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Flood Resilience Assessment of Interconnected Critical Infrastructures

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Research Article

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Data Availability
The data that support the findings of this study are available on request from the corresponding author, MVP. The data are not publicly available due to confidentiality concerns regarding critical infrastructure security.

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Competing Interests
The authors declare no competing interests.

Abstract

Undertaking systemic risk assessments of critical infrastructures (CIs) is necessary to improve understanding, mitigate impacts, and increase resilience to cascading effects of intensifying hydrometeorological hazards. This paper presents a novel quantitative approach for simulating local physical interdependencies between multiple infrastructure sectors that may be disrupted by floods. Open-source infrastructure datasets and proximity-based rules were used to generate a network graph of interdependencies, directed from critical service providers to users. The infrastructure model comprised five subnetworks: power, water, telecommunications, emergency, and transport. Stakeholder participation was incorporated in the model to assign interdependency weights according to perceived critical sector importance. Local (node-edge) resilience metrics were computed to identify critical, vulnerable, and non-redundant CIs in the network. For infrastructures located in areas under risk of floods, global resilience metrics (for whole-network degradation) evaluated failure propagation. The approach was tested in a case study of Halmstad municipality, Sweden, with a history of extreme hydrometeorological events. Results identified key power, water, and communication infrastructures with high disruption potential under flood exposure, as well as specific residential and industrial areas near hazard zones being the most vulnerable due to their extensive dependencies. Implications, limitations, and recommendations for further research for local climate adaptation planning are provided.

Keywords Systemic risk assessment, cascading infrastructure impacts, infrastructure network analysis, climate adaptation

1. Introduction

Societies rely on vital societal functions of critical infrastructures (CIs) to sustain economic development and the well-being of human populations (Polinpapilinho & Pinto, 2016). However, provision of critical services is vulnerable to extreme weather events, with increasing frequency and intensity of such events under climate change placing further pressure on CIs (Nasr et al., 2020). For example, severe flooding in Europe in 2021 claimed over 196 lives and caused more than €7 billion insurance losses in Germany alone (Cornwall, 2021). It also caused major damage to infrastructures such as highways and access routes, water and electricity supply systems, hospitals, care homes, and drug stores (Fekete & Sandholz, 2021). Early warning systems failed due to their dependency on electricity, while mobile phone and radio station data showed that 52% of response teams were hindered by road failures.

The definition of "CI" varies between countries (Pescaroli & Kelman, 2017; Rehak et al., 2018), although it is common to designate as CIs the infrastructures involved in transportation, the energy supply, telecommunications, water supply, and government and emergency services (OECD, 2008). These infrastructure systems operate in interdependent networks, with the connections between infrastructures through multiple mechanisms commonly classified as physical, geographic, cyber, and logical interdependencies (Rinaldi et al., 2001). Interdependencies enable local infrastructure failures to spread to other systems and lead to cascading effects, with major economic impacts (Boni et al., 2021; Hempel et al., 2018).

It is essential to understand the interdependencies of CI systems for being able to manage potential cascading failures and ensure reliable provision of vital societal functions. Several approaches have been developed to study interdependent CI systems, including empirical, agent-based, system dynamics, based on economics, physical flow and network theories, among others (LaRocca et al., 2015; Ouyang, 2014).

In this study, we developed and tested a network-based model to quantify vulnerabilities of CI systems under threat of hydrometeorological hazards. Although network modelling of CIs for quantifying cascading impacts has been extensively covered in the literature, those approaches have been mostly restricted to hypothetical scenarios, usually due to lack of data availability (Devineni et al., 2020; Holden et al., 2013; Johansson & Hassel, 2010; Lam & Tai, 2018; Monsalve & De La Llera, 2019). Additionally, applied studies often do not integrate CI spatial exposure to environmental hazards, considering instead a probabilistic or random failure approach (Mao & Li, 2018; Pinnaka et al., 2015; Seppänen et al., 2018). Network-based resilience assessments are typically limited to one or two infrastructure systems and do not involve multi-sectoral stakeholder participation (Ahmad et al., 2020; Arrighi et al., 2021; Nan et al., 2020).

Our novel network-based approach integrated open-source geospatial data, risk mapping, participatory surveying, and network analysis to quantify systemic CIs vulnerability. The method involved developing network topologies composed of nodes representing individual CIs and connected by edges simulating provision of vital societal functions. The network flow was directed from the service providers to the users (Holden et al., 2013). We integrated areas susceptible to 1 in 100-year coastal, pluvial, and fluvial flooding events as potential sources of critical infrastructure failures. Since OpenStreetMap (OSM) provides global CI datasets, an advantage of the interdependent CI network model presented in this paper is its inherent adaptability to a wide range of geographical locations and varying spatial resolutions.

This approach is here applied to and tested in the coastal Swedish municipality of Halmstad, which is located in the west of the country and has a population of approximately 100,000. This municipality has been subject to extreme hydrometeorological events, causing coastal and river inundation, in recent years (Englund et al., 2023). The municipality is also one of the places in Sweden with the highest likelihood of experiencing compound hydroclimatic events (Englund et al., 2022). In general, network-based approaches may be well suited for evaluation of built infrastructure vulnerabilities and climate adaptation strategies (Stewart & Deng, 2015). In local applications, such network-based models can be useful, e.g., for local governments, utility companies, and businesses to improve preparedness to hazards and prioritize adaptation investments (Hasan & Foliente, 2015).

