Spatial Inference Methods

for Decision Support in Disaster Risk Management

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Spatial Inference Methods for Decision Support in Disaster Risk Management

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Summary

The world is currently facing a growing number of disasters that are characterised by severe, widespread, and often cascading impacts on societies, critical infrastructures, and the environment. This trend is not only a consequence of changing hazard patterns but also of evolving societal conditions that amplify losses. In this context, disaster risk is commonly understood as the interaction of hazards, exposure, and vulnerability. Hazards can originate from both natural processes and human activities. Natural hazards, including river floods, heavy rain, heatwaves, and earthquakes, have historically caused significant damage and loss of life and are expected to increase in frequency and intensity, largely driven by climate change. Beyond natural hazards, human-induced hazards pose a growing challenge. These hazards may arise intentionally, for example through acts of sabotage or terrorism, or unintentionally as a result of technological failures, industrial accidents, or human error. At the same time, exposure and vulnerability are increasing worldwide due to urbanisation, population growth in hazard-prone areas, and growing dependence on critical infrastructures. Disruptions to these infrastructures can trigger cascading failures, amplifying impacts and prolonging recovery processes. Taken together, the concurrent increase in hazard intensity, exposure, and vulnerability leads to an escalation of disaster risk and highlights the urgent need for effective disaster risk management.

In this context, decision support systems represent a key component, as they enable decision-makers to make well-informed decisions in this highly complex domain, thereby reinforcing the need for novel methods to support decision-making in disaster risk management. Such decision-making processes, particularly in the time-critical disaster response phase, involve high-stakes decisions under severe time pressure and information overload. Consequently, decision support methods must provide information rapidly and in an explainable manner, while condensing it to what is most relevant for the decision context.

To address these challenges, this dissertation introduces three complementary methods to support decision-making in disaster risk management. All three methods share a common methodological core that combines Bayesian networks with a geographic information system (GIS), enabling spatial inference of decision-relevant information tailored to specific disaster risk management objectives. The novelty of this thesis lies in the development of spatial inference methods that address key requirements of disaster risk management: the methods are explainable, enabling transparency in high-stakes decision support; rapid to apply, enabling timely use under time pressure; and capable of providing condensed information, reducing the cognitive load on decision-makers.

The first method – the Emergency Response Inference Mapping Method (ERIMap) – addresses the challenge of incorporating large volumes of diverse, dynamic, and often uncertain observations in a structured manner. To this end, a typical emergency information landscape is defined, and a protocol is developed to translate observations into evidence that can be incorporated into a Bayesian network for performing inferences. The second method – the Dependent Infrastructure Services Disruption Mapping Method (DISruptionMap) – focuses on modelling cascading effects in critical infrastructure services in order to provide a comprehensive overview of service availability across the study area. It allows a flexible set of connected services to be represented using only limited input information to initialise the corresponding Bayesian network, thereby ensuring applicability

to varying service configurations and changing system contexts. The third method – the Prioritisation Recommendation Mapping Method (PrioReMap) – builds on the results of spatial inference to generate area-based prioritisation recommendations. By utilising area-specific probability distributions, this method provides unambiguous and transparent recommendations for decision-making that can be readily updated as new information becomes available.

Overall, the three methods are highly complementary and can be easily combined due to their shared methodological core – GIS-informed Bayesian networks. This common core enables their integration into an extended, risk-informed approach that supports the full information-processing chain required for effective decision support, adheres to disaster risk management requirements, and is applicable across multiple hazard scenarios and spatial scales. Specifically, such a combined approach would allow for the systematic integration of all available observations from diverse data sources, support the assessment of cascading impacts and service disruptions within systems, and ultimately provide decision-relevant recommendations that build upon all previously processed information and analyses.

Zusammenfassung

Derzeit ist die Welt einer wachsenden Bedrohung durch Katastrophen ausgesetzt, die zunehmend durch schwerwiegende Auswirkungen und weitreichende Kaskadeneffekte auf Gesellschaften, Kritische Infrastrukturen und die Umwelt gekennzeichnet sind. Diese Entwicklung ist nicht nur eine Folge sich verändernder Gefahren, sondern auch das Ergebnis sich wandelnder gesellschaftlicher Rahmenbedingungen, die durch Katastrophen verursachte Verluste verstärken können. In diesem Kontext wird Risiko als das Zusammenspiel von Gefährdung, Exposition und Vulnerabilität verstanden. Hierbei ist festzuhalten, dass Gefahren sowohl aus natürlichen Prozessen als auch aus menschlichen Aktivitäten entstehen können. Naturgefahren, wie Flusshochwasser, Starkregen, Hitzewellen und Erdbeben, haben historisch betrachtet bereits erhebliche Schäden verursacht und Menschenleben gefordert und werden voraussichtlich künftig an Häufigkeit und Intensität zunehmen, was maßgeblich durch die Klimakrise bedingt ist. Neben Naturgefahren stellen jedoch auch anthropogene Gefahren eine zunehmende Herausforderung für die Katastrophenhilfe dar. Diese können entweder vorsätzlich verursacht werden, beispielsweise in Form von Sabotageakten oder Terrorismus, oder unbeabsichtigt infolge technologischer Fehlfunktionen, industrieller Unfälle oder durch menschliches Versagen auftreten. Gleichzeitig nehmen Exposition und Vulnerabilität weltweit zu, bedingt durch Urbanisierung, Bevölkerungswachstum in gefährdungsanfälligen Gebieten sowie eine zunehmende Abhängigkeit von Kritischen Infrastrukturen. Störungen dieser Infrastrukturen können Kaskadeneffekte auslösen, die die negativen Auswirkungen dieser Störungen verstärken und den Wiederaufbau verlängern. Insgesamt führt die gleichzeitige Zunahme der Intensität von Gefahren, der Exposition und der Vulnerabilität zu einer Steigerung des Risikos und verdeutlicht den dringenden Bedarf an effektivem Katastrophenrisikomanagement.

In diesem Kontext stellen Entscheidungsunterstützungssysteme eine zentrale Komponente dar, da sie EntscheidungsträgerInnen dabei unterstützen, in diesem hochkomplexen Anwendungsfeld fundierte Entscheidungen zu treffen, was wiederum den wachsenden Bedarf an neuartigen Methoden zur Unterstützung von Entscheidungsprozessen im Katastrophenrisikomanagement verdeutlicht. Solche Entscheidungsprozesse, insbesondere in der zeitkritischen Phase der akuten Gefahrenabwehr, sind durch Entscheidungen mit potentiell weitreichenden Konsequenzen unter starkem Zeitdruck und hohem Volumen an Informationen gekennzeichnet. Dementsprechend müssen Methoden zur Entscheidungsunterstützung Informationen schnell und in nachvollziehbarer Weise bereitstellen und zugleich die Komplexität reduzieren, indem sie die für den jeweiligen Entscheidungskontext relevantesten Informationen verdichten.

Zur Bewältigung dieser Herausforderungen stellt diese Dissertation drei komplementäre Methoden zur Unterstützung von Entscheidungsprozessen im Katastrophenrisikomanagement vor. Allen drei Methoden liegt ein gemeinsamer methodischer Kern zugrunde, der Bayes'sche Netze mit einem Geoinformationssystem (GIS) kombiniert und damit die räumliche Inferenz entscheidungsrelevanter Informationen für spezifische Ziele des Katastrophenrisikomanagements ermöglicht. Der Beitrag dieser Arbeit liegt in der Entwicklung von Methoden zur räumlichen Inferenz, die zentrale Anforderungen des Katastrophenrisikomanagements adressieren: Die Methoden sind nachvollziehbar und ermöglichen transparente Entscheidungsunterstützung in kritischen Einsatzsituationen; sie ermöglichen eine

schnelle Handhabung und Ergebnisgenerierung und damit einen Einsatz unter Zeitdruck; und sie sind in der Lage, Informationen zu verdichten, um dadurch die kognitive Belastung von EntscheidungsträgerInnen zu reduzieren.
Die erste Methode – die Emergency Response Inference Mapping Method (ERIMap) – zielt darauf ab, große Mengen heterogener, dynamischer und häufig unsicherer Observationen in strukturierter Weise zu verarbeiten. Zu diesem Zweck wird eine für Notfallsituationen typische Informationslandschaft definiert und ein Protokoll entwickelt, das Observationen in Evidenz überführt, die in ein Bayes'sches Netz integriert werden kann, wodurch räumliche Inferenzen möglich werden. Die zweite Methode – die Dependent Infrastructure Services Disruption Mapping Method (DISruptionMap) – konzentriert sich auf die Modellierung von Kaskadeneffekten von Kritischen Infrastrukturen, um einen umfassenden Überblick über die Verfügbarkeit von Services im Untersuchungsgebiet bereitzustellen. Sie ermöglicht die flexible Darstellung voneinander abhängiger Services unter Verwendung lediglich begrenzter Eingangsinformationen zur Initialisierung des entsprechenden Bayes'schen Netzes und stellt damit die Anwendbarkeit auf unterschiedliche Servicekonfigurationen sowie sich verändernde Systemkontexte sicher. Die dritte Methode – die Prioritisation Recommendation Mapping Method (PrioReMap) – baut auf den Ergebnissen räumlicher Inferenz auf, um gebietsbezogene Priorisierungsempfehlungen zu generieren. Somit liefert diese Methode eindeutige und transparente Empfehlungen für Entscheidungsprozesse, die bei Verfügbarkeit neuer Informationen unmittelbar aktualisiert werden können.

Insgesamt ergänzen sich die drei Methoden und lassen sich aufgrund ihres gemeinsamen methodischen Kerns – einem GIS-informierten Bayes'schen Netz – miteinander kombinieren. Dieser gemeinsame Kern ermöglicht ihre Integration in einen erweiterten, risikoinformierten Ansatz, der die gesamte für das Katastrophenrisikomanagement erforderliche Kette der Informationsverarbeitung unterstützt, die für eine effektive Entscheidungsunterstützung erforderlich ist, die erhobenen Anforderungen des Katastrophenrisikomanagements erfüllt und über verschiedene Gefährdungsszenarien sowie räumliche Gegebenheiten hinweg anwendbar ist. Konkret würde ein solcher kombinierter Ansatz die systematische Integration aller verfügbaren Observationen aus unterschiedlichen Datenquellen ermöglichen, die Bewertung der Kaskadeneffekte und Serviceeinschränkungen in miteinander vernetzten Systemen unterstützen und letztendlich die Bereitstellung entscheidungsrelevanter Empfehlungen erlauben, die auf allen zuvor verarbeiteten Informationen und Analysen aufbauen.

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List of Abbreviations

BN Bayesian network

CI Critical infrastructure

CPT Conditional probability table

DBN Dynamic Bayesian network

DM Decision-making

DR Disaster response

DRM Disaster risk management

DSS Decision support system

GIS Geographic information system

ICT Information and communication technology

OSM OpenStreetMap

SoS System-of-systems

1 | Introduction

1.1 Background

The world is facing an increasing number of **disasters** with far-reaching impacts on societies worldwide (Cvetković et al., 2024; Ruiter et al., 2020). Disasters are characterised by severe and often widespread impacts on human health and safety, as well as the loss of property, essential services, or natural resources (Mentges et al., 2023). A disaster is triggered by a hazard and its interaction with the exposure and vulnerability of a community (Lapietra et al., 2025; Lu et al., 2024; Mentges et al., 2023). A hazard can have a natural cause (a natural hazard), predominantly associated with natural processes and phenomena, or an anthropogenic cause (a human-induced or man-made hazard), arising entirely or primarily from human activities and choices (UNDRR, 2016).

The number of disasters caused by **natural hazards** has increased substantially over the past few decades and is expected to rise even further in the future (Cutter et al., 2015; Güneralp et al., 2015; Collet et al., 2018; Feng et al., 2021; Qi et al., 2022) – a trend driven by the effects of climate change (Van Aalst, 2006). Among the wide range of natural hazards, floods are often considered among the most devastating, posing a severe threat to human life and critical infrastructures (CIs) (Nick et al., 2023; Asaridis et al., 2025; Sanderson and McAllister, 2025). In recent years, several catastrophic floods have occurred, such as the 2021 flood in Germany, which claimed more than 180 lives (Fekete and Sandholz, 2021), and the severe floods in Spain's Valencia Region in October 2024, which resulted in over 220 fatalities (Fekete et al., 2025). Other types of devastating natural hazards include earthquakes (e.g. the Turkey–Syria earthquake in 2023 (Balikuddembe et al., 2024)) and extreme wildfires (with ≈384 million hectares of land burned globally in 2023 (Kolden et al., 2024)).

In addition, disasters caused by **human-induced hazards** also contribute to the overall rise in the number and impact of disasters worldwide (Cvetković et al., 2024). Human-induced hazards can be either intentional, such as acts of terrorism or large-scale sabotage, e.g. targeting energy infrastructure, communication networks, or water supply systems, or unintentional, resulting from industrial accidents, technological failures, or human error (Arcos González et al., 2023). Examples include the leakage of hazardous substances (Iaiani et al., 2021; Bonari et al., 2024), explosions in industrial facilities (Abg Shamsuddin et al., 2023; Sezer and Akyuz, 2024), or large-scale transportation accidents (Evans, 2011). Such events can be as severe as natural hazards, especially when they affect densely populated areas or CIs.

In addition to the aforementioned sources of hazards (natural and human-induced) increasing **exposure and vulnerability** to these hazards are key factors contributing to rising disaster risk (Lapietra et al., 2025; Lu et al., 2024). Exposure describes the degree to which a system or an asset is subject to a hazard (Mentges et al., 2023; Adger, 2006). Exposure can be expressed by the situation of people, infrastructure, housing, production capacities, and other tangible human assets located in hazard-prone areas (UNDRR, 2016). Rapid urbanisation is often cited as a key driver of the increasing exposure of populations to hazards (Li et al., 2021). Vulnerability, on the other hand, describes the conditions determined by physical, social, economic, and environmental factors or processes which increase the susceptibility of an individual, a community, an asset, or a system to the impacts of hazards (UNDRR, 2016) – in other words, how strong the negative impacts of the disruptive event (e.g. a flood) would be (Mentges et al., 2023). A significant factor contributing to the increasing vulnerability of modern societies is their vital dependence on CIs, which, during disasters, are often highly exposed (e.g. flooded road segments rendering hospitals inaccessible) and face increased demand (e.g. a surge in hospital patients).

1.1.1 Disaster Risk Management

In order to tackle increasing disaster risk, effective disaster risk management (DRM) is vital, as it sets out the goals and specific objectives for disaster risk reduction, along with the actions needed to achieve them (UNDRR, 2016). Disaster risk management is composed of four individual phases that together constitute a full **DRM cycle** (see Figure 1.1), namely *Preparedness*, *Response*, *Recovery*, and *Mitigation*. Each phase comes with its own objectives, closely tied to the specific demands and challenges that arise both in the short and long term before a disaster strikes, as well as immediately after a disastrous event and in the longer aftermath. In the following, a brief overview of each phase, including its key objectives and challenges, is provided.

The **preparation phase** (corresponding to preparedness in Figure 1.1) involves activities undertaken before a disaster occurs that aim at avoiding potential consequences and equipping all relevant organisations and communities with the knowledge and capacities to anticipate, respond to, and recover from disasters (Tay et al., 2022; UNDRR, 2016). In this phase, critical resources are stockpiled, new information and communication technologies (ICT) are developed to support early warning and effective response, and emergency responders are trained (Tay et al., 2022). Challenges include identifying optimal locations to pre-position essential resources and promoting the acceptance and integration of new ICT solutions (Eberhardt et al., 2025; Weidinger et al., 2020).

The **response phase** starts directly before, during, or immediately after a disaster in order to save lives, reduce health impacts, ensure public safety, and meet the basic subsistence needs of the people affected (UNDRR, 2016). In this phase, it is crucial to assess the disaster situation using observations gathered through reconnaissance activities (Lichte, 2025) and to coordinate the initial disaster relief efforts (Ahmad Basri et al., 2021; Tay et al., 2022). The response phase is challenged by the need to allocate scarce resources based on a volatile and heterogeneous information-scape (Li et al., 2023; Comes et al., 2012).

The **recovery phase** is carried out in the aftermath of a disaster, aiming to restore the affected area to its pre-disaster state (Tay et al., 2022). In contrast to the response phase, which focuses on immediate needs, the recovery phase addresses challenges from a long-term perspective (Blackman et al., 2017). In this phase, sustained coordination and substantial resources are required to effectively carry out reconstruction efforts (Chang et al., 2011). Key challenges include disrupted infrastructures hampering reconstruction efforts and the need to balance rapid restoration with building back better to reduce future risk (Ingram et al., 2006).

The **mitigation phase** refers to actions taken after and before a disaster to reduce the effects of disasters. In contrast to the preparation phase, which focuses on activities that prepare for an effective response, the mitigation phase involves the application of measures that aim to prevent a disaster and reduce its impact (Tay et al., 2022). Mitigation measures include engineering techniques and hazard-resistant construction as well as improved environmental and social policies and public awareness (UNDRR, 2016). The mitigation of disasters is challenged by the unpredictable and increasingly severe impacts of climate change, especially when planning measures for multi-hazard, cascading, and compound disasters (Cui et al., 2021).

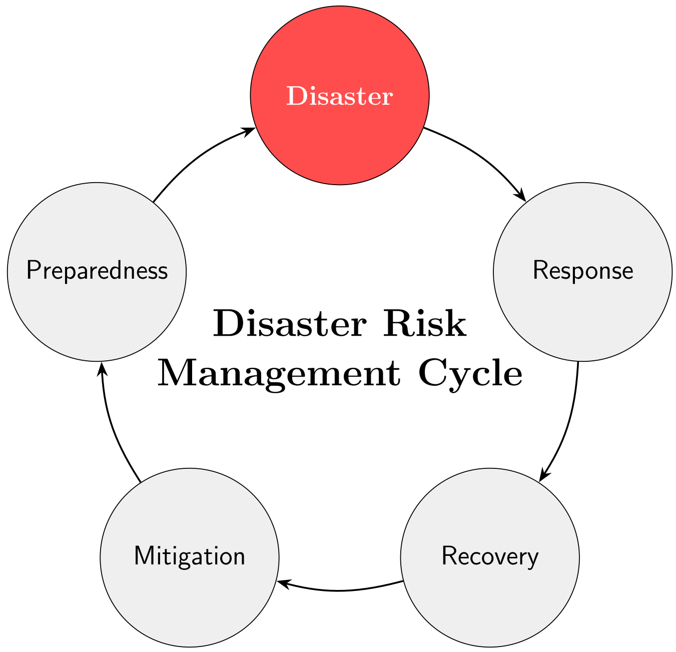

Figure 1.1: The Disaster Risk Management Cycle distinguishes between pre-disaster activities (mitigation and preparedness) and post-disaster activities (response and recovery), forming a continuous loop of risk reduction and management.

1.1.2 Critical Infrastructures in Disaster Response

Critical infrastructures play a vital role in everyday life of modern societies (Nick et al., 2023) and are especially critical to support disaster response, e.g. to power mobile networks used for communication (Deepak et al., 2019) or to provide access to healthcare facilities (Mager Pozo et al., 2025). In a large-scale disaster, multiple CIs can be disrupted simultaneously, e.g. a flood might cause disruptions in the road network, the energy distribution system, and the healthcare system. In addition, since CI often span over or supply large geographical areas (Arvidsson et al., 2023), CI failures may cause service disruptions distant from the immediate location of the disruptive event thus increasing the area impacted by the disaster. What further increases the complexity of the situation is CI dependencies that can lead to **cascading effects** (Rinaldi et al., 2001; Nick et al., 2023; Arvidsson et al., 2023), e.g. a failure of a pump disrupts the supply of cooling water, which in turn compromises the operation of a power plant and ultimately leads to the loss of electricity supply across a vast area.

As CI services are exposed to such a wide range of **direct and indirect disruptions** in a disaster, geo-referenced observations about their availability or the cause of their failure are essential for guiding disaster response for two key objectives: (1) assessing where CI services remain functional to support relief efforts, e.g. which areas can still be accessed by the road network (Mager Pozo et al., 2025); and (2) identifying priority CI components whose reconstruction would have the greatest impact on the support of relief efforts, e.g. determining which components of a electric power system to restore first (Xu et al., 2024). While some CI service failures can be directly observed, e.g. using satellite imagery to identify damaged buildings (Braik and Koliou, 2024) or roads (Chen and Lin, 2025), others must be spatially inferred to assess cascading service disruptions based on the information available, e.g. knowing that all access streets to a hospital are blocked results in the inference that ambulances cannot reach the hospital to take care of patients (e.g. see Figure 1.2).

To spatially infer cascading CI service disruptions, the complex dependencies among the services must first be understood. This is complicated by the **system-of-systems** (SoS) nature of CIs (Eusgeld et al., 2011), with each CI representing a system in itself (Ouyang, 2014; Mottahedi et al., 2021), which may be composed of networks that, in turn, consist of individual components. For example, a hospital is a system that depends on the transportation system, which is built on the road network, which in turn is composed of road segments that constitute the components (see example in Figure 1.2). A cascade of CI service failures, such as one triggered by a flood, can start with a road segment (component) being flooded, leading to reduced accessibility (network), which in turn hampers the services of the hospital (system). All these aspects – namely, identifying which component failures lead to (sub)network failures, which in turn can trigger system- and SoS-level failures – must be understood to spatially infer the full range of cascading CI service disruptions.

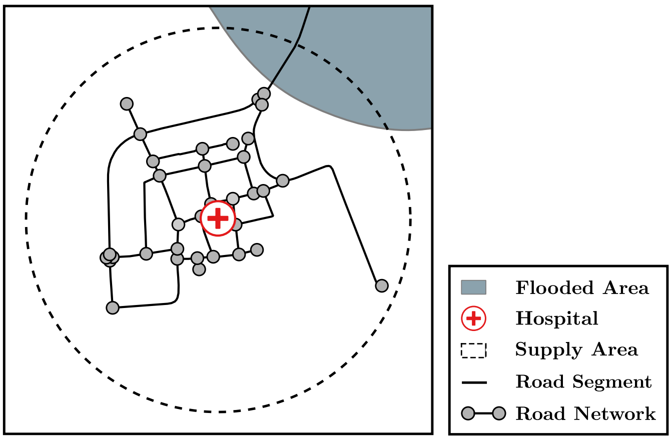

Figure 1.2: The illustrative map shows a road network with a hospital connected to it. A flood renders one critical road segment impassable, cutting off access to the hospital that serves the area with emergency care services.

1.1.3 Decision-Making in Disaster Response

Decision-making in disaster response involves a variety of complex decisions, such as allocating limited relief resources to search for people in need of assistance (Matsuki and Hatayama, 2023; Sköld Gustafsson et al., 2023), distributing material to reduce disaster risk (Arora et al., 2010; Su et al., 2016), or selecting shelter locations (Bera et al., 2023). These decisions can affect a wide range of people and can significantly influence the further course of the disaster scenario. What adds to this is that some decisions are irreversible, i.e. once a decision is made, it cannot (easily) be changed (Pauwels et al., 2000; Sunstein, 2010). Given what is at stake and the irreversibility of the decision, such decisions are often referred to as **high-stakes** decisions (Kunreuther et al., 2002; Sahoh and Choksuriwong, 2023).

While facing high-stakes decisions, decision-makers must consider a high volume of heterogeneous, spatially distributed, and dynamic observations. As decisions are often risk-based (e.g. see Marasco et al., 2022 or Safaeian et al., 2024), observations during an ongoing disaster must encompass information on the hazard, exposure, and vulnerability, as their intersection forms the foundation of disaster risk assessment (Lu et al., 2024; Mentges et al., 2023). This includes, for instance, the spatial variability of hazard intensity (Mudashiru et al., 2021), the access to CI services (Casali et al., 2024), and the presence of vulnerable population groups (Rehman et al., 2019) – information which are often uncertain at the onset of a disaster. The shear volume of such diverse, spatially explicit, and potentially uncertain observations, combined with the need to draw spatial inferences – e.g. to prioritise areas of high risk to allocate scarce resources – produces significant **cognitive load** on decision-makers.

What is more, while facing high stakes and a high cognitive load, some decisions must be made under considerable **time pressure**, further enhancing the stress on decision-makers (Paton and Flin, 1999; Son et al., 2008). Time pressure arises, when the available time for a decision is less than required to properly perform a task (Taheri et al., 2023). A lack of time can change the risk attitude (Taheri et al., 2023) resulting in more rigorous decision strategies (Chu and Spires, 2001). Especially at the onset of a disaster, when responders first arrive at the disaster scene, quick decisions, e.g. for reconnaissance activities (Lichte, 2025), must be made. Here, again, irreversibility plays a significant role that contributes to the time pressure: While waiting for more information that would justify a decision on, e.g. evacuating an area threatened by a potential nuclear accident or not (see Pauwels et al., 2000), time passes that would be vital in case evacuation becomes the only option.

Therefore, decision-making in disaster response must be performed while facing a demanding area of tension between high stakes, cognitive load, and time pressure (see left side of Figure 1.3). When the stakes are high, decision-makers certainly prefer to take as much time as needed to make a decision (*high stakes vs. time pressure*), draw well-founded conclusions to better justify high-stakes decisions (*high stakes vs. cognitive load*), and examine all available information and analysis results in detail (*time pressure vs. cognitive load*). Many decisions in DRM that have to be made under these areas of tension can be interpreted as optimisation problems (see Kamyabniya et al., 2024 for an overview on optimisation problems in disaster response) that significantly benefit from decision support systems (DSS) (Thompson et al., 2006; Rolland et al., 2010).

Decision support systems – which is any type of tool that provides processed data to support decision-making – are increasingly used in disaster response (Sköld Gustafsson et al., 2023) to coordinate disaster relief efforts (e.g. see Fiedrich et al., 2000 or Fikar et al., 2016) in several disaster scenarios, such as floods (Alabbad et al., 2024), earthquakes (Fiedrich et al., 2000; Yousefi et al., 2024), wildfires (O'Mara et al., 2024), or accidents involving hazardous materials (Zografos et al., 2000). Many DSS in disaster response are based on a geographic information system (GIS), enabling spatial analysis and visualisation to support data-driven decision-making (Kirpalani, 2024).

When it comes to the requirements for DSS in disaster response, a key priority is the **rapid** handling of observations, given the typical time pressure involved in disaster response (Morton and Levy, 2011). This includes both, a rapid integration of new observations and a rapid processing of these observation to provide the results that finally serve as the decision support. The integration of new observations in the DSS can be either fully automated, e.g. an algorithm searching for keywords in social media posts (Kersten and Klan, 2020), or manually injected in the system, e.g. a query of individual information on a tablet (He et al., 2017). A model- or simulation-based DSS that processes these input observations must often strike a balance between model fidelity and computational efficiency, as higher fidelity typically increases processing time while improved accuracy enhances the value of the results, e.g. when computing gas dispersion (Danwitz et al., 2024).

To reduce the cognitive load on decision-makers when confronted with a high volume of information, the information must be **condensed** to decrease its volume and enhance its relevance (Harvey et al., 2022). Effective support selectively filters the information most relevant to the specific objective at hand (Zhang et al., 2002; Preece et al., 2013). This process may also involve making inferences, i.e. processing the available data to get additional insights that are most important to the objective. Such inferences can include assessing risks for individual areas based on proxy data, predicting scenario outcomes, or evaluating cascading effects. A well-designed DSS thus enables decision-makers to process a higher proportion of relevant information, leading to more informed and timely decisions (Chu and Spires, 2001).

When condensing high volumes of information into selected information and inferences, it is crucial that the respective DSS makes this process transparent and **explainable** to its users (Comes, 2024; Rudin, 2022). Especially in high-stakes decision-making, transparency and explainability of how the system arrives at its inferences are essential (Rudin, 2022; Sahoh and Choksuriwong, 2023). Black box models – unlike explainable models – can be dangerous in high-stakes decisions because they may rely on untrustworthy data and are difficult to troubleshoot (Rudin, 2022). In addition, explainability is crucial to gain trust in the system, which ultimately enhances a key issue: technology acceptance (Weidinger et al., 2020; Brar et al., 2022; Meechang et al., 2020).

In conclusion, based on the areas of tension in decision-making during disaster response – namely high stakes, cognitive load, and time pressure – three key requirements for DSS are identified (see right side of Figure 1.3). High-stakes decisions create a need for explainable results, cognitive load on decision-makers calls for condensed information, and time pressure in disaster response demands rapid processing. Since these areas of tension compound one another – making the situation more challenging as they overlap – effective decision support in disaster response requires novel approaches that fulfil all requirements concurrently. Importantly, meeting these requirements is not only a matter of the final output, but of the full chain of information processing on which decision support depends: from the volatile and heterogeneous information-scape characterising disaster response, through the spatial inference of variables that cannot be directly observed, to the derivation of actionable information that efficiently supports decision-making.

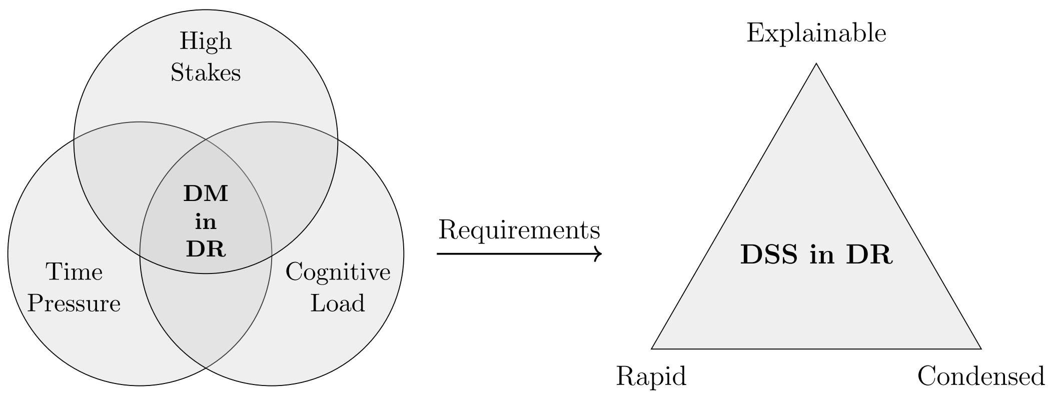

Figure 1.3: Decision-making (DM) in disaster response (DR) is characterised by three key demands that create areas of tension: high stakes, cognitive load, and time pressure. These demands place specific requirements on decision support systems (DSS), particularly the need for explainability in condensed results that must be provided rapidly.

1.2 Aim and Research Questions

In the following, first, the overarching aim of this thesis is outlined, serving as the central objective guiding the development of each individual method presented (Section 1.2.1). Second, additional complementary research questions are outlined to highlight specific gaps addressed by each individual method (Section 1.2.2).

1.2.1 Overarching Aim

This thesis is dedicated to providing novel methods to support decision-making in DRM by performing spatial inference. Spatial inference is thereby defined as *the process of deriving spatially explicit conclusions about key decision-making variables, based on geo-referenced observations*. The development of these methods is guided by the key requirements for DSS in DRM, with a particular focus on the disaster response phase (outlined in Section 1.1.3): they must support the rapid handling of spatially distributed observations and condense the available information to what is most important for decision-makers, using explainable models.

The main approach of this thesis to achieve a fulfilment of these requirements is to shift parts of the cognitive process of deriving spatial inference from the time-sensitive response phase to the less time-critical preparation phase. By formalising the cognitive process of a decision-maker (or a group of decision-makers) in a model during a phase when time is not limited, the desired knowledge can be retrieved rapidly and in a more transparent manner when time is short. Setting up the models should serve as a walk-through of the decision-making procedures during a disaster. This proactive approach enables decision-makers to embed critical information needs, and the process by which they would infer them, into a model in advance of a real disaster. During the actual response, the knowledge embedded in the model allows the rapid application of the formalised cognitive process to condense a high volume of spatially distributed observations into the desired information.

Accordingly, the overarching aim of this thesis can be summarised as the development of methods to:

> Formalise the process of deriving spatial inference on decision-critical variables during the less time-sensitive *preparation phase*, enabling rapid and explainable inferences during the time-critical *response phase*.

1.2.2 Research Questions

This thesis is guided by four research questions (RQs): one main RQ, which reflects the overarching aim of the thesis and is addressed by all of the developed methods, and three complementary RQs, each focusing on a specific aspect of formalising the spatial inference process which is addressed through one of the developed methods each.

The main RQ summarises the overarching aim of the thesis (presented in Section 1.2.1):

Main RQ: How can spatial inference be formalised during the preparation phase to provide rapid and explainable decision support for DRM?

The first step that must be formalised in the process of drawing spatial inferences during disaster response is the handling (i.e. classification and processing) of all available observations containing relevant information (Preece et al., 2013). This task is complicated by the volatile and heterogeneous information-scape typically available during disasters, which makes the uniform classification of observations difficult. Each observation may exhibit a diverse set of properties, such as being uncertain (Comes et al., 2012; Fu et al., 2021) or incomplete (Li et al., 2023; Wu et al., 2021), and it usually provides information about individual locations (Abdalla, 2016; Tzavella et al., 2022) that is valid only within a specific time frame (Turoff et al., 2004; Liu, 2021). This leads to the first complementary research question:

RQ1: How can spatial inference be drawn based on observations that are typically available during disasters?

Given the vital role of CI services in DRM and their vulnerability to disruptions from hazards, assessing their service availability is essential for ensuring effective relief efforts (Tariverdi et al., 2023). While some CI service disruptions can be directly observed, indirect (cascading) disruptions must be inferred from available observations (Rehak et al., 2018), particularly in the early stages of the disaster response when information is still limited. As CIs often span over or supply large geographical areas (Arvidsson et al., 2023), cascading effects can disrupt CI services far away from the immediate location of the disruptive event. This underscores the importance of spatially inferring CI service availability, as disruptions may arise far from the hazard's origin (spatial in nature) and may not be immediately apparent through direct observation (requiring inference). This leads to the second complementary research question:

RQ2: How can cascading effects of critical infrastructure services be spatially inferred during disasters?

To effectively coordinate disaster response efforts, decision-makers must prioritise areas most dependent on aid (Turoff et al., 2004; Bharosa et al., 2009) to allocate scarce resources efficiently (Wieland et al., 2025; Ansell et al., 2010; Armenakis and Nirupama, 2012). This requires timely information on variables relevant for prioritisation (this is the spatial inference), and a rapid, shared understanding of which areas should be prioritised. To support this process, an additional layer is necessary to further condense complexity by deriving priority areas from the current information on key variables, ultimately providing prioritisation recommendations during an ongoing disaster. This leads to the third and final complementary research question:

RQ3: How can spatial inference result in recommendations on area prioritisation for decision support in DRM?

1.3 Research Design

In the following, the research fields in which this thesis is positioned are first outlined (Section 1.3.1). Next, the spatial inference framework developed and applied in this thesis is presented, serving as a fundamental guideline for method development (Section 1.3.2). Finally, the individual contributions (publications) are presented – each introducing a novel method for spatial inference – along with the journals in which they were published and the respective author contributions (Section 1.3.3).

1.3.1 Research Fields

This section outlines how this thesis integrates into the research landscape by describing the main related fields of research, their interconnections, and how they benefit from the methods developed in this thesis. In particular, it clarifies the central contribution of this thesis: the development of novel spatial inference methods for decision support in disaster risk management. The corresponding research fields considered are Disaster Risk Management (DRM), Bayesian Networks (BNs), and Geographic Information Systems (GIS) (see Figure 1.4).

