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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 that 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.

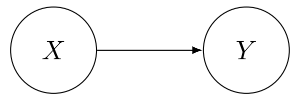
2. Bayesian networks

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.

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

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

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

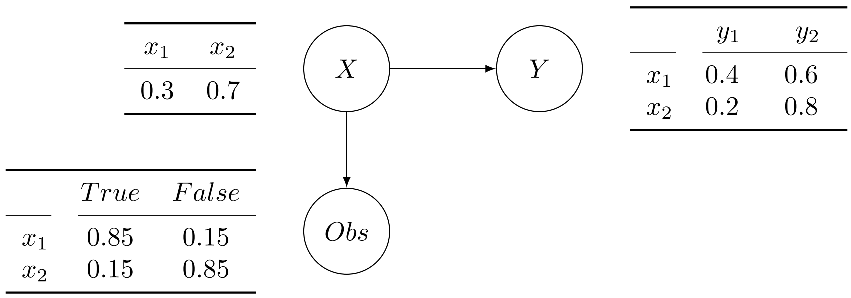


Fig. 2. Illustrative example of a BN with two initial nodes and one virtual node.

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).

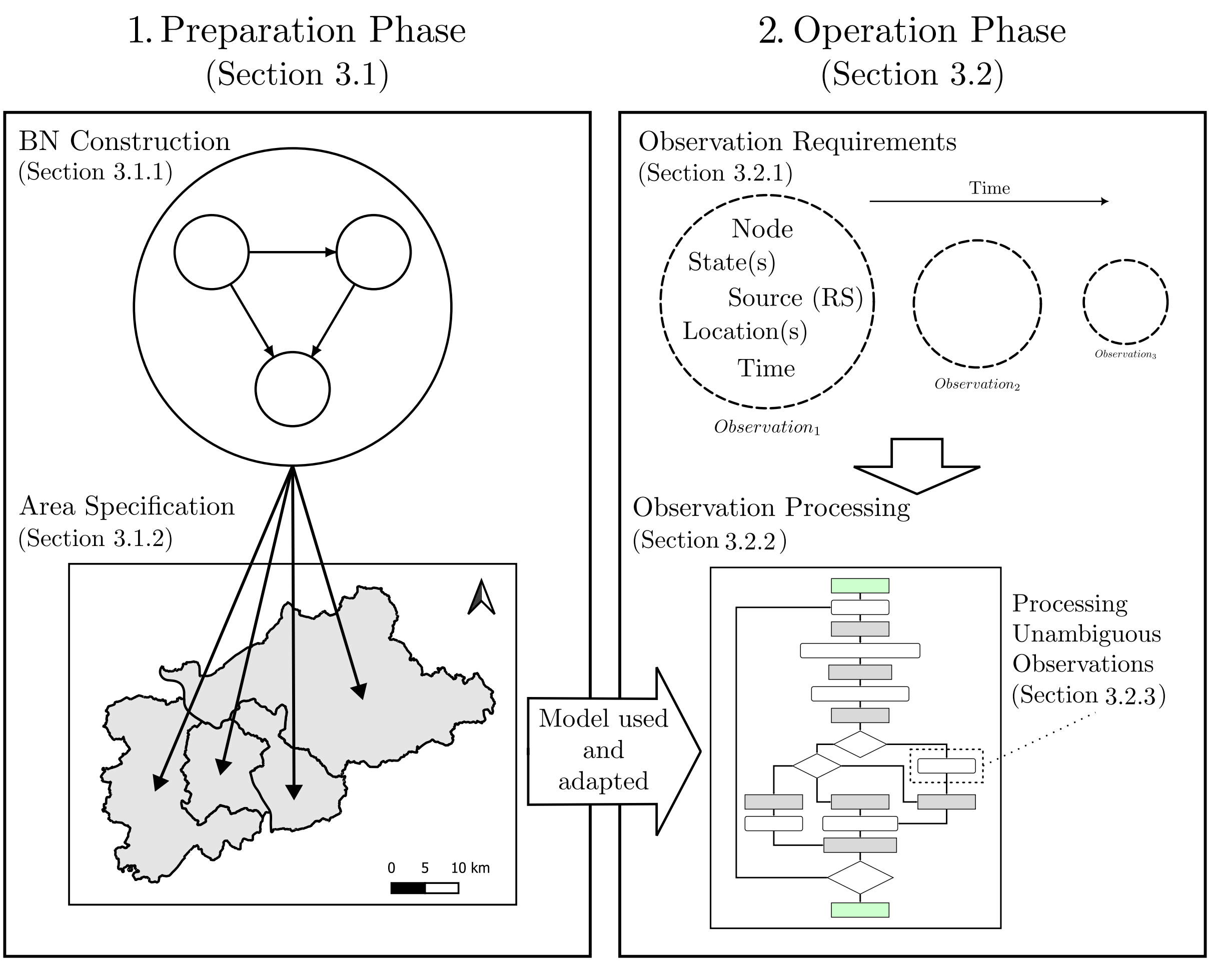


Fig. 3. Overview of the structure of the method and division of the following sections. The *preparation phase* includes the construction of the BN and specification of areas or locations. During the emergency *operation phase*, observations are collected and processed.

