in diverse contexts. Weather is routinely used in hydrology–hydraulic and urban drainage systems; real considerations of risk and damage for flooding require that the foundational principles be extended to incorporate prognostic capabilities.

Equation 3: Cross-entropy loss (why "accuracy alone" is insufficient)

For binary classification with predicted $p_i$and label $y_i \in \{0,1\}$:

$$\boxed{\mathcal{L} = -\sum_{i=1}^{n} [y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]}$$

Derivation from Bernoulli likelihood:

1. Bernoulli model:

$$P(y_i \mid p_i) = p_i^{y_i}(1 - p_i)^{1-y_i}$$

2. Likelihood over independent samples:

$$\mathcal{Lk} = \prod_{i=1}^{n} p_i^{y_i}\,(1 - p_i)^{1-y_i}$$

3. Log-likelihood:

$$\log \mathcal{Lk} = \sum_{i=1}^{n} [y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

4. Negative log-likelihood (minimize):

$$\boxed{\mathcal{L} = -\log \mathcal{Lk}}$$

6.1. Weather-Driven Hazards

Weather can be a factor that initiates or triggers a wide range of different types of natural hazards, including winter storms, wildfires, ice storms, tornadoes, severe convective storms, and tropical cyclones. These weather-driven hazards can cause tremendous devastation and loss of life and property. During the 2017 hurricane season, meteorologists predicted that two major hurricanes would strike the southeastern United States and that drought and wildfire conditions would become extreme in the western United States. These predictions resulted in a massive mobilization of local, state, and federal resources to mitigate the loss of life and property. These situations reflected the considerable efforts expended to forecast these socially disruptive weather-driven hazards.

Forecasting of the probability and severity of weather-driven hazards other than winter storms, ice storms, and drought is of sufficient temporal and spatial resolution and geographical coverage to support mobilization for response and mitigation in advance of their occurrence. Response and mitigation lead times range from six to 72 hours (for tornadoes) to weeks (for drought and the rapid intensification of named tropical cyclones). During the response phase, key resources, including the National Guard, Red Cross, and Federal Emergency Management Agency (FEMA), rapidly mobilize to support the states affected. The combination of these predictive capabilities and timely mobilization mitigates the impacts of many weather-driven hazards.

6.2. Flood and Hydrological Modeling

The availability of forecast data from numerical weather prediction models for the upcoming days has increased the attention given to short-term flood forecast and flood warning systems. Forecasts derived from those models are subject to a number of limitations, which therefore lower the quality of the forecasts produced by flood-forecast models. A number of approaches for combining information from numerical weather prediction models with hydrological models have been proposed, including model coupling and the use of assimilation techniques. Hydrological models, through embedding, assimilation, and coupling with rainfall-runoff models, are also integrated into the warning and forecast systems.

Distributed rainfall-runoff models have become statistical models in their own right, being calibrated with extensive data sets for many locations worldwide, and providing estimates of runoff generation through an empirical function for all points within the basin, and of flow routing. Within this framework, some recent studies have investigated the use of climate monitoring systems as driving mechanisms for hydrological models applied across continents. Seasonal and monthly hydrological forecasts for basins located close to the areas of tropical cyclone formation have been developed, aiming to exploit the predictability associated with the period of maximum flood risk.

6.3. Urban Search and Rescue and Crisis Mapping

Urban search-and-rescue (USAR) missions are executed to locate and assist victims trapped beneath the rubble of destroyed buildings and infrastructure, often caused by earthquakes, landslides, and blasts. Such missions are highly complex operations that typically involve numerous responders from all levels of government and the private sector, organized under the National Incident Management System (NIMS), and may take days, weeks, or even months to complete. To assist the first responders working under such multiagency, multidiscipline, and multinational conditions, high-quality situational awareness and operational support are essential. The generation of a disaster situation picture must therefore be prioritized, as these data can help to locate survivors, organize rescue assets, and allocate medical resources.

A USAR mission involves the defined search area, divided into a set of grids used for efficient task assignment to rescue teams, detection blind zones resulting from obstacles and danger points, and crisis maps that identify the locations of victims, respond teams, shelter areas, medical supply locations, and facilities ready to use. Collaborative information support involves three levels of USAR operations. The global level provides high-level information such as a 3D model of the entire site and status communication. The tactical level supports the search-and-rescue teams and dispatch centers with 3D maps of work zones, volunteer resources, the running status of teams in the zone, search tasks, and victim evidence checking. The operational level, supported by on-site sensing data, concentrates on detailed scenarios for individual rescue teams and monitors completion of the assigned tasks.

