Cascading Effects of Critical Infrastructures in a Flood Scenario: A Case Study in the City of Cologne

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ABSTRACT

Critical infrastructures, which constitute the backbone of our modern society, are increasingly exposed to natural hazards. Loss of performance or failure of a critical infrastructure can lead to cascading effects that affect even more services and citizens. Floods, as one of the most prominent natural hazards, are prone to affect multiple critical infrastructures at once, making it even more difficult to assess combined effects of these (cascading) disruptions. Hospitals are especially vulnerable in a flood scenario, as they are reliant on multiple other infrastructures, such as power and water supply or the road network. In order to prepare for upcoming events, sophisticated analysis tools are required that are capable of modeling the spatial extent of flood induced disruptions and their impact on critical infrastructure services. In this work, we present a proof of concept that focuses on the impact of multiple disruptions on hospitals. We conducted a case study on an extreme flood scenario in the city of Cologne (Germany). Historically, Cologne has proven vulnerable to river-floods, as thousands of people were affected through floods in in 1993 and 1995. The approach is based on a combination of I) a geographic information system, which makes the extent of disruptions spatially explicit and II) a Bayesian network, which is used to assess the impact of one or multiple disruptions on a single hospital. We present a work-in-progress approach in this work. The results generated using this approach enable a first comparative overview of the expected level of services of the examined hospitals.

Keywords

Critical Infrastructure, Cascading Effects, Flood Risk Management, Bayesian Network, GIS.

INTRODUCTION

Growing interdependencies of critical infrastructures (CI) in combination with increasing exposure to natural hazards contribute to society's vulnerability to CI breakdowns (Nick et al., 2023). In addition, the functionality of one CI is most often reliant on the functionality of at least one other CI (Rinaldi et al., 2001), which poses a challenge for disaster resilience. The resulting highly interconnected networks can lead to severe cascading effects in case of a single disruptive event, such as a flood (Fekete, 2019). These interdependencies can cause impacts on a local CI that can have far-reaching effects on other CI. For this reason, it is important to have an in-depth understanding of disruptions and the resulting cascading effects to better prepare for upcoming challenges. This requires sophisticated CI analysis methods that look at exposure to natural hazards and also investigate CI interdependencies enabling a prediction of cascading effects and their impacts.

In this work, we study how the impact of multiple (cascading) flood-induced disruptions on different service levels of a CI can be analyzed for flood risk management. In terms of CI, we focus on hospitals as they are crucial for disaster response and especially vulnerable to floods and failure of other CI services (Melnychuk et al., 2022). We thus require a model that (1) makes the distribution of the considered disruptions spatially explicit, and (2) enables an estimation of the effect of one or multiple disruptions on predefined service levels of a hospital. A case study of an extreme flood scenario in the city of Cologne (Germany) is conducted as a proof of concept. The final goal of the approach is to create a map that provides a comparative overview of the expected level of services between the examined hospitals.

Here, we present an approach to address these goals. The main contribution of this work is an approach for assessing the impact of multiple flood-induced cascading effects (i.e. disruptions) on hospitals. The novelty of this approach is the consideration of individual as well as combined disruptions on hospitals in a flood scenario taking into account uncertainties. We argue that it is important to consider the uncertainties both of the disruptions as well as in their impact on a hospital. As a result, the approach generates a map which can be used to compare affected hospitals to one another serving as an information tool for emergency responders in flood risk management. Especially in emergency response, it is important to consider cascading sequences triggered by natural events (Ricci et al., 2024).

The approach is based on a combination of a geographic information system (GIS) and a Bayesian network (BN) - the GIS informs the BN (as e.g. outlined in Johnson et al., 2012). The GIS is used to model the spatial extent of the considered disruptions. Geographic information systems are used extensively in emergency and crisis management, including impact analysis of natural hazards (e.g. see Tzavella et al., 2018 or Geiß et al., 2022). The Bayesian network is used to model the impact of the disruption(s) on a single hospital under consideration of uncertainties. Bayesian networks, which are probabilistic graphical models (Pearl, 1988), are often used in the literature to model the effects of natural hazards on CI (e.g. see Kameshwar et al., 2019 or Ramírez-Agudelo et al., 2021).

