Reliability Engineering and System Safety 241 (2024) 109653

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Understanding cascading risks through real-world interdependent urban infrastructure☆

L.G. Brunner [a,*], R.A.M. Peer [a], C. Zorn [b], R. Paulik [c], T.M. Logan [a]

[a] Civil and Natural Resources Engineering, University of Canterbury, New Zealand
[b] Civil and Environmental Engineering, University of Auckland, New Zealand
[c] National Institute of Water and Atmospheric Research, New Zealand

ARTICLE INFO

Keywords:
Cascading failures
Interdependent infrastructure
Risk analysis
Critical infrastructure
Urban infrastructure
Resilience
Network modeling

ABSTRACT

The prevalence of cascading failures is growing as infrastructure becomes more interdependent and climate change exacerbates more extreme hazards. After such events, the general focus is on the magnitude of direct damage or loss; it is less understood how events trigger failures throughout other infrastructure. In this work, we present a methodology to model direct and indirect impacts from an event for a multi-system network, including interconnected infrastructure and end users. We perform a case study of New Zealand's second largest city, Christchurch, investigating electricity, water supply, and wastewater networks following a range of coastal flooding events and climate change scenarios. For a 10-year average recurrence interval event given no sea-level rise, there is a 216% increase from directly impacted end users to the total number of end users that have lost at least one utility. For the same scenario, this metric is 71%, 129%, and 131% for end users who have lost electricity, water, and wastewater, respectively. The results show a larger estimate of impact on residents and a more geospatially-varied loss of service. This methodology provides insight for utility operators, emergency response, and communities on node criticality, areas of impact, and resource requirements after an event occurs.

1. Introduction

The critical infrastructure we rely upon daily to provide services such as electricity, water, and sewage disposal is largely dependent on each other [1]. For example, the pumps throughout the water supply network rely on electricity to function, and wastewater treatment plants require electricity to treat incoming sewage. Similarly, water is used for cooling in electricity generation, and a physical disruption in the water or wastewater networks could impact nearby electrical substations. Because of this interdependence (and dependence) between systems, there can be unforeseen impacts due to cascading failures, which occur when one system failure causes another system to fail. While redundancies can be incorporated into networks (such as backup generators), the increasing variability and intensity of natural hazards expected to occur as a result of climate change means we need to consider future scenarios and how cascading failures may be triggered [2]. Examples of such events include the power outages in Texas due to the recent 2021 winter storm [3], in Puerto Rico due to Hurricane Maria in 2017 [4], in the 2005 Hurricane Katrina in New Orleans [5], along the U.S. East Coast in 2012 from Hurricane Sandy [6], and in Christchurch following the 2011 earthquakes [7]. These are disruptive and costly events that call for proactive measures to develop resilient infrastructure, which are often more cost-effective in the long term. In one study looking at infrastructure in thousands of different climate scenarios for low- and middle-income countries, a $1 investment in more resilient infrastructure had a benefit of $4, with an overall net benefit of $4.2 trillion across these countries [8]. Understanding cascading impacts can help decision-makers and utility operators develop more robust infrastructure and limit damage and costs when recovering from natural hazards.

These interdependencies present a challenge for assessing and modeling risk in these systems. One framework to understand the interactions categorizes interdependence into physical, cyber, geographic, and logical interdependencies [1]. A review performed by Ouyang [9], further classified modeling approaches into six categories: empirical,

☆ This work was partially supported by the New Zealand Ministry of Business, Innovation and Employment (MBIE) Endeavour Fund (Smart Idea) project "Innovating climate risk assessment: A system-wide, geospatial approach for councils and communities" and Deep South Science Challenge (MBIE CONTRACT NUMBER: C01X14121), the Resilience to Nature's Challenges (RNC) programme, and Te Hiranga Rū QuakeCoRE. Additionally, we would like to acknowledge Orion for the electrical power data.

* Corresponding author.
E-mail address: logan.brunner@pg.canterbury.ac.nz (L.G. Brunner).

https://doi.org/10.1016/j.ress.2023.109653
Received 31 October 2022; Received in revised form 14 June 2023; Accepted 7 September 2023
Available online 19 September 2023

agent-based, system dynamics-based, economic theory-based, network-based, and others. More recently, He and Cha [10] performed an extensive review of recovery and resilience modeling of infrastructure systems under disruptive events, reiterating most of the categorizations defined by Ouyang [9]: agent-based, system dynamics-based, input–output-based, computable general equilibrium-based, network topology-based, and network flow-based approaches. He and Cha [11] also differentiated the resolution of infrastructure modeling into system-to-system level, facility-to-facility level, and system-to-facility level, where the system could mean an entire power or water system while the facility could be the specific nodes within the system such as the pumping stations and electrical substations. Each of these methodologies have their trade-offs and advantages depending on the conditions such as the particular infrastructure, data, and complexity.

Existing studies that demonstrate these methodologies and investigate hazard-related risks to infrastructure often focus on a single infrastructure system (e.g., [12–19]) or present a regional [7,11,20,21] or national [22–26], aggregated view on cascading failures. Regional and national studies assess large-scale trends or identify nationally critical nodes, while those that look at the city-scale use a similarly large data resolution or an idealized network. However, these studies have not sufficiently examined the intricacies of real-world and multiple networks or the local-level impacts on residents from cascading failures, which could highlight inequities in the community [27]. For example, Guidotti et al. [28] investigated an idealized interdependent network, which proposed a modeling framework that includes the recovery to get the infrastructure back online (also considered in [29] from a risk theory perspective, Sun and Zhang [30] for a transportation infrastructure, and González et al. [31] to power, water, and gas in Shelby County, TN, USA), but this example, which uses an idealized network, does not convey the geospatial impacts of the cascading failures on a real-world urban case study.

Among the current body of work, the models largely incorporate business-as-usual hazards, such as earthquakes, previous hurricanes, and recurring flood events, which do not address divergent, uncertain scenarios such as events influenced by climate change [32] and need to be included in modeling to support the decision-making related to these impacts [33]. This uncertain future presented by climate change is among one of many uncertainties that are often neglected in models of interdependent infrastructure [34]. Additionally, there is a lack of metrics that address the impacts at the business and residential level [35], rather focusing on the system- or infrastructure-level resilience [19, 36–38] in terms of reduction of consequence [39] and functionality loss [30]. Common metrics include lost load, in which an assumption is made about utility use across the users, and economic impact, which places a certain valuation on functionality and may lead to underestimation of the impacts to different demographics. Wang et al. [40] describes a framework to understand interdependent infrastructure, applying a network model to the power and water systems of a city in China. This study uses network statistics to compare the impacts from a regional level, assessing the functionality of the infrastructure networks as opposed to the local impacts to the residents. Other studies similarly use recovery times and network statistics to assess the resilience or impacts to infrastructure [13,41–43], which conveys the risk to the infrastructure, but stops short of understanding the residential impacts, in magnitude and geospatial location. In [44], the authors use social vulnerability indicators to look at cascading impacts from both random failures and Hurricane Irma on Tampa, Florida, however this is only for the community level and two interconnected systems (the water and transportation networks).

While many of these studies work towards developing new methodologies to model interdependent infrastructure, few test the application in real-world case studies, which are important for understanding risk and how it plays out in interdependent infrastructure systems. The need to assess the performance of these theoretical models under different hazards and real-world conditions is highlighted both in model development studies and comprehensive reviews of modeling approaches [9,10,36]. Additionally, many authors apply their models to idealized and business-as-usual scenarios (for both the network and the hazard) which may perform differently than when applied to real networks with divergent hazards, and limit their applications to one or two networks. Few of these studies, even those at the facilities level, include granularity on the scale of residential properties, which can more accurately show the social cascading impacts.