The remainder of this paper is structured as follows: First, an overview of research developments on CI network assessments is provided. Methods for identifying CI nodes, establishing interdependencies, and measuring vulnerabilities and cascading effects are then presented. Lastly, these methods are tested in the case study of Halmstad municipality and the results are discussed.

2. Infrastructure Interdependency Modelling

2.1. Network-based Approaches

Network science is a well-researched discipline, originating from graph theory, with applications in various fields (Wilson, 1986). Combining network infrastructure systems with risk mapping techniques has been suggested as a means to study multi-sector infrastructures under hazard risks at local scale (Holden et al., 2013). The network approach has been proposed for modeling multiple infrastructure systems, such as transport, power, communication, water, and natural gas systems (Balakrishnan & Zhang, 2020; Pant et al., 2016; Zhang et al., 2014).

Functionality loss as a measure of vulnerability can be used to evaluate the dependency levels among infrastructure systems, such as the dependency of the rail network in Shanghai on the power grid, found to be much higher than the dependency on the communication network (Zhang et al., 2014). Probabilistic methods have also been proposed in network analysis to estimate criticality and reliability using kernel density estimation and probability density functions (Pant et al., 2016).

Interdependency networks facilitate estimation of cascading effects due to physical node disruptions. Failure propagation analysis has been used to analyze node functionality and economic losses in water and power networks (Zhang et al., 2018). Propagation of disturbances can be investigated through various methods, for example by assuming node failure to directly impact linked nodes, determining conditional failure probabilities based on proximity, or accounting for loss of flow capacity (Mao & Li, 2018).

2.2. CI Interdependency Data

Critical infrastructure geospatial data are becoming increasingly accessible due to government initiatives (AdV, 2023; USDHS, 2021) and the global open-source collaborative project OpenStreetMap (OSM), which is built and maintained by volunteers (OSM contributors, 2022). OSM data have been extensively used in CI studies, for applications involving identification of CI hotspots (Nirandjan et al., 2022), collection of street network data (Boeing, 2017), and crisis relief efforts (Kamptner & Kessler, 2019). Although incomplete, OSM data represent different CI asset types more accurately than other reference catalogues and are suitable for use in decision-support systems (Herfort et al., 2015). However, availability of CI interdependency data remains a key challenge to studies of CI networks, due to confidentiality concerns and lack of data collection technologies (Wang et al., 2020). To overcome this limitation, Ouyang et al. (2009) developed a method to generate artificial infrastructure topologies of electric power and gas networks by creating random nodes and linking them based on minimum Euclidean distance. Another network generation algorithm for power, natural gas, and transportation systems has been developed to link nearest nodes following physical dependency-based rules (Lee et al., 2016).

The concept of synthetic networks has been recently developed to connect CI nodes through proximity using openly available transportation grid data. Previous studies have used the Python library OSMnx (Boeing, 2017) to import road networks (Ahmad et al., 2020), and to simulate power and water distribution systems (Ahmad et al., 2020; Saha et al., 2019). OSM transportation networks have also been applied to identify road-based interdependencies for emergency delivery of water and fuel, as well as household access to hospitals (Schweikert et al., 2021). In this study, OSM data is utilized to map multi-sectoral CI interdependencies instead of single infrastructure systems, distinguishing our approach from previous examples in the literature.

3. Model Description

In this study, a network-based approach was developed to simulate five CI systems providing vital societal functions (power, water, telecommunication, emergency services, and transport). The network considered was directed and weighted according to sector criticality, as defined by stakeholders. Resilience metrics were employed in vulnerability and disruption analyses at local node level and overall network level. Local and global resilience metrics were computed using the Python library NetworkX (Hagberg et al., 2008).

3.1. Mapping Interdependencies

The first step in mapping interdependencies was to collect CI geospatial data within the area of study. This was achieved using OSM's tagging system in Overpass API, complemented with information provided by stakeholders or internet queries. For each CI, latitude and longitude coordinates were retrieved, as well as the CI name if available in the database. A coding system was created to identify individual CIs by sector. In total, 30 CI types were identified and categorized into 10 sectors: *Energy Supply, Health and Medical, Information and Communication, Municipal Technical Services, Public Administration, Research and Education, Residential, Safety and Security,*

Table 1: List of identified critical infrastructure (CI) types by sector.

Sector (code)	CI type	OpenStreetMap (OSM) tag
Energy Supply (ES)	Power plant	power=plant
	Power substation	power=substation
Health and Medical (HM)	Clinic	amenity=clinic
	Hospital	amenity=hospital
	Pharmacy	amenity=pharmacy
Information and Communication (IC)	Communication tower	tower:type=communication
Municipal Technical Services (MTS)	Storage tank	man_made=storage_tank
	Wastewater plant	man_made=wastewater_plant
	Water tower	man_made=water_tower
	Water treatment plant	man_made=water_works
Public Administration (PA)	City hall	amenity=townhall
	Government office	office=government
Research and Education (ED)	Kindergarten	amenity=kindergarten
	School	amenity=school
	University	amenity=university
Residential (RE)	Residential area	landuse=residential
Safety and Security (SS)	Ambulance station	emergency=ambulance_station
	Court house	amenity=courthouse
	Fire station	amenity=fire_station
	Military base	landuse=military
	Police station	amenity=police
	Prison	amenity=prison
Trade and Industry (TI)	Industrial area	landuse=industrial
	Supermarket	shop=supermarket
Transport (T/RO)	Airport	aeroway=aerodrome
	Breakwater	man_made=breakwater
	Harbor	amenity=harbor
	Port	amenity=port
	Railway station	railway=station
	Road intersection/end	highway=secondary

Trade and Industry, Transport. Residential and industrial areas were included as CI types due to their importance as end-users of vital societal functions. All CI types and corresponding OSM tags identified within each sector are listed in Table 1.

