A Generalized Natural Hazard Risk Modelling Framework for Infrastructure Failure Cascades

Evelyn Mühlhofer[a,b*], Elco E. Koks[c], Chahan M. Kropf[a,b], Giovanni Sansavini[d], David N. Bresch[a,b]

[a] *Institute for Environmental Decisions, ETH Zurich, Zurich, 8092, Switzerland*
[b] *Federal Office of Meteorology and Climatology MeteoSwiss, Zurich-Airport, 8058, Switzerland*
[c] *Institute for Environmental Studies, VU Amsterdam, Amsterdam, The Netherlands*
[d] *Institute of Energy and Process Engineering, ETH Zurich, Zurich, 8092, Switzerland*

[*]corresponding author (evelyn.muelhofer@usys.ethz.ch)

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Abstract

Critical infrastructures are more exposed than ever to natural hazards in a changing climate. To understand and manage risk, failure cascades across large, real-world infrastructure networks, and their impact on people, must be captured. Bridging established methods in both infrastructure and risk modelling communities, we develop an open-source modelling framework which integrates a network-based interdependent infrastructure system model into the globally consistent and spatially explicit natural hazard risk assessment platform CLIMADA. The model captures infrastructure damages, triggers failure cascades and estimates resulting basic service disruptions for the dependent population. It flexibly operates on large areas with publicly available hazard, exposure and vulnerability information, for any set of infrastructure networks, hazards and geographies of interest. In a validated case study for 2018's Hurricane Michael across three US states, the model reproduced important failure dynamics among six infrastructure networks, and provided a novel spatial map where people were likely to experience disruptions in access to healthcare, loss of power and other vital services. Our generalized approach allows for a view on infrastructure risks and their social impacts also in areas where detailed information and risk assessments are traditionally scarce, informing humanitarian activities through hotspot analyses and policy frameworks alike.

Highlights

- Seamless framework, from natural hazards to infrastructure failures and basic service disruptions
- Designed for risk assessments of large-scale, real-world interdependent infrastructure systems
- Features an open-source code base, tailored to use publicly available data across many world regions
- Validated model demonstration for a historic hurricane across 3 US states and 6 infrastructure systems

Keywords
Risk assessment, natural hazards, critical infrastructures, failure cascades, basic service disruptions, system-of-systems

1. Introduction

When natural hazards disrupt critical infrastructures (CIs), their failure can be detrimental to public health, safety, security, well-being and economic activities. Whether due to an earthquake in Japan, a flooding across Western Europe or a hurricane hitting the US, lifeline disruptions are ubiquitous: loss of power and telecommunication services may compound with a dysfunctional transport system and damaged hospitals, preventing emergency responders to intervene timely, rendering villages inaccessible for days, cutting off evacuation routes, or leaving school children without access to education for up to weeks [1]–[4].

As infrastructure investments are at an all-time high [5], CI systems around the globe are more than ever exposed to natural hazards, a trend which is further exacerbated in a changing climate [6]. This poses a threat to air, road and rail transportation alike [7], [8], puts power generation at risk [9] and causes losses of billions of US dollars annually in several CI sectors [8], [9].

Since societal impacts of CI failures tend to reach far beyond the technical sphere, managing resilient infrastructure has become a prime area of concern for policy makers: CIs "directly or indirectly influence the attainment of all of the SDGs" [5] and may accrue up to 88% of all climate adaptation costs until 2050 [10]. Reducing CIs damages and basic service disruptions forms part of the agendas of the Sendai Framework for Disaster Risk Reduction, the European Commission's Programme for Critical Infrastructure Protection (EPCIP) and the 26th UN Climate Change Conference (COP26) alike. Though different in scope and nature, three key challenges of CIs in a socio-technical context are recurrent: Knowledge on the extent to which CIs are exposed to natural hazards is insufficient, especially in the Global South (cf. §25 e and f in [11]); interdependences between different CIs are often poorly understood, and cascading effects from CI failures are difficult to analyse and hence manage systematically [12], [13] ; the experienced hardship from CI failures depends on the degree and duration to which basic services are disrupted [14], yet the link between infrastructure damages, resulting service outages and affected population is not straightforward.

Capturing the response of interdependent CI systems to natural hazards, and studying the impacts of their failures onto the population, is an endeavour residing at the intersection of natural hazard (NH) risk modelling, infrastructure modelling and social vulnerability research. Traditionally, those problems have been approached with community-specific research questions and methods:

NH risks emerge through the interplay of weather and climate-related hazards, the exposure of (infrastructure) assets, goods and people to those hazards and their specific vulnerabilities (IPCC 2014). Event-based impact modelling therefore commonly relies on those three components to calculate expectable asset damages to CIs as a proxy of direct risk [15]. Efforts to capture risk levels for CIs globally are often challenged by data availability (cf. [16]), yet have been undertaken for a few hazards and CI sectors such as road, rail, airports and power generation [7], [8], [17]. Despite acknowledging the importance to embrace a systems-thinking approach for resilience [18], [19], NH risk modelers' predominant focus on 'asset scale risk' [19] often runs short of capturing CI interdependencies and 'network scale risks'. As such, the community's risk assessment methods are not yet tailored to the specificities of CIs.

In infrastructure research, CI interdependences and failure cascades have received much attention since the seminal work of Rinaldi et al. [13] and approaches to model them have converged to several state-of-the-art methods, comprehensively summarized in Ouyang [20]. Especially in studies employing network (flow) approaches (cf. [21]), research on failure cascades is often motivated by NH events as triggers [22]–[27]. Yet, most research in this domain shares some of the following tendencies: Investigated systems are mostly small-scale, representative of mid-sized towns or single community districts and illustrate dynamics for a sub-system of two infrastructure types [26], [28]–[31] (see [23], [25], [32] for counter-examples) where power, transport and telecommunication systems are investigated much more often than social facilities such as schools or hospitals. CI data is frequently based on artificial, well-defined test-beds [22], [31], [33], [34], or tailored to the (sometimes proprietary) data at hand, which is overwhelmingly based in the US, Europe and Oceania [23], [30], [35], [36]. Failure scenarios often focus on random or component-wise removals [32], [37], [38], or feature stylized shapes in lack of realistic hazard footprints [23], [33]. Study scopes and trigger mechanisms in existing CI research are hence not necessarily tailored to capture the magnitude and spatial extents of real-world NH events and CI systems.

Lastly, the technical discourse on CI failures, where impact metrics focus predominantly on functional performance benchmarks, does not link adequately to the domain of social vulnerabilities [39]. Apart from empirical case-studies using print media accounts [40], only few modelling studies have explored consequences of CI failures for (socio-economically different groups of) people [41], [42].

Despite advances in tackling this common problem space, silos persist which have inspired several stylized and theoretical frameworks on systemic CI risks at a national analysis level [19], [43]. Following this logic, our aim is to practically implement a flexible and open-source end-to-end impact model which estimates spatial patterns of people experiencing basic service disruptions caused by natural hazard-induced CI failure cascades. In line with Zio [44], who stresses the need to integrate different modelling perspectives to capture complexities of CI system failures, we showcase how synergies can be yielded by combining established methods and platforms used by CI researchers and NH risk modellers alike. The design focus of this seamless impact model is put particularly on the rapid analysis of large, interdependent, real-world infrastructure systems and the dependent population in diverse geographical regions, which are exposed to different types of natural hazards and where only limited process knowledge and data may be available. Impact estimates produced with this approach are hence thought to inform rapid hotspot assessments during emergency responses, or as a cross-national, human-centric measure of risk for policy purposes in international frameworks.

Section 2 describes the conceptual framework which was constructed to meet above-mentioned design criteria and its concrete implementation as a 'system-of-systems' [43] formulation for infrastructure networks embedded in the open-source risk modelling platform CLIMADA [45]. Section 3 exemplarily illustrates how the model can provide information services in the aftermath of disaster using a real-world case study of Hurricane Michael hitting the Florida Panhandle. A scenario analysis is performed and model outputs are validated using official reports and print media accounts, to facilitate a wider discussion on the merits and trade-offs of this approach in section 4, and to examine its adequacy for use in risk assessments, emergency response, adaptation planning and policy making.

2. Methods

The framework in Figure 2.1 illustrates the major conceptual stages developed to calculate basic service disruptions from natural hazard-induced infrastructure failure cascades, with required inputs and main outputs.

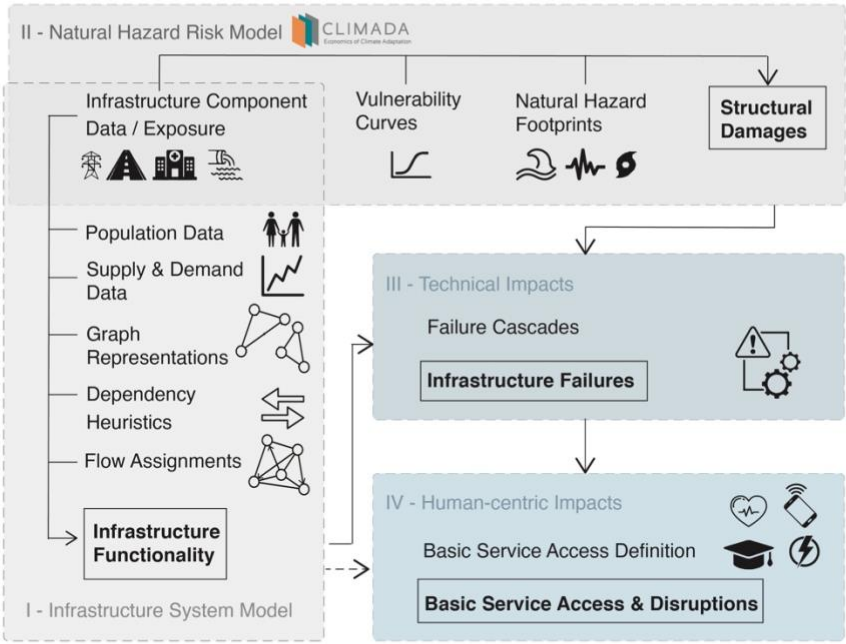

Figure 2.1 Developed framework to model the population experiencing basic service disruptions from natural hazard-induced infrastructure failure cascades. The four stages are linked within a single platform and encompass infrastructure system modelling (I), natural hazard risk modelling (II), and two spatially explicit results layers - impacts to infrastructure components (III) and to the dependent population (IV). Main outputs of each stage are in bold within a box.