Our work addresses these gaps by applying an updated network model to the real-world infrastructure of Ōtautahi/Christchurch in New Zealand experiencing the hazard of coastal flooding under climate change and shows the cascading impacts from the infrastructure level down to the household level. Specifically, we examine the electricity, water supply, and wastewater networks within the city using real-world data, and investigate how impacts across all three systems translate to the end users throughout the community and the utilities, across a range of climate change scenarios.

Therefore, we provide a quantitative assessment of direct and indirect risk and a qualitative discussion of the relative importance of its inclusion in a holistic risk assessment. We answer two important questions: (1) to what extent do indirect impacts change the assessment of risk to residents? and (2) how are impacts spatially distributed throughout the community?

The next section describes the network model that was developed and run, the case study location and hazard selected for this simulation, and the specific data used for this analysis. Section 3 describes the geospatial and numerical results of the model, which are further explained in Section 4.

2. Methodology

To begin, we developed a generalizable model of the integrated infrastructure networks and the communities they serve. Within the model, we simulate an event which directly impacts a subset of the utilities and users. Then, the properties dependent on the directly impacted assets are determined, after which the model quantitatively assesses both the direct and indirect risks from the event. Our model can be used on any city and incorporate any number of infrastructure networks as well as events (e.g. natural hazards, system failures, and malicious activity). The following subsections detail how this is conducted and introduces an application on an urban case study.

2.1. Model preparation

First, geospatial data for each selected infrastructure system (e.g., water services, telecommunications, and electricity, which we call *utilities*) and the associated end users or *properties* (e.g., households, supermarkets, and businesses) for the study area are collected as inputs to the model. All together, this collection of data sets represents the *system* in study. At this stage, connections between the infrastructure and end users have not yet been established, but a baseline scenario of the system's functionality can be determined. The other primary set of input data is the extent of the event, which is also included in the model as a geospatial data set. This could be a numeric value representing a hazard intensity, such as water depth or wind speed, or a Boolean indication of whether the area is exposed or not to the hazard. For this description, the event represents a single possible scenario, while in the case study, we iterate a series of scenarios through the model to create a portfolio of results.

Next, the impact of the event is superimposed on the system, and the system elements (here the term *elements* or *nodes* includes both utility infrastructure and end users) are designated as either functional or out of service after the event. The functionality of the system elements after being exposed by the hazard are based on fragility curves, which define a functionality after a particular amount of exposure (e.g., water depth for flooding or peak ground acceleration for earthquakes). The specific

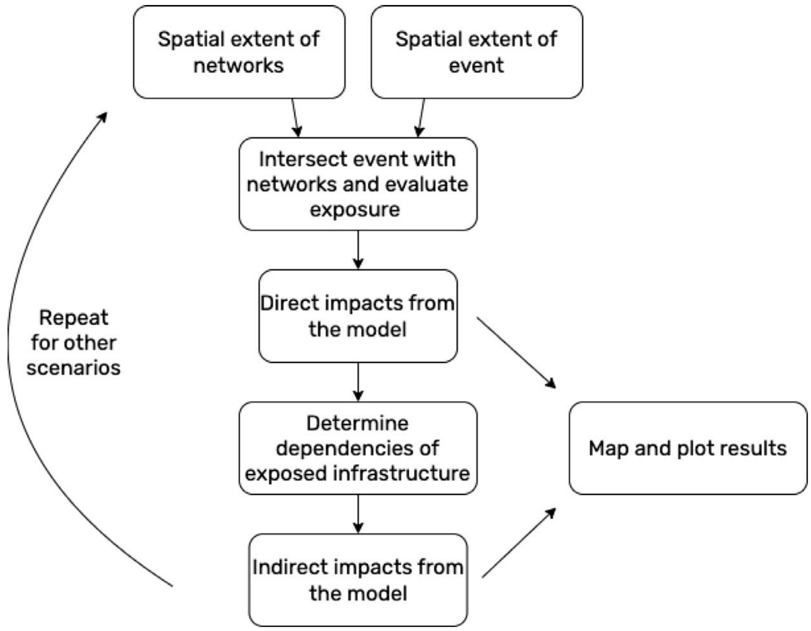


Fig. 1. Diagram showing the general workflow used to assess direct and indirect impacts.

components of the assets are not considered (e.g., the transformers or the pump housing), but rather the entire asset themselves (e.g., the substation building, the pumping station building, the residential house, etc.). For this study, we look at the worst-case scenario of exposure and simply use a single step fragility curve function, where any exposure means the particular element has failed. With imminent coastal flooding, these systems would be expected to be turned off before they are exposed or at the moment they become exposed, and households will be evacuated if any flooding has occurred. Therefore, while it is possible to incorporate partial functionality, this is not entirely insightful for this case study. The vulnerability of the links are not considered in this study, primarily for the reason that for coastal flooding, the overhead power lines and the underground pipelines are not often the critical points of failure. This model uses a network topology-based approach, and thus does not consider the specific flows throughout the systems, such as potential overloads on the electrical power or water networks. This set of results represents the direct impacts, which can be mapped to show the immediate loss of service from the event.

2.2. Network analysis

To capture the indirect impacts, we leverage a network representation of our interdependent system. Each of the system elements are represented by a vertex, or node, in our network model, which can be connected to other infrastructures or end users via an edge, or link. Depending on the situation, the edges between the vertices may follow specific rules as to which vertices they are connecting (e.g., connecting an electric zone substation to a particular grid exit point), while for others, the edges may be generated based on proximity (e.g., connecting a household to the nearest wastewater treatment plant).

The whole system (i.e., infrastructure vertices, end user vertices, and edges between these vertices) can be represented by an adjacency matrix, with the size of the matrix being proportional to the total number of vertices. Within the adjacency matrix, the edges between vertices are represented by a Boolean value (with 1 indicating a connection and 0 indicating no connection) [45]. More information on the network representation can be found in Appendix B.

With the network representation of the system, the initial loss in service from the event is cascaded through the matrix to simulate the indirect loss of service. This is done by identifying the directly impacted vertices from the superimposed event on the system, as described in the previous section, and setting any connected vertices' value to 0 in the adjacency matrix, signifying a loss in connection. This step of identifying connected vertices and setting the dependent vertices' matrix values to 0 is repeated with the disconnected vertices to capture the successive indirect impacts until there are no more dependencies. The vertices that have lost connection are recorded, so that indirect impacts can be mapped.

Another metric that has been integrated into the model is a calculation for end degree, which is a modified calculation of vertex degree. Here, we designate end degree as the total number of end users connected to a particular vertex in the network. This is a helpful metric to identify critical nodes from an end-user perspective. We calculate end degree for both the fully functional system and the impacted system (including both direct and indirect impacts). With this, we can understand the overall loss in connection throughout the system from an event. Further, we can provide insight to the utilities both in terms of which nodes lose the most service and which still have connections following an event.

This process, shown in Fig. 1, provides an approach to determine the indirect impacts that result from an event, including impacts on the infrastructure, the end users, and the system as a whole. The next section details the use of the model on a real-world network.

2.3. Case study

In this case study, the effects of a range of potential coastal flooding events on three interconnected systems in Christchurch, New Zealand are investigated: the electric power network, the water supply network, and the wastewater network.