Next, we established physical dependency rules between the CI types to create realistic representations of CI systems. These rules were grouped into five subnetworks: *Power, Water, Telecommunications, Emergency*, and *Transport*. For instance, for the Power subnetwork it was assumed that power stations provide services to power substations, which subsequently serve users nearby. The sets of rules applied for each subnetwork were as follows:

- Power: power substations receive electricity from the nearest power plant. End-users such as residential areas, communication towers, and industrial buildings receive electricity from adjacent power substations.
- Water: water treatment plants supply water towers and storage tanks, which subsequently feed end-users. Wastewater treatment plants serve users nearby.
- Telecommunications: communication towers provide mobile phone, internet, radio, and TV signals to CIs within an adopted range of 10 km (Yahya, 2019).
- Emergency: delivery of vital societal functions to all residential areas during crisis events. Includes road-based interdependencies from households to all CIs within the *Health and Medical*, *Safety and Security*, and *Public Administration* sectors, and supermarkets.
- Transport: road access from residential areas to industrial areas, airports, railway stations, kindergartens, schools, and universities.

To apply the adopted physical dependency rules and generate the subnetworks, transportation grid data for the study area were imported as a network graph using the Python library OSMnx (Boeing, 2017). Subnetworks were assumed to be composed of source or destination nodes, depending on whether the CI provides or receives vital societal functions. Therefore, the subnetworks were represented mathematically as directed graphs. Shortest path was defined as the minimum set of nodes between a source and a destination node.

3.2. Stakeholder Engagement

In this study, we introduced stakeholder perceptions in a unique manner, leveraging the inherent properties of network graphs. We objectively incorporated stakeholder perceptions as interdependency strengths at the edges of the infrastructure network model. Weighting of subnetwork edges was performed based on survey results for each provisioning CI sector. Scores from 0 to 4 were assigned for each degree of perceived importance: *not important, less important, important, very important*. After adding up the assigned values from all participants' answers, the final scores were normalized relative to the sector of highest perceived importance. Weights were applied along edges according to the normalized score of the sector providing the service. For the emergency and transport subnetworks, the edge weights were an average between survey results and the frequency of road CIs connections, to reflect the importance of the most common roads along shortest paths.

3.3. Quantifying Vulnerabilities

Local resilience metrics were derived solely from the network topology and indicated characteristics of individual CIs, such as vulnerability, importance, and redundancy, where vulnerability encompasses conditions shaped by physical, social, economic, and environmental factors that heighten susceptibility to the impacts of hazards among individuals, communities, assets, or systems (UNDRR, 2020). Importance entails assessing the relative criticality of an infrastructure concerning the consequences of a disruption in the supply of vital goods to the society (Kruse et al., 2021). Redundancy is the extent to which replaceable elements are capable of providing services during disruptions or functionality loss (Bruneau et al., 2003). In this study, these characteristics were evaluated through properties inherent to network graphs. Degree, betweenness, and closeness are the most common network metrics used to evaluate nodes (Omer et al., 2014). Averaged results per sector can provide additional insights for city planners.

Four local resilience metrics were adopted in this study:

- *Degree centrality*: normalized number of edges between a node and its neighbors. In-degree and out-degree centrality in directed graphs refer to incoming and outgoing connections, respectively. Large degrees reflect how centralized a CI is in the network and how it correlates with higher cascading effects in the case of failures. An example of CI with high degree centrality is a wastewater treatment plant, which provides services to many businesses and residences, but also requires electricity, telecommunications, and water supply.

- *In-degree strength*: sum of incoming edge weights towards a node. A node with high in-degree strength corresponds to a vulnerable CI with large dependence on vital societal functions with high weighting and thus considered particularly important in the network. An airport requiring multiple water, energy, and transport services is an example of a vulnerable CI with high in-degree strength. Consequently, in-degree strength represents the vulnerability of a node.

- *Out-degree strength*: sum of outgoing edge weights from a node. High out-degree strength represents the criticality of a CI in providing important services to many neighbors. For instance, power substations and communication towers are influential nodes in the CI network. Out-degree strength is therefore an indicator of CI node importance.

- *Betweenness centrality*: ratio between shortest paths crossing a node and all possible shortest paths. The weighted equation used to calculate betweenness centrality for node *v* in a network *V* takes the form:

  $$c_b(v) = \sum_{s \neq t \in V} \frac{\sigma(s, t \mid v)}{\sigma(s, t)}, \tag{1}$$

  where $\sigma(s, t)$ is the total number of shortest paths between nodes s and t, and $\sigma(s, t \mid v)$ is the number of shortest paths that cross *v*. A road node that is frequently travelled in the delivery of services from one CI to another has relatively high betweenness centrality. This metric is associated with the concept of node redundancy.

A combination of local resilience metrics can also provide additional insights about a CI. Nodes with large degree centrality, but low betweenness centrality, are considered redundant. Low degree centrality and high betweenness centrality mean that a node is crucial or non-redundant, because it has a reduced number of connections but still acts as an important bridge between groups of CI nodes (Devineni et al., 2020). Therefore, non-redundancy is defined as the ratio of betweenness centrality and degree centrality, as illustrated in Figure 1 for the transportation network in Halmstad municipality. Unlike node degree strength and betweenness, the application of node non-redundancy in infrastructure networks is an original concept applied in this approach.