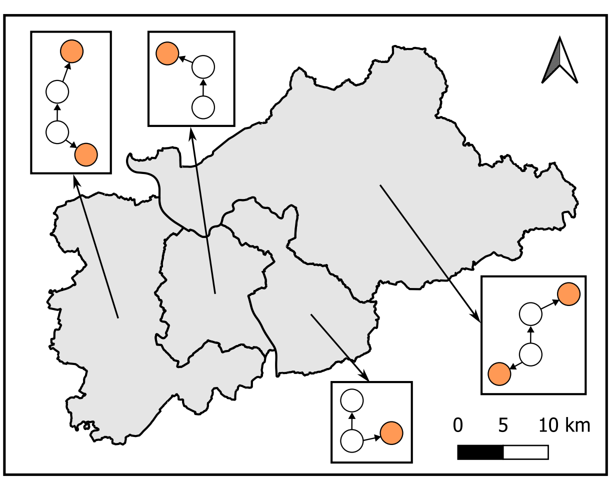


Fig. 4. Illustration of one initial BN (white filled nodes) duplicated for four different areas. For each area, different virtual nodes (orange filled) are added.

(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. $X = \{x_1, x_2, \ldots, x_N\}$, the likelihood ratio given an unambiguous observation stating node X is in state x_1 is:

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

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:

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

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

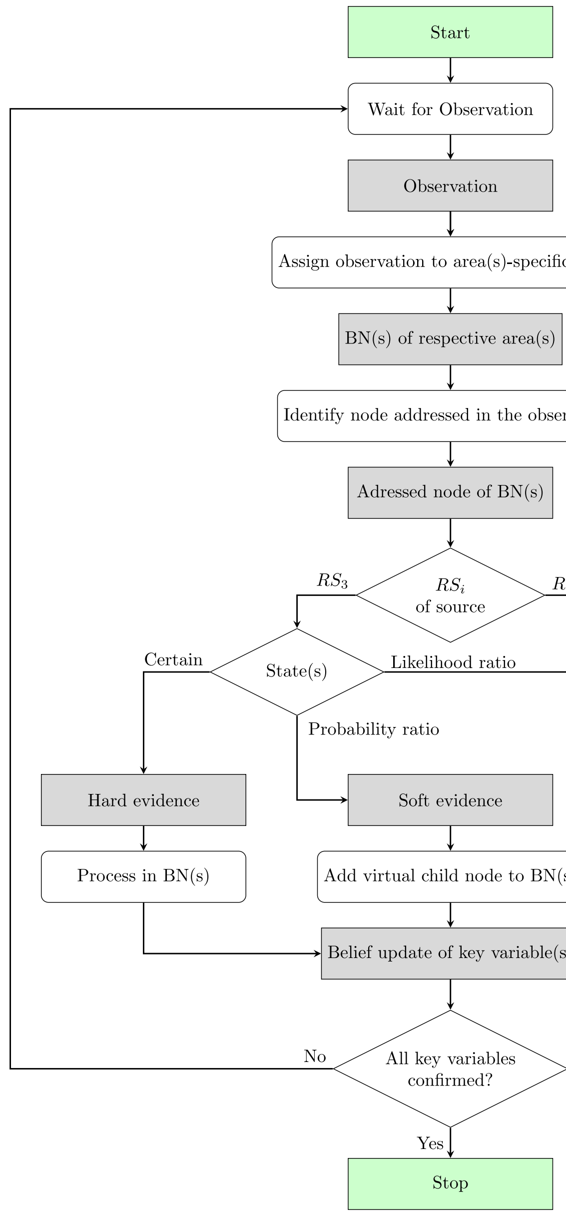


Fig. 5. Summary of the *ERIMap* method in the operation phase. Rectangles with rounded corners describe processes, gray rectangles describe the class of information. Decision nodes are diamond-shaped. Start and stop of the process are highlighted with green fill.

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.