2.3.1. Background

Ōtautahi/Christchurch, the second largest city by urban population in Aotearoa New Zealand, is a low-lying, coastal city on the eastern coast of New Zealand's South Island (Fig. 2). There are roughly 392,000 inhabitants within an area of approximately 295 square kilometers, resulting in a population density of about 1300 people per square kilometer. The city has two rivers flowing through it, the Avon River through the city center and the Heathcote River on the south side, which flow into an estuary and make certain areas more prone to

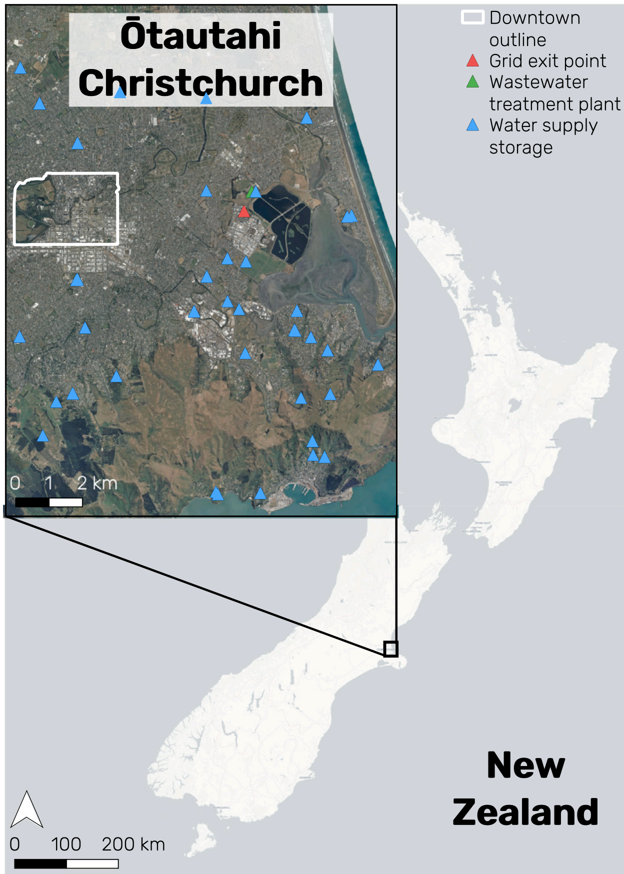


Fig. 2. Map of Ōtautahi/Christchurch in New Zealand, highlighting the downtown area and larger infrastructure nodes.

flooding from both fluvial and coastal events. Christchurch experienced severe disruptions from earthquakes in 2010 and 2011, due to ground motion as well as liquefaction [46], and wildfires in the Port Hills surrounding the city in 2017 [47], and it is threatened by coastal hazards (such as coastal flooding, coastal erosion, and rising groundwater), tsunamis, and landslides [48], which may become more common as the climate becomes warmer [49,50]. As such, it is a relevant case study for our model.

2.3.2. Coastal flooding

We focus this case study on coastal flooding, which is a relevant hazard for many communities along shorelines that will only intensify with climate change [51]. These events are often described in terms of their average recurrence interval [ARI], which is an indication of how many years are expected on average to be between events. For example, a 100-year ARI for a coastal flooding event would reflect the extent and severity of the flooding that would be expected about once every 100 years. This hazard is exacerbated by sea level rise [SLR], which can make the flooding event more frequent and/or more severe.

The data in this study for coastal flooding is based on storm-tide-driven extreme sea levels [ESL]. ESLs occur from a combination of mean sea level [MSL], storm tide (which incorporates high tide, meteorological effects, and monthly sea level anomaly), the wave setup at the shoreline, and SLR. In this study, we used ESL inundation maps from [52] for nine ARIs (2, 5, 10, 20, 50, 100, 200, 500, and 1000 years) and 0.1 m SLR increments up to 3 meters above present-day MSL. The maps were created using a static "bathtub" model and local LiDAR digital elevation models [DEMs] to map the extent and depths for inundation areas hydraulically connected to coastlines.

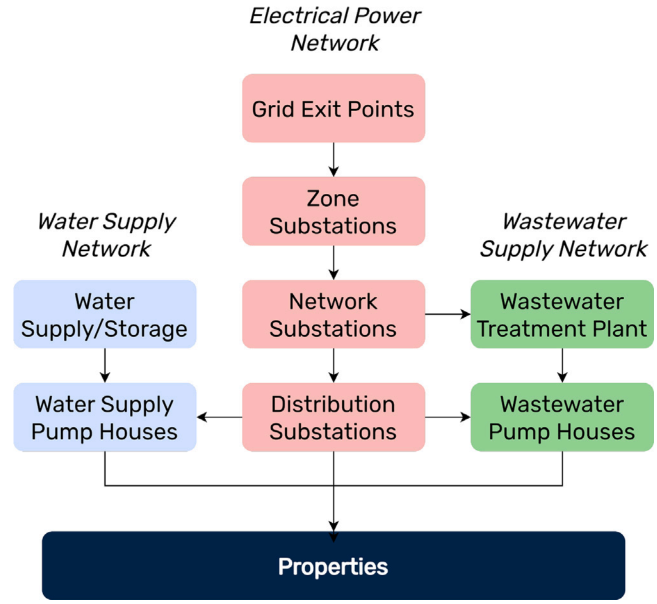


Fig. 3. Diagram of the components and connections in the Christchurch case study.

These models have been developed for the entirety of New Zealand's coastal urban areas, which includes Christchurch, at a resolution of 2 m. Further information on the methodology behind developing the coastal flooding maps can be found in [52].

2.3.3. Data

The infrastructure data used in this case study includes the electric power network [EPN], water supply network [WSN], and wastewater network [WWN] for Christchurch. The EPN contains transmission grid exit points, zone substations, network substations, and distribution substations. The WSN is made up of potable water supply/storage reservoirs and pump houses. The WWN has one wastewater treatment plant and pump houses (separate from the WSN). The three networks have dependencies on themselves, as well as on each other, notably on the EPN since certain nodes in the water and wastewater networks rely on the electricity grid for power. The end user nodes are determined via proxy, based off of the water meters throughout the city. These include residential, commercial, and industrial users. Within the model, we assume each of these have an independent dependency on the three utilities, meaning that one utility failing does not necessarily mean that the other utilities have failed.

The connections among the utilities and end user nodes were primarily automated based on closest proximity by road network distance, since most urban utility infrastructure is underneath or alongside roads. A few of the connections were updated following engagement with the utility providers. The specific dependencies between the various system components is depicted in Fig. 3.

Using these inputs as the system, the model was run for several coastal flooding hazard scenarios, varying both ARI and SLR. A hazard-specific parameter that can be varied in the model is the flooding depth at which an element is considered exposed (and thus nonfunctional). These depth thresholds can be different for each of the infrastructure networks as well as for the end users, but for this case study, it is assumed that if a node has any depth of flooding, it is at risk of failing. In practice, this could result from an operator safely shutting it off or from loss of service due to water exposure. The thresholds can be adjusted in order to capture the vulnerability, as opposed to exposure, of the utilities or households, informed by either fragility curves or by the service provider's own experience and knowledge about their assets.