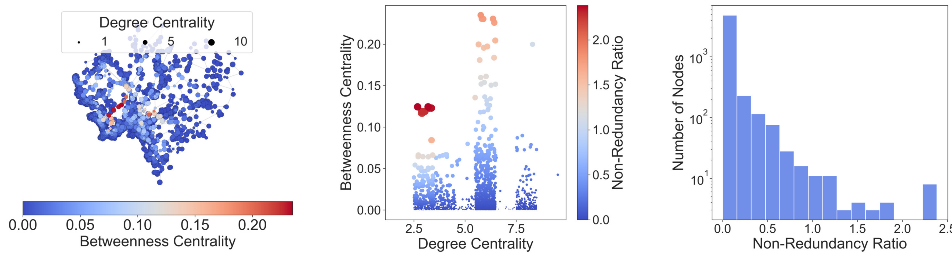

Figure 1: Illustration of betweenness centrality, degree centrality, and non-redundancy for the transportation infrastructure network in Halmstad municipality, Sweden.

3.4. *Measuring Cascading Effects*

Global resilience metrics were applied in this study to evaluate the entire network by comparing the initial network state against degraded network scenarios due to disruptions caused by hydrometeorological events. Inundation maps for river, coastal, and heavy rainfall flooding were used to select CI nodes under risk of failure. A single node was then removed from the network, causing cascading effects that were measured up to the tenth order of disruption (Mao & Li, 2018). The following three global resilience metrics were employed:

- Global network performance: average of the local clustering coefficients for all nodes in the network. A change in average clustering coefficient indicates a decrease in network connectivity (Devineni et al., 2020). It is defined mathematically as:

$$c_c(v) = \frac{1}{N}\sum_{v=1}^{N}\frac{nv}{nv_{all}}\ , \tag{2}$$

  where N is the total number of nodes in the network, nv is the number of existing connections between neighbors of node v, and nv_{all} is the number of all possible connections between neighbors of node v. The weighted version of this metric was applied in this study, meaning that nv and nv_{all} were multiplied by their corresponding connection weights.

- Global network efficiency: local efficiency is the multiplicative inverse between shortest path distances between a pair of nodes (Latora & Marchiori, 2001). Global efficiency of a network V is the average efficiency for all pairs of nodes, written as:

$$E(V) = \frac{1}{N(N-1)}\sum_{s\neq t\in V}\frac{1}{d_{st}}, \tag{3}$$

  where d_{st} is the shortest path distance between nodes s and t. This metric quantifies the efficiency of the flow of services among critical infrastructures, and does not consider edge weights.

- Number of cascading failures: total disrupted nodes in the network due to an initial CI disturbance and failure. This considers failure propagation through neighboring nodes up to the tenth order. CI nodes causing many cascading failures show high disruption potential in the entire network along the CI interdependence chain. A diagram of cascading failure propagation showing the initial network state and how the nodes are removed at each disruption order is presented in Figure 2. In this example, there is one first-order cascading failure and two second-order cascading failures.

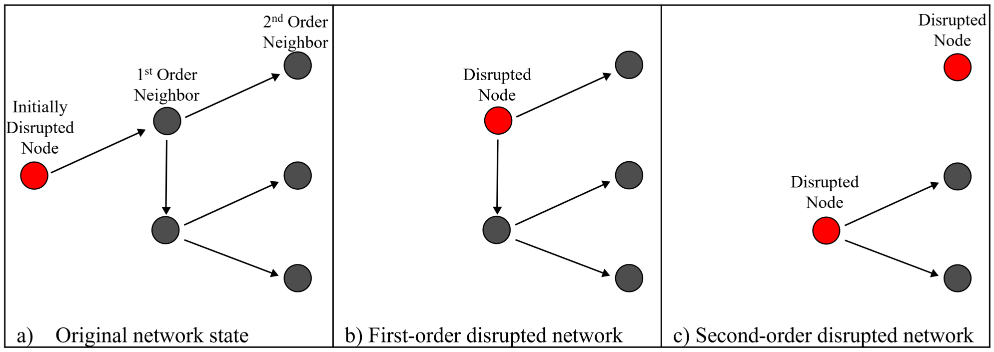

Figure 2: Illustration of cascading failure propagation from (a) the original network state to (b) first-order and (c) second-order disrupted networks.

An algorithm (Figure 3) was developed to quantify the number of cascading failures and changes in network performance and efficiency due to a single initial failure by identifying and removing neighboring nodes from the network at each failure order.

Algorithm 1 Measure Cascading Failure Propagation

```
Import initial network
Read initially disrupted node
Calculate initial network efficiency
Calculate initial network performance
Identify all first-order neighbors of the disrupted node
for Failure order n from 1 to 10 do
    Neighbours of n-order become disrupted
    Count total number of n-order disrupted neighbors
    Identify all n+1-order neighbors of the disrupted node(s)
    Remove disrupted node(s) and edge(s) from the network
    Calculate change of network efficiency at failure order n
    Calculate change of network performance at failure order n
end for
```

Figure 3: Pseudo algorithm for measuring cascading effects in a network.

4. Results

4.1. Network Generation

The interdependence weights for each CI sector according to the opinions of local stakeholders in the Halmstad test case are shown in Figure 4. Interdependencies related to the provision of electrical energy were considered by the stakeholders as the most important societal sector and therefore given unitary weight. The importance of other sectors was then scaled relative to the Energy Supply sector. Other essential sectors according to stakeholders were Safety and Security, Health and

Medical Services, and Municipal Technical Services (water and wastewater plants, storage tanks, and water towers). Infrastructure related to Information and Communication services was also highly rated by the participants. Trade and Industry services were considered the relatively least important sector for maintaining the operation of vital societal functions. The Residential sector is not included since it does not provide services to other sectors.

