Data for Critical Infrastructure Network Modelling of Natural Hazard Impacts: Needs and Influence on Model Characteristics

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Abstract

Natural hazards impact the interdependent infrastructure networks that keep modern society functional. While a variety of critical infrastructure network (CIN) modelling approaches are available to represent CI networks on different scales and analyse the impacts of natural hazards, a recurring challenge for all modelling approaches is the availability and accessibility of sufficiently high-quality input and validation data. The resulting data gaps often require modellers to make assumptions for specific technical parameters, functional relationships, and system behaviours. In other cases, expert knowledge from one sector is extrapolated to other sectoral structures or even cross-sectorally applied to fill data gaps. The uncertainties that these assumptions and extrapolations introduce and their influence on the quality of the modelling outcomes are often poorly understood and are difficult to capture. Additionally, the ways of overcoming the data availability challenges in CIN modelling, with respect to each modelling purpose, remain an open question. To address this challenge, a generic modelling workflow is devised featuring six modelling stages commonly encountered in CIN models. The data requirements of each stage are systematically defined, and literature on potential sources is reviewed to enhance data collection and raise awareness of the issue. The workflow represents model generation and validation as well as natural hazard impact assessment, recovery, and mitigation. The application of the proposed workflow and the assessment of data availability challenges are showcased in three case studies, taking into account their different modelling purposes. From this, a generalised reflection on the relation between data availability, model purposes, model performance, and aptness of the approach is derived. Finally, a discussion on overcoming the challenges of data scarcity, including the use of participatory methods, anonymised data-sharing platforms for CI operators, and event-based impact datasets, is presented.

Keywords: critical infrastructure networks, impact modelling, data availability, natural hazards

1 Introduction

Critical infrastructures (CIs) are responsible for the supply of essential services and goods. They are organised in sectors which have intra- and inter-sectoral dependencies. Owing to such dependencies within (intra-sectoral) and across (intersectoral) components of different critical infrastructure sectors, critical infrastructure networks (CINs) are formed. Disruptions in one sector can lead to impacts in other sectors and cause chain effects [1, 2]. The role of CIs in society's safety and security is receiving increasing acknowledgement due to an increasing number of threats such as extreme natural events, military conflicts, global pandemics, and cyberattacks.

The purposes that CIs serve are versatile, and societies' reliance on them is not easily conceived due to complex arrangements and dependencies between CI sectors. This especially applies to densely populated urban environments which sustain themselves due to an equally dense CIN. One way to capture CIs' supply of essential services and goods is by utilising models. Invariably, representing the multifaceted purposes of CIs results in similarly multifaceted modelling approaches, on which comprehensive overviews can be found in the literature [1, 3, 4]. Such CIN models may analyse direct disruptions caused, for instance, by natural hazards, as well as indirect disruptions caused by cascading effects transmitted through dependencies [5]. In addition to the analysis of disruptions, CIN models are used to develop and quantify measures for every step of the disaster risk reduction cycle [6 – 8].

Invariably, CIN modelling approaches rely on a range of data and information inputs. Data acquisition for modelling inputs poses a challenge, which was also identified by the United Nations [9]. The challenge of gathering input data may limit the potential utility of CIN modelling techniques in contributing to the evaluation and management of resilience in urban environments facing natural hazards. There are several reasons for the lack of availability or accessibility of this data, such as the data protection of CI users, data confidentiality of CI operators, sensitivity of CI and their essential services during conflicts, or unawareness of the benefits and data needs of CIN models. Despite the challenges in data and information availability and accessibility, CIN modelling approaches are becoming a popular tool for capturing larger-scale interdependent infrastructures, disruption, and cascading effects. Lack of data and information is often complemented by assumptions in all stages and data types of the modelling process, which may affect the quality of the output and thus the reliability of the decision made based on the CIN model outputs. The first component of a solution is to bridge the gap between missing data and information. Categorisation of the data types needed for CIN models is the fundamental step required for filling the gap. [10] and [11] outlined the need for data and methods to support empirical and predictive assessments of CI resilience. However, currently very few systematic reviews are available on the types of data needed. Second, a discussion about the implications of data availability and accessibility on model characteristics is needed. Model characteristics are further defined as the capabilities, attributes, and reliability of CIN modelling approaches and their output. Discussions on the impacts of data scarcity on models in general are given in [12]. Very few discussions have focused on how those assumptions are made to overcome data scarcity and how they affect the quality and aptness of CIN model characteristics to make actual judgements. These exchanges may lead to more thorough data acquisition practices, enable dialog with potential data providers, and lead to a better assessment of CIN model results.