In stage I an infrastructure system model calculates functional states of interdependent critical infrastructures using georeferenced information on infrastructure components, dependent population, dependency heuristics and supply and demand data. The employed modelling approach relies on a 'system-of-systems' formulation logic (cf. [23], [32], [43]), where CI systems are treated as hierarchical topological networks interconnected through dependencies between each other. The reliance on complex network theory and simpler flow calculations reduces the complexity of full-fletched physical models, yet has been demonstrated as a versatile, illustrative and data-efficient alternative capable of capturing large-scale dynamics across big system scales [23]. In stage II, structural damages to infrastructure components are computed from spatially- explicit hazard footprints and tailored vulnerability curves, using the risk assessment platform CLIMADA, which was in turn chosen for its state-of-the art performance in hazard modelling, global consistency and open-source character. Stage III feeds results from structural damage calculations back into the infrastructure system model, which triggers failures cascades along infrastructure dependencies. Results of this stage are technical failures at the infrastructure systems level. In stage IV, technical impacts of CI failures are translated to human-centric impacts. Resulting disruptions to basic service access are computed for all services provided by the CI systems under study, for the dependent population.

The following sections describe the implementation details of the framework. While emphasis is put on the conceptual choices that were made to unite models from natural hazard risk and infrastructure modelling communities, specific technical explanations referring to the practical open-source code base implementation are provided where necessary. For a list of abbreviations used throughout the text and a condensed formal description of the entire algorithm, see annex A.

2.1. Stage I: Infrastructure System Model

2.1.1. Data Requirements: Infrastructure Components, Population, Supply and Demand

Geographic data of *CI networks* - henceforth referring to the spatial representation of real-world infrastructures such as the location of schools, roads or electrical power plants - and of population must be procured at component (i.e. asset) level for the area of interest, such as a country, state or greater metropolitan area. Within the modelling framework, user-provided data sources may be ingested or high-resolution data can be obtained via automatized queries from open-source data providers such as OpenStreetMap and the WorldPop project [46]. A first step of complexity reduction and standardization then consists in limiting the diverse structural components per CI network to a few main building blocks or components. For instance, the road network could be reduced to intersections (nodes) and streets (edges), without differentiating further between road types, bridges or tunnels (c.f Table B.1 for a non-prescriptive component selection example for six main types of CI networks at various resolutions). Further, supply and demand data of the CI networks and their end-users, e.g. electricity generation and consumption statistics for the power network, as provided by the International Energy Agency (IEA), may be collected as available. This is, however, not imperative for the presented approach, as will be demonstrated throughout the method sections.

As a stylized example throughout the remainder of the model description, we consider the mobile communication (c), electric power (e) and health (h) networks represented through their most crucial components (respectively, cell towers, power plants, transmission lines, poles, and hospitals) and population grid cells (p) representing end-users as illustrated in Figure 2.2, panel BS.1. Fictitious power plant generation values and per capita electricity consumption statistics are included to demonstrate a case of demand and supply data availability, whereas such statistics are here supposed to be unavailable for all other CI networks.

2.1.2. Graph Representations

Infrastructure components are hence transformed into directed graphs consisting in nodes and edges. Within the modelling framework, corresponding cleaning and conversion algorithms are provided. In our example, the power network's plant and poles are represented by nodes and power lines as edges, while the graphs for communication and healthcare networks are made up of nodes only (see Figure 2.2, panel BS.1 (centre)). These formal representations will henceforth be referred to as *CI graph* G^j , where *j* is the system type (e.g. G^e for the electric power CI graph). In addition, geographical location *L*, initial functional state F^0 and the infrastructure-specific damage threshold D^j are set as attributes for all elements (nodes and edges) in each CI graph. F^0 is set to 1 for all elements. D^j indicates the structural damage fraction beyond which a component will lose its functionality and is a simplifying concept to derive functional states from damages. Thresholds are set arbitrarily in this example for purely illustrative purposes. The population network similarly is represented by a node-containing graph with people counts and geographical location as node attributes.

2.1.3. Dependency Heuristics

Departing from an extensive review on CI interdependence models, a list of 120 functional and logical dependencies between components of 11 different CI networks was collected (see Supplementary Materials) and consolidated within six generic rules, referred to as *dependency heuristics*:

I. Most CI networks depend on electric power supply, (cooling) water supply and information and communications technology (ICT)
II. People-hosting facilities (e.g. hospitals, schools, power plants) depend on road access
III. Dependencies can be categorized into either having redundant character, where several sources can provide necessary support (e.g. telecommunication access from any reachable cell), or being unique, where support is provided from a unique source (e.g. power from the single closest power line).
IV. Dependencies are distance-constrained (e.g. a cell tower located 500 km away will not provide relevant service, neither will a hospital which is 1500 km across the country).
V. Dependencies may entail a continuous, physical flow between source and target (e.g. water, electricity), yet can be approximated through a binary, logical connection.
VI. Population (end-users) depends on CIs for services, but not vice-versa.

These rules serve as a first starting point to identify sets of CI networks between which functional dependencies likely exist, and to sketch out a set of variables which can be fed into a quantitative dependency-search algorithm: *source*, *target*, *distance threshold*, *redundancy, road access* and *flow*. These dependency-search variables, described in more detail in Table 2.1, can be parametrized and manually adjusted to the case study at hand. The modelling framework's algorithm then places directed edges e^{jk} (dependencies) between any nodes of CI graph pairs (G^j,G^k) which fulfil the dependency conditions specified in the parametrizations of the described variables. In the stylized example of Figure 2.2, panel BS.1 ('Interdependent CI Graph'), a dependency list indicates CI network pairs which are generally hypothesized to exhibit dependencies (white underlaid). For instance, hospitals (target) are likely dependent on electric power (source), which for hospital node 6 is supplied uniquely from power node 3 (no redundancy), given that the supply point was close enough (distance < distance threshold).

The dependency-search algorithm equally allows assignment of end-users to CI networks in the absence of more detailed, yet often proprietary utility providers' customer data; the population graph is then the target of infrastructure - end user pairs (G^j, G^p) for any relevant infrastructure type *j.* The algorithm hence results in the creation of one *interdependent CI graph G* from all CI graphs and the population graph. This is illustrated in Figure 2.2, panel BS.1 ('Interdependent CI Graph'); population cluster node 12 (source), for instance, is dependent on any (redundancy) of the cell towers (target) within the set distance threshold for the provision of mobile communications, which is fulfilled by cell tower node 12.

Table 2.1 Required variables for the dependency-search algorithm between CI graphs. 'Source' and 'Target' are CI network components of different systems, previously identified from the heuristics explained above. Specific values for the variables may be filled in as adequate for the case study at hand.

Variable	Description
Source	Supporting CI component
Target	Dependent CI component
Distance Threshold	The maximum distance for establishing a link between two nodes is determined by a circle around the target with respective radius if road access is not required, else the shortest path via road edges connecting source and target nodes must not exceed the specified threshold.
Redundancy	Whether a target node is connected to all CI nodes of type source within a specified distance threshold (*TRUE*) or only to the single closest one (*FALSE*).
Road Access	Whether a road path must exist between source and target.
Flow	Whether the flow through the dependency edge is informed by a physically informed, continuous variable ('*physical'*, such as power cluster capacity), or by a binary ('*logical*') variable, indicating if supply can be provided or not based on the functional state of the source.

Next, for each combination of source-target pair *jk* for which edges e^{jk} were created in the interdependent CI graph, the attributes capacity C^{jk} and capacity threshold T^{jk} are assigned to all nodes. C^{jk} is initialized to discrete values, depending on whether a node is a source (1), a sink (-1) or neither (0) for the flow from CI network of type *j* to type *k*. T^{jk} ([0,1]) indicates what percentage of a standardized flow unit from *j* needs to arrive at a component of type *k* for it to remain functional. Bespoke hospital node 6 in Figure 2.2, panel BS.1 ('Interdependent CI graph') depends on electric power (e) and telecommunications (c), and provides healthcare services to people (p), and hence C^{eh} and C^{ch}=-1, while C^{hp}=1. For the hospital to remain functional in this example, it needs to receive at least 0.6 standardized units of power through its dependency link(s) (T^{eh}=0.6), 1 unit of telecommunications access (T^{ch}=1), and no unit of healthcare access, since it is the provider of this service (T^{hp}=0).

Geographic dependencies [13], [20] are implicitly accounted for in the framework through the spatial explicitness of all representations.

2.1.4. Flow Assignments and Infrastructure Functionality

Incorporating commodity flows in addition to a system's topology has been argued as crucial for capturing system performances adequately [31]. Yet, interdependent CI networks entail flows *within* individual networks (e.g. power in the power grid), and *across* networks (e.g. power to hospitals). Flows are furthermore of different natures, involving physical commodities (water, electricity, etc.) as well as logical dependencies (connectivity to mobile communications). To deal with this diversity, internal flows in CI networks and flows along dependencies between CI networks are treated separately. Results are then translated into binary functional states and normalized capacity values for coherence across all networks. Formally, those calculations are performed on subgraphs of the previously established interdependent CI graph *G,* henceforth denominated as G'^{j} and G'^{jk}. Subgraphs span all elements of infrastructure type *j,* and of types *j*, *k*, and linking edges e^{jk}, respectively, yet also retain their reference to the overarching graph *G*, which is hence updated. Figure 2.2, panel BS.2 provides a visual illustration of such subgraphs.