Disaster risk management (see Section 1.1.1) is the targeted field of application for the results of this thesis. This means that the methods developed here need to adhere to the requirements and challenges posed by DRM: high stakes, extreme time pressure, and significant cognitive load (see Figure 1.3). This thesis helps to address these challenges by presenting novel methods for decision support, designed specifically for the preparation and response phases. Ultimately, these methods aim to support decision-makers in large-scale disaster scenarios characterised by a need for spatially explicit information.
To fulfil these goals, the thesis uses **Bayesian networks**, which are probabilistic graphical models originally introduced by Pearl, 1985. They provide a powerful framework for decision support by enabling inference about decision-relevant variables based on prior knowledge about their dependencies and based on current observations (i.e. evidence). This thesis advances the applicability of BNs in the context of DRM, thereby improving time efficiency and reducing cognitive load in decision-making, particularly for objectives involving spatial considerations.
This thesis builds on previous works (see, for example, Johnson et al., 2011) to integrate **geographic information system** models with BNs to facilitate spatial inference. The unique contribution of this thesis lies in the integration of the two methods with the specific and demanding requirements of DRM in mind, i.e. efficiently handling extensive data and presenting it in a form that allows easy and quick interpretation by practitioners.

1.3.2 Spatial Inference Framework

The spatial inference framework of this thesis is composed of two phases (addressing the **main RQ**): the *preparation phase* (see left side of Figure 1.5) and the *response phase* (see right side of Figure 1.5).

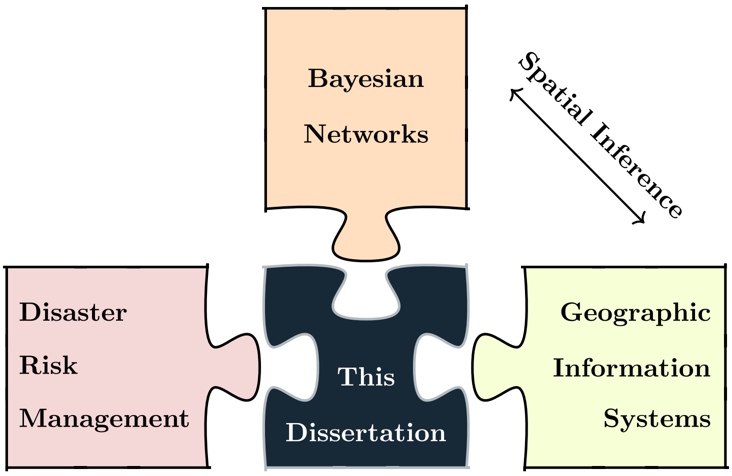

Figure 1.4: Research fields and position of the thesis. This thesis is situated at the intersection of DRM, BNs, and GIS. DRM defines the application domain, while the integration of BNs and GIS enables spatial inference and constitutes the methodological core.

In the preparation phase, a BN is first constructed to perform the required inferences (see top-left of Figure 1.5). This BN must include a target node that reflects the objective of the analysis (i.e. the key-variable for decision-making), which is decomposed through one or more layers of parent nodes, ultimately leading to independent leaf nodes. The reason to select a BN as the core of the framework stems from three aspects that are particularly critical in disaster-related contexts: (i) BNs can be constructed based on diverse compositions of available data, e.g. a combination of historical data and expert knowledge (Druzdzel and Gaag, 2000), (ii) BNs are explainable and easy to interpret as they are based on a (logical) graphical structure (Lee et al., 2022) that provides human-like interpretation of observations (Sahoh and Choksuriwong, 2023), and (iii) BNs enable the consideration of uncertainties in input data and relations between variables (Pearl, 1985) – which is crucial to avoid overconfidence when making high-stakes decisions in uncertain situations.

While BNs enable inference of a variable based on observations, they do not inherently support *spatially explicit* inference. To enable spatial inference, the BN must be duplicated and assigned to spatial units (e.g. districts or buildings) that require individual assessment (Johnson et al., 2012) resulting in a grid of BNs (see centre-left side of Figure 1.5). Within this grid of duplicated BNs, each leaf node should be informed by spatially explicit information representing its state at the corresponding location. In addition, all child nodes (up to the target node) can be informed by supplementary observations to further reduce uncertainty on the target node's state. While some information can be directly extracted from GIS layer attributes to inform BN (leaf) nodes (e.g. building type or flood depth at a specific location), other variables require prior spatial analysis involving their own modelling processes (e.g. calculating building density in an area or determining its accessibility) (see bottom-left of Figure 1.5). This combination of a BN and geospatial models to inform BN leaf nodes is hereafter referred to as a spatial inference model.

In the response phase, the spatial inference model is fed with observations from an ongoing disaster – provided by, e.g. rapid mapping technologies, responders, simulations, or sensors (see top-right of Figure 1.5). Through multiple layers of processing – corresponding to RQ1–RQ3 – these observations are used to spatially infer the state of the area-specific BN target nodes, ultimately resulting in recommendations for spatial prioritisation (see centre-right of Figure 1.5). The resulting outputs are then displayed on a map to facilitate effective support of disaster response (see bottom-right of Figure 1.5).

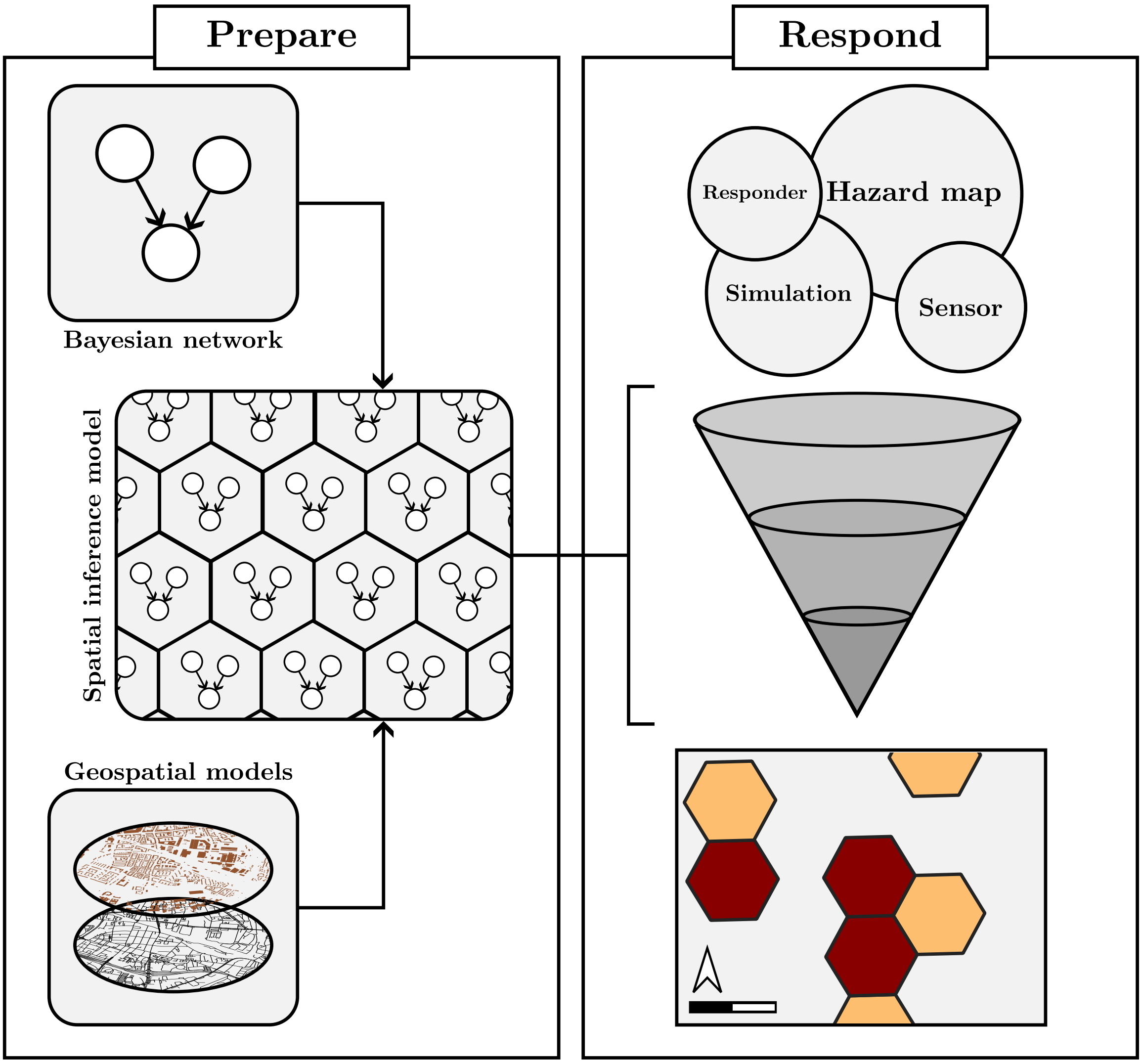

Figure 1.5: The spatial inference framework consists of two consecutive phases: preparation (left side of the Figure) and response (right side of the Figure). In the preparation phase, a BN is constructed to represent the cognitive process of decision-making procedures, and geospatial models are developed. Together, these components constitute the spatial inference model. In the response phase, the model is supplied with observations from an ongoing disaster, producing a map of spatial inferences. While the framework addresses the main RQ, the individual RQs focus on how to enrich the information obtained from the observations in order to perform spatial inferences and provide area prioritisation recommendations.

1.3.3 Developed Methods

This thesis comprises three methods that have been published in three different international peer-reviewed journals. The published articles are included in the appendix.

I. Method
Schneider, M., Halekotte, L., Comes, T., Lichte, D., and Fiedrich, F., (2025). Emergency Response Inference Mapping (ERIMap): A Bayesian network-based method for dynamic observation processing. Reliability Engineering and System Safety. DOI: 10.1016/j.ress.2024.110640.

II. Method
Schneider, M., Halekotte, L., Mentges, A., and Fiedrich, F., (2025). Dependent Infrastructure Service Disruption Mapping (DISruptionMap): A method to assess cascading service disruptions in disaster scenarios. Scientific Reports. DOI: 10.1038/s41598-025-89469-0.

III. Method
Schneider, M., Halekotte, L., Comes, T., and Fiedrich, F., (2026). Prioritisation Recommendation Mapping (PrioReMap): A method for supporting relief coordination in flood disaster response. International Journal of Disaster Risk Reduction. DOI: 10.1016/j.ijdrr.2025.105949.

The I. Method (Schneider et al., 2025a) was published in *Reliability Engineering and System Safety* (Elsevier), which is an international journal focused on publishing research and practical applications that enhance the safety and reliability of complex technological systems, for example through probabilistic methods, system analysis, and decision support systems, with a balance between academic theory and real-world relevance (Elsevier, 2025a).

The II. Method (Schneider et al., 2025b) was published in *Scientific Reports* (Springer Nature), which is an international interdisciplinary journal publishing original research from all areas of the natural sciences, psychology, medicine, and engineering. The work was published in a collection of this journal dedicated to disaster and emergency preparedness, which aims to reduce the harm caused by natural phenomena such as floods and earthquakes (Springer Nature, 2025).

The III. Method (Schneider et al., 2026) was published in the *International Journal of Disaster Risk Reduction* (Elsevier), a multi-disciplinary journal that includes research aiming at reducing the impact of natural, technological, social, and intentional disasters. It covers key topics such as multifaceted and cascading disasters, the development of disaster risk reduction strategies and techniques, and resilience against disasters (Elsevier, 2025b).

As the first author of all three articles, the author of this thesis (Moritz Schneider) contributed to their conceptualisation and development, implemented them through software, created visualisations, drafted the original manuscripts, and led the review and editing process. Lukas Halekotte contributed to all three articles by conceptualising and supervising the study, supporting the draft of the original manuscript, and taking part in the review and editing process. Frank Fiedrich contributed to all three articles by conceptualising and supervising the study, and by participating in the writing, review, and editing process. Tina Comes contributed to the first and third article by conceptualising and supervising the research, and by participating in the writing, review, and editing process. Daniel Lichte contributed to the first article through project administration and conceptualisation. Andrea Mentges contributed to the second article through the writing, review, and editing process.

2 | Summary of the Methods

This chapter summarises the three methods presented in this thesis, each addressing the main research question and individually focusing on one of the complementary research questions (RQ1–RQ3). In the summary of each method, first, the specific aim and motivation is described, followed by a summary of the key methodological components, which constitute the core of the work. Finally, the individual case study conducted to illustrate the method is outlined, including its specific objective, which leads to the development of its own BN, along with its distinctive geographical context and dataset. Note that the summary of the method follows the descriptions in the respective journal articles, which do not always fully align in terminology or structure due to the specific requirements of the journals in which they were published. Relevant deviations are highlighted in the footnotes.

2.1 Method I: Emergency Response Inference Mapping (ERIMap)

Schneider, M., Halekotte, L., Comes, T., Lichte, D., and Fiedrich, F., (2025). Emergency Response Inference Mapping (ERIMap): A Bayesian network-based method for dynamic observation processing. Reliability Engineering and System Safety. DOI: 10.1016/j.ress.2024.110640.

2.1.1 Aim and Motivation

The aim of this work was to develop a method for the comprehensive processing of observations typically available in emergencies[1], in order to draw spatial inferences – addressing RQ1. For the development of this method, the typical information-scape in emergencies is defined via the following six requirements that serve as guiding principles of its design: A method should be capable of deriving spatial inference about key variables of an ongoing emergency by processing information which is incomplete (R1: process *incomplete* information), which potentially stems from diverse sources (R2: process information from *diverse sources*), which contains uncertainty (R3: process *uncertain* information) and potentially contradictory observations (R4: process *contradictory* information), which evolves dynamically in time (R5: process *dynamic* information), and which is spatially

[1] In this work, the term emergency is used, but it refers to both emergencies and disasters.

distributed (R6: process *spatial* information). To enable the rapid handling of observations exhibiting all the aforementioned properties, the method is designed to provide a structured approach for their systematic classification and processing. This, in turn, allows for the integration of the evidence provided on the nodes in the BN to draw area-specific inference on the target node.

2.1.2 ERIMap Method

The *ERIMap* method is composed of two phases: the *preparation phase* which takes place before an event and the *operation phase*[2] which describes the application of the method during an emergency. The first step of the preparation phase is the construction of a BN model for the intended area of application and objective. The BN should include all variables that are key for decision-making in a specific emergency (e.g. a flood or a forest fire scenario) as well as variables that directly or indirectly influence (the belief about) these key variables. In the second step of the preparation phase, the spatial resolution for the emergency consideration is specified – i.e. areas are specified which should be assessed individually. Depending on the case, these areas can, for instance, correspond to districts, buildings, or specific point locations. To enable spatial inference, a duplicate of the initially constructed BN is assigned to each area. In the operation phase, new observations are classified, processed, and fed into the area-specific BNs according to a specific workflow that constitutes the core of the method. Given a new observation, it is first assigned to the respective *area*-specific BN(s) and then to the *node* which is addressed in this observation. Afterwards, the method classifies the type of evidence (hard, soft, or virtual) – which can be processed in a BN via specific protocols – based on a reliability score (e.g. RS_1: Small Reliability; RS_2: Medium Reliability; RS_3: High Reliability) of the observation source and on the reported *node state(s)*. Thus, in total, five pieces of information are required for each observation to classify it into the correct type of evidence that can be processed in the area-specific BNs, namely the location, the node, the state(s), the reliability score, and the time. Subsequently to this classification, a belief update for all key variables in the BNs of the respective areas is performed. The operation phase ends when all key variables are confirmed.

2.1.3 Case Study

The case study of this work is developed in cooperation with the plant fire brigade of the German chemical company Henkel. A chemical plant site inspired by one of Henkel's sites is used as geographical setup. The scenario in this case study is triggered by an accident between a truck and a tank wagon on a railway at a junction on the site. The accident leads to a gas leak, resulting in the dispersion of potentially hazardous gas across the site. Accordingly, the hazard map for this case study is a layer representing the expected gas dispersion and its concentration over the area – derived from a simulation conducted using the software ALOHA. In such an emergency, various additional sources of observations, beyond the hazard map, can be expected to cover the full information-scape of the emergency. For example, sensors may be used to detect critical gas levels, and emergency responders may inspect buildings. Thus, in this case study, a dynamically

[2] The operation phase corresponds to the response phase of the spatial inference framework.

evolving and spatially heterogeneous emergency situation is used to illustrate how the *ERIMap* method can support the evaluation of the emergency by performing spatial inference based on a set of diverse observations. The BN introduced in the case study consists of six variables and five edges, including the target node *People in Building Affected*. To enable spatial inference, the BN is duplicated and assigned to each building on the plant site, allowing the estimation of the probability that people in each building may be affected by the gas. A synthetic sequence of observations is created, including observations from various sources (such as sensors or eyewitnesses), each with different reliability scores and relating to specific building(s) at a given point in time. This sequence is used to compute the belief on the target variable for each building at multiple time steps. The final output, the *ERIMap*, is a dynamically evolving, spatially resolved map of beliefs regarding the target variable, which is updated each time a new observation becomes available (see Figure 2.1 that shows six time steps).

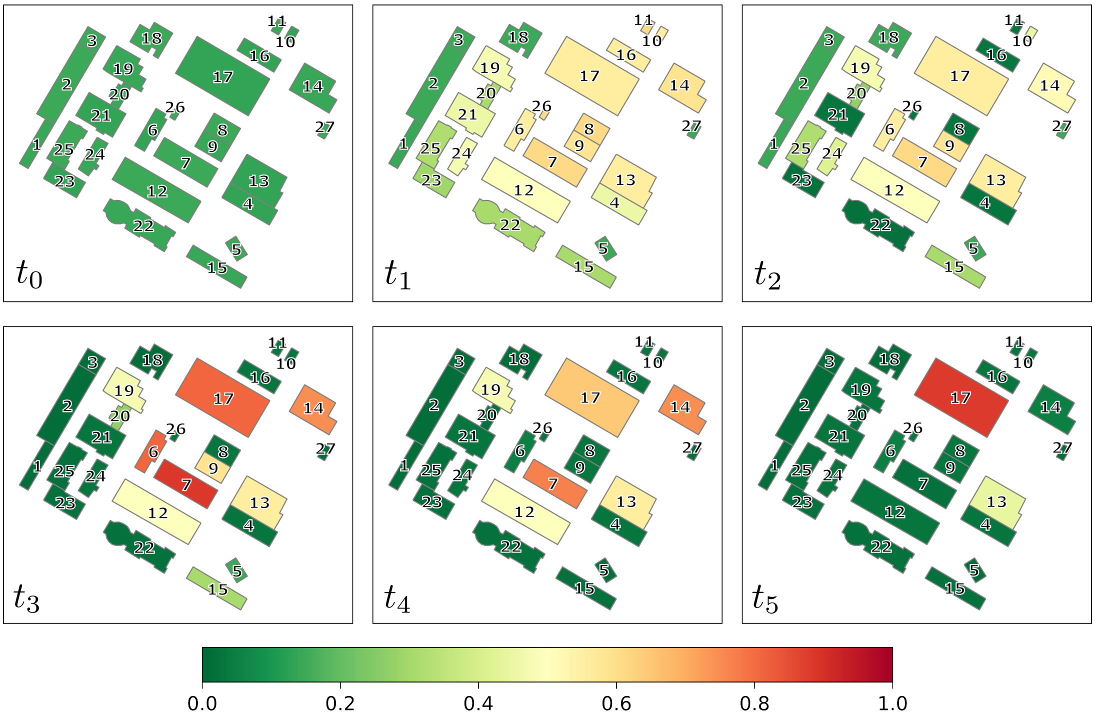

Figure 2.1: The *ERIMap* of the case study illustrates the probability of the building-specific BN target node *People in Building Affected* being in the state *True* across six time steps ($t_0 - t_5$), each incorporating newly collected and processed observations.

2.2 Method II: Dependent Infrastructure Service Disruption Mapping (DISruptionMap)

Schneider, M., Halekotte, L., Mentges, A., and Fiedrich, F., (2025). Dependent Infrastructure Service Disruption Mapping (DISruptionMap): A method to assess cascading service disruptions in disaster scenarios. Scientific Reports. DOI: 10.1038/s41598-025-89469-0.

2.2.1 Aim and Motivation

The aim of this work was to develop a method for assessing direct and indirect (cascading) CI disruptions in large-scale disaster scenarios through spatial inference, focusing on an accessible approach that facilitates the modelling of complex CI dependencies – addressing RQ2. While CI dependencies can take various forms, such as physical, cyber, informational, political, or service-centred, this work follows a service-centred approach to enable a uniform description of dependencies between CIs, based on the services they provide to each other and to society. As CIs often extend across or supply large geographical areas, their failures can cause direct service disruptions far from the immediate location of the disruptive event. Additionally, CI services can be affected by complex indirect (cascading) disruptions, as they are part of a SoS of CIs with high dependencies across sectors. Given the complex nature of CIs and their dependencies, and the resulting challenges in modelling them, the method is designed in a way that balances the level of detail in modelling service disruptions during large-scale disaster scenarios with the data requirements for model setup. The design should ensure applicability across diverse CI configurations and disaster scenarios.

2.2.2 DISruptionMap Method

The *DISruptionMap* method requires addressing the following information requirements before constructing the corresponding models: i) determine the hazard to which the method will be applied and the impact measure (IM) used to quantify its severity; ii) obtain geospatial data showing IM intensity levels in the study area; iii) select a target critical infrastructure (TCI) as the focus (i.e. end of the cascading effect chain) for analysing dependencies; and iv) collect spatial data on TCI locations and relevant CI components. Given these four bits of information, the *DISruptionMap* method can be applied. The key steps in applying the proposed method are: first, constructing the BN representing the *Service Dependency Model* of the TCI, guided by the question "*Which services must function for the TCI (and dependent CI) service(s) to operate?*", with dependent CI services as nodes and their dependencies as edges. The Conditional Probability Tables (CPTs) of the dependent nodes are populated using an approach that translates fault trees into CPTs. This approach simplifies the determination of probability values in the CPTs by expressing CI service dependencies through logical gates, which are easier to handle. In addition, a node must be added in the BN to consider the direct disruption of the hazard's IM on the TCI service, i.e. a direct parent node of the TCI node. Finally, the BN is duplicated and assigned to each TCI in the study area. The leaf nodes of the TCI-specific BNs represent potential starting points of cascading effects (e.g. accessibility). For each leaf node, a model must be developed to assess the effect of the IM on CI components and ultimately determine service availability, resulting in the *Spatial Service Models*. In combination, the two models – spatial service models informing the TCI-specific dependency models – enable the assessment of both direct and indirect CI service disruptions in the study area, given a hazard map. Ultimately, the results are presented in the *DISruptionMap*, offering a comprehensive summary of the spatially inferred information on service disruptions for all TCIs in the study area.

2.2.3 Case Study

The case study of this work is conducted in Cologne (Germany), focusing on emergency care service availability by hospitals as TCI service. Cologne's high concentration of CIs make it a relevant and complex study area to illustrate how the *DISruptionMap* method can support the assessment of cascading CI service disruptions that may lead to the failure of emergency care services. The scenario in this case study involves an extreme river flood event from the Rhine river, which flows directly through the city centre. Accordingly, the hazard map for this case study is based on a hydrological simulation representing an extreme flood scenario (referred to as HQ500), which provides spatially explicit information on flood depth, which constitutes the IM. All other geospatial data used in the case study were retrieved from OpenStreetMap (OSM), for example to reconstruct the road network or identify the locations of hospitals. The BN introduced in the case study consists of six variables and six edges, including the target node *Emergency Care* (service availability), as well as variables such as hospital accessibility and power supply. To enable spatial inference, the BN is duplicated and assigned to each hospital in the study area, allowing the hospital-specific assessment of emergency care service availability. The final output, the *DISruptionMap*, displays the availability status (available, uncertain, or failed) of emergency care services at each hospital, along with the CI services (accessibility and power supply) on which they depend (see Figure 2.2).

2.3 Method III: Prioritisation Recommendation Mapping (PrioReMap)

Schneider, M., Halekotte, L., Comes, T., and Fiedrich, F., (2026). Prioritisation Recommendation Mapping (PrioReMap): A method for supporting relief coordination in flood disaster response. International Journal of Disaster Risk Reduction. 10.1016/j.ijdrr.2025.105949.

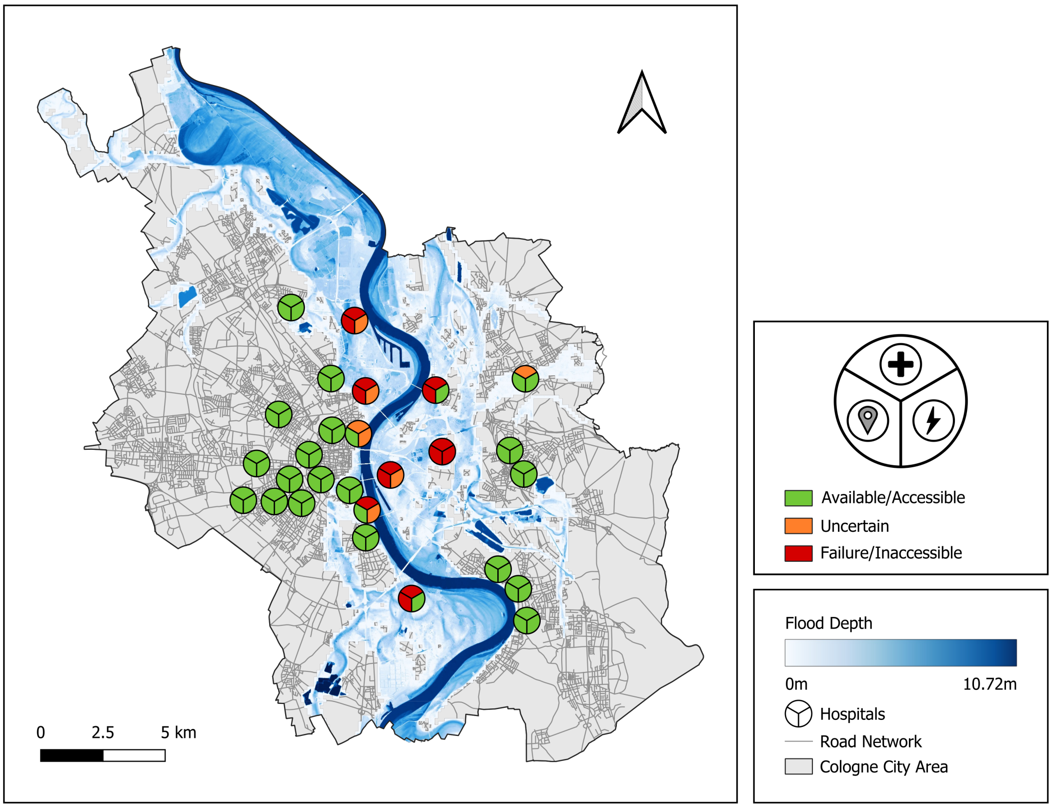

Figure 2.2: The *DISruptionMap* of the case study illustrates the availability of the services *Emergency Care*, *Power Supply*, and *Accessibility* for each hospital in the study area of Cologne, Germany. Each service can be classified as available, uncertain, or failed, providing a comprehensive overview of hospital-specific service availability.

2.3.1 Aim and Motivation

The aim of this work was to develop a spatial inference method to support relief coordination in flood disaster response[3] by providing recommendations for area prioritisation – addressing RQ3. This work is motivated by the information-scape typically available in the early stages of a flood disaster, when the actual extent of impact is often uncertain or not yet fully realised. As a result, operational impact assessments must be risk-based – relying on available proxy data to estimate where the impact is expected to be greatest. Accordingly, decision-makers must process large volumes of diverse and potentially volatile information within a limited timeframe in order to assess area-specific risks and prioritise areas most dependent on aid for the initiation of relief efforts. This combination of both versatile and numerous information, along with the need for rapid, risk-based area prioritisation, can result in cognitive overload for decision-makers, potentially hampering their capacity to manage disaster response efforts efficiently. To reduce the cognitive load on decision-makers in disaster response, the proposed method aims for a novel prioritisation recommendation method that is based on a spatial inference model tailored to the information-scape in an ongoing flood disaster.

[3]The presentation of the method focuses on floods to align with the journal's domain focus; however, it can also be applied to other types of large-scale disasters.

2.3.2 PrioReMap Method

The preparation phase of the *PrioReMap* method is composed of three main components[4]: (i) the GIS models to provide spatially explicit observations of the critical variables characterising the *Hazard*, *Exposure*, and *Vulnerability* in a flood disaster scenario; (ii) the BN used to infer the probability of the target node called *Risk of People in Need of Assistance* based on the critical variables; and (iii) the prioritisation method that translates the area-specific probability distribution of the BN target nodes into area prioritisation recommendations. To enable spatial inference at the level of individual areas, the study area is entirely partitioned into a grid of hexagonal tiles. The geospatial models generate tile-specific observations for decision-critical variables that describe the *Hazard*, *Exposure*, and *Vulnerability*. The BN is organised such that the decision-critical variables form the lead nodes, while *Hazard*, *Exposure*, and *Vulnerability* are their direct child nodes. Together, these three child nodes determine the single target child node, the *Risk of People in Need of Assistance*. Using the tile-specific probability distributions of the target node as input, the prioritisation recommendation method is applied. This method is based on an expected loss framework that balances probability and consequences. The idea of the expected loss framework is to compare different candidate actions in terms of the loss incurred if they are chosen. In the context of disaster response, this loss can be quantified using allocation-equivalent hours, defined as the delay (e.g. in hours) by which relief resources arrive after the critical time threshold. Applying the expected loss framework results in a queue of tiles ordered in descending priority. Subsequently, waves are defined as consecutive blocks of a specific size K in this global ranking, providing a transparent and interpretable prioritisation sequence for phased response under limited resources. These waves serve as the final prioritisation recommendations, i.e. which tiles to approach first. In the response phase, information about the current flood is fed into the corresponding geospatial models that inform the tile-specific BNs to generate the final prioritisation recommendations. Finally, the results of the *PrioReMap* method are displayed on a map, the *PrioReMap*, with all tiles in the study area coloured according to their prioritisation recommendation.

2.3.3 Case Study

The case study of this work is conducted in Cologne (Germany), showcasing how the *PrioReMap* can be applied during a flood response to provide recommendations of areas where people are in particular need of assistance. Cologne's dense population makes it a relevant and complex study area to illustrate how the *PrioReMap* method can support the prioritisation of areas facing the highest flood risk. The scenario in this case study involves an extreme river flood event from the Rhine river, which flows directly through the city centre. Accordingly, the hazard map for this case study is based on a hydrological simulation representing an extreme flood scenario (referred to as HQ500), which provides spatially explicit information on the flood depth across the city. All other geospatial data used in the case study were retrieved from OSM (e.g. to reconstruct the road network) and from census data for population information. In the case study, the BN introduced

[4]In the journal article, the construction of the models (BN and spatial models) is presented as part of the method rather than the case study; however, the models can be adjusted for a different case study if required.

in the method is applied, as well as the geospatial models informing the tile-specific BNs that cover the whole city of Cologne. Based on the tile-specific probability distributions of the target nodes and the expected loss framework, each tile is assigned a prioritisation recommendation. The final output, the *PrioReMap*, displays the recommendations for area prioritisation in the study area according to the prioritisation waves of size $K = 200$ (see Figure 2.3).

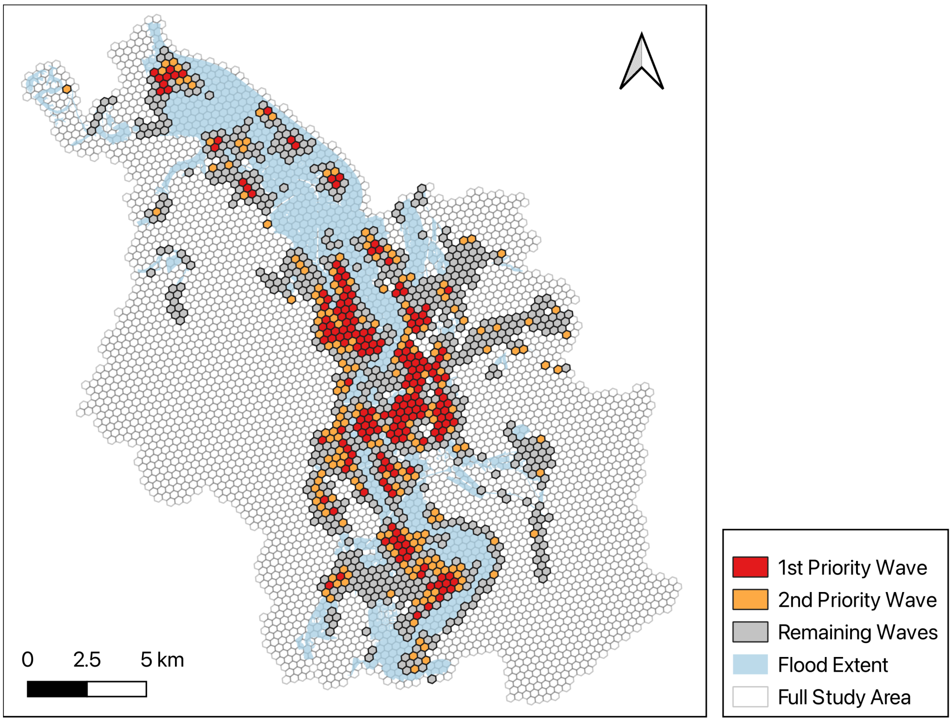

Figure 2.3: The *PrioReMap* of the case study displays the first and second priority waves as well as the remaining (exposed) waves of hexagons covering the study area of Cologne, Germany.

3 | Discussion

In the first part of this chapter, the key contributions of this thesis are outlined and discussed by reflecting on the three individual methods presented and their relation to the research questions. While each method is presented as a stand-alone approach built on a shared spatial inference framework, they focus on different stages of the observation processing chain: from observation inputs, through the assessment of cascading effects, to the provision of prioritisation recommendations. The chapter then discusses the implications of this thesis for the respective research fields and concludes by outlining its limitations and highlighting promising directions for future research.

3.1 Key Contributions

The main RQ of this thesis addresses the objective of formalising the process of deriving spatial inference on decision-critical variables during the less time-sensitive preparation phase to enable rapid and explainable inferences during the time-critical response phase. To prepare for performing spatial inference on decision-critical variables, three consecutive steps are introduced in the framework of this thesis (see Section 1.3.2) and implemented in each proposed method: (I) a BN is constructed to support inference about the state of the most decision-critical variable for DRM, represented by the target node in the network (e.g. the presence of people in need of assistance or the availability of a critical CI service); (II) to enable the spatial inference, the BN is duplicated and assigned to distinct areas (e.g. tiles or buildings) that can thus be individually assessed; and (III) geospatial (GIS) models are developed that provide area-specific evidence on the leaf nodes of the BN (e.g. to identify the use of a building or assess the accessibility of an area by the road network). Using this combination of area-specific geospatial models and a BN, spatial inference can be performed based on observations collected during the response phase of an ongoing disaster.

