SVDEM

Policy Recommendations

Erasmus + KA220-HED

SUDEM Project deliverable

1. Disasters and disaster management systems

According to reports by the United Nations on climate change, both the frequency and severity of disasters are increasing due to factors such as climate change, urbanization, extreme weather events, and improved reporting mechanisms [6]. At the same time, advances in early-warning technologies, communication infrastructures, and disaster management practices have significantly reduced disaster-related casualties, demonstrating the critical role of technological progress in improving disaster resilience [6].

Contemporary Disaster Management Systems (DMSs) generally operate according to a pipeline-based architecture composed of sequential operational phases. These phases typically include receiving and recording incident reports, validating and assessing incident severity, determining appropriate response actions, allocating resources, and subsequently dispatching and coordinating response teams. Such an architecture provides a structured and systematic workflow for managing emergency operations.

The effectiveness of these systems, however, depends heavily on the timely and accurate processing of incident information, since delays or incorrect decisions may directly affect the ability to save lives, protect infrastructure, and reduce overall damage. Incident reports may originate from a wide range of heterogeneous sources, including eyewitnesses, emergency call centres, governmental agencies, security forces, sensor networks, drones, and other automated information systems. Operators within disaster management centres play a central role in coordinating these activities and maintaining operational continuity under highly dynamic conditions.

Despite their structured nature, pipeline-oriented DMS architectures exhibit important inherent limitations. Because processing stages are tightly coupled and sequential, bottlenecks may emerge when the inflow of incident reports exceeds the available operational capacity. Under large-scale or rapidly evolving disaster conditions, growing queues and increasing operational pressure may force operators to bypass established procedures in order to accelerate response activities. Such deviations often result in ad hoc decision-making, reduced situational awareness, inconsistent coordination, and loss of centralized operational control. Consequently, the overall effectiveness, traceability, and reliability of response operations may significantly deteriorate during extreme conditions.

These limitations indicate the need for more adaptive, intelligent, and resilient disaster management approaches capable of continuously monitoring operational performance, detecting emerging bottlenecks, and dynamically supporting decision-making under uncertainty. Recent developments in Artificial Intelligence (AI), digital twins, distributed sensing, data analytics, and autonomous coordination mechanisms provide promising opportunities for transforming conventional disaster management processes into more integrated, predictive, and adaptive systems.

In this context, a holistic AI-driven approach that integrates multiple phases of the disaster management lifecycle may considerably improve the efficiency, effectiveness, adaptability, and coordination capabilities of contemporary DMSs compared with current operational practices.

This report first analyses the structural and operational limitations of state-of-the-art disaster management systems and subsequently presents a set of policy requirements and technological directions aimed at improving the performance, robustness, and adaptability of future DMS architectures.

2. Limitations of the current Disaster Management Systems and future perspectives

2.1. Bridging the Gap Between Pre-Disaster and Post-Disaster Phases

Current pre-disaster activities, including modelling, prediction, risk assessment, map partitioning, and mitigation planning, are often developed independently from the operational realities encountered during disaster response and recovery. This separation limits their practical effectiveness during real-world emergencies.

In practice, however, pre-disaster and post-disaster phases are fundamentally interdependent. The assumptions, models, data structures, and planning decisions established before a disaster directly influence the efficiency, coordination capability, and resilience of operational response processes.

We emphasise that the core operational functions of Awareness, Demand Generation, Optimisation, Performance Prediction, Tracking and Control, and Simulation (ADOPTS) must be continuously supported across all phases of the disaster management lifecycle. These functions should form an integrated operational continuum linking preparedness, response, recovery, and long-term learning.

Disaster management must therefore be designed as a unified and continuously evolving system, grounded in shared models, consistent data, and closed-loop feedback mechanisms that enable operational experience to continuously improve both real-time decision-making and future preparedness.

2.2. Acknowledging the True Nature of Disaster Response Environments

Many existing disaster management systems are designed based on idealised assumptions, including complete and reliable information, stable coordination structures, predictable workflows, and sufficient time for analysis and deliberation. Such assumptions rarely hold during actual disaster conditions.

Disaster response environments are inherently dynamic, uncertain, and time critical. Information may be incomplete, delayed, contradictory, or rapidly changing. Multiple organisations often operate concurrently with partial situational awareness, while infrastructure degradation and communication disruptions further complicate coordination.

Disaster management technologies must therefore be explicitly designed for non-ideal operational environments, where uncertainty, decentralisation, partial information, and continuous adaptation are treated not as exceptions, but as fundamental design conditions.

2.3. Full Utilisation of Advanced Digitalisation Techniques

Contemporary disaster management processes continue to rely heavily on sequential, pipeline-oriented workflows, manual coordination, and fragmented digital infrastructures. These limitations frequently lead to operational bottlenecks, reduced situational awareness, delayed decision-making, and diminished response effectiveness.