Flows within networks For networks with internal flows between sources and sink elements, infrastructure type-specific flow assignment algorithms, flexibly tailored to the data and knowledge available, are employed to update all capacity attributes C^{jk} on the corresponding subgraphs G'^{j} (for examples on flow calculation approaches, see [47] for road networks, [48] for water networks and [49] for power networks). Figure 2.2, panel BS.2 (left) illustrates this procedure for the power network, which is the only network involving internal commodity flows in this stylized example. In absence of further system knowledge apart from demand (per capita consumption data), supply (power plant generation data) and network topology, a cluster approach is employed. For each cluster in G'^{e} (here there is only one cluster), the ratio of supply (28 GWh) to demand (35 GWh) is computed, and assigned as a new relative capacity value C^{ek} (here 0.8) to all nodes in that cluster. This can be read as the power system operating at C*100% of its required capacity. Functional states *F* of the components remain unaltered in this mechanism.

Flows across networks The goal of this step is to determine the functionality *F* of each dependent infrastructure node in the interdependent CI graph based on the available capacities from other supporting infrastructure nodes. For each unique type of dependencies *jk* (e.g., power-communication, *j*=e, *k*=c) in *G*, subgraph G'^{jk} is extracted. A received supply variable M^{jk} is computed for each node in G'^{jk}. M^{jk} amounts to the sum of capacities C^{jk} received at target nodes *k* from functional source nodes *j* via an edge e^{jk}, and is hence 0 at nodes of type *j*. Technically, this flow propagation is computed on the adjacency matrix using matrix multiplication only, which is computationally efficient even for large networks. If M^{jk} is smaller than a previously set capacity threshold T^{jk}, a node loses functionality (*F*=0). Figure 2.2, panel BS.2 (right) illustrates this procedure formally (Eqs. (1) and (2)) and graphically on the electric power-mobile communications subgraph, which entails a physical, continuous variable flow, and on the mobile communications-healthcare subgraph, approximated by a binary (logic) variable flow: The cell tower node #7 receives a total of M^{ec} = 0.8 normalized units of power from the power sources it is connected to, which is greater than the capacity threshold (here set to T^{ec} = 0.6). It hence remains functional (*F*=1). Hospital node #1 receives M^{ch} = 2 logical units of supplies from both cell towers it is connected to. As this exceeds the needed (logical) units of cell tower supply (T^{ch}= 1), the hospital also remains functional (*F*=1).

Since dependency loops (inter-dependencies) can exist among CI networks, internal and inter-network flow assignment procedures are iteratively repeated until there are no more functional variable changes across any elements in the interdependent CI graph *G*.

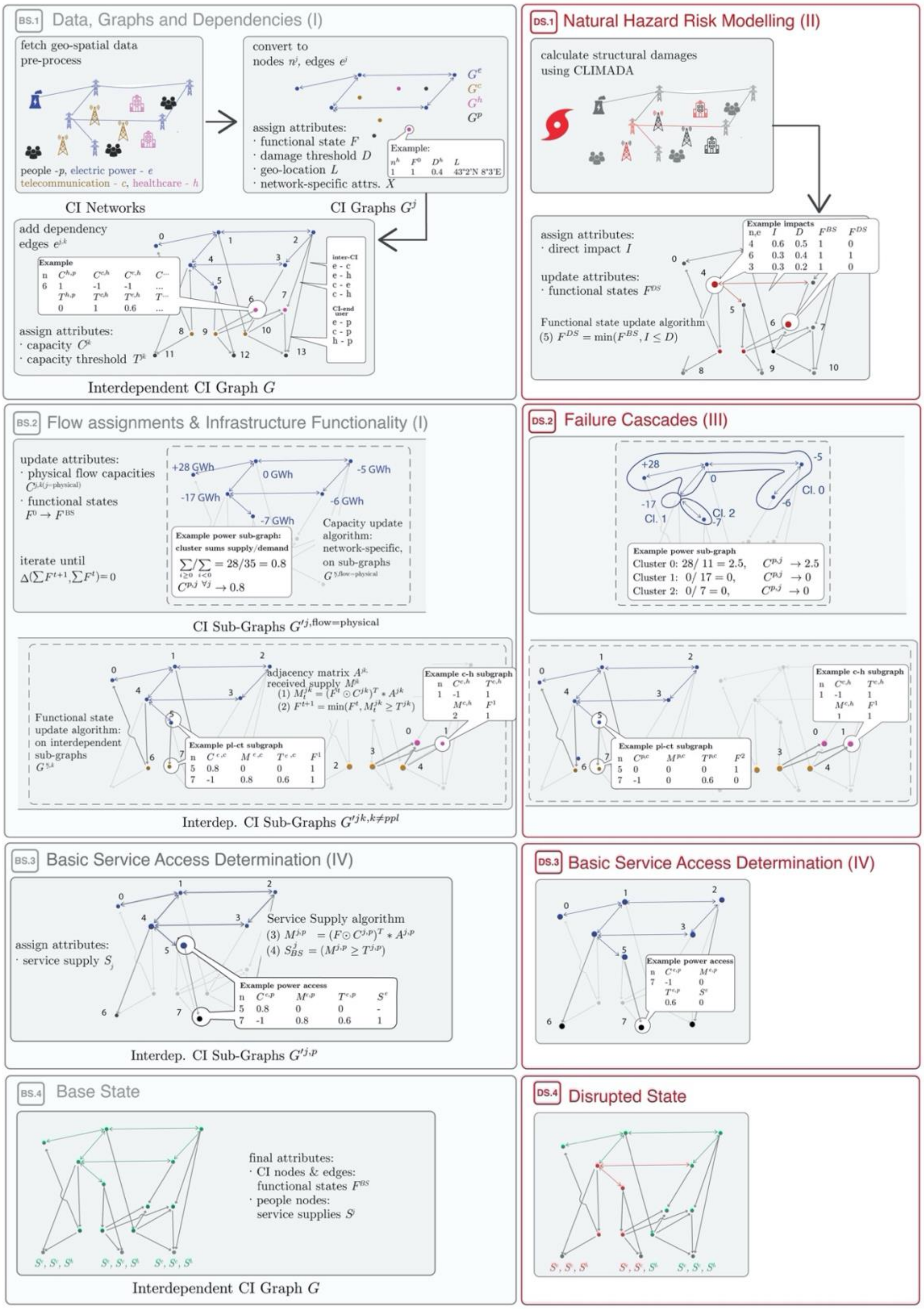

Figure 2.2 Stylized illustration of the entire modelling chain for 3 CI systems, people and a tropical cyclone event. Panels BS.1-4 (left) show the setup of the infrastructure systems model given infrastructure data, population data and dependency heuristics (BS.1), flow assignments and infrastructure functionality determination (BS.2), and basic service access determination for the population (BS.3), which hence represents the base state of the system (BS.4). Panels DS.1-4 (right) demonstrate the effects of structural damages caused by a natural hazard event (DS.1) triggering CI failure cascades (DS.2) and causing basic service disruptions to the population (DS.3). Roman numbers in brackets refer to the corresponding stages in overview Figure 2.1. Detailed explanation is given in sections 2.1 - 2.4. For a list of abbreviations and formal treatment, see annex A.

2.2. Stage II: Natural Hazard Risk Model

While several platforms for natural hazard modelling exist, the open-source and -access software CLIMADA (CLImate ADAptation) [45] is the only globally consistent and spatially explicit tool which is freely available to assess the risks of natural hazards and to support the appraisal of adaptation options [50]. The event-based modelling approach of CLIMADA has been used, among others, to conduct risk studies of tropical cyclones on assets across the globe [51], to discern impacts from river floods in a changing climate [52] and on people displacement [53], and in the wider context of Economics of Climate Adaptation studies [54]. The framework allows for a fully probabilistic risk assessment based on the IPCC risk definition [55] as a function of hazard, exposure and vulnerability.

2.2.1. Hazard

Hazard is a spatially explicit representation of the intensity of a natural physical event, such as geo-referenced wind speed for storms or water height for floods. Hazard footprints can, for instance, be based on historic records, forecasts or climate projections, or be synthetically generated to create probabilistic event sets. In CLIMADA, hazard modules are available for tropical cyclones, floods, wildfires, earthquakes, landslides, avalanches and heatwaves in different stages of maturity, yet can also be provided through user-ingested raster or vector data.

2.2.2. Exposure

Exposure refers to the geo-referenced assets or population data that are located in the area of interest. In CLIMADA, exposure modules are available to retrieve a global gridded asset dataset (LitPop [56]), critical infrastructures from OpenStreetMap, and high-resolution gridded population data out-of-the-box. User-provided data in raster or vector formats can equally be ingested. Exposures require a value assignment to capture the value potentially at risk, such as pre-computed economic (Dollar) values for LitPop, and lengths, areas or simply unity for infrastructure components (e.g. 100 m for a road section or 1 for 'a' healthcare facility).

2.2.3. Vulnerability

Vulnerability, also termed *impact function* or *fragility curve,* is an exposure-specific mapping of hazard intensity to expectable damage extent. Vulnerability curves for tropical cyclone winds on general economic asset stocks have been calibrated in CLIMADA for nine world regions [57], while the dedicated impact function module also allows to specify hazard- and infrastructure-component specific functions taken from literature, such as the HAZUS technical manuals provided by the US Federal Emergency Management Agency (FEMA).

2.2.4. Risk (Structural Damages)

Risk calculations are performed in CLIMADA by spatially overlaying hazard and exposures and mapping impacts via the corresponding impact function. Since most infrastructure exposures originally come in line or polygon formats, such shapes are interpolated to centroids at user-defined resolutions, and re-aggregated into their original shape after impact calculations. Here, risk is hence measured in terms of estimated structural damage to all infrastructure exposures, which in turn is expressed according to the respective value metric (either as damage fraction or total length/area affected). Computed structural damage values are then assigned as attribute *I* (‘*impact’*) to each corresponding element in the interdependent CI graph *G.* See Figure 2.2 panel DS.1 for an illustration of tropical cyclone risk calculations on power lines, cell towers and healthcare facilities.