The development of the required models (BN and geospatial) during the *preparation phase* serves as an early walk-through of the decision-making process typically carried out in the disaster response phase. Addressing the questions involved in model development, such as identifying the variables critical to assess disaster risk, understanding their (often uncertain) dependencies, and determining how some variables can be informed by geospatial models, is a complex and time-consuming task. However, when performed in advance, it enables a more rapid assessment of the disaster situation and condenses the information to what is most critical for decision-making. In disaster contexts, empirical data related to these questions is often scarce (Kreibich et al., 2022). As a result, relevant knowledge is typically only available implicitly through experts and practitioners (Sahoh and Choksuriwong, 2023), often necessitating the involvement of multiple experts (Zheng et al., 2020). In the development of a BN – which forms the core of the inference method to condense all available information – elicited expert knowledge can be easily integrated in the variables of the BN, their states, and their dependencies, which are quantified in the CPTs. Even when multiple experts are involved, existing tools and methods facilitate the translation of expert knowledge into a BN (e.g. see Nyberg et al., 2021). In addition to the process of integrating knowledge into the BN, which enhances transparency in how the model is designed, a BN is inherently an explainable model (Derks and Waal, 2020) and is sometimes referred to as a form of explainable AI (Sahoh and Choksuriwong, 2023).

As stated in the main research question, the aim is to support DRM while intentionally leaving the type of disaster unspecified, as the methods should be applicable to various types of disasters. It is therefore important to ensure the transferability of the spatial inference framework to different types of disasters in order to address this RQ. The proposed framework is applied in each of the three individual case studies presented in this thesis. These case studies involve different types of disasters: a human-induced disaster (a gas leak caused by an accident in the *ERIMap* case study) and a natural disaster (the flood scenarios in the *DISruptionMap* and *PrioReMap* case studies). Moreover, each case study has its own objective, resulting in its own BN used to infer a specific decision-critical variable at a particular spatial resolution: affected people across all buildings in an area (*ERIMap*), service availability across single hospitals in an area (*DISruptionMap*), and people in need of assistance across tiles covering the full area (*PrioReMap*). Finally, to further explore the applicability of the framework to different hazard map data types, which form the main observations informing the area-specific BN leaf nodes, the case studies utilise two different types of hazard map inputs: in the gas leakage scenario, multiple polygon layers represent varying gas concentration levels, while in the flood scenario, a raster layer is used to provide continuous information on flood depth. This variety across case studies demonstrates the transferability of the proposed spatial inference framework not only across different types of disasters, but also across varying objectives, spatial resolutions, and hazard map types – ultimately underscoring its broad applicability for supporting decision-making in DRM.

RQ1 is dedicated to the process of how to draw spatial inference based on observations that are typically available during disasters. This RQ is particularly addressed in the *ERIMap* method. The design of this method was guided by the typical information-scape that is available during disasters, described by six properties of a typical observation; they can be: incomplete, origin from diverse sources, uncertain, conflicting, dynamic, and spatially distributed. To enable the structured and rapid integration of diverse observations into the model, the *ERIMap* method defines five key pieces of information that allow for a uniform description of any observation, regardless of its specific properties. These include: the node and its state to which the observation refers, the reliability of the observation (expressed as a score), the geographic location it pertains to, and the time at which it was made. In this way, an interface is established between the variety of observations typically encountered in an emergency and the underlying BN model. To integrate the observations into the spatial inference process while accounting for their properties, a procedure is introduced that classifies observations into three types of evidence that can be considered in a BN: hard evidence (the exact state is known), virtual evidence (evidence with uncertainty), and soft evidence (evidence of uncertainty) (Ben Mrad et al., 2014; Peng et al., 2010). This classification is especially important to prevent overconfidence in the inference results when dealing with uncertain inputs. This is particularly critical when uncertain evidence suggests the absence of risk, as this can easily lead to misleading conclusions if not properly handled – such as an uncertain eyewitness report suggesting that a building has been evacuated. If treated incorrectly, such evidence could lead to the premature conclusion that no people remain in the building and no assistance is needed, despite the uncertainty of the observation. To further account for and avoid overconfidence – which is especially critical in high-stakes decision-making – a regret function is applied in the method, serving as a precautionary principle: emphasis is placed on the node state that is more critical (e.g. people are in the building). In this way, the *ER-IMap* method provides a versatile approach for incorporating a variety of heterogenous observations considering uncertainty and avoiding overconfidence.

RQ2 is dedicated to the assessment of cascading effects of CI services using spatial inference. This RQ is particularly addressed in the *DISruptionMap* method. The development of this method was driven by the requirement to enable the assessment of direct disruptions to a CI service caused by a hazard, as well as indirect (cascading) disruptions caused by the failure of other, dependent services. To achieve this, a target CI (TCI) service is identified that represents the end of the cascading effect chain. Using the TCI as the basis for tracing dependencies simplifies the identification process by clarifying which services are required to sustain it. This is modelled in the BN, where services constitute the nodes and the edges represent the respective dependencies. While quantifying these dependencies can become highly complex due to the often high connectivity of CI services (Rinaldi et al., 2001), a central motivation behind developing the *DISruptionMap* method was to simplify the quantification of the dependencies represented in the BN's CPTs – estimating these probability values is widely recognised as one of the most challenging aspects of BN development (Druzdzel and Gaag, 2000). The key approach to facilitate this quantification is the use of fault trees, which can be converted into a BN (Bobbio et al., 2001). Fault trees, which express dependencies using logic gates, are significantly easier to work with than manually specifying the probability values for the CPTs – particularly for users who are not familiar with BNs. In this way, the *DISruptionMap* method offers a versatile approach to spatially infer cascading CI service disruptions in disaster scenarios for a target CI service, balancing complexity of quantifying CI dependencies with the data to set up the corresponding model.

RQ3 is dedicated to the derivation of area prioritisation recommendations based on spatial inference. This RQ is particularly addressed in the *PrioReMap* method. When building on the results of spatial inference provided by area-specific BNs, it is important to first clarify what these results typically look like: the outcome of BN-based spatial inference consists of area-specific probability distributions of the target node. However, this type of result presents two significant issues, which were demonstrated using a low-dimensional example in the contribution introducing the *PrioReMap* method: (I) it is important to consider the full probability distribution to gain a comprehensive understanding of the risks involved – which increases the cognitive load on decision-makers and extends the time required to interpret the results; and (II), aggregating the probability distribution into a single variable (the recommendation) involves assigning weights or preferences to the node states – which can lead to different recommendation outcomes when performed by different users. The *PrioReMap* method addresses these issues by following a transparent approach that utilises an expected loss framework to compare multiple actions in terms of the loss of allocation-equivalent hours. Based on this comparison, tiles can be ordered in a queue of descending priority. Finally, this queue provides an easily interpretable basis for the resulting recommendations, thereby extending the typical results of probabilistic spatial inference into unambiguous recommendations that ensure transparent and actionable decision support.

3.2 Synthesis of the Methods

All three methods presented in this thesis follow the same spatial inference framework (see Section 1.3.2). As such, they all rely on a combination of a BN with geospatial models, which provide evidence for area-specific BN duplicates that can be further enriched with additional evidence resulting from observations, such as sensor data or eyewitness reports. This shared methodological core makes their synthesis into an overarching method feasible by design, where all methods sequentially condense the potentially high volume of incoming observations into distinct prioritisation recommendations (illustrated by the cone in Figure 3.1). In a combined method, the *ERIMap* method provides the interface between the outside world, handling observations of an ongoing disaster, and the spatial inference model (see upper part of the cone on Figure 3.1). Based on the five key pieces of information required to process an observation in an area-specific BN, any type of observation that provides evidence about a variable in the BN can be included, regardless of its source, level of uncertainty, or the time and location it was collected. The *DISruptionMap* method can build on the observations processed by *ERIMap* by enabling the assessment of cascading effects in CI services within the area-specific BNs (see middle part of the cone on Figure 3.1). By following a low-data and easy-to-elicit approach, the method allows for the inclusion of a large number of dependent services in the analysis. Additionally, observations unrelated to CI services can be handled either in a separate BN or within a shared BN that includes both service-related variables and others, such as the presence of people. Finally, the *PrioReMap* method can build on the probabilistic spatial inference fed by *ERIMap* and enriched by *DISruptionMap*, ultimately providing area prioritisation recommendations that support informed decision-making in DRM (see lower part of the cone on Figure 3.1).

3.3 Implications for the Research Fields

The methods presented in this thesis have implications for the research fields of DRM, BN, and GIS (see Section 1.3.1). In particular, the motivation behind these methods highlights broader implications for DRM research regarding how decision support is conceptualised under conditions of increasing data availability. While advances in areas such as remote sensing, simulation, ICT, and data mining continue to expand the volume of

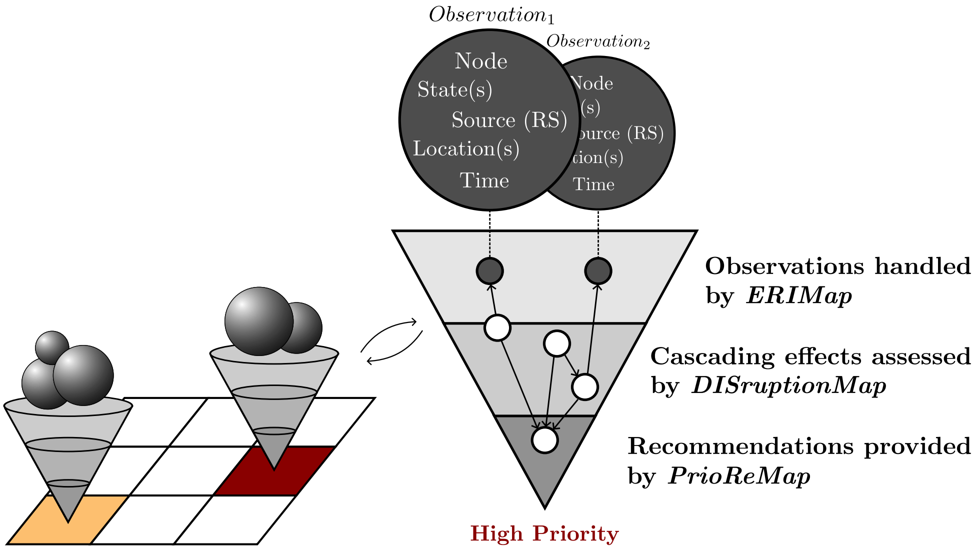

Figure 3.1: The synthesis of the methods presented in this thesis results in a combined spatial inference model (represented by the cone) that handles area-specific observations using *ERIMap*, assesses cascading effects using *DISruptionMap*, and provides recommendations using *PrioReMap*. In this way, the entire process, from processing new observations, to performing spatial inference, to generating recommendations, can be covered.

potentially relevant information for decision-making in DRM, the fundamental challenges of high stakes, time pressure, and cognitive load remain. Handling an increasing volume of information in such a demanding context is both a delicate and critical challenge for effective decision support. The methods developed in this thesis address this challenge and demonstrate that spatial inference can play a key role in structuring this information. This implies a shift in emphasis from providing *more information* towards generating *actionable information* that supports timely and well-founded decisions under uncertainty. In this context, the proposed methods highlight the importance of explainable decision support approaches that make inference processes transparent and interpretable, enabling decision-makers to understand not only what is inferred, but also why. Rather than continually expanding the set of spatially explicit information layers, DRM research should place additional emphasis on developing such spatially inferred layers that synthesise heterogeneous observations into coherent, decision-relevant representations.

In addition, this thesis has implications for spatial inference research by highlighting the complementary roles of GIS and BN-based inference in supporting decision-making in DRM. GIS contribute capabilities that are crucial in DRM, most notably the structured management of spatial data and the explicit representation of geometry, topology, and spatial proximity. Bayesian networks, in turn, contribute capabilities that a GIS alone typically does not provide, including an explicit treatment of uncertainty, the modelling of dependencies between variables, and a mechanism for updating beliefs as new evidence becomes available. Bringing these two approaches together allows that decision-relevant but not directly observable variables – often of central importance in DRM – such as vulnerability, risk, or urgency, can be represented explicitly as inferable variables. Importantly, this integration also points to a pathway towards explainable spatial decision support: the GIS component establishes where inference applies in space (the disaster scene) and provides spatially explicit data, while the BN makes the reasoning process – based on that data – transparent through belief updates driven by evidence and probabilistic dependencies. For both the GIS and BN research fields, this implies that a promising research direction in their integration lies not in a loose coupling of existing tools, but in designs in which GIS informs BN-based spatial inference at multiple levels, and BN inference results – together with their explainable structure – are treated as spatial layers that can be explored, interpreted, and visualised within a GIS environment.

3.4 Limitations and Future Research

As with any novel methodological approach, it must be acknowledged that the spatial inference framework and the associated methods presented in this thesis are subject to certain limitations that are important to understand, particularly when applying the approach in practice. While these limitations pose challenges, they also highlight intriguing opportunities for future research. In the following, the two key limitations of the proposed framework – one primarily methodological and the other primarily application-oriented – are outlined, along with corresponding directions for future research.

The key methodological limitation of the spatial inference framework lies in its dependence on the variables defined during the preparation phase. In the response phase, the inferences that can be drawn are limited to those variables explicitly included in the structure of the BN (as nodes). Each observation must correspond to a node in the BN; otherwise, it cannot yet contribute to the analysis, even if it holds relevant information for decision-making. Therefore, it is essential that stakeholders involved in the model development carefully identify all variables that may become relevant during a disaster, as the framework formalises their perspective of the disaster landscape. The effectiveness of the framework thus ultimately depends on the quality of this pre-existing structural knowledge of the decision-making process during a disaster. Since the model must be set up before an actual event occurs, it is particularly well suited for predictable or recurring disaster types in well-understood and structured environments.
To address this limitation, future research should focus on developing structured protocols or workshop formats to ensure that all decision-critical variables and their dependencies are identified during the preparation phase. The key to ensuring a comprehensive identification of these variables and their dependencies is a systematic approach that helps stakeholders think through and identify the full range of variables that could become decision-critical during a disaster. Similar efforts have been made in other DRM studies. For example, Bruijn et al. (2015) introduced the storyline approach, which guides expert workshops through the full timeline of a flood event to uncover key interactions, assess vulnerabilities, and co-develop effective risk management strategies. Similarly, scenario analysis based on morphological analysis is widely used in a variety of domains, including safety and security studies (Johansen, 2018; Álvarez and Ritchey, 2015), where participants also identify variables and their potential states for future scenarios. Ritchey (2011) further outlines how workshop design can ensure comprehensive variable elicitation. A similar workshop format should be adapted to support the development of the models – particularly the BN – in the proposed spatial inference framework, helping to ensure both

the completeness of variable selection and a shared understanding of the model structure among stakeholders. Nevertheless, it is important to emphasise that the framework is designed to support – not replace – human decision-making. In complex, large-scale disasters, unexpected variables may always emerge that were not accounted for during the preparation phase. The framework should therefore be seen as a complementary tool, offering structured insights that enhance, rather than substitute, other sources of information and expert judgment during disaster response.

The key application-oriented limitations concern the effective integration of the proposed methods into the operational structures of decision-makers who would apply them in practice. While the presented work outlines the methods and includes case studies illustrating how the resulting inferences can look like in relevant disaster scenarios, it does not address the technological tools required to support operational deployment, such as data pipelines or user interfaces. Moreover, the work does not provide guidance on how these methods should be embedded within existing command structures or decision-making workflows. In particular, questions remain regarding responsibility for maintaining and updating the methods as new information becomes available, the timing and frequency of such updates, and the identification of which actors within the operational command structure should receive, interpret, and act upon the resulting inferences or recommendations. Addressing these issues is critical for translating the proposed framework from a research setting into effective operational use.
Accordingly, an important direction for future research is the systematic transfer of the proposed methods into operational practice, with particular attention to the socio-technical requirements implied by the limitations mentioned above. First, future work should focus on developing and validating the technological tools needed for deployment – most notably robust data pipelines and a user interface (e.g. a mobile application) that enables rapid injection of new observations and visualises inference outputs on an interactive map. Additionally, such a tool should enable users to inspect not only prioritisation recommendations but also the underlying reasoning of the spatial inference. Second, research is needed to embed the methods within existing DRM protocols and command structures by specifying operational workflows and governance. Third, these implementation and integration choices should be evaluated empirically in near-operational settings – such as structured training exercises, field simulations, or serious games – across multiple disaster scenarios to assess generalisability, and to quantify effects on situation awareness and decision-making.

In conclusion, the presented spatial inference framework and its associated methods provide a strong foundation for future work, both in advancing methodological research and in supporting the development of practical applications. While this thesis establishes the feasibility and potential value of the proposed approach, further progress will depend on sustained methodological refinement and on meeting the requirements for its integration into operational decision-making contexts. Addressing these aspects will be essential for moving the proposed methods beyond a research setting and towards effective use in real-world DRM.

4 | Conclusion

This thesis addresses the growing need for intelligent and explainable decision support methods in disaster risk management (DRM), with a focus on supporting decision-making in the disaster response phase. Its overarching purpose is to introduce methods that transform all available, spatially explicit observations into decision-relevant information. This is essential because DRM decision-making is often characterised by high stakes, substantial time pressure, and large volumes of information that result in high cognitive load. Accordingly, effective decision support must deliver results rapidly, remain transparent and explainable, and condense information to what is decision-critical. To tackle these demands, the main research objective of this thesis is to:

> *Formalise the process of deriving spatial inference on decision-critical variables during the less time-sensitive preparation phase, enabling rapid and explainable inferences during the time-critical response phase.*

The methods developed and presented in this thesis all address this main objective, while each adds a specific focus – captured in individual research questions (RQs) – that corresponds to successive steps in the information-processing chain. The first method, *ERIMap*, focuses on how diverse observations typical of an emergency situation can be translated into evidence for spatial inference (RQ1). The second method, *DISruptionMap*, focuses on how cascading service disruptions can be spatially inferred based on such observations (RQ2). The third method, *PrioReMap*, focuses on how area prioritisation recommendations can be derived from the results of spatial inference (RQ3). Although each method is developed and presented as a stand-alone approach, their shared methodological core – a GIS-informed Bayesian network (BN) – allows them to be combined to cover the comprehensive processing chain from observation input to recommendation output. Individually and collectively, the methods presented in this thesis contribute to research on the explicit integration of GIS and BNs for spatial inference, addressing the domain-specific requirements and challenges of decision support in DRM.

In terms of applying the methods, three case studies were conducted, covering different hazard scenarios, spatial scales, and decision objectives. As a case study for *ERIMap*, a safety hazard is considered – namely a gas leak leading to gas dispersion across a chemical plant site – with the objective of identifying the buildings with the highest probability of people being affected. For *DISruptionMap*, a different case study is examined: an extreme river flood scenario in the city of Cologne (Germany), in which individual hospital buildings are analysed in terms of service availability. Finally, for *PrioReMap*, the same hazard (extreme river flood) and study area (Cologne) are used, but with a hexagonal grid covering the full study area to prioritise tiles where the risk of people in need of assistance is highest. Overall, these case studies demonstrate that the proposed spatial inference framework can be applied across diverse hazard scenarios, spatial dimensions, and decision objectives.

Nevertheless, the case studies also highlight key limitations that should be considered when transferring the proposed methods in practice. In particular, the construction of the BN requires domain knowledge, which makes the application better suited to terrains and decision objectives that are well known to decision-makers. A related constraint is that only variables that are explicitly defined and incorporated during the construction of the BN in the preparation phase can be considered during model application in the time-critical response phase, thereby constraining the scope of inference to the predefined BN structure. For these reasons, future work should focus on enabling the robust use of the proposed methods in practice. This includes the development of structured formats that support comprehensive BN construction during the preparation phase, ensuring that all relevant variables are considered, as well as the establishment of protocols for integrating new observations during model application and for incorporating model outputs as a coherent decision support system within operational command structures.

In summary, this thesis contributes novel, intelligent, and explainable methods for spatial inference to support decision-making in DRM. By integrating probabilistic modelling based on BNs with spatial analysis, the work demonstrates how large volumes of complex, risk-related information can be processed to infer decision-relevant variables under uncertainty. Overall, the thesis provides a foundation for further methodological and practical advances in decision support for DRM and related high-stakes domains.

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Appendix

A | Publication I

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Emergency Response Inference Mapping (ERIMap): A Bayesian network-based method for dynamic observation processing

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ABSTRACT

In emergencies, high stake decisions often have to be made under time pressure and strain. In order to support such decisions, information from various sources needs to be collected and processed rapidly. The information available tends to be temporally and spatially variable, uncertain, and sometimes conflicting, leading to potential biases in decisions. Currently, there is a lack of systematic approaches for information processing and situation assessment which meet the particular demands of emergency situations. To address this gap, we present a Bayesian network-based method called *ERIMap* that is tailored to the complex information-scape during emergencies. The method enables the systematic and rapid processing of heterogeneous and potentially uncertain observations and draws inferences about key variables of an emergency. It thereby reduces complexity and cognitive load for decision makers. The output of the *ERIMap* method is a dynamically evolving and spatially resolved map of beliefs about key variables of an emergency that is updated each time a new observation becomes available. The method is illustrated in a case study in which an emergency response is triggered by an accident causing a gas leakage on a chemical plant site.

1. Introduction

Situation awareness is crucial to emergency response. To improve the awareness of the situation, information from various sources is collected, assessed and combined [1,2]. In emergency response, the process of building situation awareness often has to be performed under time pressure, even though the stakes are extremely high [3–5]. What is more, emergencies usually are complex situations which are characterised by a multitude of spatially distributed and dynamically evolving factors. Accordingly, heterogeneous and uncertain information about very different aspects needs to be continuously combined [6] to understand the situation on the ground, and its implications for people and livelihoods. To be sure, analysing the situation is a continuous process that is interlaced with decision making [7]: as decision makers assess their options, new information becomes available to which plans need to be continuously adapted [6].

Automated or semi-automated methods to support emergency decision making need to reflect this combination of complexity and urgency [8]. We aim for a method that strikes a balance in this area of tension and is therefore able to inform emergency responders in near real-time during emergencies. This implies that the method must be able to handle (i.e. classify and process) the volatile and heterogeneous information-scape that is available during emergencies, and it needs to do so under considerable time pressure. These requirements are in stark contrast to related methods for post-disruption analyses that typically show less time-constraints (e.g. see [9,10] or [11]) and allow data to be collated and pre-processed over a longer period of time.

1.1. Information-scape in emergency response

Emergencies have widely been described as events that challenge conventional information processing, decision-making and coordination [12–14]. Therefore, the methods to address emergencies need to be tailored to this context. To address the specific information-scape that is characteristic for emergencies and to ensure that the resulting method can be applied in a variety of emergency response contexts, we analyse the emergency response literature and derive a set of six requirements (R1-R6) that need to be fulfilled *together*. These six requirements are geared to ensure versatile and comprehensive processing and mapping of the information that becomes available during emergency situations. In the following, we present the six requirements, each with a brief justification from the literature.

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In an emergency, the information available typically presents a fragmented description of the actual situation. Especially in the initial stages of an emergency, information is often scarce or incomplete [15,16]. A suitable method needs to be capable of providing meaningful insights [17,18] based on limited or incomplete information, which leads us to requirement **R1:** process *incomplete* information.

Further, emergencies are characterised by a plethora of information sources, from which data needs to be rapidly combined [19]. This entails combining information about the background (such as built environment [20], topography [21] or socio-economic information [22,23]) as well as volatile information about damage and risk (e.g., satellite imagery [24], sensor data [25,26], reports from eye-witnesses or social media information [27,28]). This leads us to **R2:** process information from *diverse sources*.

At the same time, emergency information is increasingly characterised by misinformation and noise [29]. When incorporating information from diverse sources, it should be considered that not every piece of information is unambiguous and not every information source is 100% reliable (people make mistakes and sensors malfunction). For the processing of information, this means that the level of uncertainty associated with different information sources must be taken into consideration [30,31], which leads us to **R3:** process *uncertain* information.

Another aspect when incorporating information from multiple sources – which might differ with regard to their specific perspectives, biases or levels of expertise [32,33] – is that different observations can contradict each other (source A says Yes, source B says No). A suitable method should therefore incorporate a scheme for handling this type of noisy information, leading us to **R4:** process *conflicting* information.

A characteristic aspect of assessing an emergency situation is that it is a dynamical task that extends over the entire course of the emergency – during the assessment, the situation itself as well as the available information about it develop dynamically [12,34]. For a suitable method this implies that it should be capable of dynamically incorporating new information – i.e., as the actual situation evolves and new observations trickle in, the assessment of the situation should evolve accordingly [18,35]. The dynamic information situation during an emergency leads us to **R5:** process *dynamic* information.

A last crucial aspect of emergency situations is their spatial dimension [4,36]. A comprehensive understanding of the geographic extent of an emergency and its impact at different locations is essential for an effective emergency management, e.g., for prioritising response efforts [12,18]. Therefore, a suitable method should allow for processing and mapping the spatially distributed information that characterises the emergency event. This leads us to **R6:** process *spatial* information.

To summarise, a method for processing observations in emergency response needs to meet all of the following six requirements:

- R1: process *incomplete* information
- R2: process information from *diverse sources*
- R3: process *uncertain* information
- R4: process *conflicting* information
- R5: process *dynamic* information
- R6: process *spatial* information

1.2. Research gap and main contribution

In this paper, we present *ERIMap* (Emergency Response Inference Mapping), a new method for supporting situation awareness that is designed to take into account the specific information-scape in emergency response. Because of the strength of Bayesian networks (BN) in structuring and organising uncertain information flows, we selected a BN as the core of our method. In the past, several BN-based approaches have been put forward that fulfil some of the aforementioned requirements (see Section 2.3). However, there is currently no method meets all of them. This is precisely what *ERIMap* has to offer.

With regard to the fulfilment of all requirements, it is particularly noteworthy that, to date, there are only a few methods that consider uncertain evidence in BNs (e.g. see [37]. This is crucial because the consideration of uncertain evidence is a necessary prerequisite for treating uncertain (R3) and possibly contradictory observations (R4) – and thus it is also required to responsibly fulfil R2 (e.g., when incorporating information from eye-witnesses or social media). According to the recent work of Munk et al. [38], this lack of consideration might be due to a lack of consensus on which type of uncertain evidence should be applied in which case. We address this issue by introducing a novel classification scheme (see Fig. 5) that selects the 'right' type of (uncertain) evidence for a particular observation based on a small set of pre-defined properties describing the corresponding observation source. Our classification scheme is designed to allow for a fast processing of large amounts of diverse observations, which is crucial regarding the time pressure in emergencies and the complexity of the corresponding situations. In this way, *ERIMap* supports situation awareness by mapping inferences drawn from processing incomplete, uncertain, and conflicting observations from diverse sources which evolve dynamically and are spatially distributed.

In the remainder of this work, first, some background on BNs is provided. Special emphasis is placed on the introduction of uncertain evidence, the combination of a BN and a GIS, and relevant literature that deals with observation processing in BNs. Second, our *ERIMap* method is introduced. Third, while the method is generally applicable in a variety of emergency scenarios, we decided to demonstrate it in a specific case study to provide an end-to-end walk-through of the proposed methodology. We developed the case study with practitioners from a plant fire brigade of Henkel, a multinational marked-listed chemical company, headquartered in Germany. In the scenario of the case study, a chlorine gas tank leak causes a gas dispersion throughout a chemical plant site. Fourth, the results of the case study are presented using multiple synthetic outcomes of the scenario that include different observation sequences. Finally, the proposed method is discussed and future work is outlined.

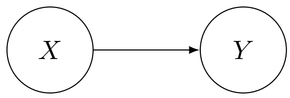
2. Bayesian networks

Bayesian networks (BNs) are probabilistic graphical models consisting of directed acyclic graphs [39] (see Fig. 1). They present a powerful tool to embed knowledge and to perform belief updates about variables given new information about other variables. In particular, they allow to draw such inference on the basis of incomplete and uncertain evidence. Bayesian networks are already used in a variety of research fields to inform decision makers (see [40] for an overview of topics). Several recent studies based on BNs have been published in the realm of decision making in complex systems, such as analyses to inform about the resilience of a system under stress [11,41], assessments to inform about the risks posed by accidents [42] or natural hazards [43], methods to inform about the reliability [44,45] or safety [46,47] of an engineering system, or methods to inform about emergency response performance [48,49].

Bayesian networks are composed of nodes representing system variables as probability distributions and directed edges representing their probabilistic dependencies [39]. Nodes can be either dependent (see node Y in Fig. 1) or independent (see node X in Fig. 1). An independent node is described by a Marginal Probability Table (MPT) (see left table in Fig. 1). A dependent node does have at least one parent node and is hence described as child node. To each dependent node, Conditional Probability Tables (CPT) are assigned (see right table in Fig. 1), containing one probability value for every possible combination of child node and parent node states. Given evidence on node Y, e.g. Y is in state y_1, the Bayes' rule (see Eq. (1)) can be applied to infer the probability of X given new evidence, i.e. $P(X|Y = y_1)$.

$$P(X|Y) = \frac{P(Y|X) \cdot P(X)}{P(Y)} \tag{1}$$

x_1	x_2
0.3	0.7



	y_1	y_2
x_1	0.4	0.6
x_2	0.2	0.8

Fig. 1. Example of a BN with two nodes, one edge, and respective marginal and conditional probability tables.

In the following, an introduction to processing various types of evidence in BNs is presented and the procedure for connecting BNs with GIS is detailed. In addition, relevant methods for processing observations using BNs are introduced.

2.1. Evidence in Bayesian networks

Belief updates in BNs require evidential findings (or observations) regarding the state of one or multiple nodes of the BN [50]. Evidence in a BN can be either certain (also called hard evidence) or uncertain [51, 52]. Uncertain evidence can be of two types: soft evidence [53] or virtual evidence [54]. Each of the three types of evidence (hard, soft, and virtual) follows a different belief update rule [52].

Given **hard evidence** on a node of a BN, the exact state of this node is known with certainty [51]. This means that an observation which provides hard evidence is considered to be undoubtedly true (in contrast to virtual evidence) and perfectly precise (in contrast to soft evidence). Entering hard evidence into a BN is straightforward: the respective node is simply set to the reported state (e.g., node Y is in state y_1) or, in terms of likelihoods, the likelihood of the reported state is set to 1 while the likelihood of all other states is set to 0 (e.g., $L(Y) = (1, 0)$).

Virtual evidence reflects uncertainty about whether a reported observation is true. It can thus be interpreted as *evidence with uncertainty* [52], which is represented as a likelihood ratio [54]. Examples of virtual evidence are matters of varying veracity or accuracy, such as information provided by an imperfect sensor [55] or information provided by a person who has only partially observed an area [56]. Given virtual evidence on a node of a BN, an additional virtual child node (node *Obs* in Fig. 2) is attached to the respective node [51]. The initial CPT (likelihood ratio) of the binary child node represents the presumed likelihood that the underlying observation is true (85% for node *Obs* in Fig. 2). The belief update about the originally addressed node in the BN (node X in Fig. 2) is then obtained by propagating hard evidence from the virtual child node, assuming that it is in state *True* (Obs = *True*).

Soft evidence considers the uncertainty which is included in a reported observation. It can thus be interpreted as *evidence of uncertainty* [52], which can be represented as a probability distribution of one or more variables [53]. Given soft evidence on a node of a BN, one is uncertain about the precise state of the node but certain about its probability distribution [51]. In contrast to virtual evidence, soft evidence can be interpreted as a new probability distribution of a variable that arose after creation of the model [55]. To enter soft evidence about one node into a BN, this evidence can be converted into a virtual evidence. To this end, the likelihood ratio of the additional virtual child node is calculated as the quotient of the probability ratio $\Lambda(X)$ and the prior probability of the addressed variable $P(X)$ (see Eq. (2)). Subsequently, $L^*(X)$ is normalised to one (see Eq. (3)). The following steps to perform belief updates in the BN are the same as for virtual evidence in case of a single soft evidence.

$$L^*(X) = \frac{\Lambda(X)}{P(X)} \quad (2)$$

$$L(x_1, \ldots, x_n) = \left(\frac{L(x_1)}{\sum_{i=1}^{n} L(x_i)}, \ldots, \frac{L(x_n)}{\sum_{i=1}^{n} L(x_i)} \right) \quad (3)$$

The conversion from probability ratio into likelihood ratio compensates for the influence of the prior distribution of node X. Given the obtained virtual evidence with the likelihood ratio $L(X)$ on node X, the posterior probability of node X is equal to the probability ratio $\Lambda(X)$ provided by the soft evidence.

Soft evidence can be fixed or not-fixed. Fixed soft evidence is implemented by assigning a new probability distribution for the respective variable and is considered as immutable, even in case of later observed evidence for other nodes in the BN [55]. In case of not-fixed soft evidence, the belief about the respective node can change in response to evidence for other nodes in the BN [55]. It should be noted that in this work we only consider not-fixed soft evidence and thus the term soft evidence always refers to not-fixed soft evidence.

2.2. Bayesian networks combined with geographic information systems

Bayesian networks are increasingly used for spatial inference. The interaction between a GIS and a BN can be bidirectional: GIS layers can be used as input for BN nodes and inference on BN nodes can be represented in a GIS. An example of a GIS input to and output from a BN is shown in Dlamini [57] who presented a BN model for fire risk mapping using GIS. Another example is shown in Wu et al. [58] who developed a BN model with the goal of estimating the probability of a flood disaster.

To simplify and automate the link between the BN and the GIS, the attributes in the GIS layers must be linked to the corresponding states of the BN's variables. For example, a node *Landuse* of a BN with states *Forest*, *Industrial*, and *Urban* can be informed by a GIS layer that includes a spatial mapping of these three types of landuse. To create the output of the GIS-informed BN, the area under consideration must be divided into subset areas in the GIS, e.g. with a tessellation approach [59]. These subset areas determine the resolution of the subsequent analysis. A subset area should show attributes that are as homogeneous as possible. In each of these areas, inference in the BN is performed using the layer attributes of the respective area in the GIS. The results of the inference in the BN for a key variable, such as *Risk of Fire* in [57], can be displayed using a heat map that colours the respective areas, depending on the probability of the risk for the respective area (e.g. see [58,60]).

2.3. Bayesian networks for observation processing

Although, to the best of our knowledge, no one has yet presented a BN-based method that fulfils all six requirements (see Section 1.1), several authors have addressed subsets of them (see Table 1) – note that, at this point, we refer to the field of BNs in general, not specifically to applications for emergency management. First of all, drawing inferences on the states of some nodes based on incomplete information regarding other nodes of the network is one of the core features of a BN (see R1 in Table 1). Integrating multiple sources to inform the BN is feasible since BNs generally allow for the incorporation of different types of input data (R2). For instance, Valtorta et al. [53] and Mrad et al. [56] presented examples of uncertain evidence that illustrate the consideration of evidence from multiple potential observation sources. To account for uncertainties associated with different observation sources, both works made use of uncertain evidence (see R3 in Table 1). In addition, Chan and Darwiche [61] dealt with the question on how to capture informal statements as uncertain evidence in a BN. The use of uncertain evidence

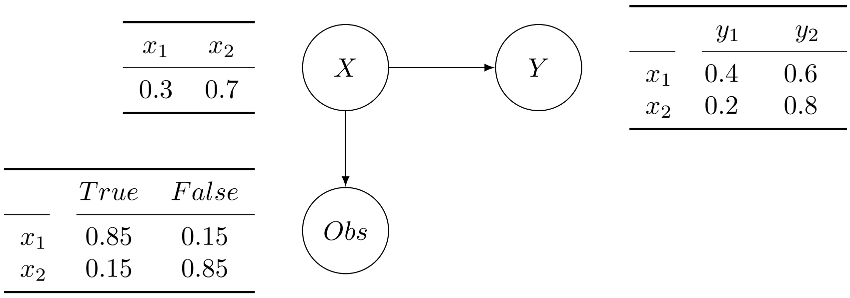


Fig. 2. Illustrative example of a BN with two initial nodes and one virtual node.