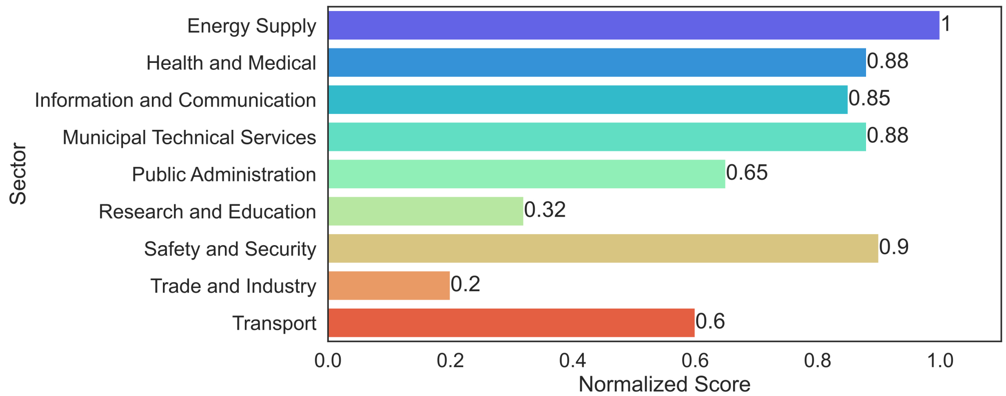

Figure 4: Stakeholder weighting of interdependencies by sector in Halmstad municipality, Sweden.

In total, 5857 CI nodes containing spatial coordinates were collected from primary and secondary sources (Table 2). Most of the nodes were road intersections or ends from OSM required to establish transport and emergency delivery interdependencies. Halmstad municipal authority provided additional data regarding elderly apartments, nursing homes, special accommodation, and kindergartens.

A multilayer network composed of five subnetworks was generated for Halmstad municipality according to the adopted physical dependency rules (Figure 5). The final number of connections between nodes was 12,646. Most of the nodes were clustered in coastal areas, especially in Halmstad City. As the Emergency and Transport subnetworks simulated road-dependent services, their topologies resembled the municipal street grid. The highest number of interdependencies was found in the Telecommunications subnetwork, due to communication towers providing services to nearby CIs via air.

Table 2: Summary of collected critical infrastructure (CI) node data for Halmstad municipality, Sweden.

Sector	Total	CI Type	Node Count
Energy Supply	26	Power plant	4
		Power substation	22
Health and Medical	57	Clinic	4
		Elderly apartment	11
		Hospital	1
		Nursing home	15
		Pharmacy	12
		Special accommodation	14
Information and Communication	30	Communication tower	30
Municipal Technical Services	15	Storage tank	2
		Wastewater plant	5
		Water tower	3
		Water treatment plant	5
Public Administration	5	City hall	1
		Government office	4
Research and Education	78	Kindergarten	30
		School	47
		University	1
Residential	218	Residential area	218
Safety and Security	12	Ambulance station	2
		Court house	1
		Fire station	5
		Military base	2
		Police station	1
		Prison	1
Trade and Industry	48	Industrial area	26
		Supermarket	22
Transport	5368	Airport	1
		Breakwater	4
		Harbor	3
		Port	2
		Railway station	1
		Road intersection/end	5357
Total			5857

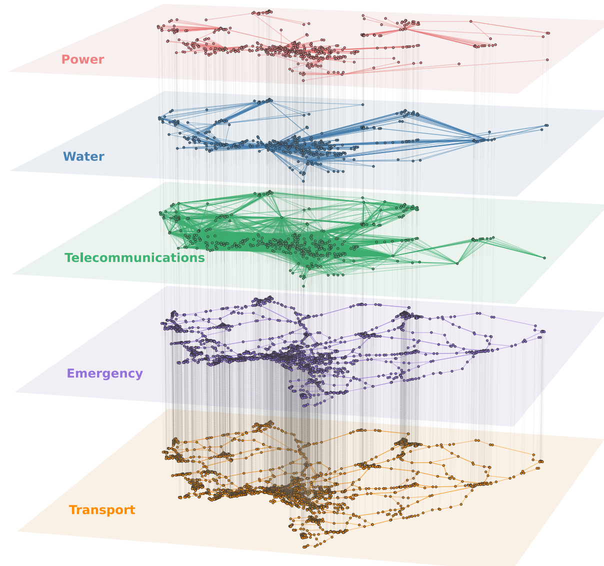

Figure 5: Multi-layer network of critical infrastructure (CI) interdependencies in Halmstad municipality, Sweden.

4.2. Vulnerability Analysis

Local network metrics were calculated for all nodes in the multi-layer network to evaluate node criticality, vulnerability, and redundancy (Figure 6). The node sizes were scaled according to the magnitude of the indicators. These metrics were used to compare characteristics between CI nodes from different sectors, as well as their relative importance within the same CI type.