Although disaster management is inherently multidisciplinary, advanced digitalisation technologies provide the primary mechanism for achieving large-scale integration, intelligent coordination, adaptive control, and operational scalability.

Advanced capabilities such as artificial intelligence, digital twins, distributed sensing, real-time analytics, simulation, autonomous coordination, and adaptive decision-support mechanisms must therefore be systematically integrated into disaster management processes to enable data-driven, adaptive, and resilient operations.

2.4. Overcoming Digital Fragmentation

Fragmentation across disaster management systems creates disjointed information environments in which agencies operate with inconsistent, delayed, or incomplete situational awareness. Unverified and conflicting information flows undermine trust, delay decision-making, and reduce operational effectiveness.

At the same time, weak communication infrastructures degrade coordination under pressure, while insufficient knowledge management mechanisms result in the loss of operational experience and institutional memory.

Disaster management systems must therefore prioritise the integration of data infrastructures, operational processes, communication mechanisms, and organisational knowledge in order to reduce ambiguity, strengthen coordination, improve trustworthiness, and enable timely and well-informed action.

2.5. System-Level Commitments for Effective Disaster Management

Effective disaster management under conditions of uncertainty, scale, and time pressure requires explicit system-level commitments that ensure coherence, reliability, adaptability, and coordination across all stakeholders.

Future disaster management systems should therefore provide:

- A unified, trusted, and continuously updated operational picture accessible to all relevant agencies and supporting multiple viewpoints
- Operationally resilient tools capable of functioning under harsh, unstable, and rapidly evolving conditions
- High-velocity and reliable data flows that evolve at the pace of the disaster itself
- Transparent coordination mechanisms providing clear visibility of responsibilities, decisions, and ongoing actions
- Consistent and complete information management mechanisms that minimise duplication, ambiguity, and blind spots
- Validation and conflict-resolution mechanisms that improve data reliability and reduce misinformation

- Real-time geospatial awareness and intelligent decision-support capabilities enabling optimised deployment of resources

- Robust operation under uncertainty, maintaining dependable functionality despite incomplete, noisy, or conflicting information

2.6. A Fundamental Shift in Design and Operational Mindset

Disaster management must move beyond technology-first development approaches, isolated organisational silos, and purely retrospective post-event analysis.

Future systems must instead adopt human-centred design principles, support seamless cross-agency interoperability, and enable continuous operational learning through feedback-driven adaptation.

This transition is essential for developing systems that remain usable, adaptable, trustworthy, and capable of evolving in response to real operational experience and emerging challenges..

2.7. Co-Creation as a Foundational Principle

The gap between researchers, developers, field responders, operational authorities, and policy makers must be systematically reduced.

Disaster management solutions should be co-created through continuous collaboration among all stakeholders rather than developed in isolation and imposed upon operational environments.

Only through inclusive, iterative, and operationally grounded collaboration can disaster management technologies achieve practical relevance, institutional trust, long-term sustainability, and effective real-world adoption.

3. Solution perspectives and technical policy recommendations

3.1. Holistic AI-driven risk management framework

We advocate the adoption of holistic AI-driven risk management frameworks [7] capable of addressing single and multiple crises triggered by extreme climate events affecting urban infrastructures, industrial facilities, and interconnected societal systems.

Recent research increasingly emphasises that multi-hazard conditions should not be treated as isolated phenomena but rather analysed and managed in an integrated manner [1–4]. In particular, the concept of NaTech, defined as Natural Hazard Triggered Technological Accidents [5], highlights the growing interdependence between natural hazards and technological systems. Modern urban environments are characterised by dense interactions among human populations, critical infrastructures, industrial facilities, transportation networks, energy systems, and digital services. As a result, a single hazardous event may propagate across multiple interconnected systems, triggering secondary failures and generating cascading, compounding, and systemic impacts.

Consequently, disaster risk management can no longer rely on fragmented, hazard-specific approaches. Instead, it requires integrated frameworks capable of modelling interdependencies, predicting cascading effects, and supporting coordinated decision-making across multiple domains and organisational boundaries.

In recent years, substantial progress has been achieved in the application of AI-driven technologies for disaster and hazard management. Advanced AI techniques have been employed in a wide range of areas, including early-warning systems, sensor- and satellite-based situational awareness, drone-assisted monitoring, fusion-based situation analysis, hazard prediction, multi-hazard risk modelling, intelligent map partitioning, and disaster logistics planning [9–19]. These technologies enable faster detection, improved prediction accuracy, enhanced operational coordination, and more adaptive response capabilities under dynamic conditions.