Table 1
Summary of main references in regard to six properties of an observation.

Reference	(R1) Incomplete	(R2) Diverse sources	(R3) Uncertain	(R4) Conflicting	(R5) Dynamic	(R6) Spatial
Chan and Darwiche [61]	✓	✗	✓	✗	✗	✗
Mrad et al. [56]	✓	✓	✓	✗	✗	✗
Giordano et al. [37]	✓	✗	✓	✗	✗	✓
Wu et al. [58]	✓	✗	✗	✗	✗	✓
Johnson et al. [63]	✓	✗	✗	✗	✗	✓
Peng et al. [52]	✓	✗	✓	✓	✗	✗
Radianti et al. [62]	✓	✗	✗	✗	✓	✓
Valtorta et al. [53]	✓	✓	✓	✗	✗	✗
ERIMap method	✓	✓	✓	✓	✓	✓

also enables dealing with inconsistent or contradictory observations, as has been practised by Peng et al. [52] (R4). Displaying the dynamic progression of key variables of a situation given new observations can also be achieved using a BN (R5). For instance, Radianti et al. [62] described a spatio-temporal model based on a dynamic BN with the intent of supporting real-time evacuation planning. And finally, by combining a BN with a geographic information system (GIS), the spatial dimension of an emergency can be considered (R6). The combination of BN and GIS has been practised several times [63], e.g., by Giordano et al. [37] to support conflict analysis for groundwater protection or by Wu et al. [58] to enable spatial analysis of flood disaster risk.

Table 1 clearly shows that no reference addresses all six requirements for observation processing in emergency response. However, the table also shows that BNs are generally suitable for the creation of a method which meets all six requirements, i.e. a method that is capable of processing observations that are *incomplete* (R1), come from *diverse sources* (R2), are *uncertain* (R3), *conflicting* (R4), *dynamic* (R5) and *spatially distributed* (R6). In this paper, we make us of BNs to create *ERIMap*, a method that covers all six requirements for information processing in emergency response.

3. ERIMap method: Emergency response inference mapping

The goal of the *ERIMap* method, is to draw inferences by processing observations from *multiple sources*, which may be *incomplete*, *uncertain*, *conflicting*, *dynamic* and *spatially distributed*. The application of the method is divided into two phases: the *preparation phase* which takes place before an event (see left side of Fig. 3) and the *operation phase* which describes the application of the method during an emergency (see right side of Fig. 3).

3.1. Preparation phase

3.1.1. Bayesian network construction

The first step of the preparation phase is the construction of a BN model for the intended area of application. The BN should include all variables that are key for decision making in a specific emergency (e.g. a flood or a forest fire scenario) as well as variables that directly or indirectly influence (the belief about) these key variables [58]. To make sure that the *ERIMap* method meets the demands of the users, all considered variables and the relationships between them should be identified in cooperation with decision makers in emergency response. Furthermore, additional sources can be incorporated to determine the probability tables of the BN (MPT and CPT), e.g., historical data or expert knowledge [64].

3.1.2. Area specification

In the second step of the preparation phase, the spatial resolution for the emergency consideration is specified – i.e., areas are specified which are to be assessed individually (see Fig. 4). Depending on the case, these areas can, for instance, correspond to districts, buildings, or specific point locations. To allow independent inference in the BN for each area, a duplicate of the initially constructed BN is assigned to each area (white nodes in Fig. 4). These initially identical BNs start to diverge as soon as they are fed with area-specific evidence – a process which is particularly impressive for uncertain evidence: Given uncertain evidence for a specific area, a virtual child node is added to the respective BN (orange nodes in Fig. 4); while BNs in other areas remain unchanged. Layers in the GIS that should serve as observation sources for the BN have to be linked to the attributes of the respective BN node states, i.e. they are used as inputs for BN nodes [63]. Besides using the GIS to inform the BN, the GIS serves to spatially display the results obtained from the BNs.

3.2. Operation phase

3.2.1. Observation requirements

One of the core features of the proposed method is a procedure for translating different types of observations into evidence that can be considered in the BN. A necessary requirement for this transfer is that an observation contains five pieces of information:

(1) The **time** at which the observation has been conducted is used to display the temporal progression of the belief about variables in the BN. For example, it is important to know if an observation stating that people are in a building has been conducted before or after an evacuation of that building.

(2) The **location** of the observation must be specified to enable the assignment of the observation to the respective area-specific BN(s).

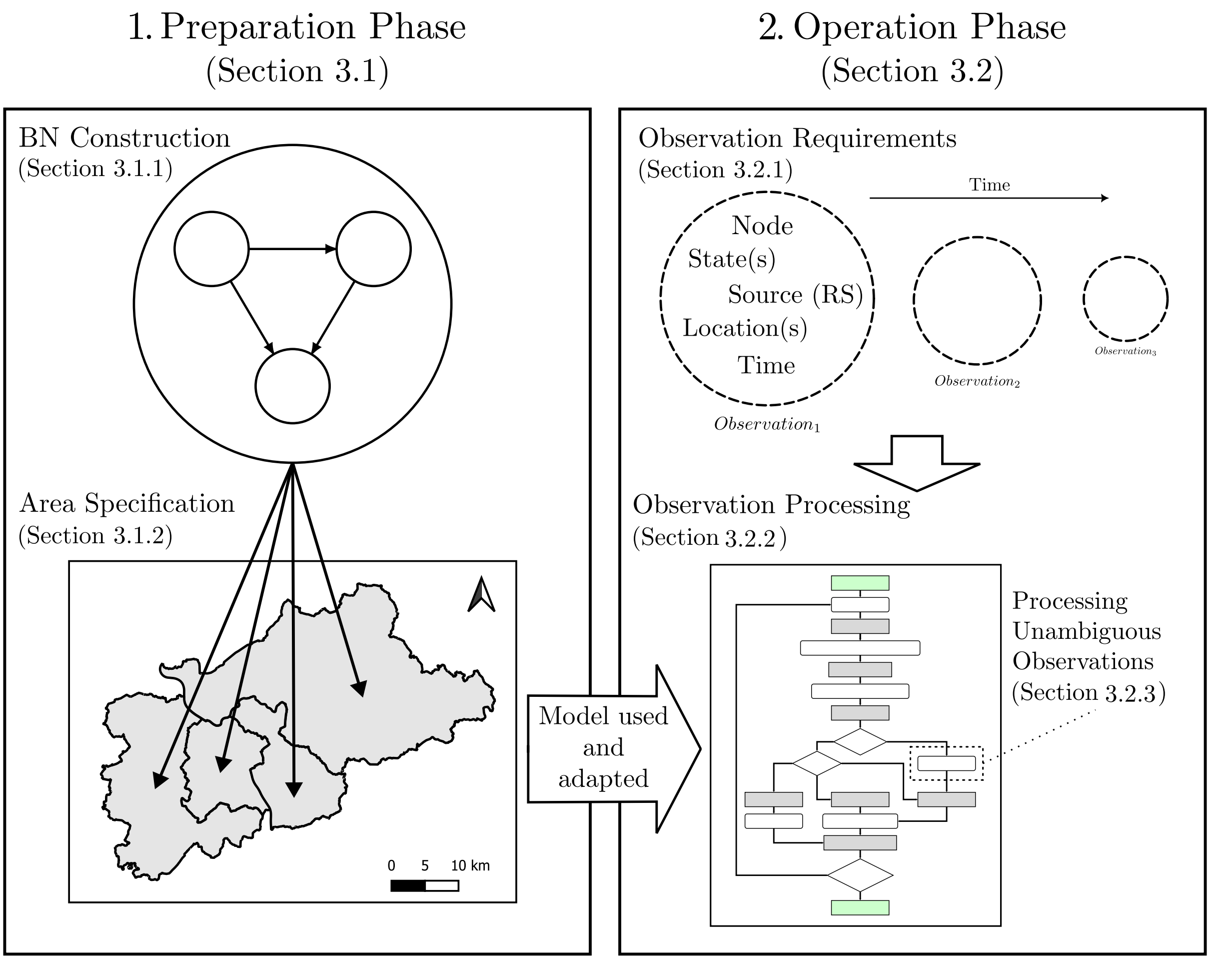


Fig. 3. Overview of the structure of the method and division of the following sections. The *preparation phase* includes the construction of the BN and specification of areas or locations. During the emergency *operation phase*, observations are collected and processed.

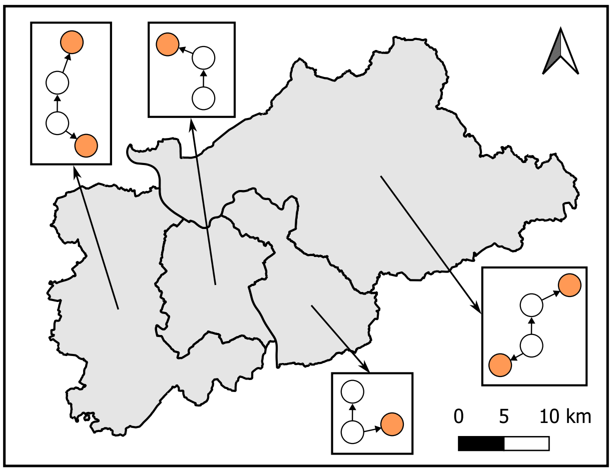


Fig. 4. Illustration of one initial BN (white filled nodes) duplicated for four different areas. For each area, different virtual nodes (orange filled) are added.

(3) The **node** about which the observation provides evidence. This information is required to assign the observation to the respective node in the BN.

(4) The **reliability of the observation source**. A source can be fully reliable or not. The classification of reliability is important to avoid excessive influence of observations from unreliable sources.

(5) The **observed state(s)** of the node. Corresponding information can originate from (I) an unambiguous statement (e.g. “there is fire”) or (II) an uncertain statement (e.g. “I think I saw a fire”).

For (I) – an unambiguous statement – hard or uncertain evidence can be considered, depending on the presumed reliability of the information source. For instance, a unambiguous observation (e.g., “there are no people in building A”) provided by an emergency response team may be considered as ‘confirmed’ (hard evidence) while social media reports may be considered as ’not fully reliable’ (uncertain evidence). In the latter case, the method introduced in Section 3.2.3 is applied.

For (II) – an uncertain statement – virtual evidence needs to be distinguished from soft evidence. In case of virtual evidence, the corresponding likelihood ratio is integrated by adding an additional virtual child node which influences the state of the respective parent node (see Section 2.1). For example, given a node called *Fire*, which is used to infer the probability of a fire occurring, a potential indication child node could be a node *Smoke Alarm* that is linked to a smoke detector. The likelihood values for false-positive and false-negative observations of the smoke detector constitute the likelihood ratio of the node *Smoke Alarm*. By performing hard evidence on node *Smoke Alarm*, $P(Fire|SmokeAlarm)$ is inferred using Eq. (1). In case of soft evidence, the obtained probability ratio describes a new probability distribution of a particular node and thus replaces the prior probability distribution following the routine outlined in Section 2.1. An example is a node *Building Use* that has initially been set up and trained for a whole city in which

80% of the buildings are apartment buildings and 20% are used for commercial purposes. If the same BN would now be used for a district in this city where commercial use of buildings is much more probable (e.g. 90%), this new probability ratio shows a higher accuracy than the prior probability of the node *Building Use* and is thus implemented using soft evidence.

3.2.2. Observation processing

In the operation phase, new observations are processed and fed into the area-specific BNs according to a specific workflow (see Fig. 5). Given a new observation, it is first assigned to the respective *area*-specific BN(s) and then to the *node* which is addressed in this observation. Afterwards, the method classifies the type of evidence (hard, soft, or virtual) based on the *reliability* score of the observation source and on the reported *node state(s)*. For an unambiguous observation provided by a source that shows a small or medium reliability (RS_1 and RS_2), the method introduced in Section 3.2.3 is applied and a virtual child node is added to the respective node in the BNs. In case of an observation provided by a source that shows a high reliability (RS_3), three cases are distinguished: (1) an unambiguous observation without uncertainty that results in computing hard evidence, (2) a probability ratio, which shows a higher accuracy than the prior distribution and thus replaces it (soft evidence), and (3) a likelihood ratio that provides evidence with uncertainty (virtual evidence). In case (2) and (3) a virtual child node is added (see Section 2.1). Subsequently to this classification, a belief update for all key variables in the BNs of the respective areas is performed. The operation phase stops when all key variables are confirmed.

3.2.3. Processing unambiguous observations

To account for uncertainty related to observations from unreliable sources, these observations are translated into virtual evidence [65]. An observation source can be classified as unreliable for several reasons, e.g. (1) it is not known whether the person who provides an observation had access to all areas; (2) a person is not sure about an observation; (3) unreliable sensors.

To translate an unambiguous observation from an unreliable source into virtual evidence, two pieces of information are used in this method: the reliability score (RS) of the observation source and the criticality of the reported node state. For the RS, using predefined scores supports a quick classification during an emergency situation. We therefore define three example RSs which describe different degrees of reliability:

RS_1: Small Reliability
RS_2: Medium Reliability
RS_3: High Reliability

A likelihood is assigned to each RS_i that quantifies the certainty of the observation. This likelihood, which can be interpreted as the chance that the observation is correct [61], is used to fill in the CPT of the respective virtual child node. Note that in case of a BN composed of only binary nodes, virtual evidence with a likelihood ratio of (0.5, 0.5) will show no effect on the respective posterior probability of the node. The likelihood values for the respective RSs should be selected in collaboration with potential users to reflect their preferences. The general case of a node X with N states, i.e. $X = \{x_1, x_2, \dots, x_N\}$, the likelihood ratio given an unambiguous observation stating node X is in state x_1 is:

$$L(X) = \left(L(RS_i), \frac{1 - L(RS_i)}{N - 1}, \dots, \frac{1 - L(RS_i)}{N - 1} \right)$$

In this way, the posterior probability of state x_1 is increased (when performing hard evidence on the respective virtual child node) and at the same time the posterior probabilities of the other node states are decreased, while the ratio between the other node states remains the same.

In a next step, a regret function is introduced to better deal with conflicting observations. Using the example of a node *People in Building*, one observation could state that people are in the building while another observation could state the opposite. In order to avoid that the two observations cancel each other out (assuming both sources share the same RS), the precautionary principle is applied: emphasise is placed on the node state that is more critical (i.e. people are in the building). This is achieved by increasing the likelihood of the critical node state by a certain percentage Θ. The derived generalised likelihood ratio thus becomes:

$$L^*(X) = \left((L(RS_i) + \Theta), \frac{1 - (L(RS_i) + \Theta)}{N - 1}, \dots, \frac{1 - (L(RS_i) + \Theta)}{N - 1} \right),$$

for x_1 being the observed critical node state. Note that the regret function is only applied to nodes whose states exhibit different levels of criticality.

4. Case study

In this section, our *ERIMap* method is applied to a case study which has been developed in cooperation with the plant fire brigade of the German chemical company Henkel. A chemical plant site inspired by one of Henkel's sites is used as geographical setup (Fig. 6). The scenario is triggered by an accident between a truck and a tank wagon on a railway at a junction on the northern edge of the site (see top right of Fig. 6). The accident results in a gas leak, and potentially dangerous gas is dispersed throughout the site. In such an emergency, various sources of observations are to be expected. Geographic information systems, for example, support the simulation of gas dispersion, sensors are used to detect critical gas doses, and emergency responders inspect the buildings. Thus, in this case study, a dynamically evolving and spatially heterogeneous emergency situation whose evaluation can benefit from diverse observation sources is considered.

In the following, first, the preparation phase (according to Section 3.1) of the case study is outlined including the development of the BN and the simulation of the gas dispersion. Second, the operation phase (according to Section 3.2) is detailed including the results for a single building as well as for all buildings in two individual scenarios.

4.1. Preparation phase

The application of our method is designed to support the situation awareness of the plant fire brigade by helping them assess the risk that affected people are in a particular building. To this end, each building of the plant site is considered as an area to be assessed individually, i.e., each building receives a separate BN. Three types of building use are considered and randomly assigned (see Fig. 6). The case study is implemented in Python based on the libraries pgmpy [66] for Bayesian networks and GeoPandas [67] for geospatial data manipulation.

4.1.1. Bayesian network and observation sources

The BN of the case study is composed of six variables and five edges representing their probabilistic dependencies (see Fig. 7). The target node of the BN is the variable *People in Building Affected*, since this node is crucial for decision making and allocating rescue teams to buildings. Information about the presence of people in a building as well as the probability of a critical gas dose inside the building represent the parent nodes of *People in Building Affected*. An additional node (*Critical Gas Dose around Building*) is the parent node of *Critical Gas Dose in Building*. This parent node is introduced to account for the uncertainty of gas dispersion from the surroundings of a building into the building itself. The presence of *People in Building* can be inferred by its two parent nodes *Building Type* and *Time of Day*. Three building types are distinguished: office buildings (11 buildings), production buildings (8 buildings), and mixed use buildings (8 buildings). *Time of Day* shows two states: 6am - 6pm (day shift) and 6pm - 6am (night shift). In this case study, it is assumed that the presence of people in an office building during the night shift is less probable than in a production building. In a mixed-use building, the probability of human presence in

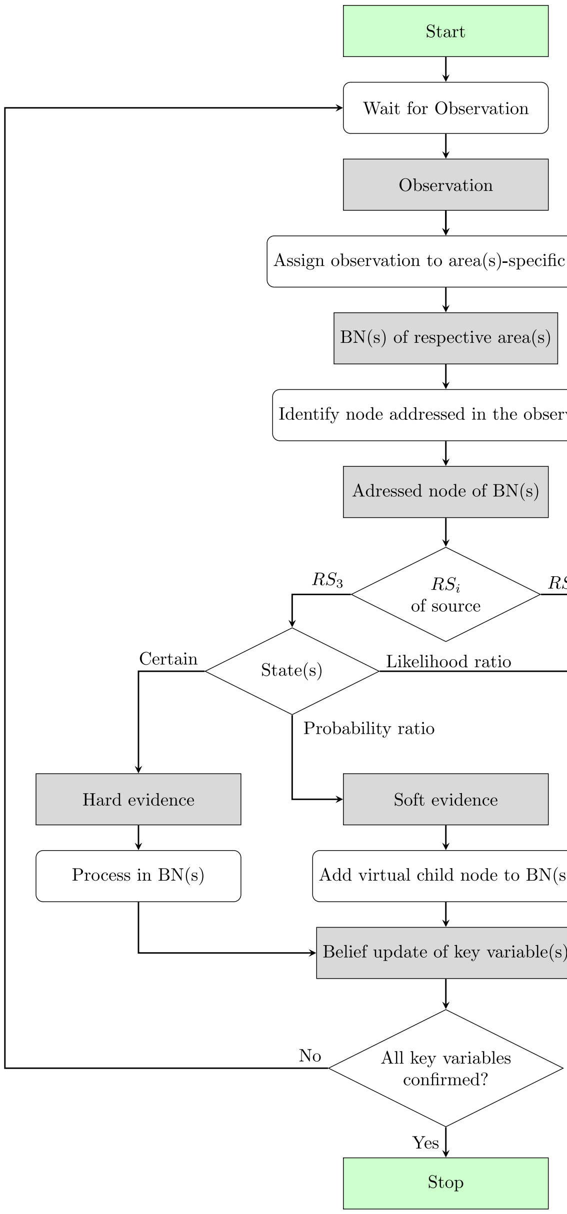


Fig. 5. Summary of the *ERIMap* method in the operation phase. Rectangles with rounded corners describe processes, gray rectangles describe the class of information. Decision nodes are diamond-shaped. Start and stop of the process are highlighted with green fill.

the building is between that of office and production buildings. During the day shift, the probability of people being in a building is high for all building types. All other nodes are binary with state names *True* and *False*. The probability values used to fill in the MPT and CPT of the BN are selected by the authors.

Table 2 shows all considered information sources including the node(s) about which each source can provide observations and the respective reliability score(s). Additionally, it is stated whether the source provides an unambiguous observation or several uncertain states. Gas sensors and the simulation in GIS are the sources that do not provide unambiguous observations. The gas sensor is assumed to operate with a known accuracy. Therefore, this source is classified with RS_3, but does not provide an exact statement – it provides virtual evidence (see Fig. 5). For the simulation of the gas dispersion, the prior probability of node *Critical Gas Dose around Building* is $(True = 0.01, False = 0.99)$ due to the fact that a critical gas dose is not expected without further indication. Given a simulation of the critical gas dose around the buildings (see Section 4.1.2), this observation provides a new probability distribution that shows a higher value than the prior probability and is thus considered as soft evidence. The other observation sources provide unambiguous statements but are of different reliability scores. The likelihood values for the RSs used in this case study are: 70% certainty for RS_1, 80% for RS_2, and RS_3 is considered as hard evidence (100% certainty). Thus, for a binary node V and an observation of RS_2 stating V is in state v_1, the corresponding likelihood ratio for the CPT of the virtual child node of V is $(0.8, 0.2)$. The Θ value used for the regret function is assumed to be 10%.

4.1.2. Gas dispersion hazard

The gas dispersion caused by a leakage in the tank wagon carrying chlorine is simulated using the *Areal Location of Hazardous Atmosphere* (ALOHA) software, a widely used tool for chemical emergencies. ALOHA provides a simplified but quick steady-state simulation of a gas dispersion of various chemicals under surrounding conditions using a Gaussian plume model [68]. The software provides three threat zones that are characterised by a steady-state gas concentration in these areas. These zones represent an equilibrium of gas concentrations in the atmosphere given constant surrounding conditions and gas leakage.

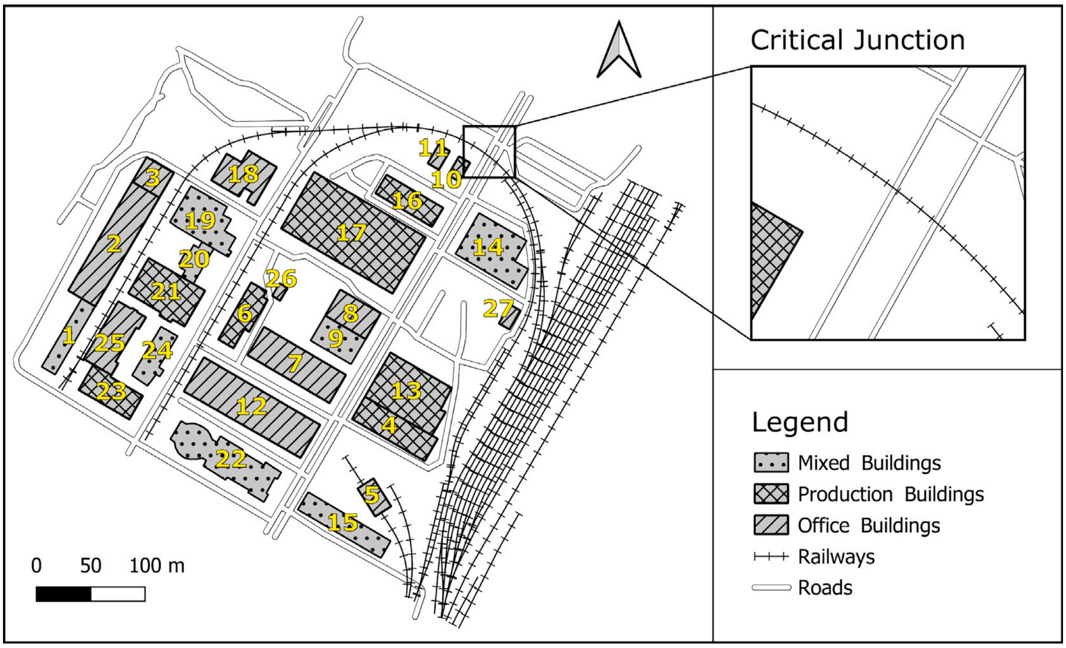
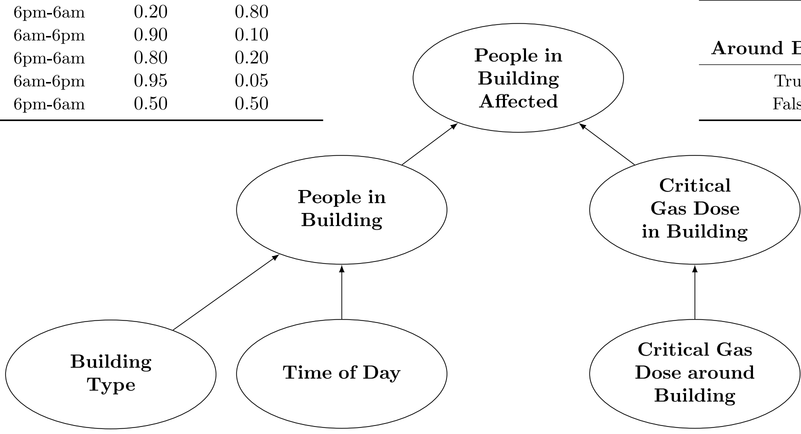


Fig. 6. Map of the chemical plant. The map shows building types, building numbers, roads, railways and the critical junction. The chemical plant is located on a greenfield site, i.e. there are no surrounding buildings.

People in Building	C. G. D. in Building	People in Building Affected	
		True	False
True	True	0.95	0.05
True	False	0.10	0.90
False	True	0.05	0.95
False	False	0.01	0.99

Building Type	Time of Day	People in Building	
		True	False
Office	6am-6pm	0.99	0.01
Office	6pm-6am	0.20	0.80
Production	6am-6pm	0.90	0.10
Production	6pm-6am	0.80	0.20
Mixed	6am-6pm	0.95	0.05
Mixed	6pm-6am	0.50	0.50

Around Building	In Building	
	True	False
True	0.75	0.25
False	0.05	0.95



Building Type		
Office	Production	Mixed
0.407	0.296	0.296

Time of Day	
6am-6pm	6pm-6am
0.5	0.5

Around Building	
True	False
0.01	0.99

Fig. 7. Bayesian network of the case study including seven variables, five edges, and the corresponding marginal and conditional probability tables.

In the case study, the accident of the tank wagon with a truck caused an opening in the tank wagon with a diameter of 5 inches. The tank wagon is fully loaded with a volume of 100 m^3. Wind is coming from north east. Fig. 8 shows the three threat zones (600 ppm, 400 ppm, and 200 ppm) on the chemical plant site emerging from the crossing at the northern edge of the site.

In order to calculate a probability distribution for node *Critical Gas Dose around Building*, the concentration of gas in the atmosphere is

Table 2
Information on the observation sources considered in the case study.

Source class	Source name	Node(s)	State(s)	RS_i
Person	Emergency Responder	*People in Building, People Affected*	unambiguous	RS_3
	Civilian	*People in Building, People Affected*	unambiguous	RS_1, RS_2
Sensor	Clock	*Time of Day*	unambiguous	RS_3
	Gas Sensor	*Critical Gas Dose in Building*	uncertain	RS_3
GIS	Simulation	*Critical Gas Dose around Building*	uncertain	RS_3
	Buildings Layer	*Building Type*	unambiguous	RS_3

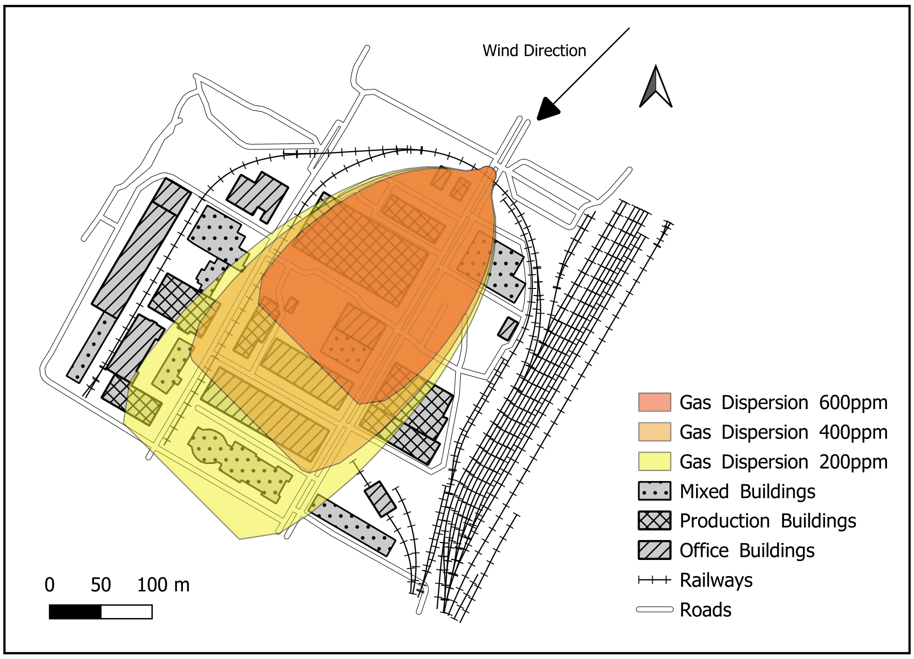


Fig. 8. Simulation of the gas dispersion emerging from the critical junction including three threat levels characterised by different steady-state gas concentrations.

converted into a probability of a critical gas dose using a probability unit function (see Eq. (4) and (5)). Probability unit (probit) functions are used to formulate a relationship between the criticality for a human being to the exposure of toxic substances [69,70]. In addition to the concentration of gas, the time of exposure t is required. The variables a, b, and n are fitted constants, each specific for one type of toxic substance. For chlorine, $a = -8.29$, $b = 0.92$, and $n = 2$. The probit value Y can be transferred into a probability of criticality using probit tables [70].

$$Y = a + b \ln(Dose) \tag{4}$$

Dose is considered as integrated concentration of chemical exposure at a given point over a specific time [70].

$$Dose = \int_0^t C^n dt \tag{5}$$

Applying the probit function for a chlorine exposure with e.g. $t = 25min$ and $C_1 = 600$ppm, $C_2 = 400$ppm, and $C_3 = 200$ppm results in a probability of criticality of 90% for C_1, 80% for C_2, and 70% for C_3.

4.2. Operation phase

4.2.1. Single building

First, the application of our *ERIMap* method in the operation phase is illustrated for a single building on the chemical plant site (building 17 in Fig. 6). For this building, the associated BN is updated in accordance with an example sequence of observations (see Table 3). Based on the dynamically updated BN, the method helps to assess the probability that affected people are present in the building at each point in time (Fig. 9).

The time of day (12:00am) and building use (production building) are known instantly and are considered as hard evidence. Processing these observations results in a high probability for the presence of people (90%) and a lower probability for people being affected (13%). The probability of the dispersion of gas into the building is unaffected by this observation, i.e. it shows the prior probability (6%). Next, the simulation of gas dispersion around the buildings is available (12:05am). Once the gas dispersion layer in the GIS shows an overlap with a building in the building layer, the observation obtained from the simulation is considered for that building and node *Critical Gas Dosis around Building* (abbreviated as C.G.D. ar. Building). If a building shows an overlap with several gas dispersion layers, the one with the highest gas concentration is considered. Since building 17 shows an overlap with all three gas dispersion layers (see Fig. 8), a gas concentration of 600ppm is assumed in the observation. In order to apply Eq. (5), an exposure time of 15 min is used under the assumption that the gas dispersion started at 11:50pm. Processing the observation obtained from this simulation, the probability of people in this building being affected jumps to 56% while the probability of node *Gas in Building* reaches 61%. Next, an observation provided by a civilian of RS_1 is available (12:08am) stating that no people are in the building, followed by an observation by a second civilian (12:12am) of the same RS_1 stating the opposite. Due to the implementation of the regret function introduced in Section 3.2.3, the observation stating that people are present in the building is considered with a higher weight. After processing these contradictory observations, the probability of the presence of people is 94%. At 12:14am, an observation by a gas sensor in the building

Table 3
Example sequence of observations for building 17.

(1) Node	(2) State(s)	(3) Source (RS)	(4) Building(s)	(5) Time
Time of Day	*6am-6pm*	Clock (RS_3)	17	12:00 am
Building Type	*Production*	GIS Layer (RS_3)	17	12:00 am
C.G.D. ar. Building	$P(0.8, 0.2)$	Simulation (RS_3)	17	12:05 am
People in Building	*False*	Civilian (RS_1)	17	12:08 am
People in Building	*True*	Civilian (RS_1)	17	12:12 am
C.G.D. in Building	$L(0.9, 0.1)$	Gas Sensor (RS_3)	17	12:14 am
C.G.D. in Building	$L(0.9, 0.1)$	Gas Sensor (RS_3)	17	12:15 am

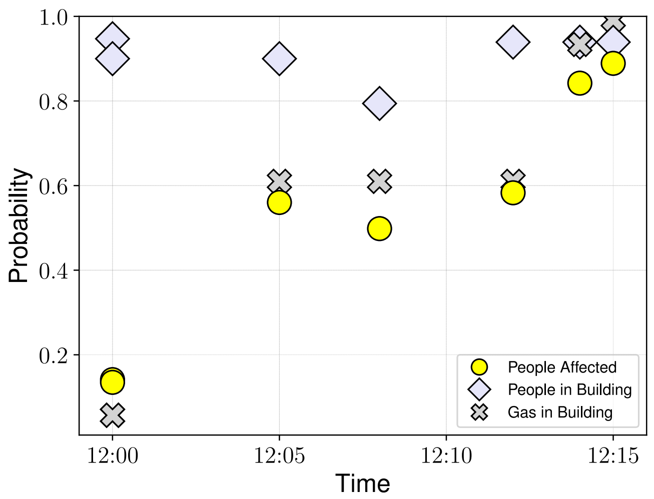


Fig. 9. Probability of nodes *People in Building Affected*, *People in Building*, and *Gas in Building* being in state *True* for multiple time steps listed in Table 3.

is available, that provides evidence with an accuracy of 90%. One minute later, a second gas sensor with the same accuracy provides an additional observation. Processing these two observations results in a probability of 99% for node *Gas in Building* and 89% for node *People in Building Affected*.

4.2.2. Results for all buildings

In order to compute the results for all buildings, two scenarios are designed that share the same gas dispersion at the chemical plant (see Fig. 8), but differ in the time of day and outcome of the situation. The two scenarios are constructed to highlight different aspects of the proposed method. The results show the probability of node *People in Building Affected* being in state *True* for each individual building at different time steps (four time steps in scenario 1 and six time steps in scenario 2). At each time step, new observations are available for multiple buildings. In the following, for each scenario, a brief summary is introduced, a table that includes the sequences of observations is provided, and results are outlined.

Scenario 1 takes place during the night shift. At the initial time step t_0, the time of day and building types obtained from the GIS are available as observations. The results of t_0 show the resulting probability that differs between 4% (for office building), 8% (for mixed use buildings), and 12% (for production buildings) (see Fig. 10). At the next time step t_1, the observations by the gas dispersion simulation (see Fig. 8) become available. Here again, a gas exposure of 15 min is assumed as a first estimate resulting in the probability distributions for soft evidence for node *Critical Gas Dose Around Building* shown in Table 4. The results show that given these observations, production buildings being located in the area of the simulated highest gas concentration (e.g. building 17) show the highest probability with 50% (see Fig. 10). In the next time step (t_2), virtual evidence provided by individuals of RS_2 becomes available, stating that there are people in some buildings and that there are no people in another group of buildings. As displayed in Fig. 10 at time step t_2, buildings 9, 13, and 17 show the highest probability with over 50%. At the last time step t_3, virtual evidence for node *Critical Gas Dose in Building* provided by gas sensors with an accuracy of 90% becomes available for multiple buildings. After processing these observations, building 17 shows the highest probability (84%), followed by building 9 (81%) and 6 (72%).