The presented work provides a categorisation and explanation of data input types for a more systematic way of thinking about data needs and assumption implications. For each data input type, a definition is given as well as literature references to existing data sets if available or approaches in need of this data type. The categorisation is based on individual stages within the CIN modelling workflow. The presented work is delimited in two important dimensions: the purpose that CIN models fulfil is to define the specific needs for data. As an example, the vulnerability of CIN to cyber-attacks and the identification of maintenance needs of infrastructure requires different information and data. In the present work, the scope is limited to only considering extreme natural events as impacts to CIN in order to explore the intricacies involved, but the defined methodology is generally applicable. The various techniques to derive the features of natural hazards, such as numerical modelling, data-driven, or empirical methods, are not outlined in this work because the focus is on the impact of extreme natural events on the exposed CIN. Another limitation is the explicit focus on CIN modelling approaches conventionally termed "network-based approaches" [3] or "graph-based modelling approaches" for gathering data needs. The represented modelling approaches are further referred to as CIN modelling approaches. These approaches have sub-categories, such as flow-based network models, which treat the flow of commodities through the CIN as the driving characteristics. Another sub-category which is also included in this work are topology-based network modelling approaches, which concentrate on the functionality of CI assets based on topological attributes of the network as defining characteristics. Other sub-categories for CIN modelling approaches, such as agent-based or system-dynamics-based approaches, must be mentioned in this context but are not considered explicitly further on due to their more specific data needs.

In the introduction chapter, the background and motivation of this work were outlined, and a short review of the literature was presented. The main purpose of this paper is to provide an overview of data needs for CIN modelling. Therefore, a generalised modelling approach is defined and elaborated in stages. Based on every stage, the required input data types are categorised, and the literature is presented for each data type. It is not intended to represent a risk management framework, but only to concentrate on the modelling workflow and risk analysis. Subsequently, arguments are collected on why the data is important for CIN modelling techniques: Three case studies are introduced with a focus on one missing input dataset per category, the assumptions that are necessary due to the missing data, and the resulting effects on the model characteristics. The present work is then discussed and concluded (cf. Sections 4 and 5).

CIN Modelling Stages & Data

2.1 A Generalised CIN Modelling Process in Stages

As previously mentioned, a wide range of data needs may be encountered throughout different CIN modelling approaches. To capture these in a systematic manner, a broadly formulated and generic multi-stage modelling process is defined, inspired by work stages frequently encountered in studies on CIN network modelling [1, 3, 7]. Each stage forms a category which is examined separately for their data needs (cf. section 2.2). It is noted that this categorisation is not exhaustive but serves as a starting point for the development of CIN modelling studies. Figure 1 shows these six stages as well as the two overarching stances. The *definition of the model purpose* drives every single stage at the beginning of the modelling assignment and is not necessarily driven by data but drives the data need. The stage of *validation, calibration, and plausibility evaluation* overarches the entire process as well since it can be applied to all modelling stages as well. Validation and model purpose thus have a distinctive role in the graphical representation of Figure 1, pointing to every other modelling stage. Additionally, Figure 1 shows that a model can be compiled by only following the stages until the stage of *impacts of natural hazards*; the two stages hereafter are only optional. This is indicated by an additional arrow branching from the path indicated by the arrows.

Models are, by definition, a simplified representation of nature or systems. Thus, the first stage of the modelling is outlining the model purpose, which is defined by the intention that applies to CIN modelling efforts. Rather than requiring much data per se, the purpose of each study focuses on the choice of modelling approach and, consequently, data requirements. The purpose frames expectations on the usability and types of results which the model should eventually provide (for instance, decision support for strategic planning, information for disaster management, creation of knowledge, awareness building) and specifies users and target groups (such as academic researchers, utility providers, regulators, etc.). Overall, the model purpose is to determine other model characteristics, such as system boundaries, potential output, and the target group. An in-depth discussion on