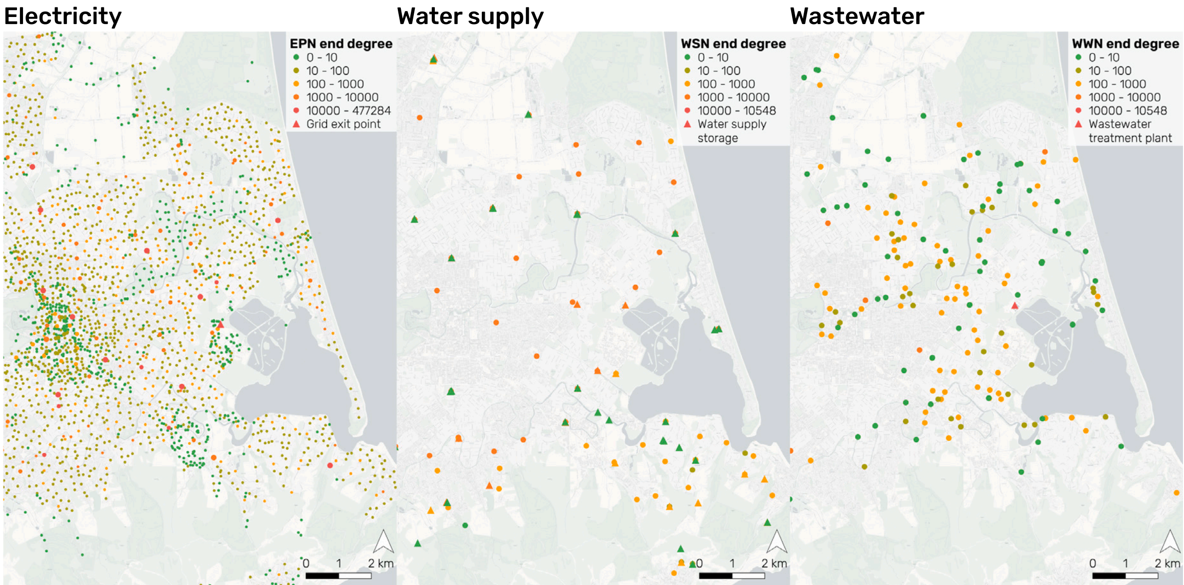


Fig. 4. End degree for the three infrastructure networks when fully functional. For the EPN, the size of the dot reflects the size of the substation. For the EPN, WSN, and WWN, the grid exit point, the water supply storages, and the wastewater treatment plant, respectively, are shown as triangles.

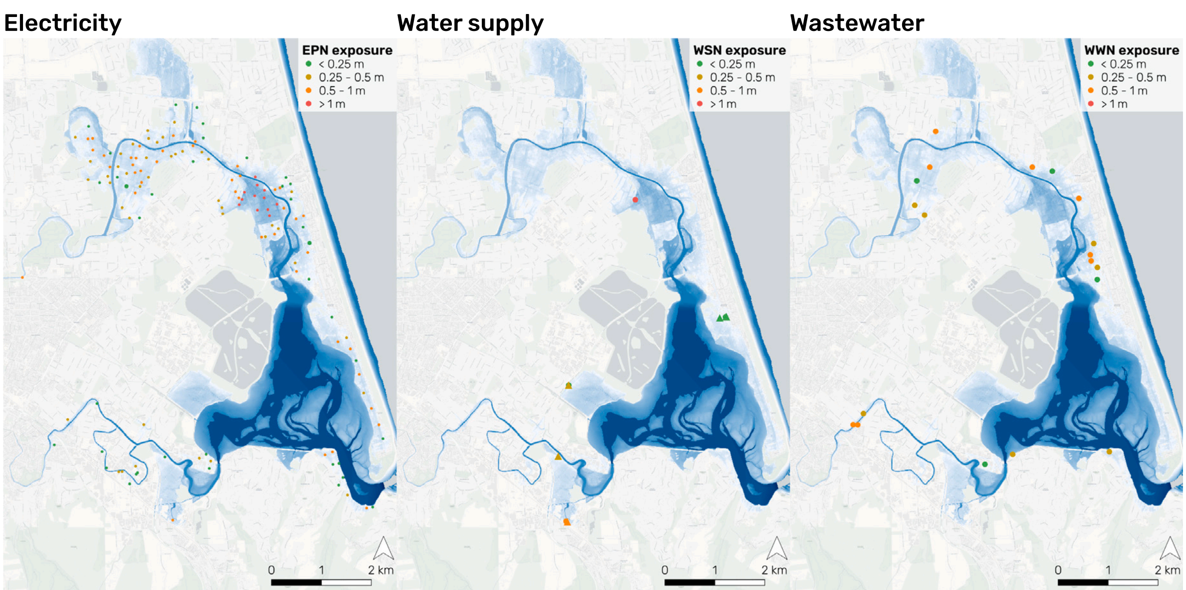


Fig. 5. Exposed infrastructure nodes during a coastal flooding event with an ARI of 10 years and no SLR. The colors indicate depth of exposure.

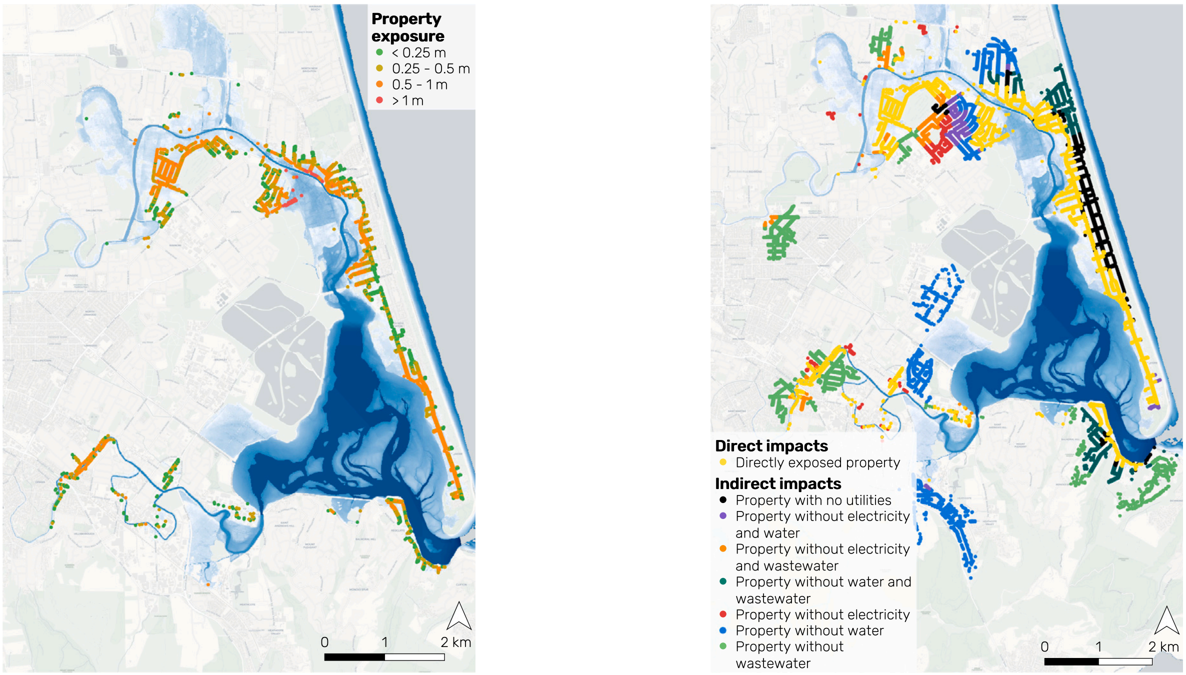
3. Results

To understand interdependence, the first step is to understand how many users depend on each of the assets under investigation. We show this in Fig. 4, which displays the infrastructure's end degree for the initial, fully functional EPN, WSN, and WWN networks. To reiterate, this degree value represents the number of end users that are connected to that node, where red colors indicate a greater number of dependent end users than green colors. The infrastructure is spatially dispersed regarding end degree, yet some infrastructure nodes appear to be susceptible to even a mild coastal flooding event (i.e., ARI of 10 years and no SLR), shown in Fig. 5.

We show the direct impacts from a coastal flooding event (with an ARI of 10 years and no SLR) on our three infrastructure networks in Fig. 5, highlighting nodes that are exposed to flooding, with the red nodes indicating greater inundation depth from this event. For this scenario, 142 EPN nodes, 12 WSN nodes, and 32 WWN nodes were directly exposed, out of 4360, 216, and 418 total nodes, respectively. As for the direct exposure on the end user nodes, 3639 out of 133,342 end users were exposed to the flooding, as shown in Fig. 6(a).