The definition of a disruption in this work follows the proposal by Mentges et al., 2023: A disruption (e.g. a damaged road) is caused by a disruptive event (e.g. a flood) and lasts as long as the performance of the system is decreased as a consequence of the event. The disruption ends when the system has recovered and can thus last longer as the disruptive event, i.e. the flood is gone but the road is still damaged. The concrete disruptions considered in this work are: the flood itself - in terms of a rising water levels, the flooding of hospital access roads (a indirect, i.e. cascading, effect), and potential blackouts caused by the flood (a second cascading effect). We selected these disruptions as the starting point for our work-in-progress approach because they are significant in their impact and are likely to occur in a flood scenario.

The remainder of this paper is structured as followed: First, our work-in-progress approach is described, including the case study of a extreme flood scenario in Cologne, Germany. Subsequently, preliminary results are presented, followed by a discussion and conclusion.

APPROACH

The approach can be divided into three steps: (1) the considered disruptions (flooded area, access road availability, and blackout areas) are modeled in a GIS environment, (2) a Bayesian network model is developed that is used to infer the effect of a single or multiple disruptions on the service levels of a hospital, and (3) the GIS and BN are combined (GIS informs the BN) to estimate the expected level of service of each individual hospital in an automated manner. In the following, the case study is presented, followed by the GIS model and its method to estimate the spatial extent of the considered disruption. Subsequently, the BN is developed and the combination of the GIS and the BN outlined.

Case Study Description

Our approach is developed and tested in the case study area of Cologne, Germany. Cologne is Germany's fourth largest city with a population of about one million people. The city is divided by the Rhine river, which is the second largest river in Germany. There have been several devastating Rhine floods in the past, for example in 1993 and 1995 (Herget and Meurs, 2010), the latter affecting 33,000 people and causing damage of 35 million euros in Cologne alone (Fink et al., 1996). A five-hundred-year flood (extreme flood) hazard map is used as exposure data in this case study (see Figure 1). Three disruptions that can be expected in a flood scenario and affect a hospital are considered in this work-in-progress approach: (1) the flood itself in terms of the rising water level, (2) a potential flooding of access roads to a hospital, and (3) potential blackouts caused by flooded transformer stations or safety shutdowns.

Open Street Map (OSM) data is used to determine access roads of hospitals in Cologne, the location of transformer stations used to determine blackout areas, and the location of hospitals. This data represents example data which was not reviewed for actuality and accuracy. The data of the extreme flood scenario called HQ 500 is provided by official sources (geoportal.nrw, 2024; geoportal of the state of NRW: www.geoportal.nrw/). In this scenario, the effect of failed or overtopped dikes, mobile flood defenses, and intrusion of ground water into old river arms is included (Fekete, 2020).

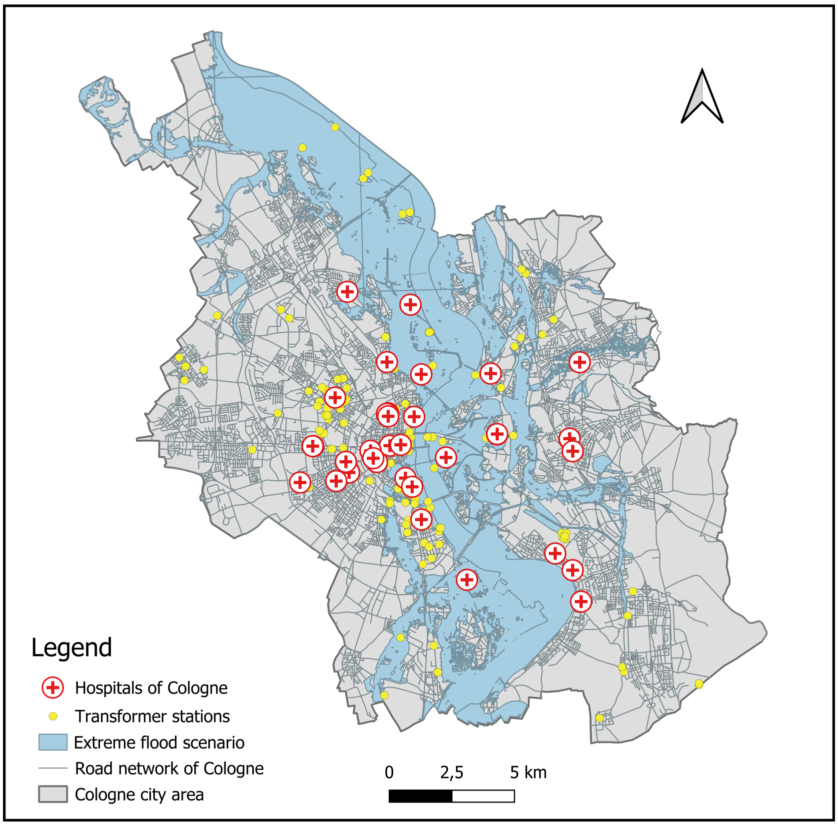

Figure 1. Map of Cologne including the extent of the assumed flood scenario, as well as the road network and locations of transformer stations and hospitals.