2.3. Stage III: Technical Impacts (Infrastructure Failures)

For each element in the interdependent graph, the impact to the corresponding component computed with CLIMADA is assigned as attribute *I*. Functional state *F* of an element is set to zero if the impact *I* exceeds the damage threshold D^j as illustrated in Figure 2.2, panel DS.1.

This change in functional states can set off a failure cascade within the graph, through both internal and dependency-induced flow changes. In order to propagate the disruption, the capacities and functional attributes of all CI components are updated by applying the algorithm described in section 2.1.4 iteratively until a new steady state is obtained. In our example illustrated in panel DS.2 in Figure 2.2, several cascades occur: The power graph is split into three clusters as a consequence of the initial failure of a node and an edge element, whereby two clusters (Cl. 1 and Cl. 2) remain without capacity as they are cut off from connection to the power plant (C^{ek}=0). Interdependencies among CI networks further propagate those disruptions (cell tower #7 is connected to a capacity-less power node, hence becoming dysfunctional; hospital #1 still receives 1 unit of supply - instead of previously 2 - from supporting cell towers, which prevents its failure).

2.4. Stage IV: Human-centric Impacts (Basic Service Access & Disruptions)

The final step is to compute basic service access (and disruptions, correspondingly) for a range of services at population nodes. Basic service access, according to the United Nation’s definition[1], is ensured through the confluence of two factors:

i. *functionality* of the CI (component) responsible for the provision of a service
ii. a notion of *accessibility* to the CI (component)

Here, we define functionality through the functional states of the infrastructure graph elements. Accessibility is defined either through literal road path availability between end-user and infrastructure (e.g. hospitals for healthcare services) or through coverage of an area around an infrastructure’s location (e.g. cell towers for mobile communication services). A qualitative summary of basic service access parametrizations for six services examined in this work is given in Table 2.2.

[1] Metadata repository to the SDGs for indicator 1.4.1 - Proportion of population living in households with access to basic services: “*Basic Services refer to public service provision systems that meet human basic needs including drinking water, sanitation, hygiene, energy, mobility, waste collection, health care, education and information technologies. […] Access to basic services implies that sufficient and affordable service is reliably available with adequate quality*.”

Table 2.2 Examples for basic service access conditions which can be implemented in the infrastructure system model.

Basic Service	Description
Mobility	Functional connection to an intact road element within a certain distance threshold.
Power	Functional connection to an intact power cluster which runs above a certain capacity ratio.
Healthcare	Existence of an intact road-path below a certain distance threshold to a functioning facility.
Education	Existence of an intact road-path below a certain distance threshold to a functioning facility.
Mobile communication	Functional connection to an intact cell tower within a certain distance threshold.
Drinking water	Functional connection to an intact wastewater treatment plant within a certain distance threshold.

The quantitative basic service access algorithm is implemented in analogy to the flow assignment and functionality determination algorithm in the previous step. For each unique infrastructure-population pair combination *jp,* for which dependency edges e^{jp} exist in the interdependent CI graph G, the subgraph G'^{jp} spanning G'^{p}, G'^{j} and $e^{j,p}$ is extracted. Received services M^{jp} are hence computed as the sum of capacities from source infrastructure nodes arriving at population nodes (see eqs. 3 and 4 in Figure 2.2, panel BS.3). Each population (target) node is then assigned a service attribute S^j, indicative of the service provided by CI type j. The service is accessible (S^j=1) if M^{jp} exceeds the capacity threshold T^{jp} *and*, additionally, fulfils the access conditions (c.f. Table 2-3), else S^j=0. While the coverage-based access conditions are implicitly accounted for through the (non-)existence of a dependency edge, the literal (road-access) condition is checked for explicitly in the interdependent CI graph G through a shortest path algorithm, calculating the distance of the path between population node and facility node. Panel BS.3 in Figure 2.2 illustrates the procedure with the example of electric power access, where population node #7 receives M^{ep}=0.8 normalized units of power, which exceeds the capacity threshold (T^{ep}=0.6) and hence the service is accessible (S^e=1).

The interdependent CI graph with functional state attributes F at infrastructure elements and service attributes S at population nodes hence defines the *base state.* Panel BS.4 in Figure 2.2 illustrates this for the three infrastructure networks and the corresponding three service types at the population network (electric power access S^e, basic information access S^c and healthcare access S^h).

Once CI component failures are determined, basic service access is re-computed as hence described. See illustration in panel DS.3 in Figure 2.2 for the given stylized example on population's power access, leading to a new, *disrupted state* (panel DS.4 in Figure 2.2).

2.5. Model Uncertainties and Sensitivity Testing

Due to the amount of consecutive stages featured in the presented modelling chain, model assumptions and representational choices in one stage may greatly influence end-results. In order to allow for evaluation of such sensitivities, Table 2.3 provides a brief discussion on the main points where model uncertainties are introduced.

Table 2.3 Drivers of model uncertainties throughout all stages in the modelling chain.

Stage	Source	Explanation
I	CI system representations	Choices on CI components included or excluded, simplifications (for instance, no differentiation between transmission lines of different voltages, approximating the communication network by cell towers, water network by water treatment plants)
	Dependency Identification	Choice of dependency rules (i.e., heuristics, between which CI systems dependencies exist)
	Dependency Parametrization	Choice of conditions for dependency establishment (i.e. distance thresholds between components identified through heuristics, path requirements, etc.)
II	Hazard Footprint	Resolution, spatial accuracy and representational validity, when in- or excluding sub-hazards (e.g. wind-fields, storm surge and torrential rainfall for tropical cyclones) or multi-hazard phenomena (compound events).
	Vulnerability Curves	Assumptions on (deterministic) relationship between hazard intensity and component damages.
	Damage-Functionality Thresholds	Assumptions on the (deterministic, threshold-based) relationship between structural damages and resulting component functionality levels.
III	Cascading algorithm	Deterministic (strict) propagation of failures along dependencies, assumption on target becoming strictly dysfunctional due to failure at source.
IV	End-user Dependencies	Uncertainties are analogous to stage I.
	Basic Service Parametrization	

Owing to the complexity of the presented approach, a one-at-the-time analysis obtained by constructing scenarios, where only one set of parameters are varied within plausible bounds at a time (such as parametrizations of dependency conditions, vulnerability curves and functional thresholds), is a good starting point for identifying key sensitivities in the system responses. More in-depth characterization of the uncertainties can then be carried-out by focusing on the identified sensitivities (see [58] for a comprehensive discussion on best practices and recommendations, catering specifically to the field of environmental modelling, and [59] for an exemplary computational workflow designed for uncertainty propagating in and multi-level sensitivity analysis of hierarchical systems, particularly interdependent CI networks). Much can be done directly in CLIMADA using the '*unsequa'* module that provides readily usable methods for state-of-the art global uncertainty quantification and sensitivity analysis based on quasi-Monte Carlo sampling [60]. In addition, the probabilistic hazard modelling approach may help estimating representational uncertainties on the trigger side.

3. Application: CI Failures and Basic Service Disruptions from Hurricane Michael

Tropical Cyclone Michael made landfall in the Florida Panhandle on the 7th of October 2018, and caused severe impacts across Florida, Alabama and Georgia, both in terms of direct asset damages (over US$ 25 billions) and lives lost (at least 43) [4], as well as in terms of CI failures (power and mobile communication outages affecting millions, among others). It was selected for demonstration based on two reasons. Ample documentation of the event permits result validation and provides a reality check on quality and information content of the developed model. Further, Michael's severity was dominated by strong winds and storm surge as opposed to torrential rainfalls [61]. The hazard can therefore be approximated by modelling only its wind-field, lending itself as an illustrative, yet simple enough example.

3.1. Model demonstration

Stage I: Infrastructure System Model (Infrastructure Functionality) We delimit the system of study to the states of Florida, Alabama and Georgia which were directly hit by hurricane-strength winds. Besides population, infrastructure systems considered are main roads, transmission power lines, power plants, cell towers, wastewater treatment plants, healthcare institutions and public schools (see Figure 3.1 column 'CIs' for geographical maps of the CI networks). Details on data sources, pre-processing and individual CI graphs generation, can be found in annex C.1.1. Generation sources and demand sinks within the power network are obtained from power plant generation and energy consumption statistics (annex C.1.2). To generate the interdependent CI graph, twelve distinct dependencies are identified in between CI networks (6) and between CI networks and population (6), and parametrized as indicated in annex C.1.3. The established interdependent CI graph consists of nearly 80'000 nodes and 500'000 edges, with dependencies making up the majority (59%) of links (see Figure C.1 for detailed graph statistics). Network flows are computed and functional states assigned to all infrastructure components in this pre-disaster configuration (termed 'base state'), resulting in all elements of the interdependent CI graph being functional. Population's basic service access rates surpass 99% for all service types considered in the base state (access to mobility, power, education, healthcare, mobile communications and drinking water).

Stage II: Natural Hazard Risk Model (Structural Damages) Track data for tropical cyclone Michael is obtained from the International Best Track Archive for Climate Stewardship (IBTrACS) project [62] . The wind field (see Figure C.2) is computed from the CLIMADA tropical cyclone module, according to the parametrization in [63]. CI-type specific impact functions for structural damages from winds are taken from literature (see annex C.2.2) and ingested into CLIMADA for all infrastructures except power plants, which are not designed to fail. All CI networks are converted to CLIMADA exposure layers for impact calculations. Structural damages are computed using the CLIMADA impact module, yielding direct impact figures as displayed in Figure 3.1, column 'Component Damages'.