Shifting from the direct impacts to including indirect impacts, Fig. 6(b) shows the loss in utility for the end users, differentiated in color by which utility or utilities they have lost service of. The amount of end users without service for each combination of loss in utility is presented in Table 1, with the number of end users without at least one utility constituting roughly 9% of the total end users.

For this case study, a sensitivity to different SLR scenarios (from 0 cm of SLR to 300 cm of SLR by 10-cm increments) as well as different ARIs (2, 5, 10, 20, 50, 100, 200, 500, and 1000 years), both of which impact the severity of the coastal flooding event, was performed. The total number of end users directly impacted, indirectly impacted, and impacted overall was calculated for each of these variations. Fig. 7 shows impacts on end users for each infrastructure system in the 10-year ARI scenario as SLR increases. As there is a rise in sea level,



(a)

(b)

Fig. 6. (a) Directly exposed end users during a coastal flooding event with an ARI of 10 years and no SLR. (b) End users without service after a coastal flooding event with an ARI of 10 years and no SLR.

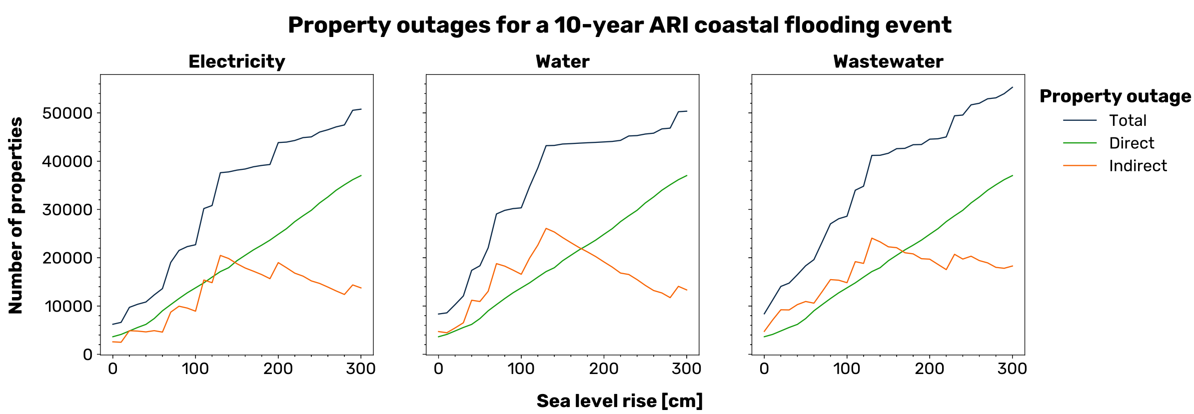


Fig. 7. Number of end users without service after coastal flooding events with an ARI of 10 years differentiated by utility as well as direct (in green) or indirect (in orange) impact.

Table 1
Breakdown of the loss in service for end users after a coastal flooding event with an ARI of 10 years and no SLR.

Utilities without service	Number of end users
EPN, WSN, WWN	4698
EPN, WSN	354
EPN, WWN	679
WSN, WWN	1032
EPN	492
WSN	2262
WWN	1982
Total	**11,499**

the direct and indirect impacts follow different patterns due to the system's composition, which will be explained later. When comparing the directly impacted properties to the total (directly and indirectly) impacted properties for the 10-year ARI and no SLR scenario, we see an increase of 71% for the electricity network, 129% for the water network, and 131% for the wastewater network (Fig. 7). These percentages are fairly constant as SLR increases, until the threshold at which the indirect values start to decrease and number of exposed properties overtakes the indirectly impacted properties. For the same 10-year ARI and 0 cm SLR scenario, there is a 216% increase between the directly impacted properties and the number of properties who lose *at least one* utility.

Two points along the "total" line in Fig. 7 are spatially shown in Fig. 8, which takes the 10-year ARI scenario and shows the jump in properties impacted when comparing the 0 cm SLR scenario with the 30 cm SLR scenario. The properties in orange represent those that have lost a utility with no SLR, while the properties in red represent the *additional* impacted properties at 30 cm of SLR. A more severe, or less frequent, ARI shifts the expected impacts, with a greater proportion of end users impacted at lower SLR scenarios. This is shown for end users who have lost *at least one* utility in Fig. 9 for a range of 3 different ARIs.

These results show how, using the methodology described, we are able to model both the direct and indirect impacts, represented as loss of service, from an event for an actual case study.

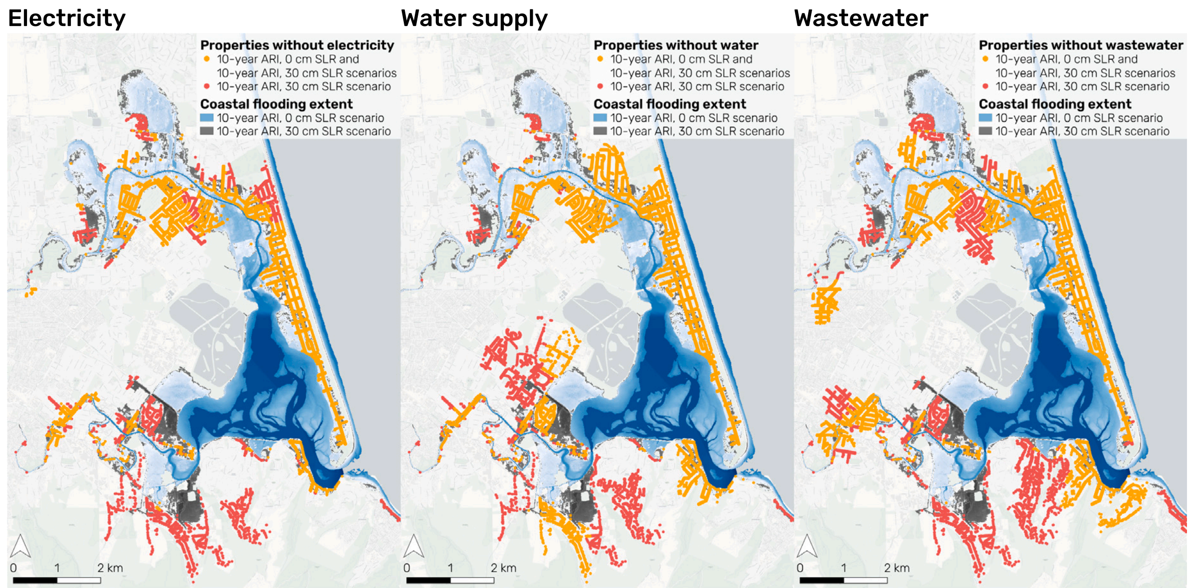


Fig. 8. End users without electricity (left), water (center), and wastewater (right) for a coastal flooding event with an ARI of 10 years and no SLR (in orange) and additional outages with an ARI of 10 years and 30 cm of SLR (in red).