GIS Model

The spatial extent of the considered disruptions (flood, blackout, and road availability) is modeled in QGIS, which is an open source geographic information system. The approaches used to assess the spatial extent of these disruptions are work-in-progress in terms of their level of detail, but sufficient for a proof of concept of the approach. In the following, a brief description of the three individual approaches - one for each disruption - is presented.

The *flood* disruption is modeled by examining whether a hospital is located within the flood propagation layer in the GIS. It is analyzed, whether the flood propagation layer shows an overlap with a hospital building (compare Figure 1). In this work-in-progress approach, we conduct a binary assessment that omits the water level.

In order to determine the *access road availability* for each hospital, a ring buffer with a diameter of 100 meters is established around each center point of a hospital. Each access road within this buffer that does not show an overlap with the flood propagation layer is identified (see Figure 2). For each buffer, i.e. each hospital, it is determined if no access road, a single access road, or multiple access roads are available.

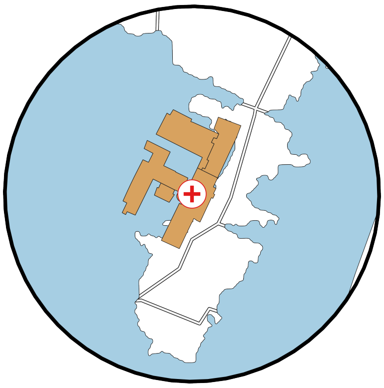

Figure 2. Example of a 100 meter buffer around a hospital showing multiple flooded access roads and one access road which can still be used.

The approach to determine blackout areas is based on a method presented by Pala et al., 2014. The method uses on Thiessen polygons (also called Voronoi diagram) without weights. In order to determine the Thiessen polgyons, an algorithm is used that grows cells (that constitute the polygons) in a raster format starting from each source point (Pala et al., 2014), which are the location points of the transformer stations in Cologne. In a next step, it is analyzed which transformer stations are within the flooded area and thus would potentially be damaged or shut down for safety reasons. The corresponding cells to these source points are considered as potential blackout areas (see Figure 3). Four different areas of different blackout probability are considered in the approach: (1) the area that shows an overlap with the flood propagation layer and the affected Voronoi cells is considered as area with highest the blackout probability (assuming a 90% probability), (2) the area that shows an overlap with the flood propagation layer but not with the affected Voronoi cells is considered as the area of medium blackout probability (70% probability), (3) the area that shows an overlap with the affected Voronoi cells, but not with the flood propagation layer is considered as an area of lower blackout probability (50%), and (4) the area that does not show an overlap with both the flood propagation layer and the affected Voronoi cells is considered as the area with zero blackout probability.

Bayesian Network

The Bayesian network (BN) is used in the proposed approach to estimate the impact of one or multiple disruptions on different service levels of each hospital. The BN is implemented in Python based on the pgmpy library (see Ankan and Panda, 2015), which is a versatile library for working with probabilistic graphical models. A BN, introduced by Pearl, 1988, is a directed acyclic graph composed of nodes representing system variables and edges representing conditional dependencies (for a brief introduction of BN see e.g. Puga et al., 2015). Nodes that interact, are connected by edges in the direction of influence. For example, an edge X → Y implies that X (the parent node) influences Y (the child node). Additionally, each node has a probability distribution attached to it that defines the chance of finding the node in a given state. Nodes that are not influenced by other nodes (no edge is pointing towards these nodes) are called marginal nodes. Nodes that are influenced by at least one other node (edge(s) pointing towards the node) are called conditional nodes. Conditional nodes have conditional probabilities that are used to infer the state of a child node given information on the states of one or multiple parent nodes.