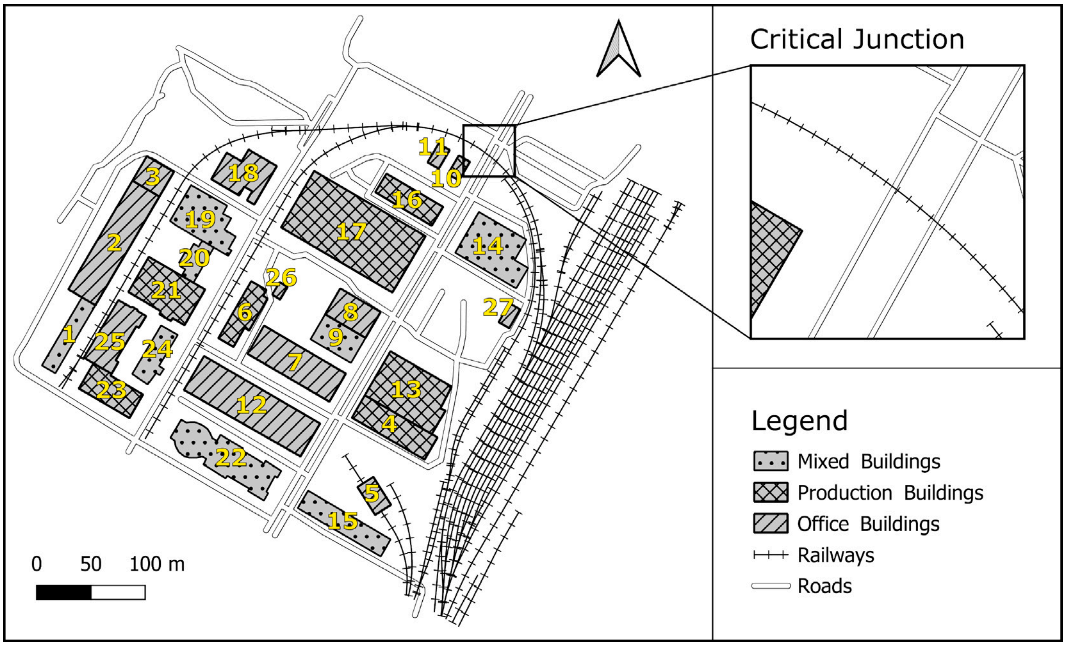
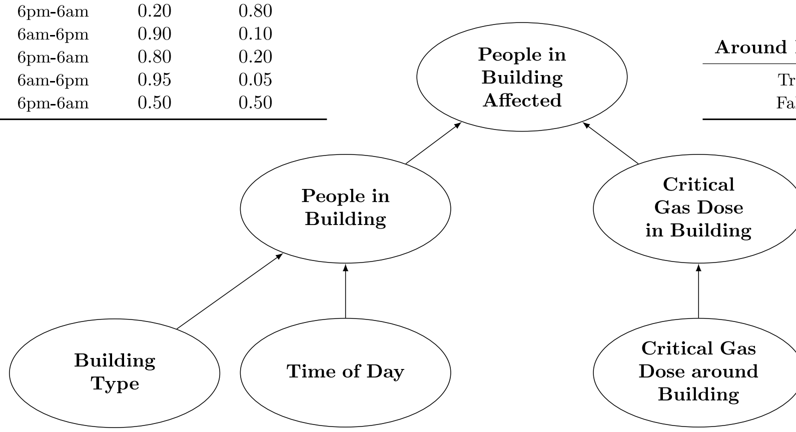


Fig. 6. Map of the chemical plant. The map shows building types, building numbers, roads, railways and the critical junction. The chemical plant is located on a greenfield site, i.e. there are no surrounding buildings.

		People in Building Affected	
People in Building	**C. G. D. in Building**	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

		People in Building	
Building Type	**Time of Day**	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