7. Challenges, Risks, and Ethical Considerations

AI systems' deployment is concerned with the responsible handling of sensitive and potentially harmful data. Natural disasters and other crises often create an environment where people feel inclined to share information, particularly via social media. Nevertheless, data privacy violations are still possible, and data protection laws such as the General Data Protection Regulation should be complied with in these time-critical situations. Data protection and security needs for systems that are built for crisis management have to be specially addressed. Ensuring safe business continuity for organisations also necessitates an adequate level of cybersecurity risk management, as malicious actors take advantage of the changed environment, e.g. by launching cyberattacks during a pandemic.

It is also important to understand that AI systems are not infallible and may produce biased information and results — in particular when large datasets are used as training and testing datasets. Evaluating them requires more than accuracy or performance measures alone. While an AI system may score extremely high based on accuracy, it may also fail to detect the minority class. Two approaches may facilitate the reliable and responsible use of AI in disaster management: AI explainability, which aims to enhance understanding of prediction and classification results, and AI accountability, which concentrates on assigning responsibility for errors and harm caused by these systems. Lastly, while the application of social media and internet content mining within disaster management enhances situational awareness by providing complementary sources of real-time information, the quality and reliability of the mined data must be thoroughly examined before being acted upon.

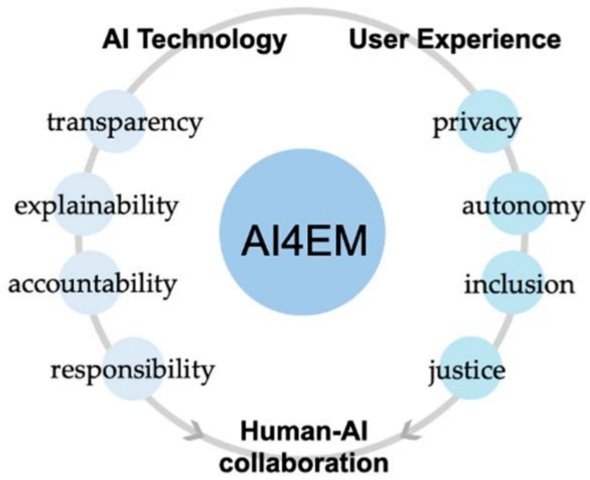


Fig 4: Challenges, Risks, and Ethical Considerations

7.1. Data Privacy and Security in Crisis Environments
Data collection, model development, and system deployment operations in disaster scenarios can require high specialisation, and naturally involve large amounts of sensitive and private data. The release of disaster prediction datasets and the acquisition of disaster response datasets pose challenges related to data privacy and security. Human subjects may be involved in the processes for data collection, and capturing and releasing users' private locations or social information are common. At the same time, the risks of exploiting AI vulnerabilities in the disaster-response processes by adversaries and malicious actors are being increasingly discussed. Addressing data privacy and security challenges in disaster environments protects human rights and interest and builds trust in prediction and response systems, contributing to building an environmentally safe society.

The cloud-computing environment brings many benefits, such as economies of scale, reduced costs, more efficient equipment utilization, and increased levels of availability and security. Nonetheless, the public cloud is out of direct control of the organisation, exposing its processes, models, and data to third-party services. Since cloud service providers (CSPs) cannot implicitly be assumed to be trustworthy, data integrity, confidentiality, and access control cannot be guaranteed when sensitive data is stored in the cloud. Security and privacy in the cloud should therefore be covered during the early stages of a disaster-response project since security issues are difficult and expensive to fix when the system is released. Disaster-response services should perform suitable auditing and certification work, and cloud-service models should fulfil the various privacy-control requirements.

7.2. Bias, Explainability, and Accountability in AI Systems
Disasters often involve the loss of human lives, property, infrastructure, business performance, and ecological suffering caused by weather fluctuations. These disasters leave the world in a state of chaos, requiring difficult decisions for restoration. Data-driven cloud computing technology is required to build quantitative decision-making systems. The system predictively evaluates the situation using data-based Artificial Intelligence solutions for physical destruction caused by any disaster.