In our approach, a variable describing the expected *Level of Service* of a hospital is the target child node of the BN. The states of this node constitute potential level of services of a hospital. At this point, it must be considered that the number of states enhances the complexity when defining conditional probabilities for this variable - for each combination of parent and child node states, one probability value must be determined. We selected a simple categorization of hospital service levels that is proposed in Witte et al., 2021: (1) *normal*, which describes the unimpaired operation of the hospital, (2) *emergency*, which describes that the hospital only performs the basic services, and (3) *failure*, which describes that the hospital should be evacuated.

The node *Level of Service* of a hospital is influenced by the considered disruptions. Thus, the three modeled disruptions (flood, road accessibility, and blackout) constitute the parent nodes of node *Level of Service* (see Figure 4). The dependencies between the disruptions are not modeled in the BN, but in the GIS model, thus all disruption

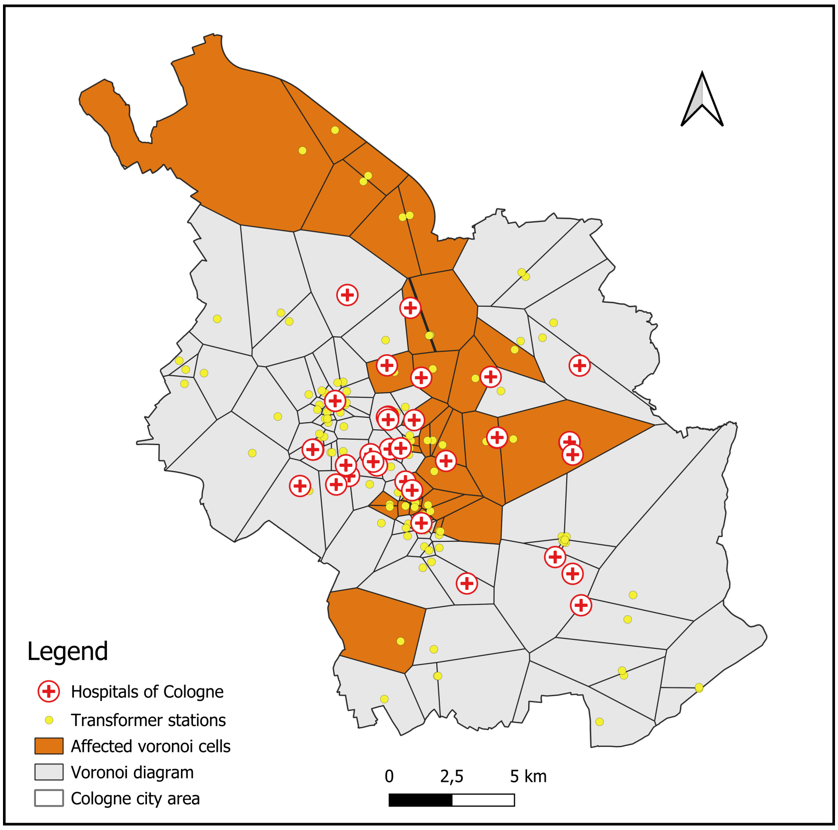

Figure 3. Map of Cologne including the transformer station-based Voronoi diagram including affected Voronoi cells that indicate areas prone to blackouts.

nodes are marginal nodes. The states of the disruption nodes are basic divisions. The nodes *Blackout* and *In Flooded Area* show binary states: *True* and *False*. The node *Road Accessibility* shows three states that describe if no access road is available, a single access road is available, or multiple access roads are available (all nodes and node states are listed in Table 1). The probability values quantifying the nodes of the BN were selected by the authors and reflect the basic dependencies between the variables - the more a hospital is exposed to disruption(s), the more likely it is to be in a state of *failure*. If a hospital is exposed to at least one disruption, the node *Level of Service* cannot be in state *normal*.

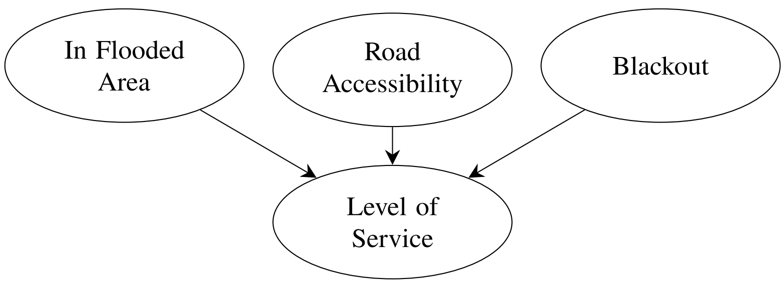

Figure 4. Bayesian network of the approach including the target node *Level of Service* and three parent nodes that describe the considered disruptions.