	In Building	
Around 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

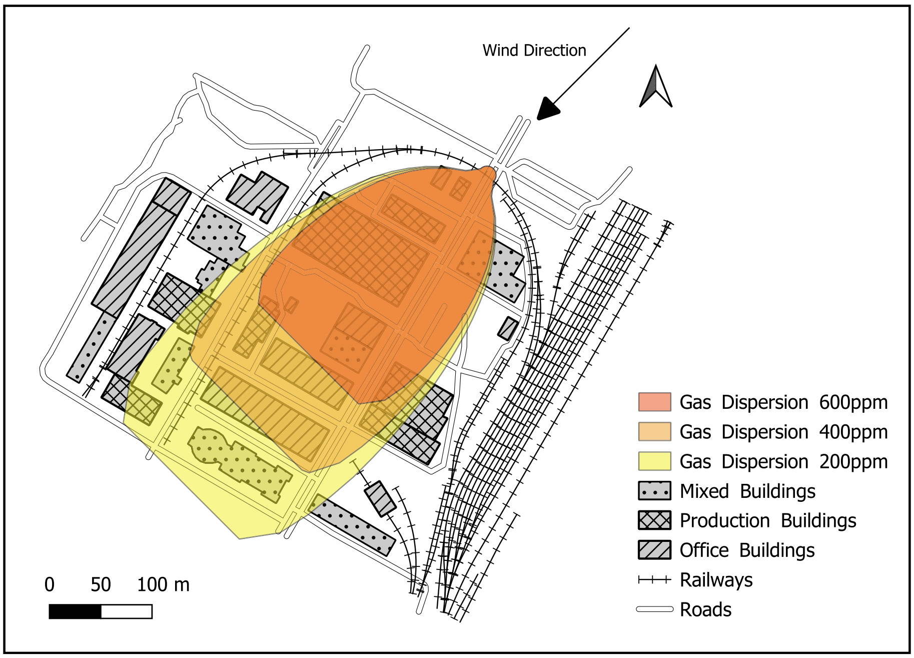


Fig. 8. Simulation of the gas dispersion emerging from the critical junction including three threat levels characterised by different steady-state gas concentrations.

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

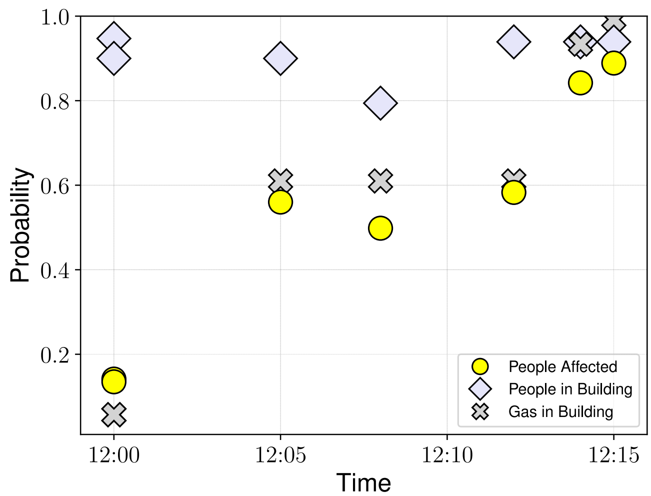


Fig. 9. Probability of nodes *People in Building Affected*, *People in Building*, and *Gas in Building* being in state *True* for multiple time steps listed in Table 3.

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

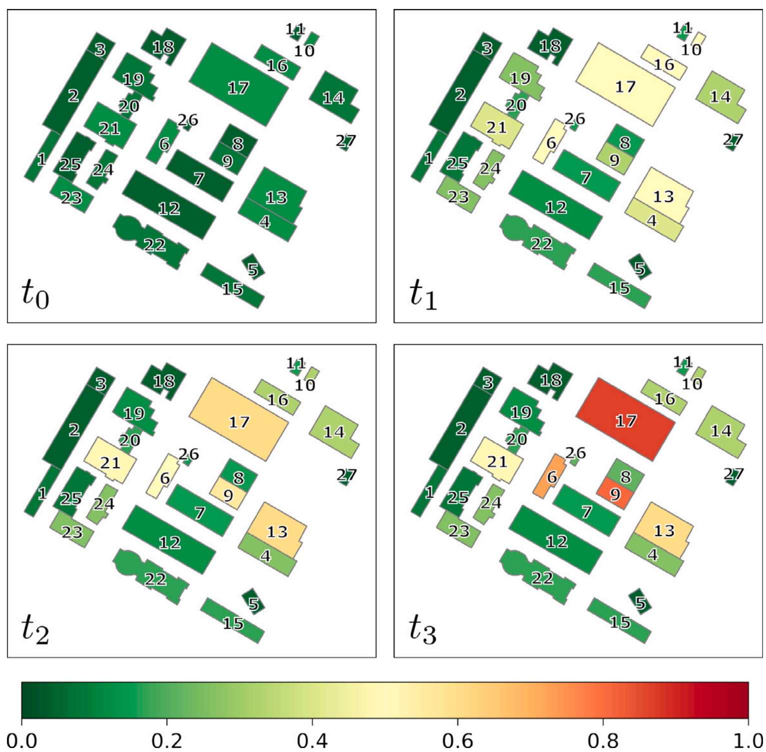


Fig. 10. Probability of node *People in Building Affected* being in state *True* for each building at four time steps of scenario 1 (see Table 4).