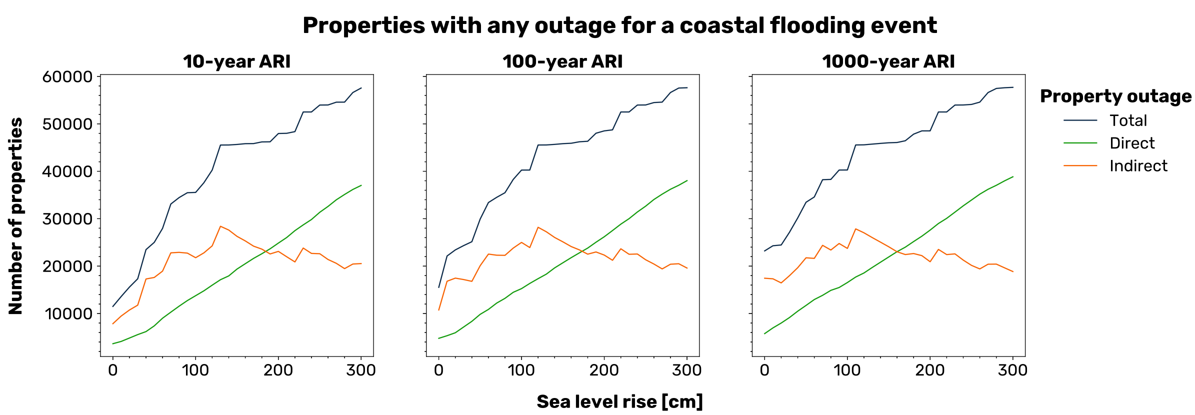


Fig. 9. Number of end users without at least one service after coastal flooding events with an ARI of 10 years (left), with an ARI of 100 years (center), and with an ARI of 1000 years (right), differentiated by direct (in green) or indirect (in orange) impact.

4. Discussion

In our paper, we seek to answer (1) does considering indirect impacts substantially change the assessment of residents impacted? and (2) how are impacts spatially distributed throughout the community?

We have shown that in Christchurch, assessments that do not include the indirect impacts of coastal flooding are not only underestimating the total impact from the event, but also missing the spatial distribution of impacts from the event, both often at the expense of understanding the community-level effects. Risk assessments that are prepared before an event occurs will often try to capture the extent of loss of service either by (a) modeling the direct exposure of the infrastructure components or by (b) using historical statistics about loss of service. However, both of these approaches fall short of capturing the extent of impact from an event. The former is often done from the perspective of the utility (i.e., since the model is based around the infrastructure nodes), so does not accurately reflect the scope of the impact on the community, while the latter does not discern between the changes or updates in the system's design.

An infrastructure exposure assessment relies heavily on the knowledge each of the various utilities have available to them during and after an event. Electricity providers are often capable of having near-real-time data about the service they provide to users, while for water or wastewater networks, their service knowledge may stop at the extent of their own infrastructure nodes (e.g., pump houses or reservoirs) unless the utility providers have invested in a monitoring/sensor network.

Using traditional statistical modeling may be useful for predicting particular event impacts, yet often struggles to incorporate the uncertainty that may occur over time (for both the disruption scenario and for the system), falling outside of the training data set. This is particularly relevant for impacts from climate change, as we can expect both disruptive scenarios we have not yet experienced and future development in urban environments.

Our work addresses the above shortcomings by assessing outages throughout the infrastructure systems and the community in a real-world case study. When considering the end users without service after a coastal flooding event with an ARI of 10 years and no SLR, about 9% of total end users have lost at least one utility and 3.5% of total end users have lost all three utilities. Of those who have lost at least one utility, only about a third were actually exposed to flooding, meaning two thirds of the end users were impacted due to an indirect impact. This difference is obvious when comparing the map of the exposed end users (Fig. 6(a)), where the impacted nodes are clustered within a tight vicinity of the rivers, with the impacted end users (Fig. 6(b)), where additional groups of properties appear as a result of the upstream outages.

In addition to serving as a quick visualization for the number and spatial distribution of affected end users, the results presented in Fig. 6(b) also reveal a more detailed assessment of which utilities have lost service. This is useful for emergency response situations, where extra supplies (e.g., clean water, portable toilets, backup generators, etc.) can be strategically deployed to at-risk areas and to provide an estimate as to how many end users might need emergency housing or accommodation.

These spatial results can be further interpreted by looking at the plots of exposed properties, indirectly impacted properties, and properties with a total loss of service in Figs. 7 and 9. The lines representing total impacts show that as SLR increases, the magnitude of impacts increases sporadically. Breaking this down into direct and indirect impacts for this system, the exposed end users steadily increase, while the indirect impacts on end users drives the variation in total impacts. The impacts of increasing SLR for properties experiencing at least one outage (Fig. 9) have a similar trend as outages per utility (Fig. 7), but have higher values of impacted end users for both indirect and total outages due to the variation in spatial distribution of each of the utility outages, which do not always overlap. The reason for the main direct and indirect trends is that direct flooding consistently impacts more properties as SLR increases, while large sections of the community are indirectly impacted all at once when an infrastructure node becomes exposed. Generally, indirect impacts increase as sea-level rise increases until a threshold, when the exposure from the event overtakes the indirectly impacted properties. Hence the peaks in indirect impacts in Figs. 7 and 9. The sharp increases in the indirect impacts line (also reflected in the total impacts line), reflect the non-linear nature of cascading failures. In particular, these indicate that there are subtle tipping points, or thresholds, inherent in our interconnected urban infrastructure that contribute to cascading failures. When these thresholds are surpassed, the impacts extend to a group of nodes (be it infrastructure or end users), causing the number impacted to jump. These tipping points are subtle in that they are not immediately obvious when looking at our systems, yet have far-reaching second and third degree impacts.

This can similarly be seen in Fig. 8, which compares the difference in service of the 0 cm SLR scenario with the 30 cm SLR scenario for a coastal flooding event with an ARI of 10 years. The cascading failure phenomena is captured by the groupings of red nodes in the maps that are not overlying any coastal flooding (indicated in blue) for the 30 cm SLR scenario.

The inclusion of cascading failures in our risk analyses can help us better understand the structure of our interconnected systems, as well as the impacts on our communities. This updated approach to impact assessments has implications for the utility operators, showing them where there are vulnerabilities in the system, as well as providing insight as to where to improve robustness in their infrastructure. For the residents, these findings can help enhance community preparedness, by advising high risk neighborhoods of possible outages as well as knowing which provisions might be needed. Similarly, our results can guide emergency response teams by indicating which areas are likely to be impacted, informing them what might be needed in those areas, and by giving them an estimate of the amount of supplies and emergency accommodation needed.

5. Conclusion

Our infrastructure is becoming more complex as it becomes more interconnected, resulting in more complex disruptions after an event occurs. The cascading failures that originate from these interdependencies are similarly intricate and difficult to model across networks. In this paper, we argue that these indirect impacts, such as cascading failures, should be incorporated in network-wide risk analyses, and provide a model to address this. We describe a methodology to assess direct and indirect impacts on a set of interconnected networks and end users and then apply this to the case study of Christchurch, New Zealand. The results from this application show that depending on the system, the indirect impacts of an event may contribute to the majority of the loss in service when compared to the direct impacts from the event. Risk assessments that neglect to include these indirect impacts are thus vastly underestimating the impact from an event. Another finding is that the outages of the various networks are not evenly spatially distributed throughout the community, meaning that different response and recovery measures may be needed. Such a city-wide assessment of the impacts to its interdependent infrastructure has not yet been performed, but we argue this is a key step in understanding a system's risk, particularly when faced with uncertain future scenarios such as climate change.

Further application of this model could include developing a suite of hazards to get a more complete picture of the risks threatening a community. With the addition of other hazards, the links between the nodes (e.g., pipelines and power lines) may play a more critical role and thus would be needed to be modeled. Two other directions for further investigation would be to include more detailed fragility curves to better understand the vulnerability of various assets as well as to incorporate the partial failure of nodes due to the loss of some network components (e.g., overload of the power grid or insufficient pressures in the water network). These applications all require more detailed data, and thus the feasibility of general application to other case studies is variable. Nonetheless, this study demonstrates how a simple data set could be used to understand the cascading failures of an urban system.

Despite the intricacy involved with cascading failures, they can provide critical insight into our systems and communities, both in their design and their vulnerabilities. Better understanding these impacts can help make more robust and resilient urban communities, and can play a larger role in the assessment and response of disruptions to our infrastructure.