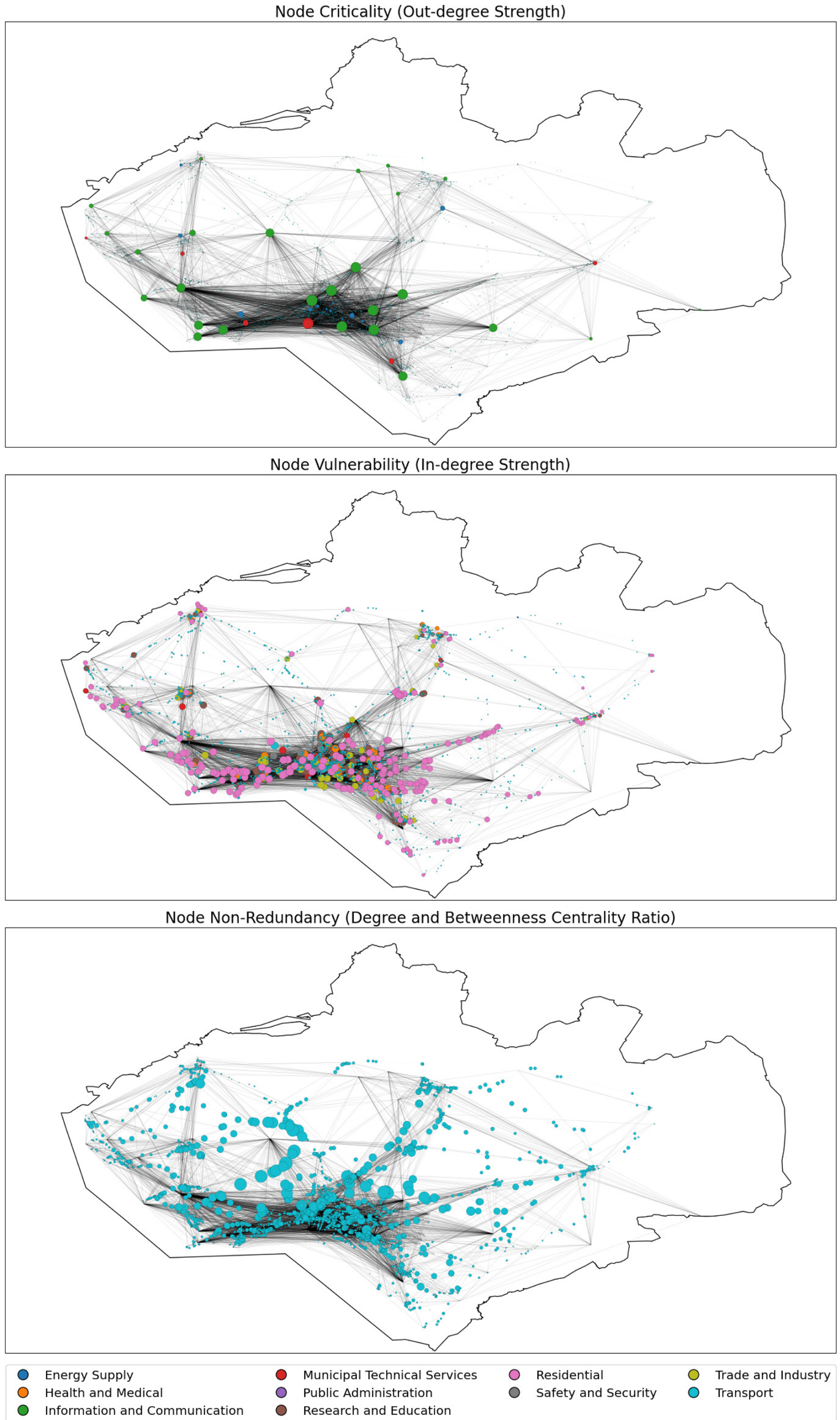

Figure 6: Local network metrics obtained in vulnerability analysis of all nodes in the multi-layer network, which were used to evaluate (top panel) node criticality, (centre) node vulnerability, and (bottom panel) node non-redundancy.

Communication towers were found to be the most provisioning CIs, due to a combination of large number of outgoing interdependencies and high weighting, especially for towers located near Halmstad City. Municipal technical services related to water treatment and supply were also critical, along with power plants and substations. Additionally, some road intersections near town entrances had relatively high out-degree strength, due to their frequent use for access of delivery services. Protecting these nodes against failure is the highest priority to guarantee stable flow of vital societal functions.

Nodes belonging to the Residential, Trade and Industry, and Research and Education sectors were generally found to be the most vulnerable, as they are strongly dependent on transport, water, energy, and telecommunication services. The airport and central railway station emerged as the most dependent CIs in the transport sector. Road nodes in rural zones were considerably less vulnerable than those in urban areas. Measures to increase self-sufficiency, such as installing small-scale energy or water sources, could be implemented to mitigate local vulnerabilities.

Road intersections that act as bridges between large groups of nodes in transmission of emergency and transport services had the largest betweenness centrality in the network, which means they are the least redundant nodes. Planning alternative routes that avoid these nodes for the delivery of road-based services would be beneficial to increase redundancy in the network, especially for emergency situations.

4.3. Disruption Analysis

Inundation maps were collected to identify nodes at risk of disruption due to 100-year return period flood events. Areas at risk of heavy rainfall were identified by environmental consultants and the data obtained were provided for this study by Halmstad municipal authority. An inundation map along the river Nissan was retrieved from Översvämningsportalen (MSB, 2022). A coastal flooding map was generated considering a projected extreme sea level of +3.11 m RH2000 (Johansson, 2018) and using land elevation data from the Swedish Land Survey (Lantmäteriet).

Altogether, 466 unique CI nodes were found to be located within at least one of the hazard areas. Heavy rainfall, coastal flooding, and river inundation areas affected 307, 168 and 31 nodes, respectively. The overwhelming majority of these nodes were road intersections or ends, but 17 CI types from eight sectors were represented in total. Figure 7 shows the distribution of network nodes and inundation areas in Halmstad municipality facing multiple hydrometeorological risks.