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

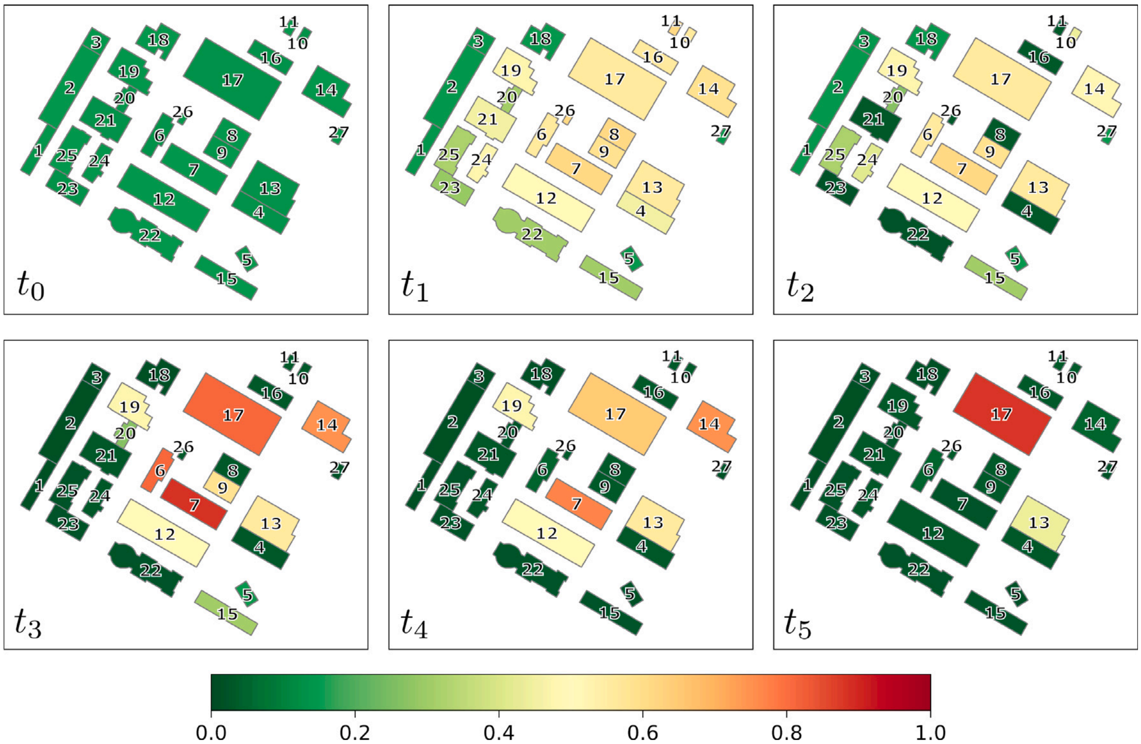


Fig. 11. Probability of node *People in Building Affected* being in state *True* for each building at six time steps of scenario 2 (see Table 5).

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.

References

[1] Endsley MR. Toward a theory of situation awareness in dynamic systems. Hum Factors 1995;37(1):32–64.
[2] Javed Y, Norris T, Johnston D. Ontology-based inference to enhance team situation awareness in emergency management. In: Santos LSMA, editor. 8th international conference on information systems for crisis response and management: From early-warning systems to preparedness and training. Information Systems for Crisis Response and Management, ISCRAM; 2011.
[3] Comes T, Wijngaards N, Van de Walle B. Exploring the future: Runtime scenario selection for complex and time-bound decisions. Technol Forecast Soc Change 2015;97:29–46.
[4] Abdalla R. Evaluation of spatial analysis application for urban emergency management. SpringerPlus 2016;5(1):2081–91.
[5] Hao Z, Xu Z, Zhao H, Fujita H. A dynamic weight determination approach based on the intuitionistic fuzzy Bayesian network and its application to emergency decision making. IEEE Trans Fuzzy Syst 2018;26(4):1893–907.
[6] Comes T, Wijngaards N, Schultmann F. Efficient scenarios updating in emergency management. In: Proceedings of the 9th international conference on information systems for crisis response and management. 2012, p. 167.
[7] Comes T, Van de Walle B, Van Wassenhove L. The coordination-information bubble in humanitarian response: theoretical foundations and empirical investigations. Prod Oper Manage 2020;29(11):2484–507.
[8] Comes T. Ai for crisis decisions. Ethics Inf Technol 2024;26(1):12.