CRediT authorship contribution statement

L.G. Brunner: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **R.A.M. Peer:** Writing – review & editing, Supervision. **C. Zorn:** Writing – review & editing, Supervision, Data curation. **R. Paulik:** Writing – review & editing, Formal analysis, Data curation. **T.M. Logan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, 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

The authors do not have permission to share data.

Acknowledgments

This work was partially supported by the New Zealand Ministry of Business, Innovation and Employment (MBIE) Endeavour Fund (Smart Idea) project "Innovating climate risk assessment: A system-wide, geospatial approach for councils and communities" and Deep South Science Challenge (MBIE CONTRACT NUMBER: C01X14121), the Resilience to Nature's Challenges (RNC) programme, and Te Hiranga Rū QuakeCoRE. Additionally, we would like to acknowledge Orion for the electrical power data.

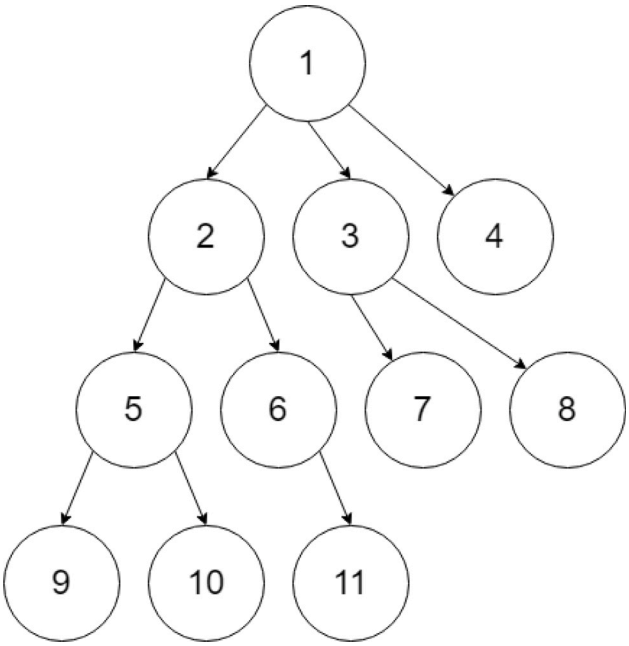


Fig. 10. Example of a directed acyclic graph.

$$A_{11\times 11} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 11. Associated adjacency matrix for the graph in Fig. 10.

Appendix A. Acronyms

ARI - Average recurrence interval
DEM - Digital elevation model
EPN - Electric power network
ESL - Extreme sea levels
MSL - Mean sea level
WSN - Water supply network
WWN - Wastewater network

Appendix B. Network analysis

The basis for modeling networks is through an adjacency matrix, which are a mathematically convenient way to represent directed and undirected graphs. Since the dependency in our networks is one-directional (e.g. electricity is flowing from the grid to the households, and water is flowing from the water supply to the households) and there are no closed cycles within the network, our system is represented by a directed acyclic graph Fig. 10.

The vertices, or nodes, in the graph are the row index and column index (i.e. node 1 is represented by the first row and the first column), while edges, also called arcs or links (which indicate dependence), are represented by a 1 in the adjacency matrix Fig. 11. For each row, which represents a node, a dependent connection on another node is shown by placing a 1 in the column which that node is dependent on. For example, if node 4 is dependent on both node 1 and node 2, then there will be a 1 located in the adjacency matrix at row 4, column 1 as well as at row 4, column 2. Considering the matrix as a whole, rows indicate any dependence that node has on other nodes, while columns indicate any dependents that node has on it.

For directed acyclic graphs, only the bottom left half of the matrix could contain 1's, while for undirected graphs and generic directed graphs, both the bottom left and the top right half could contain 1's. A single adjacency matrix can represent multiple networks by simply adding additional rows and columns for the number of nodes in the other networks.

Once the matrix is set up, calculations can be run to acquire the end degree, or how many dependents a particular node has, in order to assess the initial state of the system. To simulate a loss in connection, the values in the column of the node's index can be changed to a 0, recording the row number of those values that were turned from a 1 to a 0. Subsequently, the row number of the values changed to zero in the previous step can be used to change the dependent connections to 0, by changing the values in that column number to 0. This is repeated until there are no more dependents, recording those that have lost service in each step. Calculations can again be run to see how many connections have been lost due to the particular event, again through using the end degree for this finalized, updated adjacency matrix.

References

[1] Rinaldi SM, Peerenboom JP, Kelly TK. Identifying, understanding, and analyzing critical infrastructure interdependencies. IEEE Control Syst Mag 2001;21(6):11–25.
[2] Seneviratne SI, Nicholls N, Easterling D, Goodess CM, Kanae S, Kossin J, Luo Y, Marengo J, McInnes K, Rahimi M, Reichstein M, Sorteberg A, Vera C, Zhang X. Changes in climate extremes and their impacts on the natural physical environment. In: Managing the risks of extreme events and disasters to advance climate change adaptation. Intergovernmental Panel on Climate Change; 2012.
[3] Busby Joshua W, Baker Kyri, Bazilian Morgan D, Gilbert Alex Q, Grubert Emily, Rai Varun, Rhodes Joshua D, Shidore Sarang, Smith Caitlin A, Webber Michael E. Cascading risks: Understanding the 2021 winter blackout in texas. Energy Res Soc Sci 2021;77:102106.
[4] Kwasinski Alexis, Andrade Fabio, Castro-Sitiriche Marcel J, O'Neill-Carrillo Efraín. Hurricane maria effects on puerto rico electric power infrastructure. IEEE Power Energy Technol Syst J 2019;6(1):85–94.
[5] Reed Dorothy A, Powell Mark D, Westerman Julie M. Energy supply system performance for hurricane katrina. J Energy Eng 2010;136(4):95–102.
[6] Henry Devanandham, Ramirez-Marquez Jose Emmanuel. On the impacts of power outages during hurricane sandy—A resilience-based analysis. Syst Eng Electr 2016;19(1):59–75.
[7] Davies Alistair J, Zorn Conrad, Wilson Thomas M, Wotherspoon Liam M, Beaven Sarah, Davies Tim R H, Hughes Matthew W. Infrastructure failure propagations and recovery strategies from an alpine fault earthquake scenario: Establishing feedback loops between integrated modelling and participatory processes for disaster impact reduction. Bull N Z Natl Soc Earthq Eng 2021;54(2).
[8] Hallegatte Stephane, Rentschler Jun, Rozenberg Julie. Lifelines: the resilient infrastructure opportunity. 2019.
[9] Ouyang Min. Review on modeling and simulation of interdependent critical infrastructure systems. Reliab Eng Syst Saf 2014;121:43–60.
[10] He Xian, Cha Eun Jeong. State of the research on disaster risk management of interdependent infrastructure systems for community resilience planning. Sustain Resil Infrastruct 2022;7(5):391–420.
[11] He Xian, Cha Eun Jeong. DIN II: incorporation of multi-level interdependencies and uncertainties for infrastructure system recovery modeling. Struct Infrastruct Eng: Maint Manage Life-Cycle Des Perform 2021;17(11):1566–81.
[12] Guidotti Roberto, Gardoni Paolo, Rosenheim Nathanael. Integration of physical infrastructure and social systems in communities' reliability and resilience analysis. Reliab Eng Syst Saf 2019;185:476–92.
[13] Ouyang Min, Fang Yiping. A mathematical framework to optimize critical infrastructure resilience against intentional attacks. Comput-Aided Civ Infrastruct Eng 2017;32(11):909–29.
[14] Baratian Amin, Kashani Hamed. Probabilistic framework to quantify the seismic resilience of natural gas distribution networks. Int J Disaster Risk Reduct 2022;81:103282.