Stage III: Technical Impacts (Infrastructure Failures) Structural damages fractions of all infrastructure components are translated into binary functionality states by applying infrastructure-specific threshold values (annex C.1.3). Component failures hence initiate the failure cascade algorithm in the infrastructure systems module, both within individual CI networks and along dependencies across CI networks. Under the given system specifications, only the power network features an internal cascading mechanism, as it contains designated source nodes (power plant), sink nodes (power line nodes with customer demands) and transition nodes (all other power line nodes). A cluster approach was chosen to capture this failure behaviour, where all components in a remaining functional cluster become dysfunctional once generation capacity falls below a certain fraction of demand (here set to 60% for demonstrative purposes). Dependency-induced failure cascades are experienced across all CI networks within the interdependent CI graph. Results are displayed in Figure 3.1, 'CI failures', where initial, structural damage-induced failures and cascaded failures are marked with the respective colour code.

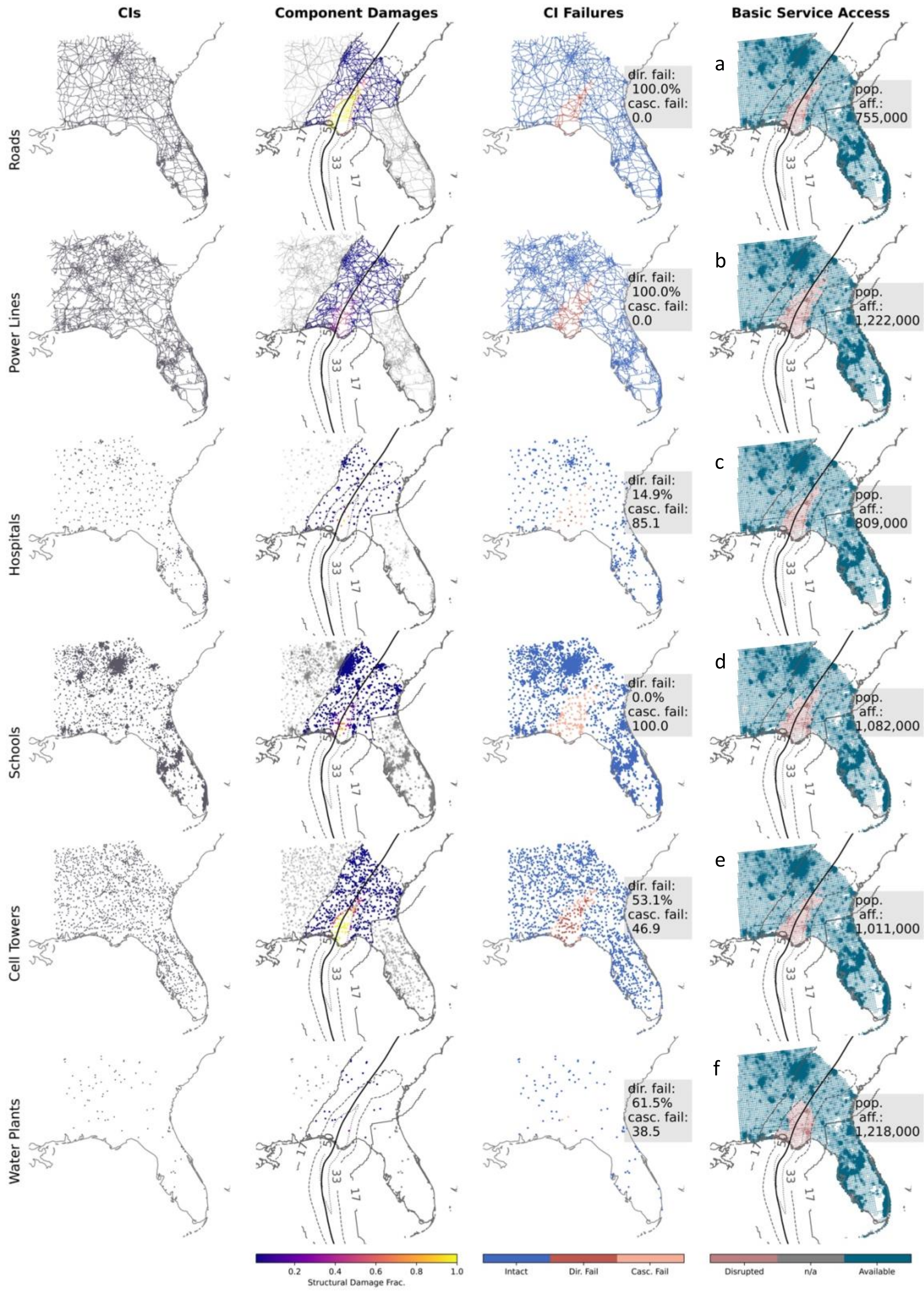

Figure 3.1 From natural hazard to basic service disruptions in four stages. Demonstration for Hurricane Michael '18 hitting the Florida Panhandle: Asset data for 6 CIs across FL, AL & GA used in the CI model (column 'CIs'), wind-induced structural damages calculated with CLIMADA ('Component Damages'), CI failure cascades triggered by the initial disruption, resulting in functional, dysfunctional and cascaded dysfunctional components ('CI failures'), population impacted from basic service disruptions following CI failures ('Basic service access', a: access to mobility, b: power, c: healthcare, d: education, e: mobile communication, f: drinking water. TC track and wind-field contour lines (m/s) are plotted in columns 2 & 4 for reference.

Stage IV: Human-centric Impacts (Basic Service Disruptions) Following the failure cascade algorithm, access to basic services are computed for all population nodes within the interdependent CI graph. For road-path constrained dependencies (access to healthcare and education, resp.), this involves re-calculation of path availability and travel distances. Figure 3.1, 'Basic Service Access' shows the disruption results for access to mobility, power, healthcare, education, mobile communication and drinking water.

3.2. Scenario Analysis

To obtain first insights on how strongly results depend on assumptions along the modelling chain, seven modelling scenarios are constructed (see Table C.4). We explore the role of interdependencies, and of parametrization decisions for impact functions and for functionality thresholds on result outcomes (annex Table C.5 for numeric results). The above presented case, referred to as 'original' parametrization henceforth, is taken as a reference.

Results are greatly influenced by the inclusion of CI interdependencies: As cascaded failures account for a significant part of all infrastructure failures in the base scenario, the removal of this impact driver drastically reduces component failures across all CI types but roads, with strong consequences for projections of service disruptions. Numbers of affected people decrease for all basic services apart from access to mobility (see Figure 3.2, blue). While the inclusion of dependencies itself plays a great role in determining the magnitude of impacts, the exact parametrizations of establishment conditions thereof (such as path distance thresholds) affect end results less strongly (see Figure 3.2, reds). Parametrization of impact functions directly and strongly influences estimates of structural damages, which has far-reaching consequences on the entire impact chain from immediate CI failures over cascades to basic service disruptions. Shifting impact functions by 15 m/s in either direction compared to the base scenario (i.e. same level of structural damage at wind intensities of 15 m/s more or less, resp.) can lead to a divergence in services disruption estimates between millions of people and almost none (Figure 3.2, greens).

Due to the resolution of the hazard footprint (360 arcsec, ca. 11 km), which exceeds most CI component lengths, results are less sensitive to the threshold assumptions between structural damage fractions and functional performance of components, since components are mostly entirely affected or not at all (see Table C.5). This may change and become increasingly important, though, at higher hazard resolutions.

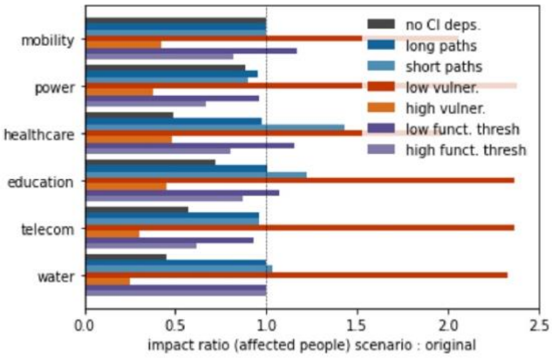

Figure 3.2 Number of people affected by basic service disruptions for seven scenarios, relative to original parametrization presented in section 3.1. Blue: no CI interdependencies, reds: allowing for shorter and longer road travel paths to social facilities, greens: higher and lower CI component vulnerability, greys: higher and lower structural damage thresholds until reaching component dysfunctionality.

3.3. Validation

The aim of this validation is to collect evidence on whether the showcased impact cascades - from CI damages to affected people - *do* happen, and whether predicted impacts, even when drawing on coarse assumptions and a set of heuristics, are in the right order of magnitude. The multiple impact stages calculated within the underlying approach are reflected in the breadth of validation sources taken into account, and span official government releases, utility providers' reports and newspaper articles (see annex C.4 for a comprehensive overview).

Even for the case study region, where information sources after natural hazard events are ample and accessible, documentation on the entire impact cascade is incomplete: structural damages are only incidentally reported across all infrastructure types, comprehensive functional outage reports are limited to the power and telecommunication sector, while accounts on basic service disruptions remain anecdotal. Figure 3.3 synthesizes this evidence, contrasting quantitative outage statistics against model outputs (panels b and e for power and telecom), and mapping qualitative service-related incidents against areas of modelled access disruptions (panels a, c, d and f for healthcare, education, mobility and drinking water). Loss of power access is captured well, both in terms of impacted people (~1.65 million reported vs. 1.22 million modelled), and in terms of spatial distribution (compare Figure 3.1 and Figure 3.3 (a) for a more detailed visual reference). Loss of mobile communication access is not reported as such, yet documented occurrences of cell site outages coincide well with spatial model predictions on failed cell towers (see Figure 3.3 (e), aggregated at county level); most county predictions lie well within a 50% margin of error, even though the impact severity is overestimated in hurricane-hit counties located further inland.

Documented incidents related to the loss of service access and infrastructure damages, such as hospital evacuations, structural damages and fatalities due to untimely care in the case of healthcare access, all lie within the modelled area of concern (Figure 3.3). Yet, road damages and mobility-related incidents were reported far less inland than model predictions (Figure 3.3 (a)), a tendency which is less pronounced, yet shared for access to healthcare and education (Figure 3.3 (c, d)), and most drastic for evidence on drinking water issues (Figure 3.3 (f)). The divergence in projected and actual disruptions to mobility confirms the importance of choosing adequate impact functions, as pointed out also in the section on scenario analysis. The road impact function used in this study was designed for disruptions from tree blow-down, which may have provided an overly pessimistic picture on (longer-lasting) structural damages.