[9] Yodo N, Wang P, Zhou Z. Predictive resilience analysis of complex systems using dynamic Bayesian networks. IEEE Trans Reliab 2017;66(3):761–70.
[10] Kammouh O, Gardoni P, Cimellaro GP. Probabilistic framework to evaluate the resilience of engineering systems using Bayesian and dynamic Bayesian networks. Reliab Eng Syst Saf 2020;198:106813.
[11] Caetano HO, Desuó L, Fogliatto MS, Maciel CD. Resilience assessment of critical infrastructures using dynamic bayesian networks and evidence propagation. Reliab Eng Syst Saf 2024;241:109691.
[12] Turoff M, Chumer M, d. Walle B, Yao X. The design of a dynamic emergency response management information system (DERMIS). J Inf Technol Theory Appl (JITTA) 2004;5(4).
[13] Quarantelli EL. Disaster crisis management: A summary of research findings. J Manage Stud 1988;25(4):373–85.
[14] Mendonça D, Wallace WA. Studying organizationally-situated improvisation in response to extreme events. Int J Mass Emerg & Disasters 2004;22(2):5–29.
[15] Li B, Lu J, Ji Y, Fan H, Li J. A dynamic emergency response decision-making method considering the scenario evolution of maritime emergencies. Comput Ind Eng 2023;182:109438.
[16] Wu B, Zhao C, Yip TL, Jiang D. A novel emergency decision-making model for collision accidents in the Yangtze River. Ocean Eng 2021;223:108622.
[17] Turoff M, Chumer M, de Walle BV, Yao X. The design of a dynamic emergency response management information system (dermis). J Inf Technol Theory Appl (JITTA) 2004;5(4):3.
[18] Bharosa N, Lee J, Janssen M. Challenges and obstacles in sharing and coordinating information during multi-agency disaster response: Propositions from field exercises. Information Systems Frontiers 2009;12(1):49–65.
[19] Comes T, Van de Walle B. Information systems for humanitarian logistics: concepts and design principles. In: Supply chain management for humanitarians: Tools for practice, Kogan Page, London. 2016, p. 257–84.
[20] Fekete A, Tzavella K, Baumhauer R. Spatial exposure aspects contributing to vulnerability and resilience assessments of urban critical infrastructure in a flood and blackout context. Nat Hazards 2016;86(S1):151–76.
[21] Geiß C, Priesmeier P, Pelizari P Aravena, Calderon AR Soto, Schoepfer E, Riedlinger T, et al. Benefits of global earth observation missions for disaggregation of exposure data and earthquake loss modeling: evidence from Santiago de Chile. Nat Hazards 2022;119(1):779–804.
[22] Geiß C, Maier J, So E, Schoepfer E, Harig S, Zapata JC Gómez, et al. Anticipating a risky future: long short-term memory (lstm) models for spatiotemporal extrapolation of population data in areas prone to earthquakes and tsunamis in lima, peru. Nat Hazards Earth Syst Sci 2024;24(3):1051–64.
[23] Fekete A, Neuner S. Spatial industrial accident exposure and social vulnerability assessment of hazardous material sites, chemical parks, and nuclear power plants in germany. Int J a Risk Sci 2023;14(2):223–36.
[24] Dotel S, Shrestha A, Bhusal A, Pathak R, Shakya A, Panday SP. Disaster assessment from satellite imagery by analysing topographical features using deep learning. In: Proceedings of the 2020 2nd international conference on image, video and signal processing. IVSP '20, vol. 35, ACM; 2020, p. 86–92.
[25] Milana E. Soft robotics for infrastructure protection. Front Robotics AI 2022;9.
[26] Huang L, Liu G, Wang Y, Yuan H, Chen T. Fire detection in video surveillances using convolutional neural networks and wavelet transform. Eng Appl Artif Intell 2022;110:104737.
[27] Fathi R, Fiedrich F. Social media analytics by virtual operations support teams in disaster management: Situational awareness and actionable information for decision-makers. Front Earth Sci 2022;10.
[28] Guo K, Guan M, Yan H. Utilising social media data to evaluate urban flood impact in data scarce cities. Int J Disaster Risk Reduct 2023;93:103780.
[29] Muhammed S, Mathew SK. The disaster of misinformation: a review of research in social media. Int J Data Sci Anal 2022;13(4):271–85.
[30] Comes T, Wijngaards N, Maule J, Allen D, Schultmann F. Scenario reliability assessment to support decision makers in situations of severe uncertainty. In: 2012 IEEE international multi-disciplinary conference on cognitive methods in situation awareness and decision support. 2012, p. 30–7.
[31] Fu M, Wang L, Zheng B, Shao H. The optimal emergency decision-making method with incomplete probabilistic information. Sci Rep 2021;11(1):23400.
[32] van de Walle B, Turoff M. Decision support for emergency situations. In: International handbooks information system. Berlin, Heidelberg: Springer; 2008, p. 39–63.
[33] Paulus D, Fathi R, Fiedrich F, de Walle BV, Comes T. On the interplay of data and cognitive bias in crisis information management. Inf Syst Front 2022;26(2):391–415.
[34] Liu Y. A multistage dynamic emergency decision-making method considering the satisfaction under uncertainty information. J Adv Transp 2021;2021(1):5535925.
[35] Comfort LK, Sungu Y, Johnson D, Dunn M. Complex systems in crisis: Anticipation and resilience in dynamic environments. J Conting Crisis Manag 2001;9(3):144–58.
[36] Tzavella K, Skopeliti A, Fekete A. Volunteered geographic information use in crisis, emergency and disaster management: a scoping review and a web atlas. Geo-spatial information. Science 2022;27(2):423–54.