Table 1. All four considered variables of the Bayesian network shown in Figure 4 including their states.

Variable	**Level of Service**	**Road Accessibility**	**Blackout**	**In Flooded Area**
State 1	Normal	None	True	True
State 2	Emergency	Single Road	False	False
State 3	Failure	Multiple Roads		

In order to calculate the posterior probability of node *Level of Service*, i.e. the probability given evidence on the disruption nodes, the BN (see Figure 4) is duplicated and assigned to each hospital. The individual BNs are informed by the results of the GIS model, i.e. it is analyzed, if a hospital is within the flooded area, if it is in one of the four blackout zones (high, medium, low, and zero probability zone), and how many access roads are available.

Two types of evidence (information about node states) gained from the GIS must be distinguished. The evidence on variable *In Flooded Area* and *road Accessibility* is considered as hard evidence - which describes that we know the exact state of this variable (within the boundaries of the model). For node *Blackout*, we defined four areas with varying blackout probability, thus we do not have evidence with certainty, but evidence of a probability distribution. In order to consider this uncertainty evidence, soft evidence, introduced by Valtorta et al., 2002, is applied. In this way, the posterior probability of node *Blackout* being in state *True* follows the probability assigned to the individual blackout zones.

RESULTS

The results (see Figure 5) are illustrated using the geopandas library in Python that enables geospatial data analysis and visualization (Jordahl et al., 2020). The BN is duplicated and assigned to each of the 35 hospitals and spatially informed by the GIS model. This results in 35 probability distributions of node *Level of Service*. Thus, for each hospital, one probability value for each considered level of service (normal, emergency, and failure) is calculated, which sum up to one. Figure 5 shows the results on three maps. Each map shows the probability of one node state (normal, emergency, failure) for each hospital. Before going into detail on the results, it must be pointed out that these results have limitations due to assumptions within the model environment and cannot be used directly to estimate realistic effects of a flood. Nevertheless, the results allow an assessment of the suitability of the approach in regard to the research objective.

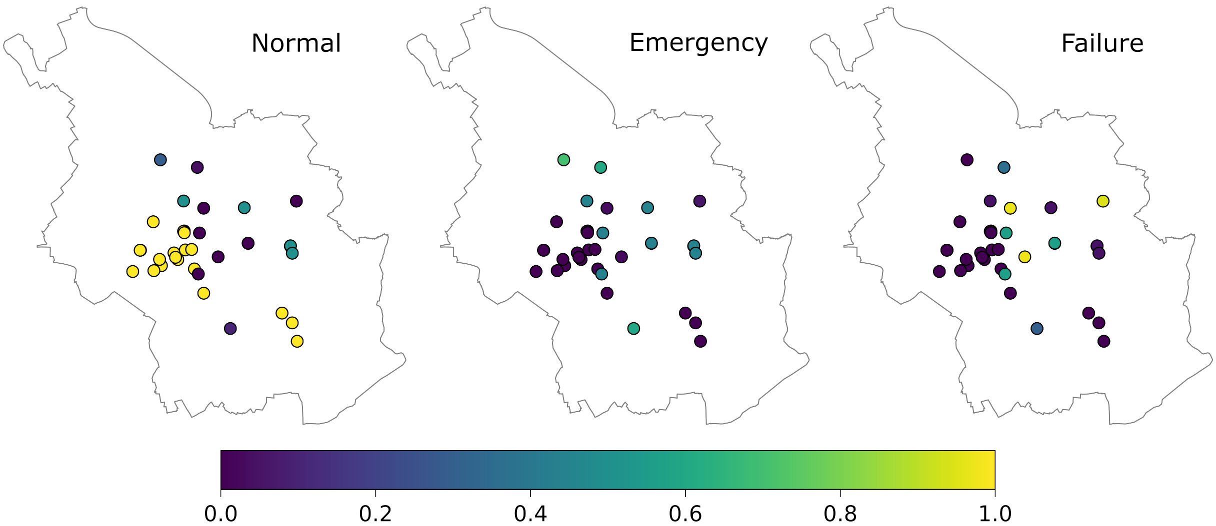

Figure 5. Preliminary results of the case study presented as three maps that illustrate the probability values of the three states of node *Level of Service*. The color of the dots (each representing one hospital) follow the colorbar at the bottom of the figure, thus, each color represents a certain probability value. Looking at one hospital on all three maps, the probability values sum up to one.