Significant research efforts have also focused on large-scale environmental monitoring and remote sensing. For example, atmospheric gas concentrations have been measured using specialised sensing equipment installed on commercial aircraft [20], while complementary observations are obtained from satellites, drones, and other in-situ sensing platforms. Such approaches support integrated environmental monitoring by combining heterogeneous data sources through AI-driven data fusion and analysis techniques. Remote sensing technologies play an increasingly important role within this context [21], and several studies have explored the use of commercial aviation infrastructures as large-scale distributed sensing platforms [22].

Taken together, these developments demonstrate the growing potential of AI-driven, data-intensive, and highly interconnected frameworks [8] for establishing more predictive, adaptive, and resilient disaster risk management systems capable of addressing the complexity of modern urban hazards.

3.2. Analysis and control risks

Based on spatial information systems and heterogeneous data sources, we advocate the use of multi-model digital-twin architectural approaches for analysing, predicting, and controlling the risks and worst-case scenarios associated with compounding, cascading, and systemic effects of hazards and multi-hazard conditions [29-35][38]. These approaches should support automated protocols, adaptive operational procedures, and continuous feedback-driven decision-making.

The identification, analysis, and management of risks and worst-case scenarios have long been recognised as central concerns in disaster management research and practice. Existing studies have addressed risk perception and interpretation by human actors [36], multi-risk assessment methodologies for complex environments [37], and the broader challenges associated with analysing interacting and cascading hazards [1]. Unlike single-hazard scenarios, multi-hazard environments introduce additional layers of complexity due to interdependencies among infrastructures, organisations, environmental processes, and human activities.

Particularly important in this context are NaTech events, where natural hazards trigger technological accidents with potentially severe secondary consequences [5]. Recovery from NaTech disasters is often significantly more difficult than recovery from conventional disasters because multiple infrastructures and industrial systems may fail simultaneously, while hazardous materials, damaged industrial facilities, and disrupted logistics further complicate response and recovery operations [23].

Several studies and policy initiatives have therefore focused on improving NaTech risk reduction and resilience. Survey-based analyses have examined the status of NaTech risk reduction strategies within European Union Member States [24], while additional research has highlighted the importance of understanding cascading multi-hazard risks and their propagation across interconnected systems [25]. Guidance documents have also been developed for operators of hazardous industrial facilities and public authorities responsible for emergency management and risk governance [26]. Furthermore, long-term qualitative analyses of NaTech research trends over the past decades demonstrate the growing recognition of interconnected and systemic disaster risks within both scientific and policy communities [27].

Despite these advances, existing approaches often remain fragmented, static, or limited to isolated risk domains. Modern disaster environments, however, require adaptive and continuously evolving mechanisms capable of integrating heterogeneous data, modelling interdependencies, simulating cascading effects, and supporting real-time operational control.

Within this context, multi-model digital twins provide a promising architectural foundation. By combining spatial models, infrastructure models, environmental simulations, sensor data, predictive analytics, and operational workflows into a unified computational environment, digital twins can continuously monitor system states, predict evolving risks, evaluate alternative intervention strategies, and support coordinated decision-making under uncertainty. Such architectures enable not only descriptive and predictive analysis, but also prescriptive and adaptive control capabilities capable of improving resilience against complex multi-hazard scenarios.

3.3. Automated decision support

Within established legal and institutional frameworks, we advocate the development of digital ecosystem platforms capable of supporting automated, predictive, and real-time decision-making processes across organisational and national boundaries throughout the entire disaster management lifecycle, from preparedness and prevention to response, rescue, and recovery operations.

Cross-Border Cooperation (CBC) has long been recognised as an important policy objective within the European Union and its neighbouring regions [39]. Hazards and disasters are inherently transboundary in nature; their effects frequently extend beyond political and administrative borders, impacting interconnected infrastructures, supply chains, transportation systems, energy networks, environmental resources, and populations across multiple regions and countries. Consequently, the effectiveness of disaster risk management increasingly depends on the ability of organisations and governments to coordinate information exchange, operational planning, and response activities across jurisdictional boundaries while respecting legal responsibilities, governance structures, and regulatory constraints.

To strengthen systemic resilience against NaTech and other complex multi-hazard conditions, advanced automated decision-support systems are essential. Such systems should be capable of continuously analysing evolving hazard conditions, assessing cascading effects, identifying required resources, coordinating rescue operations, monitoring execution, and initiating corrective actions whenever operational deviations occur [40]. The ability to perform these activities in real time is particularly critical under rapidly evolving disaster conditions where delays in decision-making may significantly amplify human, environmental, and economic losses.

In addition to instantaneous operational support, predictive decision-making capabilities are equally important. Understanding and forecasting the vulnerability of public and commercial infrastructures under NaTech and multi-hazard conditions are essential for improving preparedness, reducing systemic risks, and strengthening resilience [41]. This requires the development of continuously operating predictive models capable of estimating infrastructure degradation, operational disruption, resource shortages, and the evolving effects of hazards on response capabilities. Such predictive mechanisms can support proactive planning, adaptive resource allocation, and early intervention strategies before critical failures occur.