[37] Giordano R, D'Agostino D, Apollonio C, Lamaddalena N, Vurro M. Bayesian Belief Network to support conflict analysis for groundwater protection: The case of the Apulia region. J Environ Manag 2013;115:136–46.
[38] Munk A, Mead A, Wood F. Uncertain evidence in probabilistic models and stochastic simulators. PMLR; 2023, p. 25486–500.
[39] Pearl J. Bayesian networks: A model of self-activated memory for evidential reasoning. In: Proceedings of the 7th conference of the cognitive science society. Irvine, CA, USA: University of California; 1985, p. 15–7.
[40] Weber P, Medina-Oliva G, Simon C, Iung B. Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas. Eng Appl Artif Intell 2012;25(4):671–82.
[41] Yu Y, Shuai B, Huang W. Resilience evaluation of train control on-board system considering common cause failure: Based on a beta-factor and continuous-time bayesian network model. Reliab Eng Syst Saf 2024;246:110088.
[42] Sun X, Hu Y, Qin Y, Zhang Y. Risk assessment of unmanned aerial vehicle accidents based on data-driven Bayesian networks. Reliab Eng Syst Saf 2024;248:110185.
[43] DeJesus Segarra J, Bensi M, Modarres M. Multi-unit seismic probabilistic risk assessment: A Bayesian network perspective. Reliab Eng Syst Saf 2023;234:109169.
[44] Huang T, Xiahou T, Mi J, Chen H, Huang H-Z, Liu Y. Merging multi-level evidential observations for dynamic reliability assessment of hierarchical multi-state systems: A dynamic Bayesian network approach. Reliab Eng Syst Saf 2024;249:110225.
[45] You Q, Guo J, Zeng S, Che H. A dynamic Bayesian network based reliability assessment method for short-term multi-round situation awareness considering round dependencies. Reliab Eng Syst Saf 2024;243:109838.
[46] Bauranov A, Rakas J. Bayesian network model of aviation safety: Impact of new communication technologies on mid-air collisions. Reliab Eng Syst Saf 2024;243:109905.
[47] Kong D, Lin Z, Li W, He W. Development of an improved Bayesian network method for maritime accident safety assessment based on multiscale scenario analysis theory. Reliab Eng Syst Saf 2024;251:110344.
[48] An X, Yin Z, Tong Q, Fang Y, Yang M, Yang Q, et al. An integrated resilience assessment methodology for emergency response systems based on multi-stage STAMP and dynamic Bayesian networks. Reliab Eng Syst Saf 2023;238:109445.
[49] Ricci F, Yang M, Reniers G, Cozzani V. Emergency response in cascading scenarios triggered by natural events. Reliab Eng Syst Saf 2024;243:109820.
[50] Pan R, Peng Y, Ding Z. Belief update in bayesian networks using uncertain evidence. In: 2006 18th IEEE international conference on tools with artificial intelligence. IEEE; 2006.
[51] Mrad AB, Delcroix V, Maalej MA, Piechowiak S, Abid M. Uncertain evidence in bayesian networks: Presentation and comparison on a simple example. In: Communications in computer and information science. Springer Berlin Heidelberg; 2012, p. 39–48.
[52] Peng Y, Zhang S, Pan R. Bayesian network reasoning with uncertain evidences. Internat J Uncertain Fuzziness Knowledge-Based Systems 2010;18(05):539–64.
[53] Valtorta M, Kim Y-G, Vomlel J. Soft evidential update for probabilistic multiagent systems. Internat J Approx Reason 2002;29(1):71–106.
[54] Pearl J. Probabilistic reasoning in intelligent systems: Networks of plausible inference. Morgan Kaufmann; 1988.
[55] Mrad AB, Delcroix V, Piechowiak S, Leicester P, Abid M. An explication of uncertain evidence in bayesian networks: likelihood evidence and probabilistic evidence. Appl Intell 2015;43(4):802–24.
[56] Mrad AB, Delcroix V, Piechowiak S, Maalej MA, Abid M. Understanding soft evidence as probabilistic evidence: Illustration with several use cases. In: 2013 5th international conference on modeling, simulation and applied optimization. 2013, p. 1–6.
[57] Dlamini WM. Application of Bayesian networks for fire risk mapping using GIS and remote sensing data. GeoJournal 2011;76(3):283–96.
[58] Wu Z, Shen Y, Wang H, Wu M. Assessing urban flood disaster risk using Bayesian network model and GIS applications. Geomat Natural Haz Risk 2019;10(1):2163–84.
[59] Rohr A, Priesmeier P, Tzavella K, Fekete A. System criticality of road network areas for emergency management services - spatial assessment using a tessellation approach. Infrastructures 2020;5.
[60] Dlamini WMD, Simelane SP, Nhlabatsi NM. Bayesian network-based spatial predictive modelling reveals COVID-19 transmission dynamics in Eswatini. Spatial Inf Res 2022;30(1):183–94.
[61] Chan H, Darwiche A. On the revision of probabilistic beliefs using uncertain evidence. Artif Intell 2005;163(1):67–90.
[62] Radianti J, Granmo O-C, Sarshar P, Goodwin M, Dugdale J, Gonzalez JJ. A spatio-temporal probabilistic model of hazard- and crowd dynamics for evacuation planning in disasters. Appl Intell 2015;42(1):3–23.
[63] Johnson S, Low-Choy S, Mengersen K. Integrating Bayesian networks and geographic information systems: Good practice examples. Integr Environ Assess Manage 2012;8(3):473–9.
[64] Druzdzel M, van der Gaag L. Building probabilistic networks: Where do the numbers come from? guest editors' introduction. IEEE Trans Knowl Data Eng 2000;12(4):481–6.
[65] Vomlel J. Probabilistic reasoning with uncertain evidence. Int J Neural Mass-Parallel Comput Inf Syst 2004;14(5):453–6.