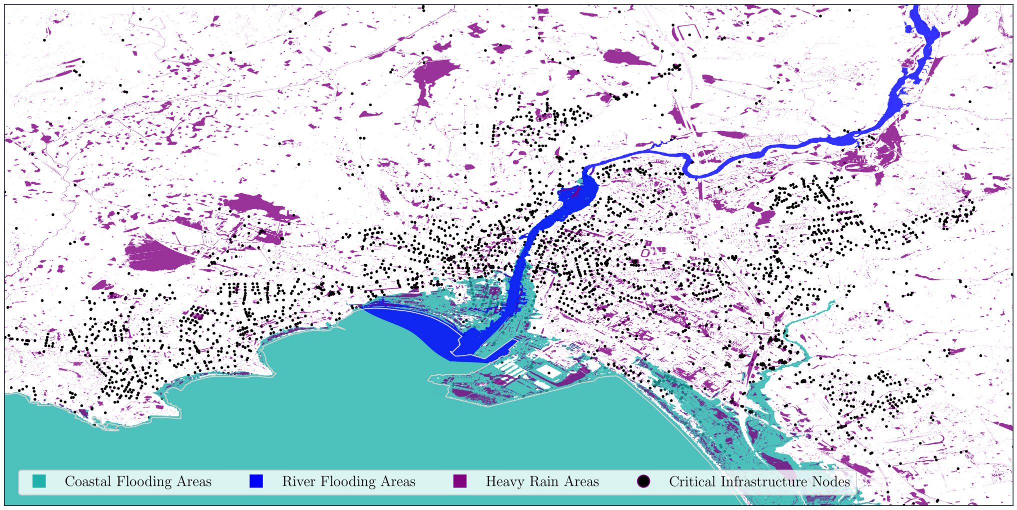

Figure 7: Critical infrastructure nodes in or near Halmstad City facing once in 100-year hydrometeorological risks.

To identify the most disruptive CIs, each node under risk was individually removed from the network of infrastructure interdependencies. Propagation of disruptions along the network was then measured through the number of cascading failures, change in network performance, and change in network efficiency. The three most critical nodes for each indicator are highlighted in the plots in Figure 8. Of all nodes facing hazard risks, six nodes (1.3%) stood out in terms of cascading impacts.

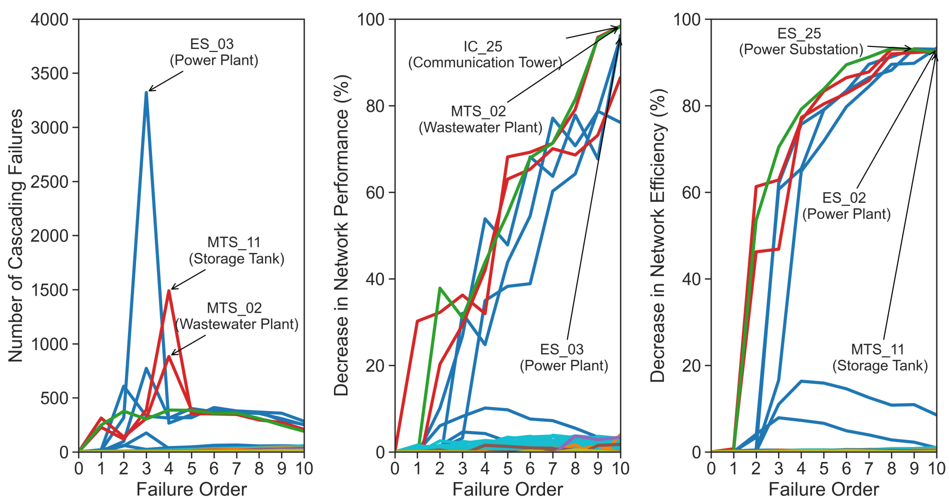

Figure 8: Results of disruption analysis for the top three critical infrastructures (CIs) in each global resilience indicator for Halmstad municipality, Sweden.

The largest disruptions were found for CIs belonging to electric power, water, and telecommunications sectors. Those cascading failures propagated from the service providers to directly dependent CIs such as industrial areas and hospitals. The failures then continued propagating along road nodes near the dependent CIs, since those are used to provide access for transport-based dependencies. Disruption of a power plant located in an area at risk of coastal and river flooding (ES 03) potentially caused 5930 cascading failures. This disruption would directly affect 13 power substations in Halmstad City that provide electricity to many CIs, including 21 communication towers. Those towers combined provide services to thousands of nodes, hence the high number of cascading failures.

Based on decreases in network performance, failure of a wastewater plant (MTS 02) caused the greatest connectivity loss in the entire network, followed closely by a communication tower (IC 25) and a power plant (ES 03). This means that these disruptions affected clusters of interdependent CIs to a large degree. Consequently, the network of interdependencies was held together by much weaker ties than originally. After the tenth order of disruption, a decrease of up to 98% in network performance decrease was observed.

The global efficiency parameter was calculated according to the unweighted and undirected formulation provided in the NetworkX package. The resulting global efficiency of the interdependent network without disruptions (E=0.15) was comparable to that of the transportation network. The greatest decreases in network efficiency were observed due to cascading disruptions caused by a power plant (ES 02), a power substation (ES 25), and a storage tank (MTS 11). This means that these cascading disruptions removed important nodes responsible for the efficient flow of societal services. The maximum loss of efficiency stabilized at around 93% for all six most disrupted nodes, which may indicate a limit for this specific network structure.