Scenario 2 takes place during the day shift. At t_0, the time of day and building types obtained from the GIS are available as observations. The probability differs between 14% (for office and mixed use buildings) and 15% (for production buildings) (see Fig. 11). At t_1, the observations provided by the gas dispersion simulation (see Fig. 8) becomes available (same as in scenario 1). Illustrated in Fig. 11 at t_1, the probability for the respective buildings varies between 14% (e.g. building 1) and 61% (e.g. building 7). At the next time step t_2, hard evidence provided by officials, i.e. humans of RS_3, becomes available stating that multiple buildings are evacuated, i.e. node *People in Building* is in state *False*. Additionally, observations by other individuals of RS_2 become available also stating that no people are in multiple other buildings. Buildings that are evacuated show a maximum probability of 3% (e.g. building 8) and thus stand out clearly in Fig. 11 at t_2. At t_3, sensor information from gas sensors with an accuracy of 90% becomes available, providing observations that include virtual evidence for multiple buildings. At the same time step, more buildings are evacuated and thus observations by officials of RS_3 become available. Buildings that are not yet evacuated can quickly be identified (see Fig. 11). After this time step, building 7 shows the highest probability of node *People in Building Affected* being in state *True* with a probability of 89%. At t_4, again, more buildings are officially evacuated and two observations become available each stating that no people are affected in building 7 and 17. These observations are provided by humans of RS_1 resulting in a decrease of probability for those two buildings. At the last time step t_5, more buildings are evacuated, an observation becomes available stating that affected people have been sighted in building 17, and an additional observation is provided by a human of RS_2 stating that no people are in building 13. At this time step, only building 13 and 17 are not yet evacuated with building 17 having a significantly higher probability of affected people compared to building 13.

5. Discussion

In this paper, we introduced *ERIMap*, a novel Bayesian network-based method for supporting situation awareness tailored to the specific information-scape in emergency response. This specific information-scape can well be expressed via six requirements which have served as guiding principles for the design of the *ERIMap* method. In accordance with these requirements, the *ERIMap* method is capable of deriving insights about an ongoing situation by processing information which is incomplete (R1: process *incomplete* information), which potentially stems from diverse sources (R2: process information from *diverse sources*), which contains uncertainty (R3: process *uncertain* information) and potentially contradictory observations (R4: process *contradictory* information), which evolves dynamically in time (R5: process *dynamic* information) and which is spatially distributed (R6: process *spatial* information).

Regarding the first requirement (R1: process *incomplete* information), using a BN as the core of the method allows to incorporate

Table 4
Sequence of observations of scenario 1.

(1) Node	(2) State(s)	(3) Source (RS)	(4) Buildings	(5) Time
Time of Day	*6pm-6am*	Clock (RS_3)	all	t_0
Building Type	*Office*	GIS Layer (RS_3)	2, 3, 5, 7, 8, 11, 12, 18, 25, 26, 27	t_0
Building Type	*Production*	GIS Layer (RS_3)	4, 6, 10, 13, 16, 17, 21, 23	t_0
Building Type	*Mixed*	GIS Layer (RS_3)	1, 9, 14, 15, 19, 20, 22, 24	t_0
C.G.D. ar. Building	$P(0.3, 0.7)$	Simulation (RS_3)	15, 20, 22, 23, 25	t_1
C.G.D. ar. Building	$P(0.6, 0.4)$	Simulation (RS_3)	4, 12, 19, 21, 24	t_1
C.G.D. ar. Building	$P(0.8, 0.2)$	Simulation (RS_3)	6, 7, 8, 9, 10, 11, 13, 14, 16, 17, 26	t_1
People in Building	True	Human (RS_2)	9, 13, 17, 21	t_2
People in Building	False	Human (RS_2)	4, 10, 16, 19	t_2
Gas in Building	L(0.9, 0.1)	Gas Sensor (RS_3)	6, 8, 9, 17, 26	t_3

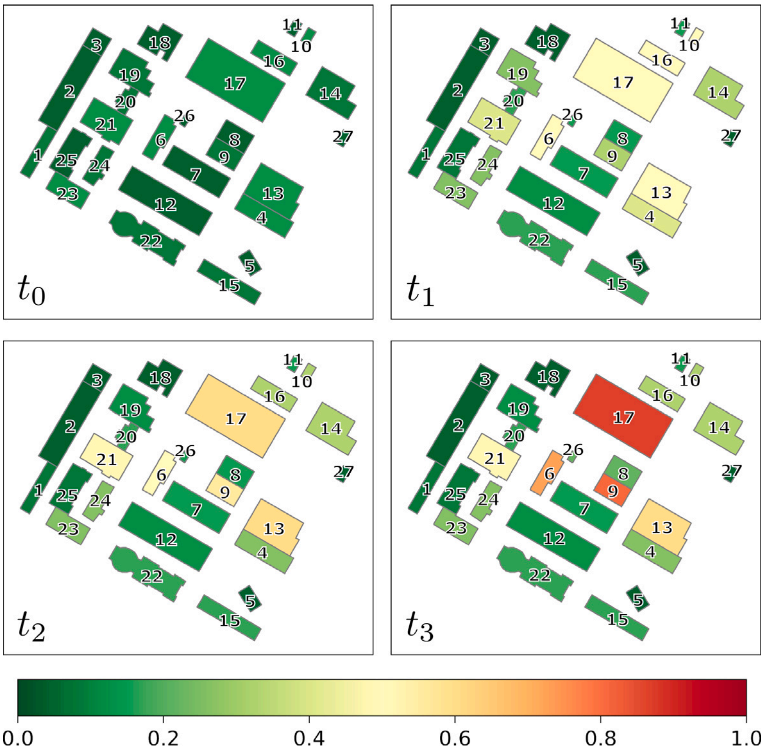


Fig. 10. Probability of node *People in Building Affected* being in state *True* for each building at four time steps of scenario 1 (see Table 4).

Table 5
Sequence of observations of scenario 2.

(1) Node	(2) State(s)	(3) Source (RS)	(4) Buildings	(5) Time
Time of Day	*6pm-6am*	Clock (RS_3)	all	t_0
Building Type	*Office*	GIS Layer (RS_3)	2, 3, 5, 7, 8, 11, 12, 18, 25, 26, 27	t_0
Building Type	*Production*	GIS Layer (RS_3)	4, 6, 10, 13, 16, 17, 21, 23	t_0
Building Type	*Mixed*	GIS Layer (RS_3)	1, 9, 14, 15, 19, 20, 22, 24	t_0
C.G.D. ar. Building	$P(0.3, 0.7)$	Simulation (RS_3)	15, 20, 22, 23, 25	t_1
C.G.D. ar. Building	$P(0.6, 0.4)$	Simulation (RS_3)	4, 12, 19, 21, 24	t_1
C.G.D. ar. Building	$P(0.8, 0.2)$	Simulation (RS_3)	6, 7, 8, 9, 10, 11, 13, 14, 16, 17, 26	t_1
People in Building	False	Human (RS_3)	4, 8, 11, 16, 21, 22, 23, 26	t_2
People in Building	False	Human (RS_2)	10, 14, 20, 24	t_2
Gas in Building	L(0.9, 0.1)	Gas Sensor (RS_3)	6, 7, 14, 17	t_3
People in Building	False	Human (RS_3)	1, 2, 3, 24, 25, 27, 10, 18	t_3
People in Building	False	Human (RS_3)	5, 6, 9, 15, 20	t_4
People Affected	False	Human (RS_1)	7, 17	t_4
People Affected	True	Human (RS_2)	17	t_5
People in Building	False	Human (RS_3)	7, 12, 14, 19	t_5
People in Building	False	Human (RS_2)	13	t_5

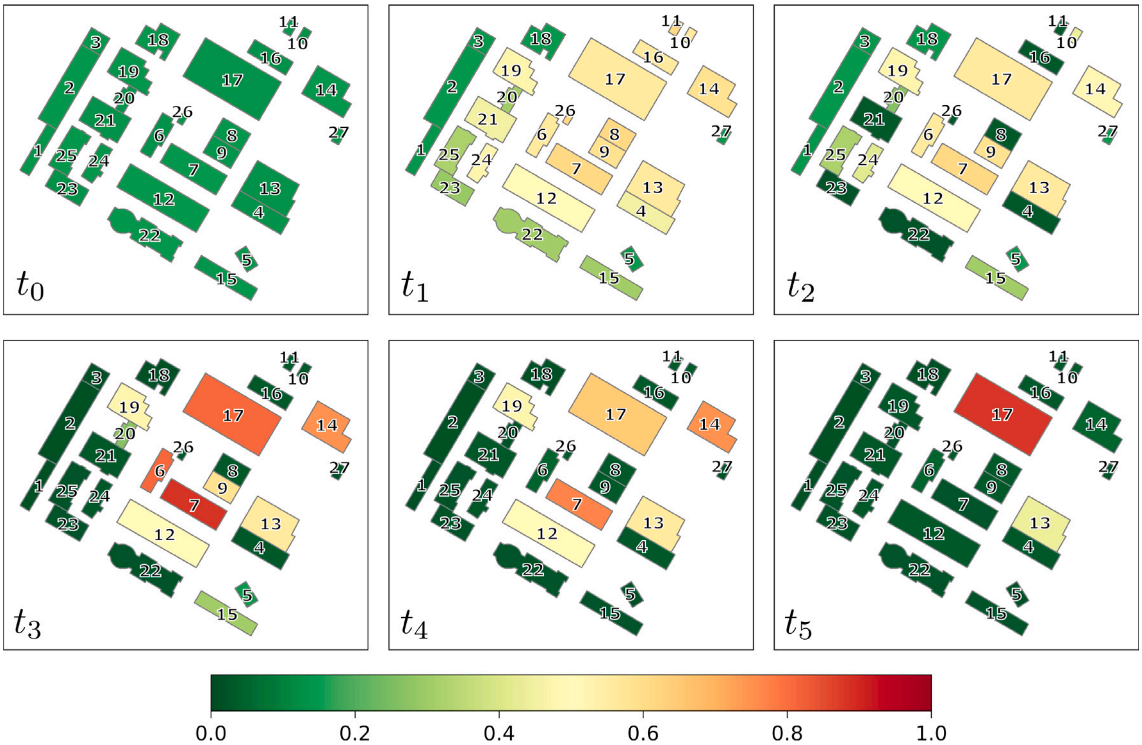


Fig. 11. Probability of node *People in Building Affected* being in state *True* for each building at six time steps of scenario 2 (see Table 5).

pre-existing knowledge about important system variables and their interrelations into the assessment of an actual emergency situation (e.g. see [71]). In this way, the method can draw inferences about an ongoing emergency situation based on incomplete information. For instance, already in the initial stages of the case study, the *ERIMap* method provides an estimation on where the presence of affected people can be expected, based solely on information regarding the building types, the time of day, and the estimated gas dispersion.

Regarding the second requirement (R2: process information from *diverse sources*), we have demonstrated how observations provided by different individuals, different sensors, GIS layers and simulations inform the *ERIMap* method. Considering multiple sources increases the amount of information which can be utilised in the assessment of the situation, but without creating cognitive overload that is typically hampering emergency management [72]. The *ERIMap* method condenses and combines all single pieces of information into a single output; in the case study, the probability of affected people being in a building.

In emergencies many observations contain a certain degree of uncertainty (R3: process *uncertain* information). However, in the literature, there are only few papers that apply uncertain evidence in BNs (e.g., [37]). According to Munk et al. [38], this might be due to a lack of consensus on which type of uncertain evidence should be applied in which case. A core feature of our *ERIMap* method is a classification scheme which selects the 'right' type of evidence based on the reliability of the observation source (quantified by reliability scores) and the precision of the reported observation (a specific indication or a likelihood). Every piece of information can then be fed into the BN, taking into account the degree and type of uncertainty associated with it. In short, the *ERIMap* method provides an evidence-specific protocol for hard, for soft and for virtual evidence.

The utilisation of uncertain evidence is also important for addressing the fourth requirement (R4: process *conflicting* information). Our *ERIMap* method contains two tools for dealing with conflicting observations, both of which rely on the utilisation of uncertain evidence: (1) reliability scores which favour observation sources which are considered more trustworthy and (2) a regret function which favours observations which report critical states ("there are people in building A") over observations which report non-critical states ("there are no people in building A"). While reliability scores and regret functions cannot dissolve the issue of conflicting observations, they can still provide a structured way for dealing with this type of noisy input. In particular, they allow to shift considerations on how to deal with conflicting information from the time-critical operation phase (during the emergency) to the non-time-critical preparation phase (prior to the emergency).

In the case study, we have demonstrated that the *ERIMap* method is capable of providing a dynamically evolving (R5: process *dynamic* information) and spatially resolved (R6: process *spatial* information) picture of the current state of belief about an emergency situation. Due to the established protocol for translating observations into evidence, every new observation can directly be utilised to update the BN-based assessment of the current situation. Furthermore, the use of area-specific BNs in our *ERIMap* method allows to cover the spatial dimension of emergencies. The implementation of the area specification is kept quite simple. It is realised by initially assigning duplicates of the same BN to every subarea within the study site. The area-specific output is then obtained by feeding each BN with area-specific evidence. While we assume that this simple approach is sufficient for many applications, it should be noted that it can easily be adapted to more complex demands, for instance, one could use different BNs for indoor and outdoor areas or for different types of buildings. In the same manner, the spatial resolution of the *ERIMap* can be adjusted according to the demands of the addressed emergency response team.

Besides fulfilling all requirements, a final advantage of BNs is that, due to their graphical structure, they represent explainable models whose dynamics are comprehensible, even for people who are not familiar with their technical details [73]. Using an explainable model facilitates engaging experts and potential users in the development and validation of the model. In this way, the model can be established even if the data situation is not satisfactory. In addition, the graphical nature of the model facilitates adjustments to the preferences of emergency responders. What is more, keeping the process of drawing inferences from observations transparent enhances the acceptance by potential users – an aspect that is crucial in emergency response [74]. Especially in domains where decisions have a direct impact on people – such as in emergency response – there is a certain reluctance to trust black box models [75] and ease of interpretation is vital [76].

A main limitation of the *ERIMap* method is that, for setting up the BN at its core, the method relies on structural knowledge about the emergency in question which exists prior to the actual emergency situation which it should help to assess. Importantly, the value which the method adds to this assessment ultimately depends on the quality of this pre-existing knowledge. This implies that eliciting this knowledge during the preparation phase is of utmost importance for the successful application of the *ERIMap* method. While we have highlighted the importance of engaging users in this process, we have not covered how their knowledge can best be elicited for the use in the *ERIMap* method. While this is an aspect that has already been addressed for BNs (e.g. [77] or [78]), it will nevertheless be important to establish a corresponding procedure which is specific to the *ERIMap* method. Another implication is that the method is particularly well suited for rather common or expectable types of emergencies in well-known (and structured) territories. The *ERIMap* method thus seems promising for supporting the operation of emergency response teams in emergencies which are considered particularly relevant in specific facilities, for instance, for gas leakages on chemical plant sites (our case study), for fires in office buildings or airports, or for floods in cities situated near rivers or coasts. To what extent the *ERIMap* method can also contribute to assessing important variables of an unexpected or unforeseen emergency situation is less clear and should be further explored in future studies.

A technical aspect which has not yet been covered in the *ERIMap* method are mechanisms for performing belief updates in the BNs which are not directly tied to newly available observations but which rely on presumably predictable inner system dynamics. For instance, in future work, it could be insightful to consider the movement of people (e.g., evacuation of buildings), the dispersion of hazardous material (like gas or smoke) or the increasing criticality of being exposed to such material using dynamic Bayesian networks [79] and spatially interlinked area-specific BNs. However, in how far belief updates based on presumed dynamics can and should be utilised to assess real emergency situations needs to be evaluated in dialogue with potential users.

One limitation of this paper is that we still need to empirically test the impact of the *ERIMap* on situation awareness. First feedback from potential users (e.g., members of the Henkel fire brigade) is thoroughly positive. However, in order to verify its positive impact on situation awareness, future work should include empirical testing and validation of the method in practice. To this end, the method should be established in a real setting and then be evaluated in training exercises with responsible practitioners. This evaluation procedure should at best be performed for multiple case studies that include different types of emergency scenarios. The method can be applied for all types of emergencies that require a fast processing of large amounts of diverse observations under time pressure – conditions that are present in a variety of emergency situations. For the further development of the *ERIMap* method this implies that future work should focus on facilitating the transfer of the *ERIMap* method into practice focusing on applicability in multiple types of scenarios. In particular, future research should focus on (1) how expert knowledge can best be compiled in the preparation of the *ERIMap* method; on (2) developing a user interface, i.e. an application on a mobile device, which facilitates a quick and straightforward injection of observations (including the five pieces of information, e.g., the reliability score) and which displays the results in an interactive map; on (3) how the method can be effectively integrated into existing emergency response protocols, such as determining who is responsible for injecting new observations and who will receive the resulting information, i.e. the dynamically evolving map.; and on (4) empirical and experimental testing and measuring the impact of the *ERIMap* on situation awareness, e.g., in training sessions or serious games.

6. Conclusion

In this work, we introduced a novel method called *ERIMap* (Emergency Response Inference Mapping) that can support the situation awareness of emergency responders by processing diverse observations gathered during an ongoing emergency and summarising the belief about key aspects in a dynamically evolving emergency map. The method is tailored to the specific information-scape in emergency response that we defined by six key requirements: information can be incomplete, come from diverse sources, be uncertain, conflicting, dynamic, and spatially distributed. To obtain a method that fulfils all six requirements, we combined a BN-based model, capable of performing inferences based on diverse observations, with a GIS used to consider the spatial aspects of an emergency. Given a small set of observation properties, the method classifies the included evidence in terms of its uncertainty, and performs area-specific inference on the key variables for decision makers. The result is a dynamically evolving map displaying the belief about key variables of the emergency scene. Illustrated in a case study of an emergency response triggered by a gas leakage at a chemical plant site, the results show that the methods reduces information complexity by condensing all observations into a concise picture of the situation. In this way, the cognitive load on decision-makers in emergency response can be reduced thus supporting them in taking high stake decisions.

CRediT authorship contribution statement

Moritz Schneider: Writing – original draft, Writing – review & editing, Methodology, Conceptualization, Visualization, Software. **Lukas Halekotte:** Writing – original draft, Writing – review & editing, Supervision, Conceptualization. **Tina Comes:** Writing – review & editing, Supervision, Conceptualization. **Daniel Lichte:** Project administration, Conceptualization. **Frank Fiedrich:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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B | Publication II

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Dependent Infrastructure Service Disruption Mapping (DISruptionMap): A method to assess cascading service disruptions in disaster scenarios

Moritz Schneider[1]✉, Lukas Halekotte[1], Andrea Mentges[1] & Frank Fiedrich[2]

Critical infrastructures provide essential services for our modern society. Large-scale natural hazards, such as floods or storms, can disrupt multiple critical infrastructures at once. In addition, a localized failure of one service can trigger a cascade of failures of other dependent services. This makes it challenging to anticipate and prepare adequately for direct and indirect consequences of such events. Existing methods that are spatially explicit and consider service dependencies currently lack practicality, as they require large amounts of data. To address this gap, we propose a novel method called *DISruptionMap* which analyzes complex disruptions to critical infrastructure services. The proposed method combines (i) spatial service models to assess direct service disruptions with (ii) a service dependency model to assess indirect (cascading) service disruptions. A fault tree-based approach is implemented, resulting in a significant decrease in the information required to set up the service dependency model. We demonstrate the effectiveness of our method in a case study examining the impact of an extreme flood on health, transport, and power services in Cologne, Germany.

Keywords Critical infrastructure, Cascading effects, Flood risk management, Bayesian network, GIS

Critical infrastructures (CIs) form the backbone of modern societies[1], providing them with essential services, including mobility, electricity, and healthcare. These services are increasingly exposed to a growing number of natural hazards[2,3], such as floods, storms, or earthquakes. Such large-scale disruptive events often damage multiple CIs simultaneously, e.g. a flood might cause disruptions in the road network, the energy distribution system, and the healthcare system. As CIs often span over or supply large geographical areas[4], CI failures can lead to service disruptions far away from the immediate location of the actual disruptive event. Additionally, modern CI systems can be subject to complex indirect hazard impacts: CIs are highly interdependent across different sectors[1,5], e.g. a power plant depends on a steady supply of cooling water and in turn provides electricity to numerous other CI systems. These dependencies can be of various types (e.g. physical, cyber, informational, political[6] or service centered[7,8]) and can cause indirect disruptions due to the failure of one infrastructure inducing the failure of other subsequent infrastructures—often referred to as cascading effects[4]. Overall, the prediction of the consequences of large-scale hazardous events is a complex task that requires multiple stages of impact analyses (each stage adding some element of uncertainty to the issue): (1) the direct impact of a hazard on infrastructure components, (2) the impact of component failures on the system level and (3) the impact of the failure of one system on other systems.

Several approaches have been put forward to describe the direct impact of natural hazards on CIs. Multiple works focus on spatial models of direct CI disruptions caused by e.g. storms[9], floods[10], earthquakes[11], or explosions[12]. These works use GIS-based overlay analyses of hazard exposure areas and CI locations to estimate the impact in affected areas. Some of these works also consider uncertainties in CI failures depending on the intensity of CI component exposure, e.g. modeled by fragility curves (see Serrano-Fontova et al.[13] for an overview). Other works focus on the (quantitative) modeling of CI dependency patterns and associated cascading effects[14,15], with some also accounting for uncertainties in their analyses[6,7,16]. These approaches

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differ with regard to the modeling technique, e.g. there are network models, input-output-models, multi-agent systems, or Bayesian networks[4].

Few studies combine spatial CI exposure assessments with CI dependency models[4,17–19]. Such methods to assess (cascading) CI disruptions usually rely on a potentially high volume of different types of data: geo-referenced data of CI locations and hazard distribution for a specific scenario[20], data for the assessment of direct CI disruptions[13], and data for indirect CI disruptions[6]. As suitable historical data on severe disruptive events that caused serious cascading failures is scarce, researchers often need to rely on expert knowledge. The need to effectively integrate expert knowledge results in a characteristic area of tension: on the one hand, a certain level of detail is required for an accurate description of the CI dependency network[17]. On the other hand, the burden on individual experts to deliver large amounts of data should be limited, to ensure practicality of the method – an aspect that is often lacking in this context[4]. The level of detail thus needs to be balanced with the simplicity of the modeling approach.

To address this, we developed a method called Dependent Infrastructure Service Disruption Mapping (*DISruptionMap*). *DISruptionMap* enables a spatial assessment of direct as well as indirect CI service disruptions and allows the effective integration of expert knowledge while requiring a minimum amount of information. It is composed of GIS-based spatial models (to assess the direct CI disruptions) and a Bayesian network-based service dependency model (to assess indirect CI disruptions). Bayesian networks (BNs)[21] are powerful tools to model CI dependencies and associated uncertainties[22,23]. They can be constructed solely based on expert knowledge, but also using a combination of expert knowledge and other data sources. Here, we construct a BN by describing CI dependencies as services, such that the dependencies can be consistently and uniformly defined across different types and sectors of CIs. The resulting information on (cascading) service disruptions throughout the affected area can be used by practitioners for planning of disaster response measures or training exercises.

The remainder of this paper is organized as follows: first, we provide an overview of the *DISruptionMap* method, highlighting the main steps for its application (for a more detailed description, see "Methods"); second, we demonstrate the method through a case study of a 500-year flood scenario in the city of Cologne (Germany), examining disruptions to multiple CI services with a focus on hospital emergency care services; finally, we discuss limitations of our proposed method and the opportunities it offers for future research and for the application in disaster management.

DISruptionMap method: dependent infrastructure service disruption mapping

The *DISruptionMap* method requires several steps of preparation: i) determine the specific hazard causing the disaster scenario (e.g. a 500-year river flood event), along with an impact measure (IM) to quantify its severity (e.g. water depth for a flood); ii) find geospatial data which shows the expected IM intensity levels within the study area, e.g. a map showing the flood depth; iii) identify a target critical infrastructure (TCI) that describes the service of central interest and serves as a starting point for a top down approach to reflect (T)CI dependencies in the study area; and iv) collect spatial data on TCI locations and CI components, with the type of CIs first being identified during the development of the service dependency model. Given these four bits of information (the specific disaster scenario and its IM, geospatial IM intensity data in the study area, the TCI, and spatial data on the (T)CI), the *DISruptionMap* method can be applied.

The key steps to apply the proposed method are (see "Methods" for details, and Fig. 1 for an overview in the context of the case study): (i) Building *Spatial Service Models*, i.e. develop spatially explicit models to assess direct CI service disruptions based on the hazard-specific IM intensity map, and (ii) Developing the *Service Dependency Model*, i.e. a Bayesian network-based CI service dependency model to assess indirect disruptions. This service dependency model is replicated for each TCI in the study area to individually assess the (combined) disruptions on the TCI service, e.g. the TCI is a hospital and thus the service dependency model is duplicated and assigned to each hospital in the study area. In combination, the two models (spatial and dependency models) allow to assess both direct and indirect CI service disruptions within the study area. Finally, the results are displayed on a map, providing a both concise and comprehensive summary to the large volume of (spatial) information on the service disruptions for all entities in the study area.

Case study of a flood scenario in the city of Cologne

We illustrate our proposed method in a case study conducted in Cologne (Germany), focusing on emergency care service availability by hospitals during an extreme river flood scenario (Fig. 2). Cologne, one of Germany's largest cities with over one million inhabitants, is vulnerable to river floods: the Rhine river runs right through the city center. The city has experienced several devastating floods, e.g. in 1993 and 1995, with significant impacts on citizens and economic damages[24,25]. Moreover, a flood event that occurred in the Ahr Valley (Germany) in 2021 further underscored the importance of effective flood risk management in this region[26]. Cologne's dense population, immediate proximity of the city center to the Rhine river, and high concentration of critical infrastructures make it a relevant and complex study area for testing the proposed method.

The GIS data used in this case study stems from a hydrological simulation of an extreme flood scenario (also called 500-year flood, see Fig. 2) that is provided by the state of North Rhine-Westphalia[27]. It includes failed or overtopped dikes, mobile flood defenses, and groundwater intrusion into old river arms[20]. The analysis of such extreme flood scenarios is mandatory under the European flood directive and is available for all major German rivers[20]. Furthermore, we use CI location data from Open Street Map (OSM) for the spatial service models. Note that the data retrieved from OSM is not checked for accuracy and completeness and can thus not be transferred directly to the real-world infrastructures in the study area. The case study is intended as a proof of concept of the proposed method using example data retrieved from OSM.

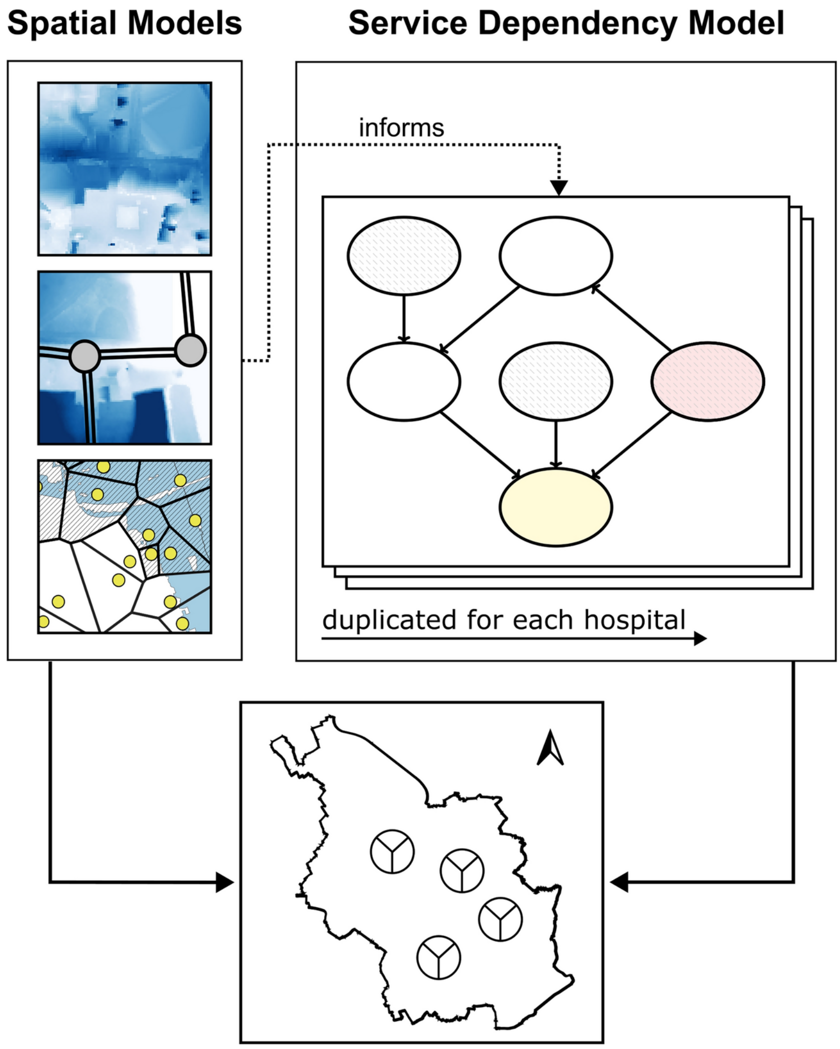

Fig. 1. Summary of the proposed method, using the case study as an example. The proposed method combines GIS-based spatial service models with a BN-based service dependency model (i.e. GIS informs BN). The results are displayed on a comprehensive map of the study area (the *DISruptionMap*) to help gain a quick overview of the high volume of (spatial) information.

In the following, first, we describe the development of the service dependency model (implemented in Python using the pgmpy library[28]); second, we detail the development of the spatial service models (using the geopandas library[29]); and finally, we present the *DISruptionMap* of the case study that summarizes all model results in a comprehensive overview of hospital-specific service disruptions in the study area (developed in QGIS).

Service dependency model

In this case study, we examine hospitals as target critical infrastructures (TCIs) and their dependencies on other services. In specific, we focus on the availability of *emergency care* addressing services provided to patients who require immediate attention due to a sudden or unexpected condition. Thus, the target node of the BN-based service dependency model is *Emergency Care*. To quantify the direct impact of the flood scenario on the emergency care services of an individual hospital, the impact measure node *Flood Depth at Hospital* is introduced as a parent node of the target node (Fig. 3). As highlighted in previous research[18], hospitals crucially rely on power supply (for emergency care services) and road network accessibility (for emergency vehicles and goods supply). Therefore, the services *Accessibility* and *Power Supply* are introduced as parent nodes of node *Emergency Care*. In Germany, two redundant power supply sources are mandatory for hospitals: supply by the power grid and a backup generator which is located within the hospital. Therefore, we introduce two additional parent nodes to the node *Power Supply*: *Power Supply Grid* and *Power Supply Generator*. The power generator is located within the hospital and thus it can also be considered as a child node of node *Flood Depth at Hospital*. Ultimately, the full BN (Fig. 3) describing all dependencies of the target node *Emergency Care* consists of three dependent nodes (*Emergency Care, Power Supply,* and *Power Supply Generator*) that each require one Conditional Probability Table (CPT). For the node *Flood Depth at Hospital*, we distinguish between four categories of flood depths. All other nodes are treated as binary, i.e. they show two states (Table 1).

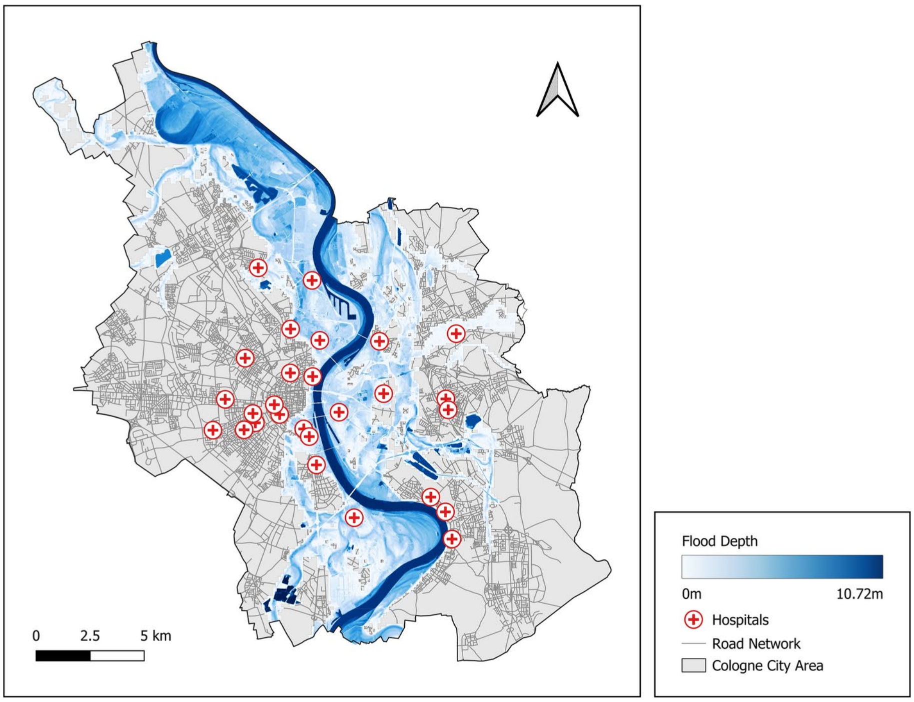

Fig. 2. Map of the case study region. The city of Cologne is displayed along with the locations of hospitals, the road network, and the flood depth in a scenario of a 500-year flooding (HQ500).

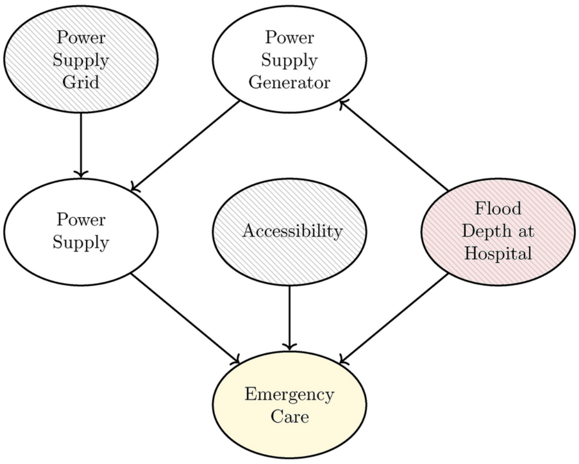

Fig. 3. Bayesian network-based service dependency model of the case study. The model includes six nodes including the target node *Emergency Care* highlighted with yellow fill. Leaf nodes that are informed by the spatial models are highlighted with dashed fill. The node directly informed by the hazard map is highlighted with red fill.

Two categories of nodes within the dependency model are informed by spatial information: for the direct disruption, *Flood Depth at Hospital*, which measures the flood depth at the immediate location of the hospital itself, and, for the indirect disruptions, *Power Supply Grid* as well as *Accessibility*, which analyze service failures caused by the flooding of transformer stations or roads at a distance from the hospital. For instance, a flooded road segment 1 km away from the hospital could render it inaccessible.