The growing need for advanced automated decision-support systems must also be understood within the context of contemporary disaster management technologies. Disaster Management Centres (DMCs) provide command-and-control infrastructures responsible for detecting emergency conditions, coordinating response activities, and minimising the impacts of disasters [42]. Their establishment, architecture, and operational procedures have been extensively studied in the literature [43,44]. Modern DMCs are increasingly supported by sophisticated digital infrastructures, including sensor networks, geographic information systems, communication platforms, remote sensing technologies, and large-scale data processing systems.

Despite these technological advances, many operational decisions within current DMCs remain heavily dependent on manual human coordination. Based on information displayed through operational dashboards and monitoring systems, human operators typically perform resource allocation, dispatching, tracking, and operational control activities manually. Under large-scale and rapidly evolving disaster conditions, however, purely human-centred coordination approaches may become insufficient due to cognitive overload, information fragmentation, time pressure, and the complexity of interdependent operational processes.

For this reason, future disaster management systems should evolve toward integrated digital ecosystems combining AI-driven analytics, digital twins, predictive simulation, autonomous coordination mechanisms, and real-time decision-support services. Such systems can augment human operators by enabling faster analysis, adaptive coordination, predictive reasoning, and scalable operational control while preserving accountability, transparency, and compliance with legal and organisational frameworks.

3.4. Mitigating NaTech risks for citizens using smart-city infrastructure

We advocate the integration of disaster management systems with smart-city infrastructures in order to improve the understanding, monitoring, and mitigation of NaTech and multi-hazard risks affecting citizens from a holistic perspective encompassing personal well-being, social stability, public safety, economic continuity, and urban resilience.

A smart city is commonly defined as an urban environment that utilises interconnected sensing, communication, and information technologies to collect, process, and analyse data for the efficient management of urban assets, infrastructures, and services [45,46]. Within this context, smart-city infrastructures provide an important technological foundation for enhancing disaster resilience through continuous monitoring, real-time situational awareness, adaptive coordination, and data-driven decision-making.

NaTech and multi-hazard events can severely disrupt urban life by affecting critical infrastructures, transportation systems, healthcare services, energy networks, communication systems, supply chains, and economic activities. As urban systems become increasingly interconnected, the societal consequences of cascading failures may extend far beyond the directly affected areas. Efficient and adaptive mitigation and adaptation strategies are therefore essential for reducing the impact of such hazards on citizens and urban environments. Digitalisation technologies constitute one of the primary enabling mechanisms for achieving these objectives.

A considerable body of research has examined the impact of disasters on citizens and urban societies. Existing studies have investigated citizen behaviour during crises, public preparedness, emergency response participation, and societal resilience [47,48]. However, many of these studies focus primarily on isolated hazard scenarios. More recently, increasing attention has been directed toward understanding awareness, perception, and management of multi-hazard conditions [49]. For example, European stakeholder-oriented studies have identified several major challenges in hazard risk management, including governance of multi-hazard risks, knowledge integration, limitations of existing disaster management approaches, translation of scientific knowledge into policy and operational practice, and insufficient availability of reliable data [28].

Additional research has explored risk assessment methodologies for multi-hazard conditions [50], the combined effects of interacting crises such as floods and pandemics [51], and the resilience of critical infrastructures such as energy systems under multi-hazard environments [52]. These studies collectively highlight the need for integrated and adaptive approaches capable of addressing interconnected societal, technological, and environmental risks.

Within this context, smart-city infrastructures are increasingly proposed as enabling platforms for disaster management and urban resilience. Mitigation and adaptation strategies frequently include infrastructure modernisation, resilient urban planning, intelligent transportation management, and advanced early-warning systems [53–57]. Many proposed solutions rely on large-scale deployments of sensors, Internet of Things (IoT) networks, and distributed monitoring infrastructures to collect real-time information about evolving hazard conditions and their impacts on urban systems [58].

Building upon these data infrastructures, a variety of AI and machine-learning techniques have been developed to predict hazard propagation, assess urban vulnerabilities, optimise emergency operations, and support adaptive mitigation strategies [59]. For example, several studies focus on optimising urban drainage systems and flood management processes under extreme rainfall conditions [60]. Furthermore, systematic literature reviews have demonstrated the growing importance of integrating smart-city infrastructures with multi-hazard management frameworks to improve resilience, coordination, and operational adaptability [61].

Taken together, these developments indicate that future disaster management systems should evolve toward integrated smart-city ecosystems in which sensing infrastructures, AI-driven analytics, digital twins, predictive models, and operational control systems cooperate continuously to support the safety, well-being, and resilience of urban populations under complex and rapidly evolving hazard conditions.

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