5. Discussion

5.1. Multi-Sectorial Infrastructure Interdependency Mapping and Evaluation

Hydrometeorological hazards were integrated in the approach to identify potential CI node disruptions and their cascading effects. Network-based analysis has previously been shown as useful for quantifying the consequences of a crisis in CIs, yielding a consequence-based risk management approach (Katopodis et al., 2018). The present test case study showed how application of this method can be done and be useful for planners and policy makers tasked with selecting relevant climate adaptation measures for minimizing the direct and indirect impacts and increasing the resilience of interconnected infrastructure systems. Local planners must also prioritize investments in climate adaptation, and the network modeling approach identifies specific locations and areas that need to be particularly protected or modified to increase system resilience. These results can help policy makers in developing optimal risk mitigation strategies in order to reduce cascading impacts on CIs (Iturriza et al., 2018).

The vulnerability analysis approach presented here can be applied to a very large number of nodes, due to its relatively low computational requirements. It can also be used to rank infrastructures based on indicators for criticality, vulnerability, and redundancy according to standard network metrics. Thus, the method is also useful for high-level assessments where there are large uncertainties or insufficient knowledge regarding climate risks. Additionally, it also provides more dimensions when measuring propagation failure paths, listing specific CIs affected by systemic disturbances, and quantifying the escalation of cascading effects by neighborhood order. In this study, limiting the neighborhood to the tenth order was enough to observe major escalations of failure in the infrastructure network. The method may be even more suitable for a smaller number of nodes, known to be under risk, considering the intensive computational demands.

The network approach adopted in this study did not capture the current CI state in terms of age, degradation level, susceptibility to impacts, or use of backup systems. Only physical interdependencies were simulated, representing the material flows of goods and services. Moreover, the approach did not include descriptive analysis of whether different CI types were affected differently by a particular hazard. However, these analysis conditions reduced the required amount of input data and parameters and targeted only some fundamental interdependencies in the context of flood risks, enabling the inclusion of multiple CI sectors and their user-provider interactions in the model. In turn, this facilitated the practical operationalization of the framework in a test case study, which is rare and in great demand (Fekete, 2019). Instead of considering several societal sectors, the approach can provide additional insights by being refined for a particular sector to consider detailed aspects related to demand, supply, and transmission of services or goods. For instance, the effects of network disruptions can be quantified in terms of human population affected if this information is allocated in the network nodes. Modifying connection rules between CI nodes can allow consideration of other interdependency types. Future studies could also include different types of nodes to represent interactions and decision-making by actors on climate adaptation, as elaborated in the Institutional Network Analysis approach (Mesdaghi et al., 2022).

5.2. Challenges and Future Directions

Lack of primary data was a major challenge in the implementation and validation of the network-based model in a concrete test case study. The accuracy of the results depends on the completeness of the open-source dataset, stakeholder feedback, and the relevance of proximity rules. Due to confidentiality concerns, local informants were reluctant or unable to provide detailed infrastructure information. Data were not available for some infrastructure systems, such as gas or the internet. However, OSM provided adequate information on major power, water, and transportation CIs, with the advantage of being free and available worldwide. According to (Kelic, 2017), stronger partnerships with system owners are necessary for reducing data uncertainties and for developing and validating heuristics. Creating secure platforms and systems for interdependency data sharing among CI stakeholder organizations is necessary to enable more collaborative and effective management of cascading risks (Castrucci et al., 2012; Petrenj et al., 2021).

Terminology used to communicate modeling methods was found to be another challenge in this study. Even though the basic methods and assumptions of the network model were relatively simple, some advanced network graph metrics and concepts were difficult to communicate effectively in practical terms. In order to facilitate communication between sectors and improve understanding and engagement with the results, in engagements with local stakeholders we used a terminology that described actual impacts on infrastructure systems, instead of network science jargon.

The proposed approach can be replicated in other municipalities around the world, with focus on coastal areas also requiring consideration of flooding risks due to sea level rise. Additionally, it is possible to expand the infrastructure network model from local-regional to national levels, representing high-level interdependencies between municipalities and regions. There is a need to develop user-friendly and effective decision-making tools for CI management based on network science that can allow planners to interact and view results as well as conduct their own analyses. The proposed approach can be applied in production of visualization tools that assist users in managing complex climate risks. To shift from climate risk assessments to practical implementation, future research also needs to link and recommend specific actions and strategies that increase CI resilience to associated climate risks. Recommended solutions would be dependent on infrastructure type, nature of the hazard, and whether the infrastructure is classified as a provider or user of services.

6. Conclusions

This study presents a novel approach for mapping and evaluating multi-sector CI interdependencies that uses open-source data and physical interdependency rules based on proximity, stakeholder participation, and resilience metrics. The approach is useful for managing multiple hydrometeorological hazards and cascading risks between CIs, and for identifying prioritized infrastructures and areas suitable for climate adaptation planning. The test case study results showed that infrastructures relating to power generation, water distribution, and communication towers generated the largest cascading effects when disrupted by extreme flooding events. Residential and industrial developments located near hazard areas were the most vulnerable infrastructure type, due to their reliance on many types of services.

Traditionally, climate risk assessments have generally considered only direct hazard effects on infrastructures, leading planners to largely neglect indirect effects on dependent users. The present approach is novel in combining practices and assumptions from previous research on infrastructure networks with stakeholder engagement to overcome interdependency challenges of data availability and risk management. Since infrastructure failure propagation can escalate rapidly, the approach can estimate associated cascading risks, reduce uncertainties, and improve climate risk management for various CIs and related users.

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