Next, the CPTs are filled with probability values, starting with the CPT attached to node *Power Supply Generator*. Here, four probability values are required, one for each state of node *Flood Depth at Hospital* (None, Low, Medium, and High), e.g. the probability of the power supply by the hospital failing given a medium flood depth: $P(Power\,Supply\,Generator : Failed|Flood\,Depth\,at\,Hospital : Medium) = 0.75$. In the case study, we use exemplary failure probability values that increase with rising flood depth (Table 2). The second CPT is attached to node *Power Supply* with its parent nodes *Power Supply Grid* and *Power Supply Generator*. This sub-network expresses an AND gate (see "Methods"), i.e. both parent nodes must fail for the child node

Flood depth (D)	Accessibility	Emergency care	Power supply	Power supply generator	Power supply grid
None (0m)	Accessible	Available	Available	Available	Available
Low ($D \leq 0.5m$)	Inaccessible	Failed	Failed	Failed	Failed
Medium ($0.5m < D \leq 1.2m$)					
High ($D > 1.2m$)					

Table 1. Variables (nodes) and respective states of the BN.

	Power supply generator	
Flood depth at hospital	Available	Failed
None	1	0
Low	0.75	0.25
Medium	0.25	0.75
High	0	1

Table 2. CPT of node *Power supply generator*.

		Power supply	
Power supply grid	Power supply generator	Available	Failed
Available	Available	1	0
Available	Failed	1	0
Failed	Available	1	0
Failed	Failed	0	1

Table 3. CPT of node *Power Supply*.

to fail as well. Thus, no further information is required for the CPT (see Table 3). The third CPT (attached to node *Emergency Care*) shows three parent nodes (*Flood Depth at Hospital*, *Power Supply*, and *Accessibility*). This sub-network represents an OR gate with an additional uncertainty on the impact of node *Flood Depth*. Thus, if either the hospital is inaccessible or the power supply failed, the emergency care service definitely fails. In cases of available power supply and accessibility of the hospital, the impact of the flood depth is uncertain for states *Low* and *Medium*. For this constellation of node states, we again use exemplary failure probability values that increase with increasing flood depth (Table 4).

Spatial service models

Each leaf-node of the hospital-specific service dependency model (dashed nodes in Fig. 3) is informed by a specific spatial model. The evidence for these nodes can take two forms: regular evidence, i.e. a binary value indicating whether the service is available or unavailable (e.g. node *Accessibility* is in state *Inaccessible*); or soft evidence, i.e. a probability ratio of service availability[30] (e.g. the probability ratio of node *Power Supply Grid* available versus unavailable is (0.8,0.2)). Node *Flood Depth at Hospital* is informed by the extreme flood raster layer (Fig. 2) and does not require an additional model. The spatial service models to inform the nodes *Power Supply Grid* and *Accessibility* of each hospital-specific service dependency model are outlined in the following.

Accessibility model

To evaluate hospital accessibility in the study area, the road network is reconstructed using Open Street Map (OSM) data[31]. The resulting network topology features nodes representing road crossings and edges representing road segments[32] (Fig. 4). Edges are characterized by their length and the maximum flood depth along the section, which is determined from the flood scenario raster layer. In this model, hospital accessibility is represented by two distinct states: *Accessible* and *Inaccessible*. We assume that each road segment in the network can be used (ignoring e.g. one-way streets) and hospitals are accessible if at least one route to the hospital exists where the flood depth for all passed road segments is below 27 cm. This threshold value is based on studies which suggest that a flood depth between 27 cm and 30 cm is the critical point for safely passing through a flooded road segment[32,33]. We argue that these assumptions are sound for emergency scenarios, specifically when considering exclusively emergency response vehicles such as ambulances and fire trucks.

For the routing algorithm, we defined multiple source locations on the east and west side of the Rhine river with sufficient distance from flooded areas. To minimize potential biases introduced by the source location, multiple locations are necessary. For instance, a single source location at the west side of the river might not reveal a feasible path to a hospital, whereas an alternative source location at the east side of the river would demonstrate a viable route. A hospital is considered accessible if a route from at least one source location exists

Flood depth at hospital	Power supply	Accessibility	Emergency care	
			Available	Failed
None	Available	Accessible	1	0
None	Available	Inaccessible	0	1
None	Failed	Accessible	0	1
None	Failed	Inaccessible	0	1
Low	Available	Accessible	0.75	0.25
Low	Available	Inaccessible	0	1
Low	Failed	Accessible	0	1
Low	Failed	Inaccessible	0	1
Medium	Available	Accessible	0.25	0.75
Medium	Available	Inaccessible	0	1
Medium	Failed	Accessible	0	1
Medium	Failed	Inaccessible	0	1
High	Available	Accessible	0	1
High	Available	Inaccessible	0	1
High	Failed	Accessible	0	1
High	Failed	Inaccessible	0	1

Table 4. CPT of node *Emergency care*.

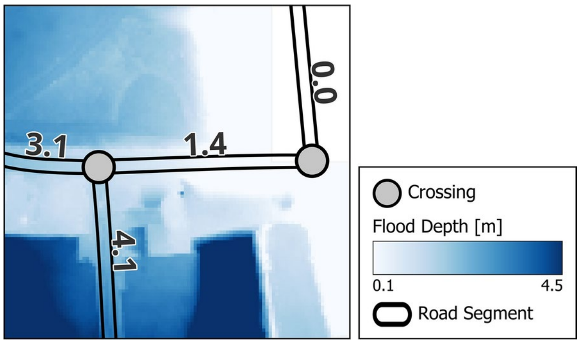

Fig. 4. Example area including the reconstructed road network and flood depth layer. Nodes represent crossings and edges represent road segments that include the maximum flood depth at each segment. Additionally, the flood depth raster layer is illustrated that is used to obtain the maximum flood depth at each road segment.

that fulfills the aforementioned criterion. For each source node, the routing algorithm is applied to each hospital in the study area. The outcomes, categorized into the two states (*Accessible* and *Inaccessible*), are then calculated for each hospital to inform the hospital-specific service dependency models.

Power supply grid model

The power supply of a city depends on the proper functioning of substations, transmission lines, distribution lines, and transformer stations. Substations are crucial hubs that transform high-voltage electricity from the transmission lines to medium voltage levels that are distributed within the city by distribution lines. Transformer stations, which are distributed throughout the city, step down this medium-voltage power to household-friendly voltages. In this case study, we focus for simplicity on the failure of transformer stations caused by the flood. Therefore, we need two models, one for the failure probability of a transformer station given the site-specific flood depth and one that assesses the blackout area if a transformer station fails.

To estimate the failure probability of a transformer station, we use a fragility curve. Fragility curves illustrate the probability of a system or component failing as a function of a given impact measure (IM) of a hazard. Thus, fragility curves show how likely a system is to fail, i.e. become "fragile", under different levels of stress. They can be based on empirical data, simulations, and expert knowledge. If no sufficient empirical data is available, expert knowledge should be included[34,35]. Here, we use a fragility curve to describe the relation between the flood depth (IM) and the failure probability of a transformer station. Pita et al.[35] conducted a study on the development of a fragility function for building damages under stress of a flood, i.e. the flood depth for a given period of exposure. Based on empirical data, they showed that the fragility of a building in a flood scenario follows a lognormal cumulative distribution function (lognormal cdf). When empirical data was missing, they used anchor points elicited from experts to fit a lognormal cdf distribution. We follow their approach and use single data points

Query	Probability of failure	Flood depth
–	0%	0.0 m
No damage up to what depth?	0%	0.2 m
Highest uncertainty of damage at what depth?	50%	0.8 m
Very likely damaged from what depth?	90%	1.2 m
Surely damaged from what depth?	100%	1.8 m

Table 5. Example data points for the fragility function of a transformer station of the case study. Example queries are listed that can be used to elicit a set of probability values and flood depth values serving as data points to fit the fragility curve.

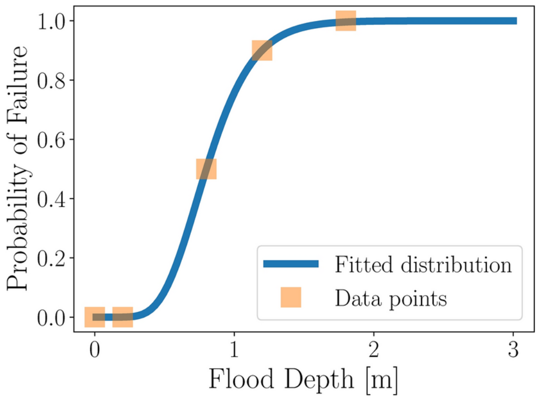

Fig. 5. Fragility function of a transformer station under the stress of a flood. The data points (see Table 5) are used to fit a lognormal cdf using a least-square curve fit algorithm.

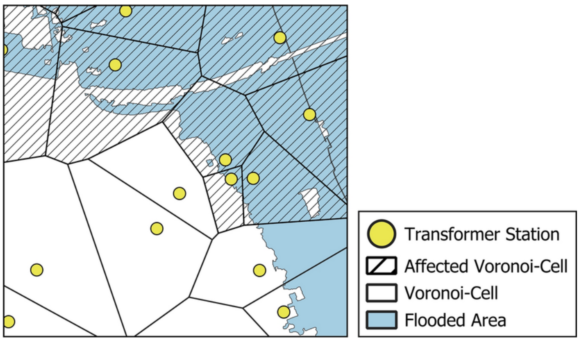

Fig. 6. Example area and Voronoi cells affected by the flooding. Transformer stations serve as the source points for the Voronoi diagram. Transformer stations situated within the flooded area are classified as affected, along with their associated Voronoi cells (highlighted with dashed fill).

which can be queried by experts (see Table 5 for example queries and associated data points) and a non-linear least squares curve fit for the fragility curve (Fig. 5).

To identify a potential blackout area for each transformer station, we adapt the Voronoi diagram approach presented by Held et al.[36]. Voronoi diagrams partition space into regions called cells, each representing the area closest to a source point among a set of given points. In this study, transformer stations serve as the source points, and each cell corresponds to the area nearest its respective transformer station (Fig. 6).

Results and visualization

From the total of 27 hospitals we examined, eight hospitals are located within the flooded area, with flood depths ranging from 1 cm to 2.38 m. Six hospitals are deemed inaccessible, either because their access streets are directly impacted by the flooding or because they are disconnected from the road network due to multiple flooded segments at a greater distance. For five hospitals, power supply is uncertain, i.e. the probability of state *Available* for node *Power Supply* is neither zero nor one. One hospital shows a certain power failure ($P(Power\ Supply : Available) = 0$), i.e. both the supply from the grid and the backup power generator fail.

Seven hospitals show a complete failure of emergency care service, caused either by inaccessibility, power supply failure, a high level of flooding, or a combination. Two additional hospitals show uncertainty in the states of the emergency care service.

In the following, the results for two individual hospitals are outlined in detail, illustrating two cases of special interest: accessibility within the flooded area and inaccessibility outside of the flooded area (Fig. 7). Subsequently, the *DISruptionMap* of the case study is presented that summarizes all model results (spatial models and hospital-specific service dependency models) and thus displays a quick overview of service availabilities at all hospitals within the study area (Fig. 8).

Single hospitals

Two selected hospitals illustrate contrasting impacts of the disruption. Hospital (1) (see left side of Fig. 7), situated within the flooded area, with a maximum flood depth of 1.12 m, remains accessible despite the flooding. In contrast, hospital (2) (see right side of Fig. 7) is not directly affected by the flood but becomes inaccessible due to flooded road segments that disconnect the hospital from the overall road network. The transformer stations for both hospitals are located within the flooded area, with varying water levels: 0.55 m at the station for hospital (1) and 2.2 m for hospital (2). According to the fragility curve (Fig. 5), these flood depths result in a probability of transformer station failure of 14% for hospital (1) and 100% for hospital (2). These results are subsequently used to infer the availability of the other services, i.e. nodes *Power Backup Generator*, *Power Supply*, *Emergency Care Service*.

The probability that hospital (1)'s backup power generator is still functional is 25%, due to a medium flood depth at the hospital. In combination with the 14% of the transformer station failure, this leads to an inferred probability of 90% that the hospital possesses reliable power supply. The probability of emergency care service availability is 23%. This value is inferred based on the information on nodes *Power Supply*, *Accessibility*, and *Flood Depth at Hospital*. Hospital (2) shows 100% service availability of the power supply by the backup generator. This results, due to the OR gate, in a 100% service availability of node *Power Supply*. Nevertheless, due to the crucial dependency (modeled by the AND gate) on the accessibility of the hospital for the emergency care services, the resulting probability of emergency care service availability is 0%.

DISruptionMap of the case study

The *DISruptionMap* method summarizes all insights from the individual models (spatial models and hospital-specific service dependency models) in a single map, the *DISruptionMap* (Fig. 8). This comprehensive map facilitates the exploratory analysis of the results and thus can help to quickly inform decision-makers. In comparison to the initial map of hospital locations and the flood distribution of the extreme flood scenario (Fig. 2), the *DISruptionMap* provides additional information on (cascading) service disruptions. The *DISruptionMap* of the case study presented shows the availability of the services of *Emergency Care*, *Power Supply*, and *Accessibility*, allowing to explore the hospital-specific service disruptions in the study area.

Discussion and conclusion

In this paper, we introduce *DISruptionMap*, a novel method to spatially assess cascading CI service disruptions in large-scale disaster scenarios. Our method consists of three core elements. First, direct disruptions of CI components, e.g. transformer stations or road segments, are assessed using a GIS-based overlay analysis of CI component locations and a hazard map[4]. The approach allows to consider uncertainties in the direct CI component disruption by using a fragility curve that describes the probabilistic relation between an impact

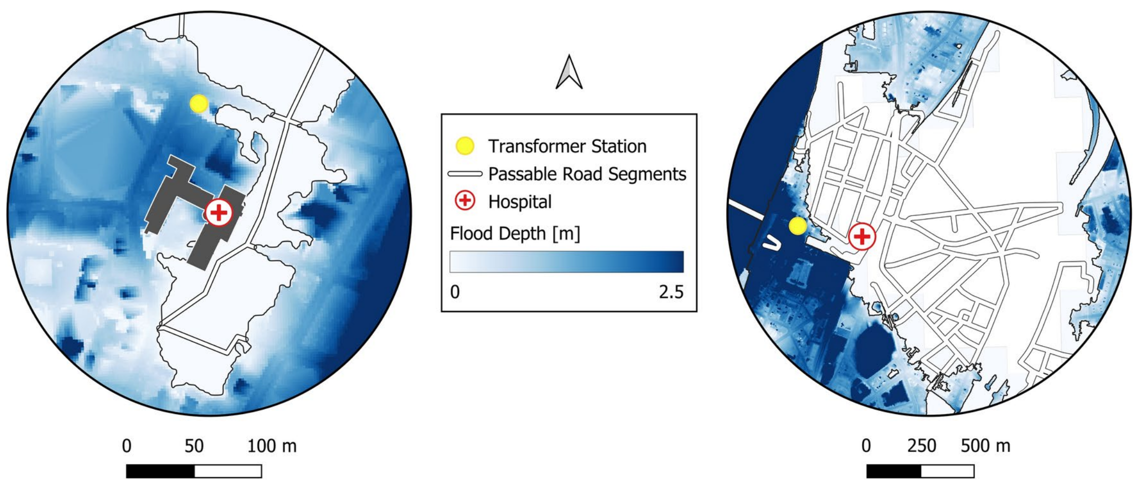

Fig. 7. Two example hospitals of the case study. Hospital (1) (see left side) is accessible but within the flooded area (1.12 m). Its respective transformer station is also within the flooded area (0.55 m). Hospital (2) (see right side) is inaccessible but not within the flooded area (0 m), while its respective transformer station is within the flooded area (2.2 m).

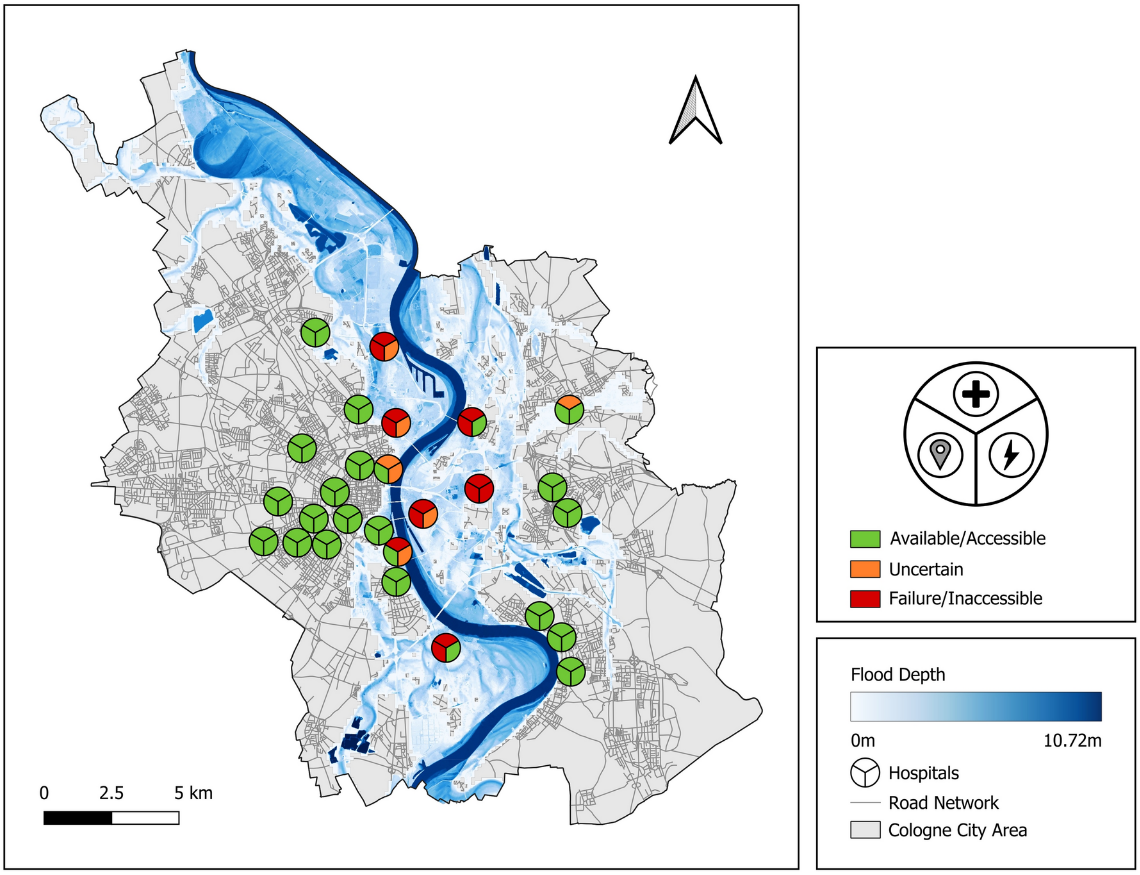

Fig. 8. The *DISruptionMap* of the case study. The map shows the availability of the services *Emergency Care*, *Power Supply* and *Accessibility* for each hospital in the study area. The services *Emergency Care* and *Power Supply* can be either *Available* (green), *Uncertain* (orange) or *Failed* (red) while the *Accessibility* can show the states *Accessible* (green) and *Inaccessible* (red).

measure (IM) obtained from the hazard map and potential failure states of (CI) components (see Fig. 5). Second, the spatial impact of component failures on the corresponding CIs and the area they supply is assessed. This is achieved via CI system models which allow a spatially explicit determination of CI service availability in dependence on component failure, e.g. which areas are no longer accessible if certain road segments are flooded (Fig. 4) or which areas are no longer provided with power if certain transformer stations have failed (Fig. 6). Third, indirect (cascading) disruptions are assessed, i.e. the failure of one CI leads to a failure of another dependent CI. For this, we introduce a Bayesian network-based CI dependency model that is replicated for each target CI (TCI) in the study area – a procedure similar to the method presented by Schneider et al.[37]. To enable a uniform description of CI dependencies across different sectors[7], we follow a service-centered approach: a TCI is described by the service it provides to society (a hospital provides emergency care) while other CIs are described by the service they provide to other CIs (a generator provides power to the hospital). In this way, a spatial assessment of indirect service disruptions on the TCI can be conducted for each TCI entity, e.g. all hospitals in a city. By combining the GIS-based component failure models and spatial CI models with the BN-based CI service dependency model (GIS informs BN[38]), both direct and indirect CI service disruptions can be assessed.

A central motivation for the development of the *DISruptionMap* method was practicability[4]. We aimed for a maximally intuitive work flow based on a minimum amount of additional information, compared to what is required for classic hazard maps. The resulting approach relies on data available from standard data sources – i) static hazard maps are readily available for different hazard scenarios[15,39], ii) CI locations can be collected from OSM, web services provided by governmental registry offices, or they can be obtained directly from local CI providers, and iii) expert knowledge can easily be integrated into the analyses, e.g. for setting up the service dependencies within the BN-based model. To facilitate the integration of expert data, we use a fault tree for creating the CPTs of the service dependency model[40,41]. The fault tree-based approach reduces the amount of input information required for the CPTs, by using logical operators (i.e. gates) to describe the conditions for service availability. This significantly reduces the workload for the consulted experts[42]. Regarding geospatial data concerning CI architecture, we have also demonstrated how existing data gaps can be closed with simple assumption-based models (we derived the local distribution grid based on Voronoi cells). It should however be clear that, whenever available, existing data sources should be used. In this context, data provided by official governmental services or CI providers should generally be preferred over OSM data, as corresponding data sets tend to be more accurate and complete. When using OSM data, possible inaccuracies due to missing, misplaced, or falsely labeled geo-information should be considered[43]. For this purpose, existing methods for classifying and enhancing the quality of OSM data can be utilized (see, e.g. Brovelli and Zamboni[44] or Biljecki et al.[45]). In the end, it should be clear that the *DISruptionMap* can only be as good as the underlying data (the correct localization of service failures relies on data that displays the correct location of infrastructure elements).

In its current form, *DISruptionMap* relies on four main simplifying assumptions for incorporating service dependencies in the analysis of disaster risks. If needed, this basic framework can be easily extended, depending on the requirements of the chosen use case. For instance, instead of using binary variables, a higher granularity of service availability states could be implemented (e.g. Grafenauer et al.[16] use a five-point scale between service availability and failure). However, this would require much more data to set up the BN and a more detailed assessment of direct hazard impacts, e.g. multiple fragility curves, one for each failure state. Another potential extension concerns the uncertainty in the effect of the failure of one infrastructure on the service provision of another. For instance, a power outage certainly causes traffic disruptions[6], but to what extent the traffic system is still functional without power depends on many other factors such as the amount of traffic that has to be regulated by traffic lights. In our *DISruptionMap* method, the implementation of uncertain service dependencies is rather straightforward due to the probabilistic nature of BNs: the deterministic (AND and OR) gates in the fault tree procedure could be replaced by probabilistic or noisy gates[40], leading to more complex CPTs with a greater variety of probability values within the range of zero to one. Given more complex CPTs, the robustness of the results of the service dependency model to (small) variations in the probability values of the CPTs can straightforwardly be addressed using sensitivity analysis[46,47]. However, the practicality and effectiveness of including probabilistic gates and the need for sensitivity analysis should first be discussed and tested with potential end users as this implies a higher workload for the consulted experts and can lead to results that are difficult to interpret without background knowledge on the statistical methods used to perform sensitivity analysis.

A potential extension which is less straightforward to implement is the consideration of the time dimension. In reality, both the evolution of a hazard scenario and the characteristics of the induced cascading (infrastructure) service failures show temporal dynamics[4,48]. For example, the flood depth at critical road segments may vary over time and fuel-based emergency power generators operate for limited time spans, depending on fuel reserves. First of all, this extension would require a dynamic map for specific hazard scenarios, e.g. a dynamic simulation of flood propagation. Such simulations are costly in their development, not likely to be available for various hazards, and would thus drastically reduce the applicability of the method. Furthermore, including the time dimension would require to explicitly describe how infrastructure dependencies vary over time. This can be achieved by introducing a dynamic BN (DBN) which allows to quantify temporal dependencies between variables of the BN over multiple time steps (see, e.g.[49,50] for DBN-based methods in the context of engineering and CI systems). The procedure of introducing a DBN requires additional data to set up the CPTs between individual time steps (see, e.g.[7,22] for similar approaches, which do not explicitly consider the spatial dimension). While developing a DBN based on expert knowledge or a combination of data sources is generally possible (e.g., see Chang et al.[51] for an overview of studies), it might decrease practicality due to the complexity of eliciting the specific temporal data. Nevertheless, a corresponding extension is worth tackling in future studies as it would also allow to include variables that model restoration activities of CI components, e.g. the time required to repair damaged transformer stations. In this way, the method could also be extended to enable resilience assessments of CI systems[50,52].

Lastly, it would certainly be desirable to extend our method to include CI *inter*dependencies. While a CI dependency refers to a one-directional relation of the state of one CI on the state of another CI, an interdependency describes a bi-directional connection (i.e. a feedback loop) between two CIs[5]. However, in a BN, such a feedback loop cannot be directly represented since a BN is by definition acyclic (i.e. it does not contain loops). A work-around to include interdependencies in a BN-based method could be to use the output of the BN-based service dependency models again as an input for the spatial service models – a complex procedure that would require much more data, which is difficult to elicit from experts. A second option, which is closely tight to the introduction of temporal dynamics, is to use a DBN to model service interdependencies between time steps. While a BN model does not allow to include loops, a DBN allows to introduce links from one child node at t_n to a parent node at t_{n+1}, i.e. it enables loops over multiple time steps[49].

To conclude, the *DISruptionMap* method balances the level of detail in modeling complex CI service disruptions during large-scale disaster scenarios and the amount of data required to set up the corresponding models. Building *DISruptionMap*, we made sure that the method mainly relies on data that is easy to acquire and that its structure enables a straightforward elicitation and integration of missing data. Also, *DISruptionMap* is highly versatile: it can easily be applied to various hazard scenarios, sets of services, and study areas. Therefore, the method is suitable for local disaster management authorities that already use hazard maps, have access to the standard data sources, and possess the professional expertise to set up the models. For these authorities, *DISruptionMap* provides a low-threshold add-on that allows to incorporate information on cascading effects to existing hazard maps that allows to incorporate cascading effects in the analysis of and the preparation for disaster risks.

Methods
Infrastructure service dependency model
The development of the BN-based CI service dependency model is divided into two steps that ensure a systematic model construction for a specific disaster scenario and region: (i) *Graph Development*, starting from the target critical infrastructure (TCI) and the impact measure for the hazard under consideration and (ii) *Quantification of Service Dependencies*, based on expert knowledge.

Graph development
The proposed method centers around a TCI, serving as the starting point for an iterative approach which seeks to identify dependencies of the TCI on other services. Starting from the TCI, we ask 'What services must be present for the TCI to function?'. Each identified service is represented by a node that is linked to the TCI (Fig. 9). Each service can be further detailed, i.e. again serving as a starting point for the proposed inquiry. This iterative process should be repeated until all leaf service nodes (i.e. nodes with no incoming edges, represented by the dashed nodes in Fig. 9) show a predominant direct disruption by the hazard. The leaf nodes themselves are later informed by the spatial service models. In addition, one variable describing the impact measure (IM) is added as a child node to the node *Service TCI* (Fig. 9) to account for the disruption of the TCI service due to the hazard. In this way, the service dependency model accounts for direct disruptions (see leaf nodes in Fig. 9) and indirect disruptions (see *Service II* in Fig. 9) on the TCI service.

Quantification of service dependencies
The dependencies among individual services are defined via conditional probability tables (CPTs) within the BN. For each dependent node (see node *Service II* and *Service Target CI* in Fig. 9), a CPT is required that includes the probabilities for all combinations of parent and child node states. To estimate the respective probabilities, there are generally two options: historical data and expert knowledge. The availability of historical data for large-scale hazard scenarios that caused serious cascading events is often limited. Therefore, in this work, we use expert knowledge to build an accurate and reliable BN despite the absence of sufficient empirical evidence. We propose the utilization of a fault tree approach as a straightforward and effective means to describe dependencies that keeps the required information for setting up the CPTs at a minimum. Fault-trees can be translated into BNs[40,41], and are thus easily integrated into the proposed BN-based method.

Fault trees require a graphical model that shows all possible paths leading to a specific failure. The directed acyclic graph (DAG) of the BN mirrors this fault tree structure (Fig. 10). In fault tree analysis, AND and OR gates are used to combine the effect of (service) failures into more complex configurations, enabling the identification and quantification of potential failure paths in a system. AND gates require that all input services (e.g. service A and B in Fig. 10) are functional in order to provide the output service (service C). They are represented by a $\cap$ symbol. OR gates, on the other hand, require that at least one input service is functional for the output service to be available. They are represented by a $\cup$ symbol. Given a BN configuration of only one child node with its parent nodes (e.g. see Fig. 10), an expert only needs to provide one piece of information: whether this combination is best represented using an AND or an OR gate. Given this decision, the respective CPT attached to the child node can be automatically populated (constituting eight probability values in the example of Fig. 10).

Spatial models

The spatial models are highly dependent on the services being modeled. Nevertheless, they share certain requirements that need to be fulfilled to provide the output required for the TCI-specific service dependency models. The BN-based CI service dependency model is replicated and assigned to each TCI in the study area

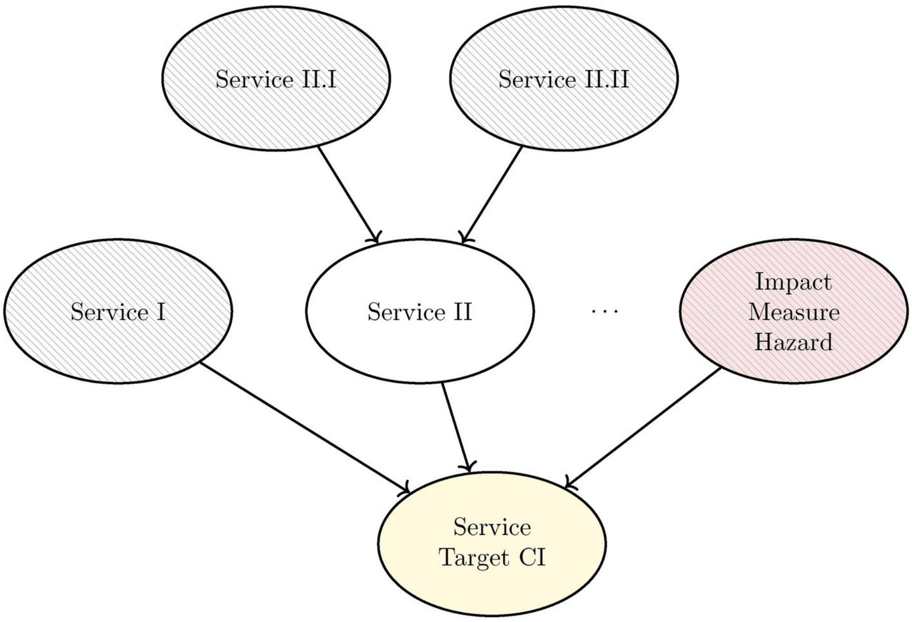

Fig. 9. Generic graphical structure of the method. The graph centers around a target CI (TCI) service variable (highlighted with yellow fill) which serves as the starting point of an iterative approach to identify service dependencies. The node representing the impact measure of the hazard (highlighted with red fill) is introduced as a parent node of the target node. Additionally, the graph features nodes that are solely informed by other nodes (white fill) and leaf nodes that are informed by the spatial service models (dashed fill).

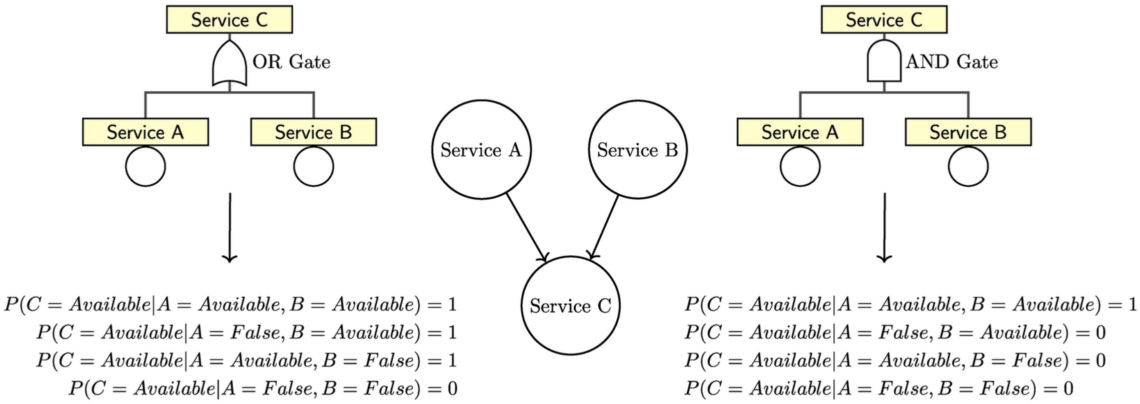

Fig. 10. Example of an OR Gate (left side) and an AND Gate (right side) in Fault Tree and BN (middle) representation (adapted from[40]). Both fault trees and BN show the same set of services (nodes) and the same structure (edges). Below the Gate representations, the respective translation of the Gate into the probability values for the dependent node *Service C* is illustrated.

(see *ERIMap* method[37]), e.g. all fire stations in a specific district or all hospitals in a city. These TCI-specific BNs are then informed by the spatial service models. These spatial service models must meet three key requirements: (i) they must provide detailed, spatially explicit information about the status of each infrastructure service. This includes, for instance, which locations are inaccessible due to road network disruptions. (ii) The information provided must match the requirements of the leaf nodes in the BN. For example, if a node describes power supply by the power grid, the spatial service model must explicitly indicate the affected areas. (iii) The output of these models must be either unambiguous (the service states *Available* or *Failed*; this is processed as hard evidence in the BN) or constitute a probability ratio (e.g. $P(Available) = 0.8$ and $P(Failed) = 0.2$; this is treated as soft evidence, see[37]).

Data availability

The datasets generated during the current study are available from the corresponding author upon request.

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Prioritisation Recommendation Mapping (PrioReMap): A method for supporting relief coordination in flood disaster response

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ABSTRACT

To effectively coordinate the response to a flood disaster, decision-makers have to prioritise areas that are in most urgent need of assistance. This prioritisation often has to be carried out under time pressure and on the basis of incomplete information, creating a high cognitive load for decision-makers. Methods that integrate Bayesian networks into GIS to draw spatial inference can inform this prioritisation process. However, existing approaches are not equipped to address the time pressure and unclear information-scape that is typical for a flood disaster. In this work, we present a novel spatial inference method for area prioritisation that is designed to address these time and information constraints. The core of this method is a GIS-informed Bayesian network, integrated into an expected loss framework, that can be set up during the preparation phase. The method can then quickly provide area prioritisation recommendations for disaster relief, which has the potential to support decisions-makers during the response phase. In this way, our method provides a means of shifting some of the most time-consuming aspects of the decision-making process from the time-critical disaster response phase to the less critical preparation phase. To illustrate how our method can support rapid and transparent area prioritisation, we present a case study of an extreme flood scenario in Cologne, Germany.