Validation results for mobile communications, healthcare and education access highlight the importance of incorporating dependencies and failure cascade into the model, yet also show caveats of adequate parametrization: The relatively accurate projection of people affected by cell site outages could not have been reproduced without power interdependencies, as the scenario analysis showed above. Similarly, several hospitals which were not directly damaged reported evacuations due to water and power supply issues, while many of the indirect deaths were linked to either patients or emergency workers not getting physical access to healthcare facilities in time. This confirms the general validity of incorporating such CI dependencies into infrastructure functionality calculations, and the importance of people's road path availability into bespoke service access computations. Such dependency specifications can, however, also propagate errors and over-estimate disruptions, as seen with access to education: The estimated 45'000 students reported to be missing school due to closures [1] fall short of the approximately 145'000[2] projected by the model. This is partly due to the non-redundancy between end-users and educational facilities: Contrary to hospitals, where any facility within reach can be chosen, people are assigned to one fixed school. When damages to such facilities or their supporting CIs are hence over-estimated, this will transmit directly to over-estimations of education access disruptions throughout the entire assignment surroundings.

Lastly, the case of water access disruptions demonstrates that a high degree of system simplification can become problematic: In absence of better data, the drinking water system was proxied by water treatment plants only. As a consequence, the model projected large areas of disruption from a single failing facility, which seems not to be the behaviour observed in those real-world water systems. Similarly, caution should be taken when approximating the telecommunications network - consisting in more and more resilient sub-networks than mobile communication structures only - through cell towers.

Despite the fact that some service disruptions were less extensive than modelled, the integration of a hazard model and a CI model based on relatively simple dependency heuristics and readily available open-source data allowed to capture important failure dynamics within one interoperable calculation chain. The model reproduces impacts in the correct order of magnitude, allows to trace back impact drivers to parametrization decisions in each stage of the impact cascade, and to re-calibrate mechanisms. It further

[2] number of affected population corrected by by fraction of people enrolled in preK-12 (13.4%)

gives a social dimension to technical CI failures, mapping out areas of disruption for basic services which are not consistently monitored by official sources. While those are promising features, there is demand for an even more refined picture, as remarked by a reporter in the aftermath of TC Michael: “While the coastal devastation has become obvious, some disaster experts are most concerned about the conditions farther inland. […] These are some of the most socially vulnerable places in the entire country, low-income counties with high proportions of older adults, and many people with disabilities and chronic illnesses” [64].

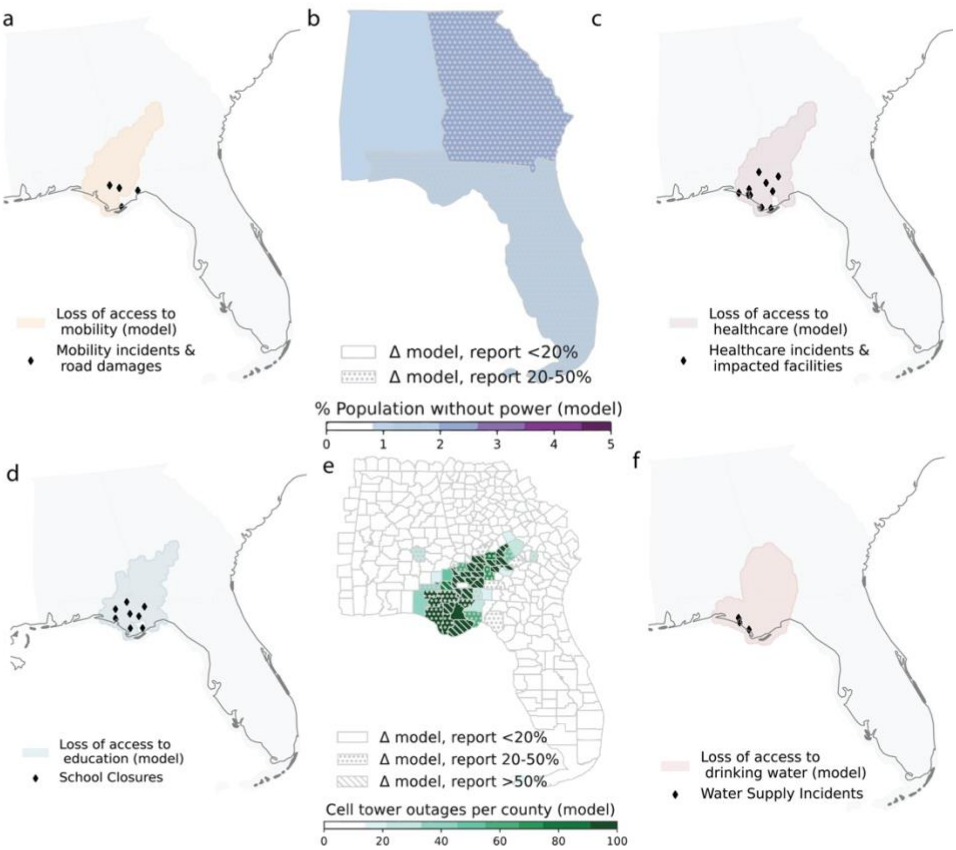

Figure 3.3 Validation results for power outages (a), cell site outages (b), water supply issues (c), healthcare-access related incidents and hospital damages (d), road blockages, structural damages and mobility incidents (e) and school closures (f).

4. Discussion

The developed modelling framework was designed for interoperability, transferability and scale. Interoperability is achieved though the embedding of an infrastructure system model into the risk assessment platform CLIMADA, allowing for a streamlined workflow from natural hazards to social impacts. The linkage to an event-based hazard simulation engine is a way forward from the use of stylized polygons in absence of physically-informed hazard footprints [23], [65], hypothetical events [22] or return period maps which are not representative of individual events [66]. Transferability is ensured both theoretically and practically: While we provide readily available suggestions on infrastructure and population data sources, dependency heuristics, impact functions and hazard models, the framework can handle both proprietary and/or other open-source data (e.g. regional or national-level developed data). This allows to investigate other infrastructure types, hazards, dependencies and case study regions of interest to the user: For instance, vulnerability functions may be altered to capture the important effect of deterioration through ageing of infrastructures [67], or dependencies re-parametrized with different distance thresholds to account for locally specific cell tower ranges [68] or travel speeds [69]. The scale criterion is integrated in the design of the infrastructure system model, which requires few technical specifications, and relies mainly on network topology and a set of heuristics for dependency and flow assignment procedures, enabling the study of large systems.

The results simulated must be interpreted as a first indicator on impact hotspots and peak disruptions from the angle of people at risk. The simplifying nature of network-based approaches has been recognized earlier as a necessary trade-off against capturing large system scales at which natural hazards can occur [18], [22]. The merit of the developed system model's approach therefore lies in the possibility of working at a globally consistent basis with several interdependent CI systems, yet does not replace specialized system models [31], [48], [49], [70] for detailed local analyses and individual infrastructure system optimizations.

The three information levels on infrastructure risk which the model provides (structural component damages, failure cascades, and service disruptions), align well with the highly diverse nature of real-world impact data, which is often anecdotal and encompasses several of those risk layers. This offers the versatility to calibrate and adjust parameters in the model based on evidence, such as tailoring impact functions to match print media coverage on structural damages, or amending dependency heuristics to fit utility provider's outage reports. To the best of our knowledge, only few quantitative modelling studies [71] incorporate such feedback possibility. Obtaining results on direct and cascading infrastructure failures further allows to quantify the role of infrastructure dependencies in causing wide-spread impacts: Validation in the presented case study empirically confirmed that the extent of observed impacts could not be reproduced without the inclusion of dependencies between infrastructure networks, which is in line with findings from other research on infrastructure interdependencies [72], [73].

The scenario analysis highlighted that structural damage functions and dependency parametrizations are sources of considerable uncertainties in the model. How to capture the diverse nature of interdependencies, which adequately accounts for the varying 'coupling strengths' [13], [27] between CI networks observed in reality, is a topic of ongoing research. The presented use of capacities, capacity thresholds, redundancies and road-path availability checks in the parametrization of infrastructure dependencies (annex A) is a pragmatic compromise between elaborate mathematical frameworks with many conditionalities (for instance [74]) and implementation feasibility for large networks with limited process knowledge and data availability. We refine commonly employed user-assignment procedures relying purely on geospatial conditions (e.g. Voronoi tessellations) or on shortest path algorithms without alternative targets [32], [43], [75]. Yet, modelling of back-ups for failing dependencies (such as generator availability for power-dependent components [71]), changing demand patterns for infrastructure-related services among end-users as a reaction to natural hazard occurrences [76], [77] or the reduction in functionality as opposed to binary failures [74] upon dependency disruptions may improve currently implemented cascading dynamics. Furthermore, the threshold approach employed to relate structural damages to loss of component functionality is a simplification for the notoriously challenging task of developing consistent performance indicators [27], [78], for which research in the engineering community may lead to future insights.

Our approach does not feature an explicit notion of time. Since the modelled structural damages to infrastructures need to surpass a certain threshold for the components to become dysfunctional, this implies that the model captures rather longer-lasting disruptions. Yet, since impact severity is a function of time and timing [79], making it an explicit variable can be insightful: While for healthcare access a few hours of disruptions in the immediate aftermath of a natural hazard event may be extremely relevant, they may be less so for access to schools, especially if occurring on a weekend. Introducing time could further provide an informative indication on restoration and recovery dynamics [80], [81] when introducing repair times and 'snapshots' of the interdependent CI network at various moments, and capture oscillating or non-convergent functional behaviours which interdependent systems can exhibit.