[15] Schäfer Benjamin, Witthaut Dirk, Timme Marc, Latora Vito. Dynamically induced cascading failures in power grids. Nature Commun 2018;9(1):1975.
[16] Zhang Lin, Wen Huiying, Lu Jian, Lei Da, Li Shubin, Ukkusuri Satish V. Exploring cascading reliability of multi-modal public transit network based on complex networks. Reliab Eng Syst Saf 2022;221:108367.
[17] Ahmad Ali. Increase in frequency of nuclear power outages due to changing climate. Nat Energy 2021;6(7):755–62.
[18] Poljanšek Karmen, Bono Flavio, Gutiérrez Eugenio. Seismic risk assessment of interdependent critical infrastructure systems: The case of European gas and electricity networks. Earthq Eng Struct Dyn 2012;41(1):61–79.
[19] Cimellaro GP, Tinebra A, Renschler C, Fragiadakis M. New resilience index for urban water distribution networks. J Struct Eng 2016;142(8):C4015014.
[20] Adachi Takao, Ellingwood Bruce R. Serviceability of earthquake-damaged water systems: Effects of electrical power availability and power backup systems on system vulnerability. Reliab Eng Syst Saf 2008;93(1):78–88.
[21] Wang Fei, Magoua Joseph Jonathan, Li Nan. Modeling cascading failure of interdependent critical infrastructure systems using HLA-based co-simulation. Autom Constr 2022;133:104008.
[22] Bellè Andrea, Zeng Zhiguo, Duval Carole, Sango Marc, Barros Anne. Modeling and vulnerability analysis of interdependent railway and power networks: Application to British test systems. Reliab Eng Syst Saf 2022;217:108091.
[23] Stødle Kaia, Metcalfe Caroline A, Brunner Logan G, Saliani Julian N, Flage Roger, Guikema Seth D. Dependent infrastructure system modeling: A case study of the St. Kitts power and water distribution systems. Reliab Eng Syst Saf 2021;209:107421.
[24] Zorn Conrad, Pant Raghav, Thacker Scott, Shamseldin Asaad Y. Evaluating the magnitude and spatial extent of disruptions across interdependent national infrastructure networks. ASME J Risk Uncertain B 2020;6(2):020904.
[25] Buldyrev Sergey V, Parshani Roni, Paul Gerald, Stanley H Eugene, Havlin Shlomo. Catastrophic cascade of failures in interdependent networks. Nature 2010;464(7291):1025–8.
[26] Thacker Scott, Pant Raghav, Hall Jim W. System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures. Reliab Eng Syst Saf 2017;167:30–41.
[27] Hasan Samiul, Foliente Greg. Modeling infrastructure system interdependencies and socioeconomic impacts of failure in extreme events: emerging R&D challenges. Nat Hazards 2015;78(3):2143–68.
[28] Guidotti Roberto, Chmielewski Hana, Unnikrishnan Vipin, Gardoni Paolo, McAllister Therese, van de Lindt John. Modeling the resilience of critical infrastructure: the role of network dependencies. Sustain Resil Infrastruct 2016;1(3–4):153–68.
[29] Smith Andrew M, González Andrés D, Dueñas-Osorio Leonardo, D'Souza Raissa M. Interdependent network recovery games. Risk Anal 2020;40(1):134–52.
[30] Sun Jingran, Zhang Zhanmin. A post-disaster resource allocation framework for improving resilience of interdependent infrastructure networks. Transp Res D 2020;85:102455.
[31] González Andrés D, Dueñas-Osorio Leonardo, Sánchez-Silva Mauricio, Medaglia Andrés L. The interdependent network design problem for optimal infrastructure system restoration. Comput-Aided Civ Infrastruct Eng 2016;31(5):334–50.
[32] Oboni Franco, Oboni Cesar H. Convergent leadership-divergent exposures. Springer International Publishing; 2021.
[33] Liu Wei, Song Zhaoyang. Review of studies on the resilience of urban critical infrastructure networks. Reliab Eng Syst Saf 2020;193:106617.
[34] Reilly Allison C, Baroud Hiba, Flage Roger, Gerst Michael D. Sources of uncertainty in interdependent infrastructure and their implications. Reliab Eng Syst Saf 2021;213:107756.
[35] Koliou Maria, van de Lindt John W, McAllister Therese P, Ellingwood Bruce R, Dillard Maria, Cutler Harvey. State of the research in community resilience: progress and challenges. Sustain Resil Infrastruct 2020;5(3):131–51.
[36] Sun Wenjuan, Bocchini Paolo, Davison Brian D. Quantitative models for interdependent functionality and recovery of critical infrastructure systems. In: Ettouney M, editor. Objective Resilience: Objective Processes, Vol. 2. American Society of Civil Engineers; 2022, p. 127–229.
[37] Pant Raghav, Barker Kash, Zobel Christopher W. Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors. Reliab Eng Syst Saf 2014;125:92–102.
[38] Nan Cen, Sansavini Giovanni. A quantitative method for assessing resilience of interdependent infrastructures. Reliab Eng Syst Saf 2017;157:35–53.
[39] Bruneau Michel, Chang Stephanie E, Eguchi Ronald T, Lee George C, O'Rourke Thomas D, Reinhorn Andrei M, Shinozuka Masanobu, Tierney Kathleen, Wallace William A, von Winterfeldt Detlof. A framework to quantitatively assess and enhance the seismic resilience of communities. Earthq Spectra 2003;19(4):733–52.
[40] Wang Shuliang, Hong Liu, Chen Xueguang. Vulnerability analysis of interdependent infrastructure systems: A methodological framework. Physica A 2012;391(11):3323–35.
[41] Sharma Neetesh, Gardoni Paolo. Mathematical modeling of interdependent infrastructure: An object-oriented approach for generalized network-system analysis. Reliab Eng Syst Saf 2022;217:108042.
[42] Permann May Robin. Genetic algorithms for Agent-Based infrastructure interdependency modeling and analysis. 2007.
[43] Kong Jingjing, Zhang Chao, Simonovic Slobodan P. Optimizing the resilience of interdependent infrastructures to regional natural hazards with combined improvement measures. Reliab Eng Syst Saf 2021;210:107538.
[44] Rahimi-Golkhandan Armin, Aslani Babak, Mohebbi Shima. Predictive resilience of interdependent water and transportation infrastructures: A sociotechnical approach. Socioecon Plann Sci 2022;80:101166.
[45] Barabási Albert-László, Pósfai Márton. Network science. Cambridge University Press; 2016.
[46] Bannister S, Gledhill K. Evolution of the 2010–2012 canterbury earthquake sequence. N Z J Geol Geophys 2012;55(3):295–304.
[47] Langer ER, Mc Lennan J, Johnston DM. Editorial: Special issue on the port hills wildfire. Aust J Disaster Trauma Stud 2018;22. Port Hills Wildfire Special Issue.
[48] Know your hazard risks. 2022, https://www.cdemcanterbury.govt.nz/hazards, Accessed: 2022-10-6.
[49] Christchurch City Council. Catalogue of coastal hazard adaptation options. Tech. rep., 2021.
[50] Tonkin & Taylor. Coastal hazard assessment for christchurch district: summary report. Tech. rep., 2021.
[51] Hall CM. Case study New Zealand: Planning responses to coastal climate change risks: The case of Christchurch and the Akaroa Harbour, New Zealand. In: Jones A, Phillips M, editors. Global climate change and coastal tourism: recognizing problems, managing solutions and future expectations. CABI Books; 2018, p. 231–46.
[52] Paulik Ryan, Stephens Scott, Wild Alec, Wadhwa Sanjay, Bell Rob G. Cumulative building exposure to extreme sea level flooding in coastal urban areas. Int J Disaster Risk Reduct 2021;66:102612.