1. Introduction

Flooding is among the most common and devastating natural hazards, posing severe threats to human life and critical infrastructures [1–3]. Due to climate change and urbanisation, the flood risk for urban areas has substantially grown in the recent past and is very likely to grow further in the future [4–7]. Therefore, cities around the globe need to develop appropriate strategies for dealing with an increasing flood disaster risk. One of the most demanding tasks in dealing with a disaster is the effective coordination of response efforts [8]. An effective response requires a rapid yet comprehensive assessment of the situation [9,10]. One crucial aspect of this assessment is the identification and prioritisation of the most impacted areas in the disaster zone, which helps to coordinate the rapid and efficient allocation of limited resources [11,12].

In the initial stages of a flood disaster, the actual impact of the event is often not exactly known or has not yet fully developed [9]. Effectively, this means that operational impact assessments need to be risk-based – they can only estimate where the impact is expected to be highest, based on available proxy data. Since disaster risk results from the intersection of hazard, exposure, and vulnerability [13–15], all three dimensions need to be considered when identifying and prioritising at-risk areas. This includes, for instance, the spatial distribution of the hazard intensity [16], the density of residential buildings [17], the accessibility of

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critical infrastructures (CI) [18,19], and the location of vulnerable people [20]. Accordingly, decision-makers have to handle a large amount of different and potentially volatile pieces of information [21,22]. On top of this, there is the issue that, especially at the onset of a flood, the available information tends to be uncertain [23], particularly in terms of human adaptive behaviour [24]. This combination of versatile and numerous but also volatile and fragmentary information has been shown to result in cognitive overload on decision-makers that can hamper their capacity to manage disaster response efforts efficiently [25,26].

A suitable tool for reducing the cognitive load on decision-makers are decision support systems that consider the available information, process it, and present it in a concise manner. In the context of flood disaster risk reduction, a combination of geo-information systems (GIS) and Bayesian networks (BNs) has been proven to provide valuable support for *long-term* decision making, e.g. for informing flood mitigation by identifying flood prone areas [27,28], or flood protection by assessing potential CI failures [29,30]. By combining a GIS with a BN, area-specific assessments that include a variety of spatially distributed variables can be conducted (e.g. see [14] or [27]). In this context, the popularity of BNs stems from three aspects that are particularly critical in disaster-related contexts: (i) BNs can be constructed based on diverse compositions of available data, e.g. a combination of historical data and expert knowledge [31], (ii) BNs are explainable and easy to interpret as they are based on a (logical) graphical structure [32], and (iii) BNs enable the consideration of uncertainties in input data and relations between variables [33] – which is crucial to avoid overconfidence when making high-stake decisions in uncertain situations [23].

Existing GIS-informed BN models are designed to inform strategic decisions in disaster risk reduction. As a result, they are not equipped to support the decision-making process in flood disaster response, which is characterised by the tension between temporal urgency and the complexity of the situation. However, BN-based approaches are generally well suited to address the particularities of disaster situations. A BN-based approach, designed to reflect the cognitive process that leads to disaster response decisions, can be utilised to draw some of the more time-consuming aspects of the decision-making process out of the time-critical disaster response phase and treat them during model development, which can be carried out in the preparation phase. This involves addressing questions regarding (i) the variables that are critical for disaster risk, (ii) the dependencies between these variables, (iii) the level of risk that justifies area prioritisation, and (iv) the treatment of uncertainties in the available information. Properly treating these questions is a non-trivial and time-consuming task that must take into account different needs and thus may require consultation with multiple experts [34]. Accordingly, holding appropriate discussions when time permits and moulding the results into a comprehensible model (that is the BN) can help decision-makers to make faster, better justified, and thus more confident decisions when time is short.

In this work, we present a novel method called *PrioReMap* (Prioritisation Recommendation Mapping) that supports decision-maker in coordinating relief measures in the event of flood disasters. The method includes two layers that together constitute the contribution of our work: (i) a novel area prioritisation method that is informed by (ii) a novel GIS-informed BN model that is tailored to the information-scape in an ongoing flood disaster. The resulting recommendations can help decision-makers allocate scarce resources to priority areas or to select appropriate locations for temporary storage, shelters, field hospitals, or command centres.

In the remainder of this paper, we first provide the background on GIS-informed BN models, especially in the context of flood disasters (see Section 2). Based on the literature, we derive design properties of such models. We demonstrate the need for a new approach based on these design properties via a stylised case (see Section 3). Subsequently, we present our method for area prioritisation (see Section 4). We illustrate the effectiveness of our *PrioReMap* method in a case study of a flood scenario in Cologne, Germany (see Section 5). Finally, the proposed method is discussed and future work is outlined (see Section 6).

2. Background: GIS-informed Bayesian networks

The combination of GIS and Bayesian networks has become increasingly popular for spatial inference. For instance, GIS-informed BN have been applied to optimise the placement of charging stations for electric vehicles [35], to find the most suitable sites for pumped hydro energy storage [36], to evaluate the suitability of underground space as a resource for urban development [37], or to identify suitable areas for timber production under conservation constraints [38]. In disaster risk reduction, this approach has frequently been applied for creating risk maps, e.g. for fire [39], avalanches [40], or ecological risk [41]. GIS-informed BN models are particularly well established in the context of flood disaster risk reduction (see Table 1 for an overview).

Although the objective of GIS-informed BN can differ, their construction tends to follow three general design properties (DP1-DP3):

DP1 – Discrete target node represents the analysis objective. The first step in constructing a GIS-informed BN is the specification of a target node that reflects the objective of the analysis (see Table 1). For example, [14] present a BN-based approach to identify areas of high flood disaster risk, which is reflected in the target node *Flood Disaster Risk*. The possible outcomes of the analysis are then set by the states that this target node can adopt. In all applications of GIS-informed BN for flood risk, the target nodes show discrete states, which can be (i) binary states, such as *Yes* and *No* or *True* and *False*, or (ii) higher granularity state descriptions, such as *High*, *Medium*, and *Low* (see Table 1). The motivation for using discrete instead of continuous states is that models in this context are often primarily built from expert knowledge, and discrete states are often easier to elicit from experts.

DP2 – Study area is divided into sub-areas. To develop the GIS models, the study area must be divided into smaller subset areas that are individually assessed. To achieve this, the area can be divided by using regular tiles, such as squares (e.g. see [14]) or spatially distributed components, such as buildings (e.g. see [23]). These subset areas determine the resolution of the subsequent analysis.

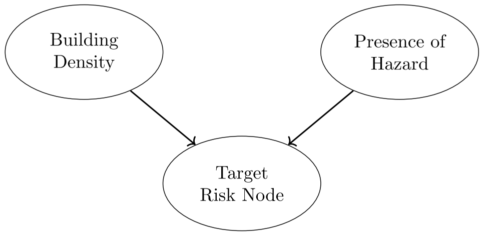
Table 1
GIS-informed BN models for flood disaster preparedness in the literature.

References	Analysis objective	Target node	Target node states	BN leaf nodes
[29]	Analysis of hospital service disruptions	Emergency Care	True, False	Flood Depth at Hospital, Accessibility, Power Supply Grid
[14]	Flood disaster risk assessment	Flood Disaster Risk	Extreme High, High, Moderate, Low, Very Low	Inundation Extent, River Network Density, River Buffering, Population Vulnerability, Economic Vulnerability, Building Vulnerability
[27]	Integrated flood risk assessment in data-scarce mega-cities	Flood Hazard Probability	Yes, No	Remote Sensed Urban Structure Types, Proximity to Large Scale Green Infrastructure, Topography, Proximity to River, Proximity to Coast
[42]	Flood risk assessment for road infrastructures	Flood Risk Factor	Low, Medium, High	Extreme Precipitation Susceptibility Index, Historical Records, Repair Cost, Light Traffic, Population Density, Soil, River Density
[43]	Disaster-causing factor chains on urban flood risk	Inundation	Yes, No	Elevation, Population Density, Annual Rainfall
[30]	Quantify resilience of roadways network infrastructure	Resilience	Low, Medium, High	Reliability, Recovery (of road network components)
[28]	Assessing urban flood disaster risk	Flood Disaster	Yes, No	River Density, Proximity, Elevation, Impervious Area, Per Unit GDP, Road Density, Population Density, Rainfall Duration
[44]	Assessing benefits of early warning systems	Vulnerability	Low, Medium, High	Emergency Personnel, People Risk Awareness, Reliability

DP3 – Leaf nodes are informed by GIS models. The target node, which is decomposed through one or more layers of parent nodes, leads to independent leaf nodes that are ultimately informed by the area-specific GIS models. For example, the target node *Flood Disaster Risk* in [14] has three parent nodes called *Hazard*, *Exposure*, and *Vulnerability*, which, in total, depend on six parent (leaf) nodes. Using the example of node *Exposure*, which has two parent (leaf) nodes called *River Network Density* and *River Buffering* that are ultimately informed by two individual GIS models. For each individually assessed area, spatially explicit information on all BN leaf nodes must be provided. When informing the area-specific BN leaf nodes with geospatial data, two cases of evidence must be distinguished: hard evidence and soft evidence. Hard (or regular) evidence describes a deterministic value that gives the exact state of a leaf node. Soft evidence, on the other hand, describes a probability ratio of a leaf node.

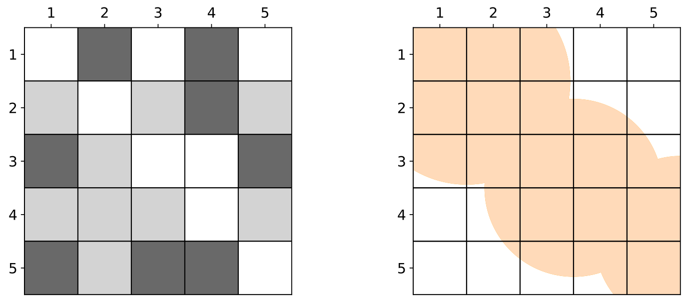
3. Motivation and main requirements - from layers to decision support

Based on the aforementioned basic design properties (**DP1-DP3**) of GIS-informed BN models in the literature (see Section 2), we construct a simple (low-dimensional) example model to illustrate how even a basic example yields results that can become difficult to comprehend – a critical issue especially under time pressure.



Building Density	Presence of Hazard	Target Risk Node		
		High	Medium	Low
High	True	1.00	0.00	0.00
High	False	0.00	0.00	1.00
Medium	True	0.75	0.25	0.00
Medium	False	0.00	0.00	1.00
Low	True	0.25	0.50	0.25
Low	False	0.00	0.00	1.00

Fig. 1. Low-dimensional BN model composed of the directed acyclic graph (left side) and CPT (right side).



(a) Homogeneous spatial data. (b) Heterogeneous spatial data.

Fig. 2. Example GIS-data on a 5*x*5 matrix. Fig. 2(a) shows (homogeneous) building density geo-data in each cells with three configurations (high density in dark-grey, medium density in light-grey, and low density in white) processed as hard evidence. Fig. 2(b) shows geo-data that is not too tightly bound to the boundary of the cell processed as soft evidence.

The BN of this example features a *Target Risk Node* with three states (*High, Medium*, and *Low*) (following **DP1**) and two parent nodes (see left side of Fig. 1): (i) a node *Building Density* with three states (*High*, *Medium*, and *Low*); and (ii) a node *Presence of Hazard* with two states (*True* and *False*). The corresponding conditional probability table (CPT) attached to the *Target Risk Node* follows a simple structure: Given the presence of the hazard, cells with a high building density are most likely to obtain a high risk, followed by those with a medium building density, and those with a low building density (see right side of Fig. 1). As a geographical setup, we introduce a 5×5 matrix (see Fig. 2) with 25 cells (following **DP2**). Each cell of the matrix represents one subset area, i.e. the BN is duplicated and assigned to each cell. The two leaf nodes of each BN are informed by individual GIS layers (following **DP3**). The node *Building Density* is informed by a layer containing geo-data of the density of residential buildings that is assumed to be homogeneous in each cell (see Fig. 2(a)) and processed as hard evidence in the BN. The node *Presence of Hazard* is informed by a layer containing geo-data of the hazard distribution that is not tight to the boundaries of the cells (not homogeneous in every cell, see Fig. 2(b)) and processed as soft evidence in the BN.

The GIS-informed BN model provides probabilities for each cell to be in a state of *High*, *Medium*, or *Low* risk. Based on the corresponding heatmaps (Fig. 3), tendencies of high risk areas can easily be identified, especially in comparison to having only the two layers of geo-data (see Fig. 2). Accordingly, the model is already capable of reducing the cognitive load on potential decision-makers.

Looking more closely at the results, they reveal one cell that stands out with a 100% probability of high risk (see cell in row one, column two, i.e. cell (1,2), in Fig. 3). While this cell should clearly be prioritised when considering only the high risk matrix, cells (3,5) and (4,5) also show similarly high probabilities of high risk (~80%). However, the two cells differ in their remaining probability distribution: in cell (3,5), the remaining ~20% is assigned to low risk, whereas in cell (4,5), it is assigned to medium risk. As a result, the probability distribution of cell (4,5) can be considered more critical, despite having the same probability for the most severe (*High*) state (*Issue I*) – this example underscores the importance of taking the entire probability distribution into account when prioritising cells. A different prioritisation issue becomes apparent when comparing cells (2,1) and (3,1). While cell (3,1) exhibits a slightly higher probability of high risk (~84% vs. 75%), cell (2,1) shows a higher probability of medium risk (25% vs. 0%). As a result, the prioritisation depends on whether emphasis is placed solely on high risk or on a combination of high and medium risk levels, i.e. the prioritisation depends on the decision-maker's preferences (*Issue II*).

To conclude, while the presented low-dimensional example demonstrates the general suitability of a GIS-informed BN model for area prioritisation, it also highlights issues associated with applying this method in time-critical response efforts. Even though the entire setup is very simple, quickly comprehending the results (*Issue I*) and choosing a set of cells to prioritise (*Issue II*) is still not straightforward and can lead to a high cognitive load (especially under time pressure) as well as discrepancies in prioritisation among different responders — this is where our proposed method aims to enhance the literature by offering precise recommendations for area prioritisation. We argue that these recommendations should be based on the entire probability distribution of the target node (rather than solely on the most severe state), in order to further reduce cognitive load (thus avoiding *Issue I*) and to promote consistency in recommendation outcomes across responders by introducing a transparent expected loss framework (thus avoiding *Issue II*).

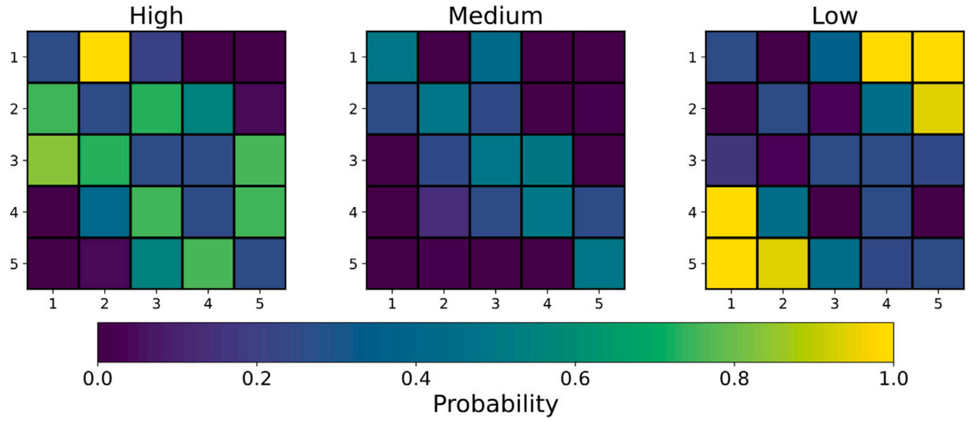


Fig. 3. Heatmaps presenting the state probabilities of the *Target Risk Node* (see Fig. 1) calculated using the cell-specific geo-data (see Fig. 2) to inform the cell-specific BN leaf nodes.

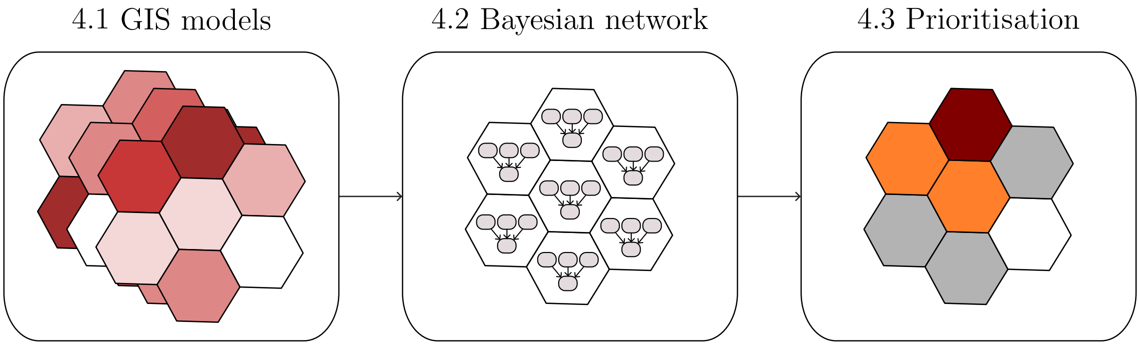


Fig. 4. Summary of the *PrioReMap* method. The method is structured in three stages: the development of tile-specific spatial models that represent the variables used for prioritisation, the construction of a BN that formalises the cognitive process of assessing risk based on these variables, and the prioritisation procedure that generates the final prioritisation recommendations.

4. Method: Prioritisation Recommendation Mapping (PrioReMap)

The method presented here is designed to support responders in prioritising areas in an ongoing flood disaster where the risk to people is high. It is composed of three main components (see Fig. 4): (i) the GIS models to provide spatially explicit observations of the critical variables characterising the *Hazard*, *Exposure*, and *Vulnerability* in a flood disaster risk scenario (see Section 4.1); (ii) the Bayesian network used to infer the probability of the target node called *Risk of People in Need of Assistance* based on the critical variables (see Section 4.2); and (iii) the prioritisation method that translates the probability distribution of the target node into prioritisation recommendations (see Section 4.3). When applying the method in disaster response, information about the current flood is fed into the corresponding GIS and then processed by the BN and the expected loss-based prioritisation method to compute the area prioritisation recommendations.

4.1. GIS models

The GIS models capture the spatial variables most relevant for assessing flood disaster risk and ultimately for prioritisation. The development of these models follows two consecutive steps: first, the tiling of the case study area, a procedure essential for operationalising the spatial resolution at which prioritisation is carried out. Second, the individual GIS models, each providing a tile-specific assessment of the critical variables used for prioritisation.

4.1.1. Hexagonal tiling

To enable the prioritisation of individual subset areas, i.e., specific zones within the broader disaster area, the study area is divided into a grid composed of uniform hexagon tiles (see Fig. 5). Hexagonal tiling is a well-established practice in geospatial applications, as it ensures uniform neighbour distances, reduces edge effects, and provides a consistent spatial representation [45]. For this purpose, the H3 system is utilised, a geospatial indexing system that partitions the Earth's surface into hexagonal tiles at multiple resolutions [46]. Each hexagon at every resolution is assigned a unique index key, allowing every tile to be readily identified. Since H3 is widely adopted across domains, including disaster response (e.g. see [12]), it further facilitates applicability of the method. The suggested resolution applied in the method presented is resolution 9, where each cell covers approximately $0.1\ \mathrm{km}^2$, which captures neighbourhood-level detail.

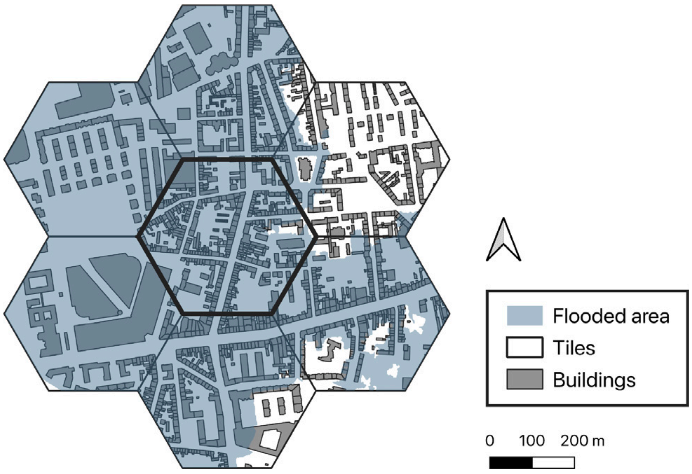


Fig. 5. Example hexagon including neighbouring hexagons.

4.1.2. Individual models

In the following, the GIS-based models representing the variables characterising the *Hazard*, *Exposure*, and *Vulnerability*, which together constitute the key contributors to *Risk of People in Need of Assistance* during a flood, are presented, along with typical thresholds describing their severity (these thresholds are later used for variable discretisation). Each assessment or analysis outlined corresponds to an individual tile.

The following variables characterise the (flood) *Hazard*. A first key variable is the *Flood Depth*. This variable is critical to assessing flood risk because water depth directly determines both potential damage and life-threatening conditions. It is represented by the maximum flood depth within a tile, which serves as a practical summary measure of severity (particularly in combination with the following variable). Two critical thresholds are applied: a depth of 30 cm, cited as the point at which the ground surface is no longer visible [47] and streets no longer passable [48,49], and a depth of 150 cm, at which damage to, e.g., buildings can become severe [47].

A second important variable is the *Flood Coverage* [14], defined as the proportion of the tile surface that is inundated. This variable is critical to assessing flood risk because the extent of inundation determines how much of the built and natural environment is exposed. It complements flood depth in characterising overall flood hazard severity.

The following variables characterise the *Exposure*. One central variable is the *Population*, i.e., the number of people living within a tile [28,42]. This variable is critical to assessing flood risk because it indicates how many people may be directly affected in a flood event. The information is derived from census data, which provides an approximated population count on a $100\,\mathrm{m} \times 100\,\mathrm{m}$ grid. To obtain tile-level values, the centroids of the census grid cells are assigned to the hexagonal tiles in which they fall, and the respective counts are aggregated per tile. Although the census and hexagonal grids do not align perfectly, the higher granularity of the census grid ($0.01\,\mathrm{km}^2$ compared to $0.1\,\mathrm{km}^2$ for the hexagonal grid) ensures sufficient precision for this aggregation. Because absolute population numbers can differ considerably between study areas (e.g., a maximum of 100 people per tile in a small town versus more than 1000 in a large city), relative measures are required. For this purpose, the 70th and 95th percentiles are used to identify tiles with comparatively high population concentrations within each study area.

A further relevant variable is the presence of *Points of Interest (PoI)*, which capture locations where large numbers of people may be present during daytime. This variable is critical to assessing flood risk because such facilities can greatly increase potential exposure during specific times of day. These include schools, care facilities, and tourist attractions, as well as critical infrastructures such as train stations. Here, only the presence or absence of one or more PoI are determined per tile. The location of these PoI can, for example, be obtained from OpenStreetMap (OSM).

The following variables characterise the *Vulnerability*. An essential variable is the *Access Road*, which describes the accessibility of a tile via the road network. This variable is critical to assessing flood risk because evacuation options strongly influence the vulnerability of affected populations. The accessibility is modelled using an adapted version of the accessibility model presented in [29]. To this end, the road network of the study area is reconstructed using OSM data [50], resulting in a network topology that features nodes representing road crossings and edges representing road segments [48]. Road segments that show a flood depth of more than 30 cm [48,49] are assumed to be impassible and are thus excluded from the topology. We assume that each remaining road segment can be used for evacuation purposes regardless of any traffic regulations such as one-way streets. For the routing algorithm, we defined multiple destination locations (places to escape to) that are sufficiently distant from flooded areas and which are very well connected to the road network to assess whether one can, in general, escape from a tile to a distant, unexposed area via the road network. To minimise potential biases introduced by the destination location, multiple locations are necessary.

A second variable of importance is the *Access Local*, i.e., the proportion of unexposed area in the immediate surroundings of a tile. This variable is critical to assessing flood risk because nearby safe areas directly determine short-term evacuation opportunities. It is estimated by calculating the percentage of the flooded area of all neighbouring tiles (see Fig. 5).

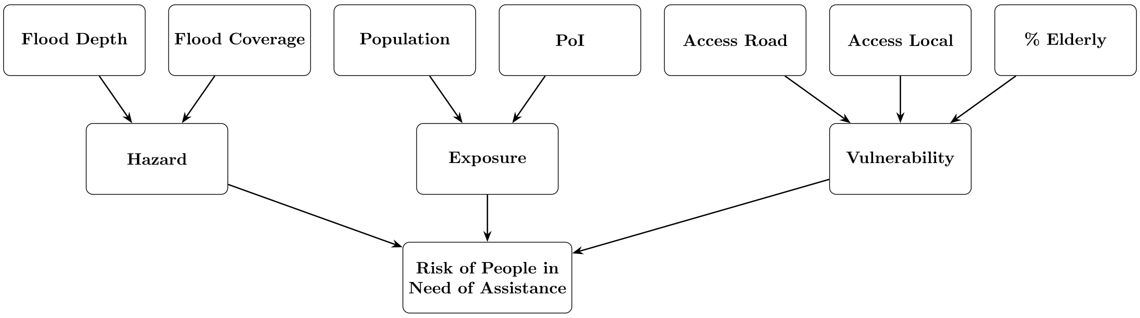


Fig. 6. Bayesian network to infer the *Risk of People in Need of Assistance*. The BN is composed of eleven variables (four conditional nodes and seven marginal nodes).

Finally, the percentage of elderly (*% Elderly*) is another decisive variable, as elderly citizens tend to require more assistance during evacuation in flood disasters [51,52]. This variable is critical to assessing flood risk because elderly populations often face greater difficulties in evacuation. It is determined by calculating the proportion of residents aged 67 years and older (obtained from the census data) relative to the total population within a tile.

4.2. Bayesian network

The BN represents the spatial inference model that integrates all tile-specific information into the posterior probability distribution of the target node *People in Need of Assistance*, which is essential for allocating relief resources. The BN reflects the cognitive process [53] of deriving this inference from all available information and enables its application to all tiles in a timely manner. In the following, we first outline the graphical structure of the BN, i.e., its nodes and edges, then describe the method used to populate the CPTs. Finally, we introduce the approach for handling observations provided by the spatial models, i.e., how they are considered as evidence for the leaf nodes of the BN.

4.2.1. Directed acyclic graph

The graphical structure of the BN follows a hierarchical organisation, where the leaf nodes correspond to the spatial models, i.e., each leaf node is informed by a single spatial model. In line with the structure proposed by [14], the BN specifies three child nodes – *Hazard*, *Exposure*, and *Vulnerability* – which represent the contributors to disaster risk [15]. The leaf nodes are grouped under these child nodes, with each leaf node serving as a parent of the factor it informs. Together, these three child nodes determine the single target child node, the *Risk of People in Need of Assistance* (see Fig. 6).

4.2.2. Conditional probability tables

Setting up the CPTs of a BN is widely recognised as one of the main challenges in their application, as this process can require a large number of probability values [31]. Since our aim is to reflect the cognitive process of an emergency responder, it is essential that expert knowledge can be easily incorporated and that the procedure for defining the CPTs remains transparent. To meet this requirement, all variables in the BN are discretised, meaning they are represented by discrete states even when the underlying variable is continuous in nature (e.g., flood depth). Threshold-based discretisation substantially reduces the number of probability values required, as each CPT must specify one value for every combination of parent-node states and child-node states. This approach is well established in domains where expert knowledge plays a central role and/or data availability is limited (see the references in Table 1).

In order to further facilitate the elicitation and provide a transparent support method, an adapted approach of the ordered logistic regression (ordered-logit) model proposed by [54] is used. This approach provides a structured way to translate qualitative parent states into quantitative probabilities for an ordered categorical child node C (i.e. nodes *Hazard*, *Exposure*, *Vulnerability*, and *Risk*). The process unfolds in three steps. First, each variable V has a finite set of ordered states $\mathcal{S}_V = \{s_1, \dots, s_{K_V}\}$, which are mapped to a severity score between 0 (least severe) and 1 (most severe) using a severity mapping function

$$x_V : \mathcal{S}_V \to [0, 1]. \quad (1)$$

This allows categorical states to be represented numerically in a consistent and interpretable manner – e.g., the parent *Flood Depth* might assign scores of 0.00 to *none*, 0.33 to *shallow*, 0.67 to *moderate*, and 1.00 to *deep*, so that being in the state *moderate* corresponds to a severity of 0.67. Second, when a child node C depends on multiple parents $\mathcal{P}(C) = \{P_1, \dots, P_m\}$, the individual severity scores of their current states $\mathbf{s} = (s_1, \dots, s_m)$ are combined into a single aggregated severity measure

$$\eta_C(\mathbf{s}) = \sum_{j=1}^{m} w_{C,P_j}\, x_{P_j}(s_j), \qquad \sum_j w_{C,P_j} = 1, \quad (2)$$

where the weights w_{C,P_j} represent the relative importance of each parent and are normalised to sum to one. Finally, this aggregated severity is linked to the probability distribution over the child's ordered states via the ordered-logit model. With slope parameter β_C and a sequence of thresholds $\tau_{C,1} < \cdots < \tau_{C,K_C-1}$, the cumulative probability of the child being in state k or below is

$$\Pr(Y_C \le k \mid \eta_C) = \sigma\big(\beta_C(\tau_{C,k} - \eta_C)\big), \qquad \sigma(z) = \frac{1}{1+e^{-z}}. \tag{3}$$

Subtracting consecutive cumulative values gives the probability of each specific category, thereby completing the corresponding CPT of the child node. All model parameters used to apply the order-logic method for the presented BN can be found in Appendix A.

4.2.3. Observation handling

While discretising a continuous variable into states is required to facility expert knowledge elicitation for CPT construction, it introduces sharp threshold effects, where a minimal change in a value provided by a spatial model could shift the evidence from 100% *moderate* to 100% *deep*. To enhance the robustness of the BN model against such threshold effects, soft evidence is applied by distributing probability mass smoothly across the discrete bins (which correspond to the variable states). Given an observation d^*, the weight for each bin i with edges $[b_i, b_{i+1})$ is computed as

$$w_i = \int_{b_i}^{b_{i+1}} \mathcal{N}(x; d^*, \sigma^2)\, dx, \tag{4}$$

where

$$\mathcal{N}(x; d^*, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\!\big(-\tfrac{(x-d^*)^2}{2\sigma^2}\big) \tag{5}$$

is the normal density, and σ controls how gradual the transition is between bins. These weights, which sum to one, are entered as soft evidence in the BN rather than hard evidence. For example, for the node *Flood Depth* with states {none, shallow, moderate, deep} defined by cut points $\{0.0, 0.1, 0.5, 1.5\}$ m, an observed value $d^* = 0.49$ m with $\sigma = 0.1$ m yields approximate weights [0.01, 0.65, 0.34, 0.00], indicating that shallow flooding is most plausible but moderate flooding remains possible, with no abrupt jumps at the bin boundaries.

4.3. Prioritisation

The BN provides a probability distribution p_r over the risk states $R = \{\text{None}, \text{Low}, \text{Med}, \text{High}\}$ of the target node *Risk of People in Need of Assistance* for each tile. To translate the probabilistic output of the BN into concrete prioritisation recommendations, we apply an expected loss framework. This approach has been used in the literature to derive action recommendations from probability distributions (e.g., [55,56]). In this way, the decision process combines probabilistic reasoning with a cost-based criterion to balance probability and consequence.

The idea of the expected loss framework is to compare different candidate actions $a \in A$ in terms of the loss that will be incurred if they are chosen. In the context of disaster response, this loss can be quantified using *allocation-equivalent hours*, defined as the delay in hours by which relief resources arrive after the critical time threshold. To this end, risk states R of the BN target node are associated with deadlines T_r that specify the maximum acceptable delay for allocating relief resources. In the context of flood response, [57] provides an overview of the timeframes of decisions and needs assessments after floods. In addition, we draw on the *Report on Field-Based Decision-Makers Information Needs from the Digital Humanitarian Network* to derive and calibrate the thresholds [58]. On the basis of these references, indicative thresholds are assumed: about 24 h for urgent first aid (high risk areas), around 72 h for rapid needs assessment (medium risk areas), and up to one week for less urgent cases (low risk areas). The action set $A = \{\text{Immediate}, \text{Deferred}, \text{Extended}\}$ corresponds to three urgency levels aligned with the risk states: an *Immediate* action recommends mobilisation within $t_{\text{Immediate}} = 24$ h, a *Deferred* action within $t_{\text{Deferred}} = 72$ h, and an *Extended* action within $t_{\text{Extended}} = 168$ h. Thus, for an action $a \in A$ with response time t_a and a state $r \in R$ with maximum acceptable delay T_r,

$$\text{over-allocation}(a, r) = \max\big(t_a - T_r,\ 0\big), \tag{6}$$

and

$$\text{under-allocation}(a, r) = \max\big(T_r - t_a,\ 0\big) \tag{7}$$

is defined. Under-allocation captures the penalty of exceeding the required response time (too late), while over-allocation captures the cost of committing resources earlier than strictly necessary, which may reduce efficiency by preventing their use in more time-critical locations. The overall loss is

$$L(a, r) = \rho \cdot \text{under-allocation}(a, r) + (1 - \rho) \cdot \text{over-allocation}(a, r), \tag{8}$$

where ρ is the tuning parameter that balances the penalty between under-allocation and over-allocation, with $\rho = 0.5$ describing equal penalties, $\rho = 1$ meaning only under-allocation is penalised, and $\rho = 0$ meaning only over-allocation is penalised. We introduced this parameter to reflect the fact that under-allocation (i.e., responding too late) is typically more critical in disaster response and should therefore be penalised more severely. Although values smaller than 0.5 are technically feasible, they imply penalising over-allocation more heavily than under-allocation, which might not be meaningful in practical applications. The expected loss is then

$$EL(a) = \sum_{r \in R} p_r \, L(a, r). \tag{9}$$

In this formulation, rather than committing to a single most likely state, each possible action $a \in A$ is evaluated over the entire probability distribution by computing its expected loss. This ensures that uncertainty is explicitly incorporated: states with higher probability contribute more strongly, while even low-probability states influence the outcome if their associated costs are severe. For each tile the *critical delta*

$$\delta_i = EL(\text{Extended})_i + EL(\text{Deferred})_i - EL(\text{Immediate})_i \tag{10}$$

is computed, which quantifies the relative advantage of assigning tile i to the *Immediate* action. Sorting all tiles by δ_i in descending order yields a stable, deterministic queue. Selecting the top K tiles minimises the total expected loss under the constraint that K tiles are prioritised as *Immediate*. The parameter K – the *target count* – can be specified in multiple ways depending on planning needs: as an absolute number of tiles (e.g. $K = 200$), as the number of square kilometres covered (e.g. $4\,\text{km}^2$ resulting in a tile resolution dependent K), or as a percentage of the exposed disaster area (e.g. 20% resulting in a study area dependent K). The top K tiles are recommended for *Immediate* action, while the remainder are recommended for *Deferred* action. Subsequent waves are defined by consecutive blocks of size K in this global ranking, providing a transparent and interpretable prioritisation sequence for phased response under limited resources.