Lastly, our estimates of post-disaster basic service disruptions add an often-neglected human-centric dimension to the discourse on infrastructure risks [82], which both academic models, utility providers or government post-disaster reports do not usually capture systematically (cf. [41] as a rare exception); the holistic approach further allows to include under-represented sectors in CI research such as healthcare [42] and education. This can offer valuable information to emergency responders with limited resources, and decision makers facing multi-criteria investment decisions alike [41], [82], [83]. However, and especially as research on social vulnerability is still in its infancy [39], it will be important to take a closer look at the differential impacts of basic service losses on different parts of the population, such as the poor, the elderly or non-native speakers, which have repeatedly been shown to dispose of fewer coping mechanisms [14], [84].

5. Conclusion

Critical infrastructures such as powerlines, roads, telecommunication and healthcare systems across the globe are more exposed than ever to the risks of extreme weather events in a changing climate. CI failure models often operate at local scales with high data requirements and low transferability, focussing on the technical performance side. Natural hazards are often not explicitly modelled as a disruptive scenario therein. Natural hazard models, in turn, frequently focus on direct damages to assets, which neglect the networked and interdependent character inherent to critical infrastructure systems.

To bridge those gaps between infrastructure modellers and natural hazard risk modellers, we draw on well-established methods in both communities to develop an interoperable, coherent and open-source modelling framework for assessing spatially explicit, large-scale risks from infrastructure failure cascades and their social impacts induced by natural hazards. Embedded into the risk assessment platform CLIMADA, a state-of-the-art tool for natural hazard impact calculations and adaptation options appraisal, we demonstrate a network theory-based infrastructure systems model designed to require few technical details apart from commonly available asset location and population data, which can handle many types of infrastructure networks and captures interdependencies among them based on a set of heuristics. The framework hence offers a three-layered view on infrastructure risks in terms of on infrastructure component damages, technical failure cascades, and human-centric basic service disruptions. It is readily transferrable across geographies, and can be tailored to include CI systems, interdependencies and hazards of interest to the user.

The validated case study on Hurricane Michael across the US states of Florida, Georgia and Alabama for six interdependent CI networks showed that the established modelling chain captures impact hotspots and reproduces failure cascade dynamics, which could not be obtained when looking at structural infrastructure damages alone. It also showed how real-world impact data, such as outage reports and print-media accounts, can be used to iteratively refine and calibrate the model.

Projecting spatially explicit locations of service disruptions experienced by the dependent population as a result of infrastructure failures further adds a novel layer of risk information, which is usually not available on the ground.

While we do not offer the one single "comprehensive methodological approach with a platform of linked models and data interoperability for modelling infrastructure interdependencies for a range of different stakeholder concerns and decision contexts" [82] our approach takes a step into this direction. We provide a tool apt for decision making-contexts involving large geographic scope and the effects of several interdependent CI systems' responses to disruptions for the population: The global consistency of the approach permits a comparative view of risk across countries, relevant for international policy frameworks; adaptation planning and infrastructure investments for resilience can be evaluated under their aversion potential for different types of human-centric impacts and under trade-offs amongst different CI sectors; post-disaster hotspot analyses can lead to more targeted humanitarian relief and recovery activities.

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Data Availability

CLIMADA risk assessment platform is accessible on GitHub (https://github.com/CLIMADA-project/climada_python for impact calculations, https://github.com/CLIMADA-project/climada_petals for the infrastructure system model). Code for reproducing case study results and figures is accessible under https://github.com/CLIMADA-project/climada_papers/tree/main/202208_critical_infrastructure_nw_risks. All raw data sources needed for reproducing calculations are mentioned in the text and annex.

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Annex

A. Formal treatment of the developed modelling chain

G^j	graph of CI network j
n_i^j	i[th] node in G^j
e_{mn}^j	directed edge from n_m^j to n_n^j
G	interdependent CI graph, spanning all graphs G^j, G^k, ... of investigated CI networks and all e^{jk}
e_{mn}^{jk}	directed dependency edge from n_m^j to n_n^k
G'^j	subgraph of G spanning all elements of G^j
G'^{jk}	subgraph of G, spanning all elements G^j, G^k and e^{jk}
A^{jk}	adjacency matrix of G'^{jk}
L_i	geo-spatial location of graph element i (node and edge attribute)
F_i	functional state of graph element i (node and edge attribute)
I_i	structural damage ('impact') of graph element i (node and edge attribute)
E_i	exposure value of graph element i (node and edge attribute)
D_i	damage threshold of graph element i (node and edge attribute)
C_i^{jk}	capacity for node i for type of flow passing between CI types j and k (node attribute)
T_i^{jk}	capacity threshold for node i for type of flow passing between CI types j and k (node attribute)
M_i^{jk}	capacity supply at node i for type of flow passing between CI types j and k (node attribute)
S_i^j	service supply at node i for type of flow delivered by CI type j (node attribute)
$H(L)$	hazard intensity at geographic location L
$V(H)$	hazard intensity-dependent vulnerability curve

Initialization

0. $\forall\, j$ create G^j with n^j(nodes-only) or n^j, e^j (nodes and edges) and set attributes $L,\ F,\ D,\ E,\ X$
   L: geo-location in latitude and longitude; specific to each n_i^j, e_i^j
   F: functional state ({0, 1}). Set to 1 $\forall\, n^j,\ e^j \in G^j$
   D: fraction (]0, 1]) of structural damage I beyond which $F \to 0$; specific to n^j, e^j
   E: value of the physical network element - set to 1 $\forall\, n^j,\ e^j \in G^j$
   X: further attributes specific to n^j and/or e^j
1. Create interdependent CI graph $G = \sum_j G^j$
   $\forall$ combinations of (jk) in list of identified CI dependencies:
   Create e_{mn}^{jk} between n_m^j and n_n^k if linking conditions (distance, redundancy criterion, etc.) fulfilled
   Assign node attributes $C^{jk}, T^{jk}\ \forall\ n \in G$:
   $$C_i^{jk}: \begin{cases} -1 \text{ if } n_i^j \\ 1 \text{ if } n_i^k \\ 0 \text{ else} \end{cases},\ T_i^{jk}: \begin{cases} [0{,}1]\ n_i^k \\ 0 \text{ else} \end{cases}$$

Flow Assignment & Functional State Update

2. $\forall\, j$ where $G^j \ni\ n^j, e^j$: extract G'^j from G.
   Perform internal flow calculations according to adequate algorithm.
   Update $C^{jk},\ F\ \ \forall n^j$ in G, where required.
3. $\forall$ combinations of (jk) where $k \neq {'people'}$, extract G'^{jk} from G; update $F\ \forall\, n^k$:
   $M^{jk} =\ \left(F \cdot C^{jk}\right)^T * A^{jk};\ F = \min\left(F,\ M^{jk} \geq T^{jk}\right)$
4. Repeat 2. and 3. until $\Delta F = 0$

Basic Service Access Determination

5. $\forall$ combinations of $(j, people)$, extract $G'^{j,people}$ from G. Assign attribute S^j to n^{people}:
   $M^{j,people} = \left(F \cdot C^{j,people}\right)^T * A^{j,people}$
   $S^j = \left(M^{j,people}\ \geq T^{j,people}\right)$

Natural Hazard Impact Calculation & Functionality State Update

6. Assign structural damage attribute $I\ \forall\, n, e \in G$:
   $I = H(L) * V(H) * E$
7. Update $F\ \forall\, n, e \in G$:
   $F =\ \min\left(F, I \leq D\right)$

Cascade & Functional State Updates

8. Update $C^{jk},\ F\ \ \forall\, n, e\ \forall(jk, k \neq people)$ in G according to 2. - 4.

Basic Service Access Update

9. If road access is a linking condition for dependency combination $(j, people)$:
   Re-check path existence and length of path between $n^j, n^{people}\ \forall\ e^{j,people}$; else delete $e^{j,people}$ from G
10. Update $S^j\ \forall\ n^{people}$, $\forall\ (j, people)$; see step 5.

B. Modelling Choices for CI Networks

Table B.1 CI networks and their components, in edges (E) and nodes (N). First column suggests a simple sub-selection of network components to represent the systems in a standardized low-complexity setting, second column proposes additional components if data is available.

CI system	Simplified representation	Extension possibilities
Road	N: intersections E: streets	N: tunnels, bridges E: -
Electric Power	N: power generation plants E: transmission lines	N: transmission & distribution substations, power poles E: low-voltage distribution lines
Telecommunication	N: cell towers E: -	N: internet exchange points, data centres, central offices, base stations, poles E: landlines, fibre-optic cables, submarine transmission lines
Wastewater & Water Supply	N: water treatment plants E: -	N: wells, reservoirs, tanks, cisterns, pumps, water bodies E: water pipelines, water tunnels, rivers
Healthcare & Emergency Services	N: hospitals, clinics E: -	N: doctors' practices, dentists, pharmacies, nursing homes
Educational Facilities	N: schools E:	N: universities, childcare centres, kindergartens
End-users	N: people clusters E: -	

C. Case Study

C.1. Infrastructure System Model Inputs

C.1.1 Infrastructure Component Data

*Table C.1 Geo-coded infrastructure asset data used in the case study, section 3. *) HIFLD: Homeland Infrastructure Foundation-Level Data*

Infrastructure	Source	Data description, Pre-processing
Roads	OpenStreetMap	*Data*: Retrieved from data dump at geofabrik.de for states FL, AL, GA matching tags highway= (motorway | motorway_link | trunk | trunk_link | primary| primary_link) using the OpenStreetMap module in CLIMADA. *Pre-processing*: Line merging, roundabout cleaning, duplicate removal, linking unconnected cluster
Hospitals	HIFLD*: Hospitals	*Data:* All amenities in states FL, AL, GA incl. 20kms buffer around outer borders *Pre-processing*: -
Power lines	HIFLD: Electric Power Transmission Lines	*Data:* All lines in in states FL, AL, G *Pre-processing*: Line merging, duplicate removal, linking unconnected cluster
Power plants	HIFLD: Power Plants	*Data:* All amenities in states FL, AL, GA incl. 20 km buffer around outer borders *Pre-processing*: -
Educational facilities	HIFLD: Public Schools	*Data:* All amenities in states FL, AL, GA incl. 20 km buffer around outer borders *Pre-processing*: -
Cell towers	HIFLD: Cellular Towers	*Data:* All amenities in states FL, AL, GA incl. 20 km buffer around outer borders *Pre-processing*: -
Wastewater	HIFLD: Wastewater Treatment Plants	*Data:* All amenities in states FL, AL, GA incl. 20 km buffer around outer borders *Pre-processing*: -
People	WorldPop Gridded Population Count	*Data:* United States of America, 1km UN-adjusted, 2020. *Pre-processing*: Re-gridded raster data on population counts to resolution of 10 km x10 km, vectorized, cropped at outer borders of states FL, AL, GA

C.1.2 Power Supply & Demand Data

Table C.2 Population data, energy supply and demand data used for case study in section 3.