[66] Ankan A, Panda A. pgmpy: Probabilistic graphical models using python. In: Proceedings of the 14th python in science conference. Citeseer; 2015.
[67] Jordahl K, den Bossche JV, Fleischmann M, Wasserman J, McBride J, Gerard J, et al. geopandas/geopandas: v0.8.1. 2020.
[68] Brusca S, Famoso F, Lanzafame R, Mauro S, Garrano AMC, Monforte P. Theoretical and experimental study of Gaussian plume model in small scale system. Energy Procedia 2016;101:58–65.
[69] Schubach S. A measure of human sensitivity in acute inhalation toxicity. J Loss Prev Process Ind 1997;10(5):309–15.
[70] James M. Simplified methods of using probit analysis in consequence analysis. Process Saf Prog 2014;34(1):58–63.
[71] Waal AD, Ritchey T. Combining morphological analysis and bayesian networks for strategic decision support. ORiON 2007;23(2).
[72] Van de Walle B, Brugghemans B, Comes T. Improving situation awareness in crisis response teams: An experimental analysis of enriched information and centralized coordination. Int J Hum-Comput Stud 2016;95:66–79.
[73] Schaberreiter T, Bouvry P, Röning J, Khadraoui D. Support Tool for a Bayesian Network Based Critical Infrastructure Risk model. In: Schuetze O, Coello CA Coello, Tantar A-A, Tantar E, Bouvry P, Moral PD, Legrand P, editors. EVOLVE - A bridge between probability, set oriented numerics, and evolutionary computation III. Studies in computational intelligence, Heidelberg: Springer International Publishing; 2014, p. 53–75.
[74] Weidinger J, Schlauderer S, Overhage S. Information technology to the rescue? explaining the acceptance of emergency response information systems by firefighters. IEEE Trans Eng Manag 2020;1–15.
[75] de Waal A, Joubert JW. Explainable Bayesian networks applied to transport vulnerability. Expert Syst Appl 2022;209:118348.
[76] Lee C-C, Comes T, Finn M, Mostafavi A. Roadmap towards responsible ai in crisis resilience management. 2022.
[77] Hassall KL, Dailey G, Zawadzka J, Milne AE, Harris JA, Corstanje R, et al. Facilitating the elicitation of beliefs for use in Bayesian Belief modelling. Environ Model Softw 2019;122:104539.
[78] Morris DE, Oakley JE, Crowe JA. A web-based tool for eliciting probability distributions from experts. Environ Model Softw 2014;52:1–4.
[79] Murphy K. Dynamic Bayesian networks: Representation, inference and learning [Ph.D. thesis], 2002.