The preliminary results show that 20 hospitals are not affected by one of the three considered disruptions, i.e. $P(Level\ of\ Service = Normal) = 1$ (see bright yellow-colored circles in the left image in Figure 5). 17 hospitals are located west of the Rhine river and three hospitals are located in the south east of Cologne. Seven hospitals show a probability of 0% for state *Normal*, i.e. they are affected by at least one disruption. Two of these hospitals show the highest probability of state *Failure* with 97% (see bright yellow-colored circles on the right image in Figure 5). These hospitals are located close to the Rhine river and are within the flooded area as well as within a potential blackout area (leading to the highest probability of a blackout), and no access roads are available. One additional hospital shows a high probability of state *Failure* with 94%. This hospital is located near a tributary of the Rhine and is located within the flooded area and an affected Voronoi cell, but there is one access road still available.

DISCUSSION AND CONCLUSION

Cascading effects are of increasing interest in research, not only in the context of supply chains, but also with regard to the interconnection of natural hazards and related impact chains. However, concrete assessments, showcasing how these interactions and cascading effects play out are still needed. The presented work-in-progress approach provides a first step to assess cascading effects and resulting multiple disruptions on hospitals in a flood scenario. By introducing a BN, the effect of a single or multiple combined disruptions is modeled including consideration of uncertainties in both the intensity of the disruption and the effect on different service levels of a hospital. Using a GIS model, the spatial extent of the disruptions is modeled. By combining both models (GIS informs BN), each considered hospital can be individually assessed with regard to its exposure to the considered disruptions. In this work, we presented a proof of concept of the approach. The preliminary results (see Figure 5) show that hospitals highly exposed to the considered disruptions can quickly be identified as well as hospitals that are not affected at all. Hospitals that are exposed to a subset of the considered disruptions can also be identified, but require a more detailed examination to assess the severity.

Nevertheless, in order to enable a more detailed and realistic assessment of hospitals exposed to flood-induced disruptions, several steps are required within future work to improve the approach. The resolution of the node *Level of Service* could be enhanced, thus considering a more detailed description of hospital services. These services can vary depending on the type and resulting capabilities of a hospital, i.e. some hospitals have specialized services such as fire burn status beds (Fekete et al., 2017). In addition, the resolution to assess the spatial extent of the disruptions can be improved. For example, in the presented work, only a binary assessment of whether a hospital is within the flooded area or not is conducted. Within future work, the height of the flood at each hospital building could be taking into account - data on the flood height is also made available by public services. The method to assess road accessibility could also be improved. In the presented approach, only a single ring buffer is used to determine access roads of a hospital. This analysis neglects the accessibility of these roads from a greater distance - a part of a road near a hospital might not be flooded, but the road might not be accessible from a greater distance. In addition, the type of access roads (e.g. a highway or a small road) could be considered as well as if the access roads to a hospital are passable. The method to assess potential blackout areas can also be improved to allow a higher resolution of blackout areas, e.g. by implementing the weighted Voronoi diagram method presented by Pala et al., 2014 or an analysis based on a reconstruction of the power grid (e.g. see Medjroubi et al., 2017).

When enhancing the complexity of the approach, more data is required to build the BN. Especially, the conditional probability table attached to node *Level of Service* requires extensively more data when considering a higher resolution of both the parent (disruption) nodes and the granularity of the description of hospital services (states of node *Level of Service*). As this data is likely to originate from expert surveys, supporting tools (e.g. see Morris et al., 2014) should be used to elicit probability distributions from experts. However, Bayesian networks also allow data from different sources, such as historical or simulated data, to be combined, which is a major advantage when modeling rare event scenarios, such as the extreme flood scenario of the case study.

To conclude, we presented our work-in-progress approach to assess the effects of multiple (cascading) disruptions on the services of hospitals in a flood scenario. The approach is based on a combination of two models (GIS and Bayesian network) allowing to spatially assess the impact of the considered disruptions on individual hospitals under consideration of uncertainties in disruption exposure and impact. In this work, we presented a proof of concept of the approach in a case study of an extreme flood scenario in the city of Cologne. The preliminary results are promising and enable a first comparative overview of the expected level of services of the examined hospitals. This can support decision-makers in emergency management, but also researchers of other disciplines to better visualize and understand the abstract concepts of cascading effects. It can also help to illustrate how different sectors, such as health, energy, and transport, can be analyzed using one model.

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