The set of tiles classified as *Immediate* can also be updated dynamically at run-time. There are two potential causes for an update: (i) new observations may become available that change the underlying risk probability distribution p_r, which in turn modifies the expected losses and queue ordering; or (ii) once a certain number of *Immediate* tiles have been inspected, the same number of tiles from the head of the remaining queue can be promoted to *Immediate*, thereby maintaining the target count K while ensuring continuous allocation of resources.

5. Application of PrioReMap: A case study of a flood disaster in Cologne, Germany

We illustrate the *PrioReMap* method in a flood scenario in Cologne, a German city with more than one million inhabitants [29]. In the past, the city of Cologne has proven to be vulnerable to river floods. For instance, in 1993 and 1995, the city experienced floods with severe consequences for its inhabitants and the local economy [59,60]. The city's vulnerability stems from its immediate proximity to the Rhine river which runs right through the densely populated city centre. Recently, the importance of an effective flood risk management in this region has been demonstrated by the flood disaster in the Ahr Valley in 2021 [61,62].

The case study is intended to showcase how the *PrioReMap* can be applied during a flood response. We choose data that resembles the information that is typically available during an ongoing flood. For the flood hazard layer (that includes the flood extent and depth), we use data from a hydrological simulation of an extreme flood scenario (also called 500-year flood or HQ500 [63]), which is typically used to create flood risk maps and inform flood protection planning (e.g. see [64]). As this dataset has the same structure as flood hazard layers generated by rapid mapping technologies, it could easily be replaced with the most recent snapshot of the flood to capture its temporal evolution during an actual event. For the assessment of the population density, we use census data at a $100\ \text{m} \times 100\ \text{m}$ resolution, which provides both the total number of people in each cell and demographic details, such as the number of individuals older than 67 years. Furthermore, we use OSM data that comprises building locations, PoI locations, and the road network. As it is reasonable to assume that this information does not change over the course of a flood event, there is no need to replace it with real-time data. However, the data should be checked for accuracy and completeness before being transferred to a real-world application.

5.1. Model results

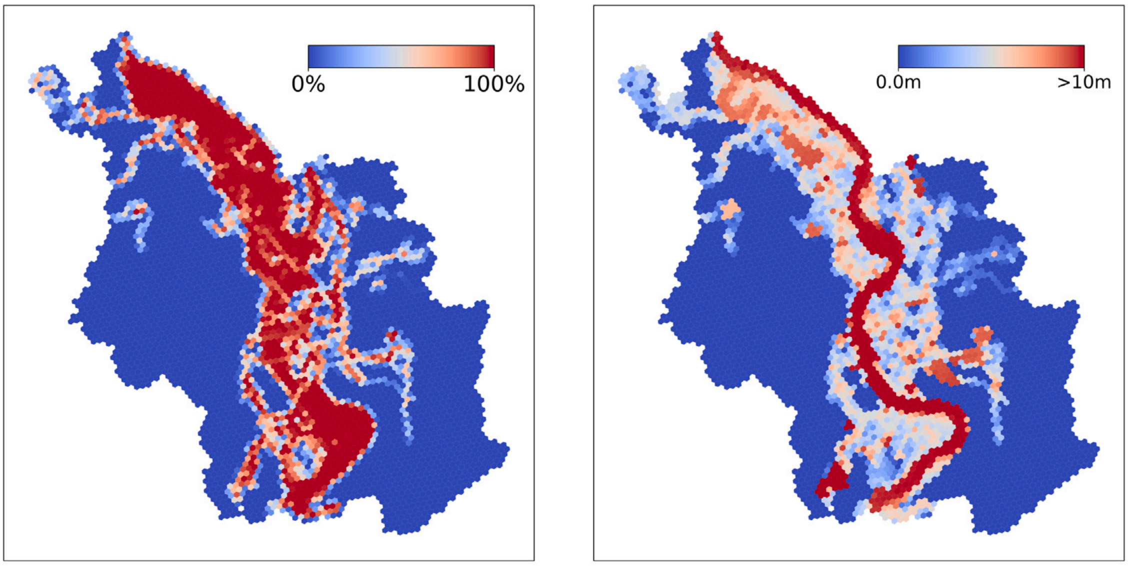
5.1.1. GIS models

The first spatial model, which provides observations on the flood hazard, reveals that 2044 tiles are flooded, ranging from 0.01 to 100 percent coverage (Fig. 7(a)). The second model, analysing the maximum flood depth per tile, shows values ranging from 4 cm to 12.75 m (Fig. 7(b)). The model analysing the presence of people (contributing to the assessment of exposure) indicates that 2283 tiles are populated, with up to 2933 individuals per tile (Fig. 8a()). In 790 tiles, at least one PoI is present (Fig. 8(b)). The spatial models assessing vulnerability show that 666 tiles are rendered inaccessible due to flooded road segments (Fig. 9(a)), while 2574 tiles have at least one neighbouring tile flooded, up to cases where all neighbours are fully flooded (Fig. 9(b)). Finally, in 1917 tiles, people aged 67 and older are present (Fig. 9(c)).

5.1.2. GIS-informed BN models

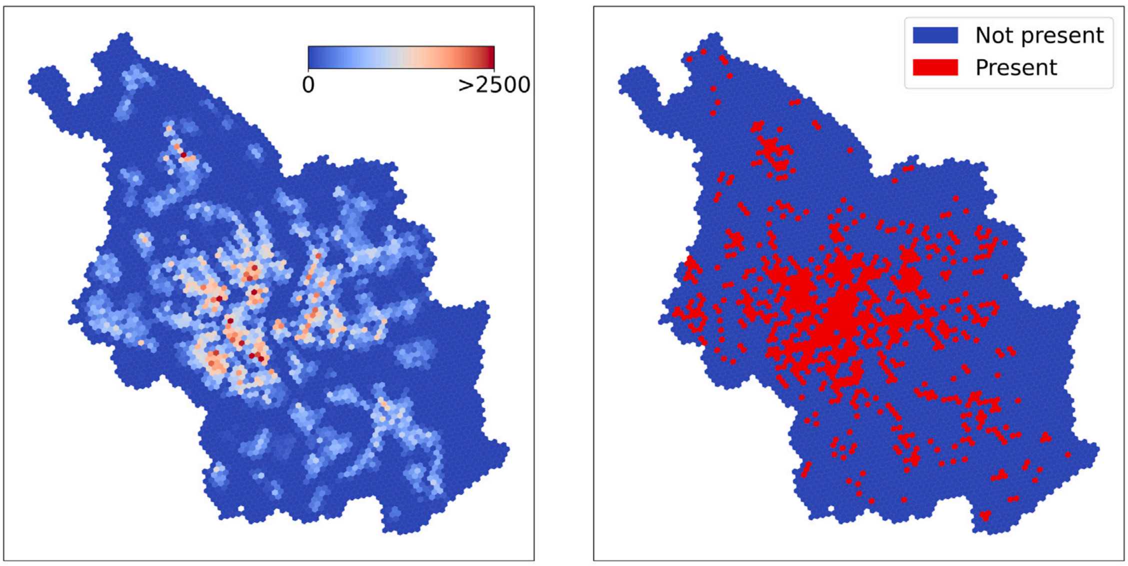
Using the results of the GIS models (see Section 5.1.1) as inputs for the tile-specific BNs (see Section 4.2), the probability distribution for the states of the target node *Risk of People in Need of Assistance* is calculated for each flooded tile in the study area (see Fig. 10).

The results reveal several spatial clusters of tiles with high probability of the *High* state: 80 tiles have probabilities exceeding 75%. Two large clusters occur on both sides of the Rhine in the city centre (coinciding with the centre of Fig. 10(a)), along with a



(a) Flood Coverage. (b) Flood Depth.

Fig. 7. Spatial models hazard.



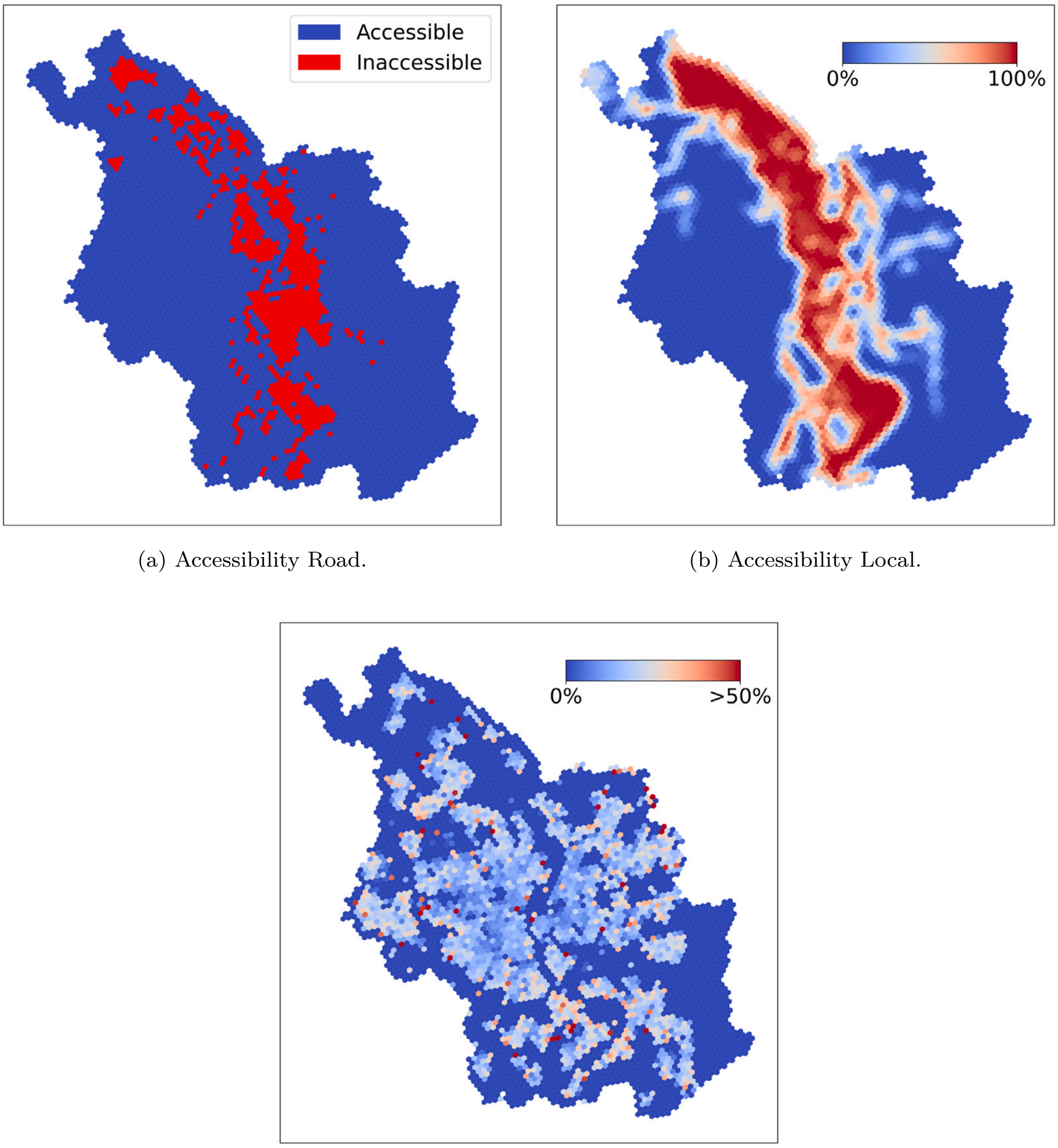
(a) Population. (b) PoI.

Fig. 8. Spatial models exposure.

small cluster in the north and another in the south. Probabilities for the *High* and *None* states range from 0 to about 80%, whereas those for *Medium* and *Low* range from 0 to about 50%. This pattern reflects the ordered-logit model, which tends to accentuate the extreme categories (*High* and *None*). A probability of 100% for the *High* state is not reached because no tile simultaneously exhibits the maximum flood depth and the maximum population density in the case study. Likewise, a probability of 100% for the *None* state is not observed because only tiles with some flood coverage are analysed.

5.2. Prioritisation recommendations

As a potential configuration for the final *PrioReMap*, the wave size is set to $K = 200$, which given 1096 exposed tiles, yields five full prioritisation waves plus a final partial wave. The penalty parameter ρ is set to 0.75, making under-allocation penalised three times more strongly than over-allocation. The resulting *PrioReMap* (Fig. 11) explicitly depicts the first and second prioritisation waves; for simplicity and accessibility, the remaining waves are summarised — it should be noted that this constitutes an example



(a) Accessibility Road.
(b) Accessibility Local.
(c) % Elderly.

Fig. 9. Spatial models vulnerability.

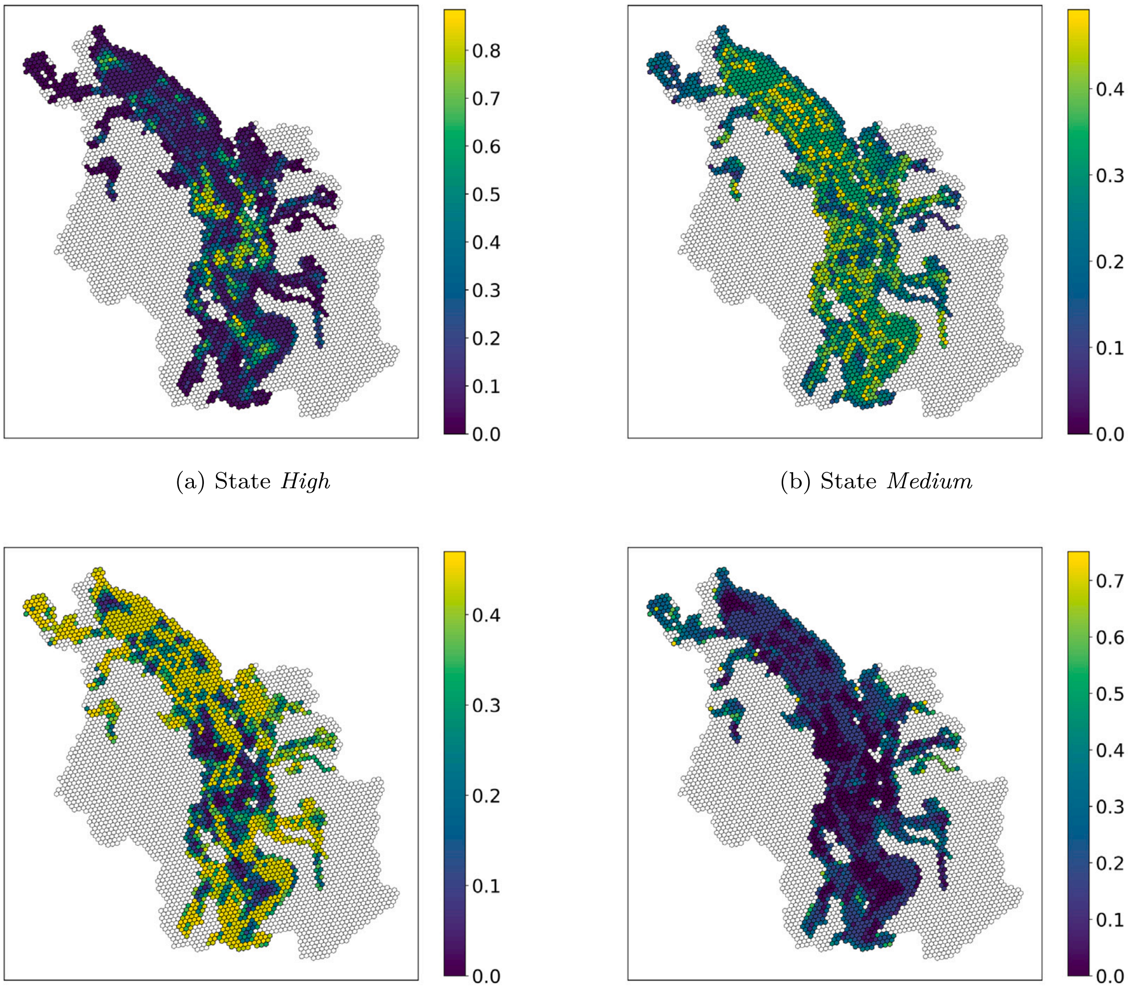
visualisation, which can be adapted to user preferences. The first prioritisation wave exhibits several dense clusters, alongside a small number of isolated tiles. Tiles in the second prioritisation wave frequently surround those in the first, while also forming a few smaller stand-alone clusters as well as some isolated tiles.

A sensitivity analysis on variations of the penalty parameter ρ, together with an additional corresponding illustration of the *PrioReMap* of the case study, is provided in Appendix A.

6. Discussion

In this paper, we introduce *PrioReMap*, a novel method that provides area prioritisation recommendations in flood disaster response. The method consists of three core elements. First, a grid of BNs used to infer the spatially distributed *Risk of People in Need of Assistance* based on spatial variables, such as the population density and the accessibility of unexposed areas. Second, GIS models that inform the leaf nodes of the tile-specific BNs in the grid using a flood hazard layer. Third, a prioritisation method that translates the tile-specific probability distributions of the *Risk of People in Need of Assistance* into distinct prioritisation recommendations.

A central motivation for developing our *PrioReMap* method was to create a decision support system that meets the requirements of decision-makers that coordinate flood disaster response. Two essential requirements are that recommendations for area prioritisation



(a) State *High* (b) State *Medium*

(c) State *Low* (d) State *None*

Fig. 10. Results of the GIS-informed BN model.

can be obtained rapidly, since time is usually short, and that the process that leads to these recommendations is transparent, since there is a reluctance to trust black box models in high stake decisions [32,65]. To achieve rapid recommendations, the *PrioReMap* method shifts parts of the decision-making process from the time-critical response phase to the less time-critical preparation phase. Setting up the models (GIS models and BN) prior to an actual disaster can be considered as an early walk-through of the decision-making process that allows stakeholders to identify and discuss relevant variables for prioritisation (the nodes of the BN), including the one that mirrors the response objective (the target node). This approach also makes the process that leads to a recommendation transparent as setting up the BN requires to formalise the reasoning for prioritising certain areas in a comprehensible structure (that is the BN, see also [66] who introduced BNs as a formalism of human reasoning under uncertainty). Another advantage of creating this structure of reasoning before an actual disaster is that it allows to integrate the perspectives of multiple stakeholders and the knowledge of multiple experts (see [67] or [68] for elicitation methods) into the decision-making process, an aspect that is particularly valuable in emergency decision-making, where selection problems are often solved by group decisions [34].

Ultimately, *PrioReMap* combines multiple geospatial variables into a single categorical index that assigns disaster relief priority to every tile. Aggregating several variables into one index is a delicate task that requires careful selection and an appropriate representation of their interplay [69] (e.g., vulnerability without exposure does not result in risk). A BN-based approach was chosen for aggregation into a probability distribution of the risk variable, as BNs provide a logical framework to explicitly model interactions between variables via CPTs. This approach has already proven effective in flood disaster preparedness (see Section 2). To reduce knowledge elicitation effort during BN construction, the number of required probability values was minimised by discretising all variables (e.g., continuous flood depth) and applying an ordered logistic regression model. This facilitates elicitation by defining discrete states (e.g., low flood depth defined as 0.01–0.3 m) and thus significantly reduces the number of probability values required to set up the CPTs. However, discretisation introduces threshold effects: small input changes may cause abrupt probability jumps (e.g., from 100% low to 100% medium). To avoid such effects and improve robustness, we applied a soft evidence approach that distributes probability mass across states. Within future work, optimisation methods for discretisation could be tested, such as the approach by [70] for discretisation of BN variables in rare-event modelling.

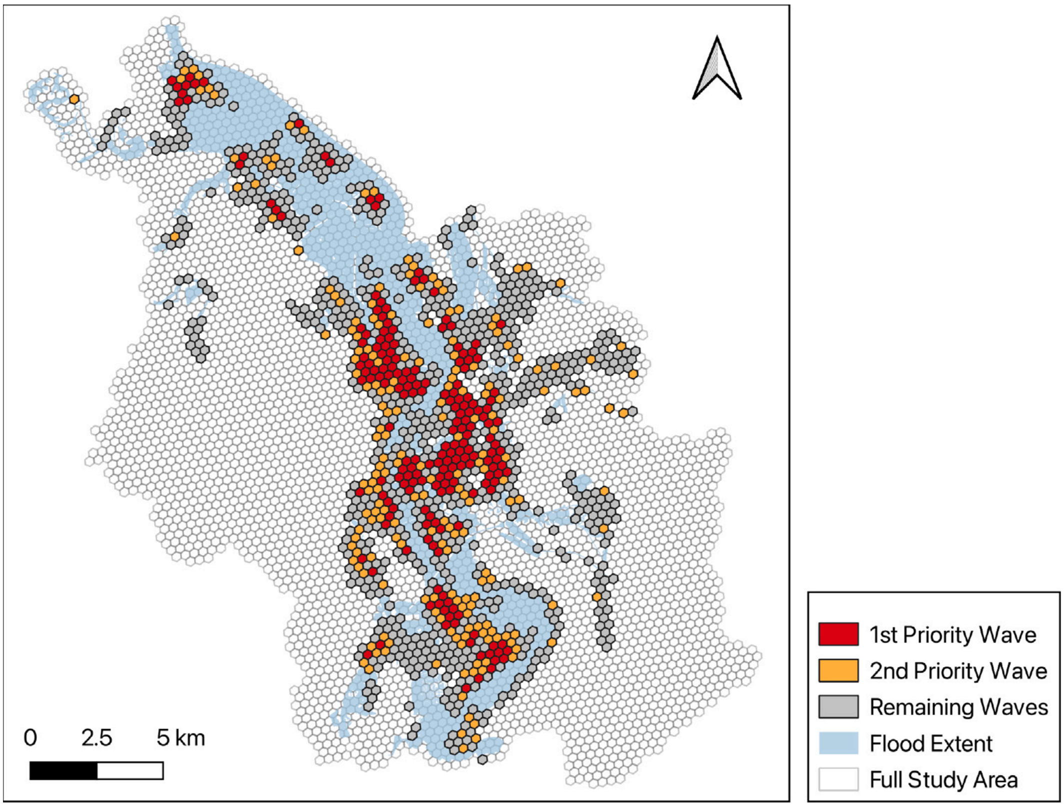


Fig. 11. *PrioReMap* of the case study. In this example visualisation, a wave size of 200 tiles is used. The 1st and 2nd prioritisation waves are shown individually, while the remaining waves are summarised to provide a clearer overview of the most critical tiles. The flood extent is also mapped to support rapid identification of the full flooded area and to facilitate comparison between wave sizes and the flooded area.

During the preparation phase, BN behaviour and the resulting recommendations based on the expected loss method can be explored through case studies using simulated flood scenarios such as the one presented in the case study of this work. Such explorations can and should be applied to tune the model in a way that it reflects the preferences of the responsible disaster responders as well as context-dependent specifics, such as local terrain or available resources. This includes parameters such as the time thresholds used to calculate the expected loss. These thresholds can be set by stakeholder consultations or considering local response protocols, practices, experiences, and hazard dynamics.

In the response phase, however, the allocation-penalty factor ρ becomes most critical, as it allows prioritisation recommendations to be adapted to current resource constraints. The more limited the resources are compared to the affected area, the higher this parameter should be set, since prioritisation must then focus more strongly on avoiding under-allocation in the most critical tiles. Given variations in ρ, sensitivity analysis for the case study demonstrates that the model remains highly robust, particularly for the highest-ranked tiles (see Fig. 12), making it a reliable method for disaster response planning.

In the presented case study, the geospatial data that is required to set up the GIS models is obtained from OSM data – a common source of geospatial data used to support humanitarian disaster relief efforts worldwide [71]. However, if available, data from official government services or critical infrastructure providers is generally preferable as it is typically more accurate and complete [29]. Fortunately, potential end users, such as disaster responders, are likely to have access to this high quality data. When relying on OSM data, potential inaccuracies – such as missing, misplaced, or incorrectly labelled geo-information – must be taken into account [72]. For example, newly constructed roads may be missing from the road network, leading to a false assessment of the accessibility of tiles, or buildings may not be labelled properly, resulting in missing PoIs. Ultimately, such false assessments due to inaccurate data can influence the final area prioritisation recommendations, which is why checking data quality is essential. To address this issue, existing methods for classifying and improving the quality of OSM data can be applied (see, e.g. [73] or [74]). In the end, it is important to emphasise that the effectiveness of *PrioReMap* is directly tied to the quality of the underlying data.

Another essential geospatial data input is the flood hazard layer. While flood inundation is an inherently dynamic phenomenon, we treated it here as a static snapshot within the present case study, using the maximum extent of a simulated flood scenario (HQ500). A limitation of the current method is therefore that the implementation of the flood layer is static. Dynamic flood evolution or live data assimilation is not yet supported. This exemplary inundation layer has the same data structure as layers generated by rapid mapping technologies (see [75] for a step-by-step guide on how to generate such layers using open-source data and tools). The method can in principle be adjusted to display the temporal dynamics of flood inundation by replacing the flood inundation layer at run-time when new information becomes available.

We identified four directions for future research that we consider particularly promising. First, the analysis can be extended to include additional dynamic observations, such as eyewitness reports, emergency calls, or sensor data, which provide further details about the situation during a flood disaster. To achieve this, the *PrioReMap* method could be combined with a method like the *Emergency Response Inference Mapping* method (see [23]), which allows for the integration of dynamic and uncertain or ambiguous observations. The integration of such observations should be carefully discussed with potential end users beforehand, as relying on them for decision making may introduce new uncertainties and hamper accountability. For instance, the absence of emergency calls from a particular area does not necessarily indicate lower urgency — people in those areas may simply lack mobile coverage or access to other communication channels.

Second, an aspect that becomes increasingly relevant when incorporating such additional dynamic observations is the presence of spatial dependencies that can lead to spatial inferences between tiles. For example, if a sensor measures a certain flood depth in one tile, the flood depth in neighbouring tiles could be inferred spatially. For this, given a spatial model predicting flood inundation, a data-assimilation framework can be implemented to combine model predictions with sensor measurements (e.g., see [76]).

Third, the *PrioReMap* could be applied in the context of sectorisation. Sectorisation is a common procedure in the context of emergency relief that organises the disaster region into sectors that require comparable operational demands and thereby allows responders to effectively distribute emergency relief resources (e.g. see [77]). The *PrioReMap* could be integrated in a sectorisation procedure that considers the geographic extent of an area as well as the number of (high) priority tiles within that area.

A limitation of the *PrioReMap* method is that it yet needs to be validated in practice. A fourth aspect of future work is therefore using *PrioReMap* in different scenarios and contexts, and compare the suggested prioritisation against actual operational decisions. Here, both empirical field research during real incidents as well as observational studies during training exercises or serious gaming sessions are promising ways ahead.

7. Conclusion

In this work, we introduced a novel method called Prioritisation Recommendation Mapping (*PrioReMap*) that has the potential to provide rapid and transparent recommendations for area prioritisation in flood disaster response. The benefit of the method is that it allows to shift some of the most time-consuming aspects of the decision-making process from the time-critical response phase to the less time-critical preparation phase. This is achieved as the core of the method is build by a Bayesian network (BN) that includes the different variables that account for flood disaster risk (hazard, exposure, vulnerability) and whose logical structure reflects a comprehensible line of argumentation for prioritising certain areas over others. Ultimately, the output of the method, that is the *PrioReMap*, is obtained from a grid of those BNs. The leaf nodes of these BNs are informed by multiple GIS models that require a flood hazard layer as input. We illustrated the applicability of the *PrioReMap* method in a case study of an extreme flood scenario in the city of Cologne, Germany, showcasing how the method condenses a large volume of spatially explicit information into distinct area prioritisation recommendations. Corresponding recommendations can help decision-makers identify the most at-risk areas in a flood disaster and thus support an effective allocation of scarce resources.

CRediT authorship contribution statement

Moritz Schneider: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Lukas Halekotte:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Tina Comes:** Writing – review & editing, Supervision, Conceptualization. **Frank Fiedrich:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

A.1. Ordered-logit model parameters

The ordered-logit model requires severity scores x_V for each variable V of the BN (see Table 2), which map categorical states onto the unit interval. In addition, it uses parent weights $w_{C,P}$ that specify the relative influence of a parent variable P on its child C (see Table 3). For each child node $C \in \{\text{Hazard}, \text{Exposure}, \text{Vulnerability}, \text{Risk}\}$, the parameters are identical with $\beta_C = 10$ and cut-points $(\tau_{C,1}, \tau_{C,2}, \tau_{C,3}) = (0.25, 0.50, 0.75)$. Since these variables have $K = 4$ ordered categories (none $\prec$ low $\prec$ medium $\prec$ high), the ordered-logit formulation requires exactly $K - 1 = 3$ cut-points to partition the real line.

Table 2
Variables with their states and corresponding severity scores x_V.

Variable	States	Mapping to $[0, 1]$
Flood Depth	none, shallow, moderate, deep	0.0, 0.33, 0.67, 1.0
Flood Coverage	0%–10%, 10%–50%, >50%	0.0, 0.5, 1.0
Population	none, low, medium, high	0.0, 0.33, 0.67, 1.0
PoI	absent, present	0.0, 1.0
Access Road	accessible, inaccessible	0.0, 1.0
Access Local	accessible, inaccessible	0.0, 1.0
% Elderly	0%–10%, 10%–50%, >50%	0.0, 0.5, 1.0
Hazard	none, low, medium, high	0.0, 0.33, 0.67, 1.0
Exposure	none, low, medium, high	0.0, 0.33, 0.67, 1.0
Vulnerability	none, low, medium, high	0.0, 0.33, 0.67, 1.0

Table 3
Parent weights $w_{C,P}$.

Child	Parent	Weight
Hazard	Flood Depth	0.65
Hazard	Flood Coverage	0.35
Exposure	Population	0.75
Exposure	PoI	0.25
Vulnerability	Access Road	0.40
Vulnerability	Access Local	0.40
Vulnerability	% Elderly	0.20
Risk	Hazard	0.45
Risk	Exposure	0.30
Risk	Vulnerability	0.25

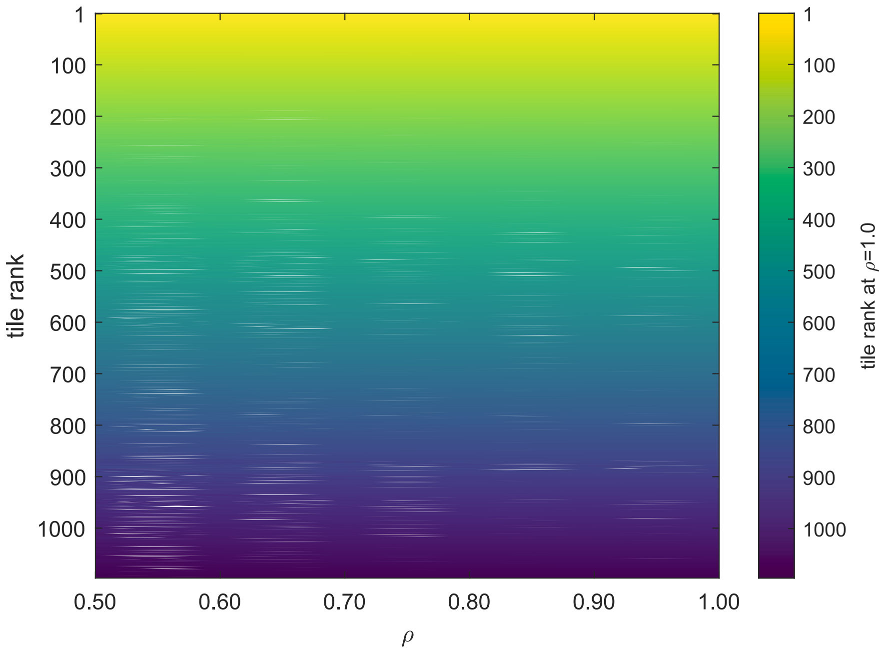


Fig. 12. Robustness of tile ranking with respect to variations in the under- vs. over-allocation penalty ρ. Rank 1 denotes the most critical tile. The results are compared against the baseline in which only under-allocation is penalised ($\rho = 1$, see corresponding spatial distribution in Fig. 13), with ρ varying between 0.5 (equal penalty) and 1 (only under-allocation penalised).

A.2. Sensitivity analysis

The prioritisation method (Section 4.3) is applied to all exposed tiles in the study area, yielding a ranked list of 1096 tiles. To test the robustness of the derived recommendations, we consider how the ranking of the 1096 tiles changes (see Fig. 12) depending on

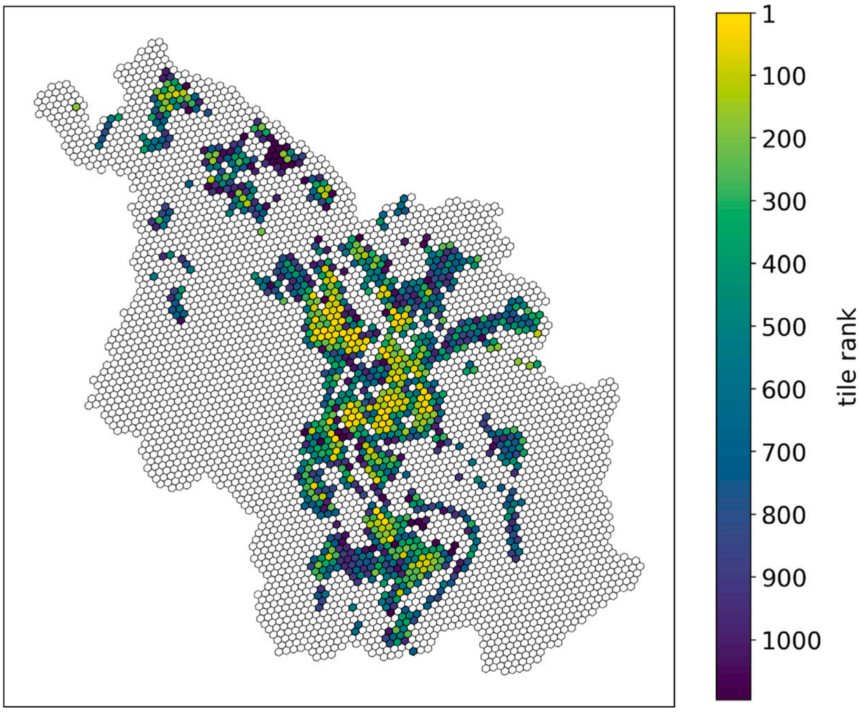


Fig. 13. Tile ranking for $\rho = 1$ for the case study scenario (corresponding to Fig. 12). Rank 1 corresponds to the most critical tile, while Rank 1096 corresponds to the least critical tile in the ranking.

the penalty factor ρ (similar to the procedure outlined in [78]), which governs the relative penalty for under- versus over-allocation. This variable can be considered the key parameter for adjusting the *PrioReMap* to changing resource constraints during the response phase. The changes in the ranking with varying ρ indicate that the recommendations are highly robust (which can be seen by the stable colour coding in Fig. 12), while still allowing for minor adjustments in the tile rankings as ρ varies. The overall correlation between the rankings is pretty high (Spearman's rank correlation of 0.9998 and Kendall's τ of 0.9895 between rankings at $\rho = 1$ and $\rho = 0.5$). Accordingly, the recommendation method shows a robust behaviour, which is especially critical for the highest-priority (most critical) tiles. Considering that tiles are summarised into waves (e.g., waves of 200 tiles), the differences between successive waves can be expected to be even smaller.

Data availability

Data will be made available on request.

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