Natural disasters have occurred throughout human history, posing a constant challenge to the current balance of control. In the age of high technology-enabled living, weather-related disasters still occur, but the manner of Siddhartha's solution has changed. Earlier approaches relied on ancient scriptures, beliefs, and observations provided by experienced citizens. Technology-enabled solutions indicate how location-based monitoring of metadata can organize and reduce space for information acquisition and transit. Monitoring systems are capable of acquiring on-location metadata, which need to be inductively modeled to predict future values based on meteorological data, allowing those in the danger zone to be informed in a timely manner by using seasonal data. These warning messages assist people in making informed decisions. Cloud computing technology provides an IT-enabling environment for building data management systems that support simple-to-complex decision-making processes for preparation, execution, and recovery.

7.3. Reliability, Trust, and Human–AI Collaboration
A major challenge faced by so-called cyber–physical systems concerns the need to trust the decisions that are taken by such systems. On the one hand, these systems have a strong component of the human decision-maker, whose experience is irreplaceable and whose skills to assess the features of the domain are unique, while, on the other hand, the AI-tools generate results providing, in many cases, a level of complexity that the operator cannot fully understand. Trust in a decision-support tool is a prerequisite for effective human–AI collaboration and data-driven decision-making. Some existing decision-support systems enable a successful human–AI collaboration since they supply enough explainability and thus trust to the operator making use of the data-driven results on a cyber–physical system. In the context of predictive systems, reliability can however be proven by success on the field.

Its sensitivity ties the accuracy of especially the machine-learning-based algorithm to successful sensor deployment. During the last years, several researchers, exploiting the Toronto Flooding dataset, successfully proved that for every flooded area, the size of flooded areas can be accurately predicted, supporting thus the successful definition of proactive emergency plans. A continuous weather-driven wild-fire database has also been released for subsequent machine-learning-based wild-fire prediction model development and assessment. Image-based wild-fire detection models have been detailed as a fully autonomous device that, once trained in supervised mode, can grown in the field in an unsupervised manner. On the Crisis-Mapping platform, the link between the internal performance of the Spatial–Temporal Reconstruction model (the element able to “fill” the empty slots, where no external data, like semantic and real images, are available) and the quality of the final map has been made explicit. To be used in AI mode, Crisis-Mapping has to be yet assessed.

8. Conclusion

Recent advances in artificial intelligence (AI) and cloud computing have the potential to reshape disaster management by facilitating prediction, response, and recovery. Cloud-enabling services bolster existing data management, data- and model-driven systems, and decision-support tools. In turn, AI augments situational awareness, offers a multi-dimensional view of prediction quality, and enhances the prediction and interpretation of system behavior through data-driven models.

The tremendous increase of data results in novel technologies and methods capable of addressing these challenges to a degree previously unthinkable. AI, cloud computing, and the Internet of Things can not only address emerging issues but also ameliorate the prediction and occurrence of many weather-driven hazards. Indonesian weather data illustrate that more countries and regions are making their historical weather data available for research and forecasting purposes. Such data may be used to predict the occurrence of heat waves, cold waves, heavy precipitation, and other weather phenomena that are becoming more frequent with climate change. AI systems may also analyze the associated images to detect how weather affects people and their activities. In regions facing vertical urbanization, urban flooding, or industrial development, an AI-based flood model may be developed to predict flooding over a short duration and/or area. The flood model can provide inaccurate flood locations with high confidence to support both human decision-making and AI systems.

8.1. Emerging Trends

Cloud computing and Artificial Intelligence-based decision-making support systems are endowed to fulfill these requirements. Cloud computing allows to virtualize geographical distribution of information and communication technology, which is required for efficient, cost-effective and timely data-management, and decision-making for disaster management and prediction. AI-based decision-support decision support systems are used for data-driven disaster management prediction system from huge repositories of multi-sensor, heterogeneous, multi-scale, multi-temporal data. Technologies, such as machine learning, deep learning, and hybrid artificial intelligent systems combined with pattern matching, case based-and knowledge based-reasoning, support generation of prediction system for disaster management, on the foundations of hazard characterisation, impact assessment, procedure generation, situational awareness and operational support.

Automated, real-time, people-independent, prediction-oriented decision support systems are gradually becoming an unavoidable characteristic of modern-day disaster management. Integrated cloud based architectures providing data acquisition, data fusion, data quality assurance, data analytics and sharing through formal and informal platform are becoming indispensable requirement for providing timely, relevant and accurate information to all stakeholders who can fulfil their requirements for decision-making related to disaster management. Such architecture span weather driven hazards, urban flooding, flood modelliing and urban search and rescue. Data privacy and security, bias explainability, trustworthiness and reliability of AI systems, and continuous human role in decision process in automated systems are the important issues related to such systems.

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