Variable	Source	Data description
Supply	HIFLD: Power Plants	Same data source as for geo-location data of power plants in the region of interest. Electric energy supply taken from power plants net annual generation, given in column *NET_GEN.*
Demand	International Energy Agency (IEA) World Energy Balances	Total electric energy consumption for entire USA, all sectors, 2019.

Calculation of electric power demand per people cluster (cf. Table C.1): Total electric energy consumption / total US-population * population count of cluster

Calculation of electric power supply per power plant (cf. Table C.1): Directly taken from data source.

Supply / demand balancing in undisrupted state: Addition of an import/export element to the power plant data frame with supply amounting to difference between total power plants supply in region of interest and total energy consumption in region of interest.

C.1.3 Dependencies

Table C.3 Dependencies identified between CI networks (#1-#6) and between CI networks and end-users (#7-#12). Dependency parametrizations are used to link individual CI graphs and population graph into one interdependent CI graph. Decisions for certain parameter settings are discussed in the paragraph below.

Dep	Source	Target	Redun-dancy	Road access	Dep. type	Flow type	Func. Thresh	Dist. Thresh. [m]
1	power line	celltower	TRUE	FALSE	functional	physical	0.6	
2	power line	education	TRUE	FALSE	functional	physical	0.6	
3	wastewater	education	TRUE	FALSE	functional	logical	1	
4	power line	health	TRUE	FALSE	functional	physical	0.6	
5	wastewater	health	TRUE	FALSE	functional	logical	1	
6	power line	wastewater	TRUE	FALSE	functional	physical	0.6	
7	celltower	people	FALSE	FALSE	end user	logical	1	30000
8	education	people	TRUE	TRUE	end user	logical	1	40000
9	health	people	FALSE	TRUE	end user	logical	1	100000
10	power line	people	TRUE	FALSE	end user	physical	0.6	
11	road	people	FALSE	FALSE	end user	logical	1	30000
12	wastewater	people	TRUE	FALSE	end user	logical	1	

Selection of distance thresholds: A combination of sophisticated guess (such as 30 km being a generous diameter for cell tower reach [68] or hospitals being at most 100 km from persons, which equals a travel time of little more than the "golden hour" crucial in medical emergencies, when considering average travel speeds on a highway [69]), and iterative refinements such that service access levels in stage IV were >99% for all basic services across the area of investigation in a base state simulation with undamaged CIs. For instance, setting cell tower ranges to 15 km would have resulted in 6.7 M customers without mobile communication access in the base state, whereas the hence chosen range (30 km) resulted in only a few hundred persons without coverage. For dependencies where no distance thresholds are set, target elements are linked to the closest element of the respective source type, irrespective of its distance. This is the case for all non-redundant dependencies where it is obvious that such a link must exist (e.g. educational and healthcare facilities having power and water access).

Selection of redundancy specification: Water and power are modelled to be supplied through a single source per dependent target. Mobile communication is modelled to be provided from any source within distance thresholds, as connectivity can be established through any reachable cell site. Healthcare can be provided from any reachable healthcare facility, but school enrolments are usually fixed, hence each population clusters dispose of only one non-substitutable education link. Road access is assumed to be provided by any reachable road within the given distance threshold.

Selection of flow types and functionality thresholds: Physical variables for power demand and supply across the modelled area were available and capacity in the network is hence calculated as the ratio of power demand to power supply in each network cluster. Functionality thresholds for power dependencies could therefore be expressed as a continuous fraction with regard to the capacity ratio. It was set here to 0.6 in absence of any component-specific information, to interpreted as "if demand-to-supply ratio in the power network cluster to which the dependent component is linked, drops below 0.6, the component will turn dysfunctional". All other dependencies are, in absence of physically informed flow metrics, logical dependencies. As such, they either provide supply from a functional source, or they do not, if the source is dysfunctional. Functionality thresholds for logical dependencies are hence trivial and set to 1. Road paths between population nodes and social facilities (hospitals, schools) were computed based on a Dijkstra's shortest path algorithm.

C.1.4 Infrastructure Interdependent CI Graph Specifications

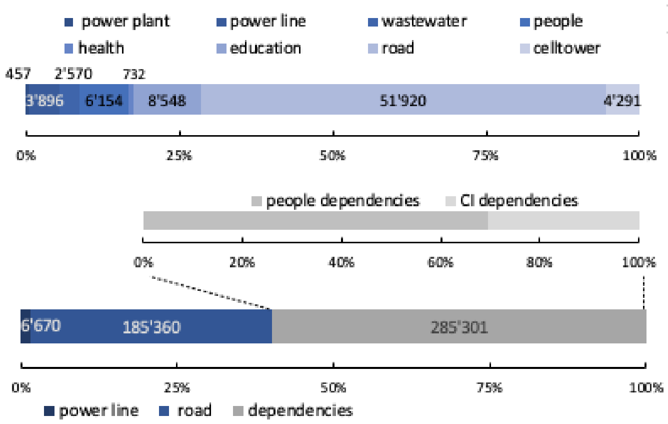

Figure C.1 Specifications of node (1st bar plot) and edge elements (2nd bar plot) in the interdependent CI graph, constructed for the case presented in section 3.1.

C.2. Natural Hazard Risk Model Inputs

C.2.1 Hazard Footprint

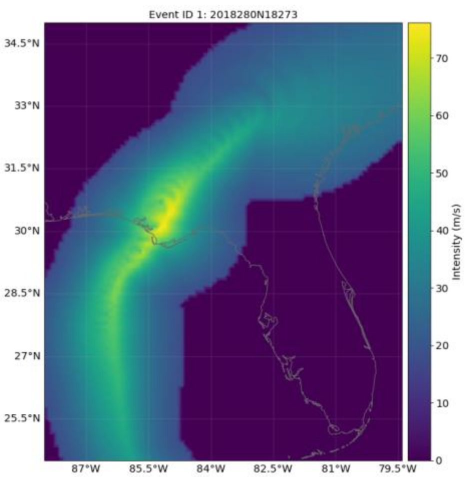

Figure C.2 Map of Hurricane Michael wind-field intensity, computed with CLIMADA from Michael's hurricane track. Track data from IBTrACS, implemented wind field algorithm from [85].

C.2.2 Vulnerability Curves

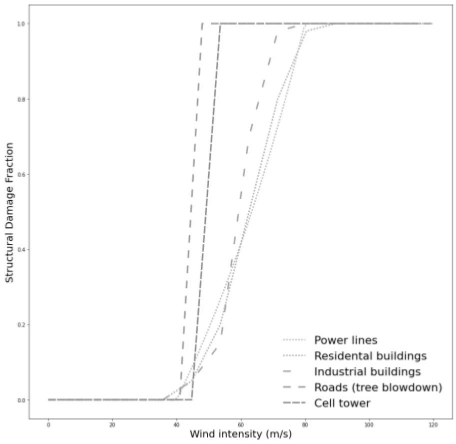

Figure C.3 Impact functions used for structural damage calculations from hurricane wind field in section 3.1, for all CI types. Note that y-axis represents fraction of structural damage to components for all CIs except power lines, for which it is failure probability. Sources: power lines in [58], residential building and industrial building (both for z=0.35) in [87], roads in [8], cell towers: step function taken from interview with cell tower provider stating they are "built to withstand winds of up to 110 miles per hour".

C.3. Scenario Analysis

C.3.1 Scenario Selection and Results Overview

Table C.4 Scenarios to study the sensitivity of end results (number of people experiencing basic service disruptions) to assumptions throughout the modelling chain. For parameterizations details, see supplementary material.

Scenario	Description	Stage
No CI inter-dependencies	Removing any functional dependencies between CI networks.	I
Longer path threshold	Increasing allowed distance thresholds for end-user travel paths	I / IV
Shorter path threshold	Decreasing allowed distance thresholds for end-user travel paths	I / IV
Low component vulnerability	Shifting impact functions to withstand higher hazard intensities.	II
High component vulnerability	Shifting impact functions to withstand lower hazard intensities.	II
Low functionality threshold	Decreasing damage thresholds for component dysfunctionality.	II
High functionality threshold	Increasing damage thresholds for component dysfunctionality.	II

Table C.5 Results of scenario analysis: Amount of people experiencing service disruptions in each scenario due to hazard-induced failure cascades, relative to disruption numbers in the originally chosen parametrization as described in section 3.1. The 7 selected scenarios are described in Table C.4 and discussed in section 0. Parametrizations of the scenarios are listed in the supplementary material.

Access to Basic Service	original	No CI Inter-dep.	Longer path thresh.	Shorter path thresh.	Low vulner-arbility	High vulner-ability	Low funct. thresh.	High funct. thresh.
Mobility	100	100	100	100	205	42	116	81
Power	100	88	95	90	238	37	96	66
Healthcare	100	48	97	142	196	48	115	80
Education	100	72	100	121	236	45	106	87
Mobile Comms.	100	57	95	96	236	30	92	61
Water Supply	100	45	100	103	232	24	100	100

C.3.2 Scenario Parametrizations

See Supplementary Material.

C.4. Validation Sources

See Supplementary Material.