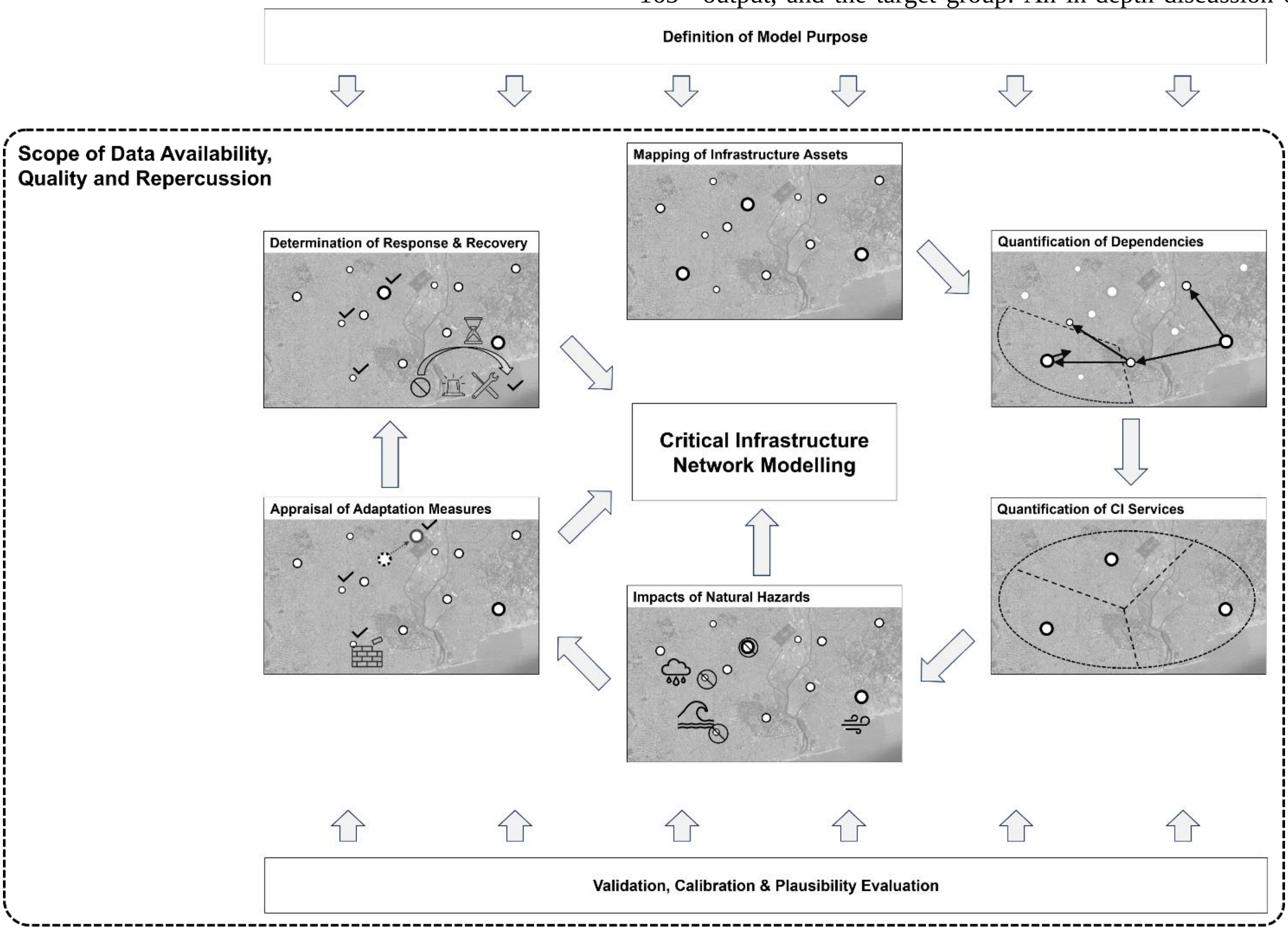

Figure 1: Generalised stages of critical infrastructure network modelling for hazard assessments including overarching stances of model purpose and validation.

the relation between model purpose, data needs, data availability, and model characteristics is given in Section 3.

The next stage is defined as the *mapping of infrastructure assets*. The intention of this stage is to set up a network representation of the CI under study, considering their topological characteristics. This includes the transformation of information on physical infrastructure components into network elements, such as nodes and links or vertices and edges. Nodes represent individual entities, and links represent the dependencies between those entities.

Consecutive to asset mapping is the *quantification of dependencies*. In this stage, dependencies within CIN (intra-sectoral) and between different infrastructure networks (inter-sectoral) are identified, quantified, and included as explicit network model elements.

The next step is the *quantification of CI services* for the assembled network. The objective of this stage is to obtain a quantifiable extent of the service levels provided by the CIs under study, including information on the service area, recipients of the services, and demand patterns for these services.

In the stage of *impacts of natural hazards*, the exposure of infrastructure assets to natural hazards and their consequences are considered. Knowledge is needed on the area and type of natural hazards causing structural damage, as well as on the impact-functionality relationships linking infrastructure damage to their ability to provide their services.

The subsequent stage involved the *appraisal of adaptation measures*. The target of this stage is to evaluate the effect of measures (designed for adaptation, mitigation, or other purposes) implemented at any potential level of the system under study (i.e. infrastructure network components, dependencies, network structure, etc.) on a specified target metric.

Approximating the steps of the disaster risk reduction cycle, is done in the following stage *determination of response and recovery*. The objective of this stage is to analyse the post-disruption behaviour of the modelled system and its trajectory until it reaches a certain performance state (such as pre-disaster service levels or a new status quo). Not considering the response and recovery will lead to an inaccurate representation of disruptions and, ultimately, an incomplete representation of CINs under the impact of natural extreme events.

The final stage is the *validation, calibration, and plausibility evaluation* stage of the individual stages before and refers to the examination of the system behaviour with sufficient accuracy. The stage can consist of the calibration of input parameters, checking for plausibility, or the verification of input and output data [13, 14]. Several model validation approaches exist [15, 16] that entail different data requirements. Usually, this is performed by comparing field or experimental data to the model output, referring to the same (or a sufficiently similar) scenario. Finally, it must be noted that model validation should also be carried out according to the purpose of the model rather than aiming to achieve a perfect representation of the studied systems.

2.2 Data Needs Derived from CIN Modelling Process Stages

Grounded in the stages of the generalised modelling process defined in Section 2.1, an in-depth literature review is conducted to collect frequently occurring data needs, types, and, if available, potential data sources. These data types are introduced for every modelling stage, as shown in Figure 2. Every icon indicates a type of data and information that can be relevant for CIN modelling.

2.2.1. Mapping of Infrastructure Assets

Spatially explicit modelling studies start out with a need for geospatial information on CI component locations as point elements and occasionally as polygons describing infrastructure extent as well. Depending on the spatial scale and geographical region of interest,

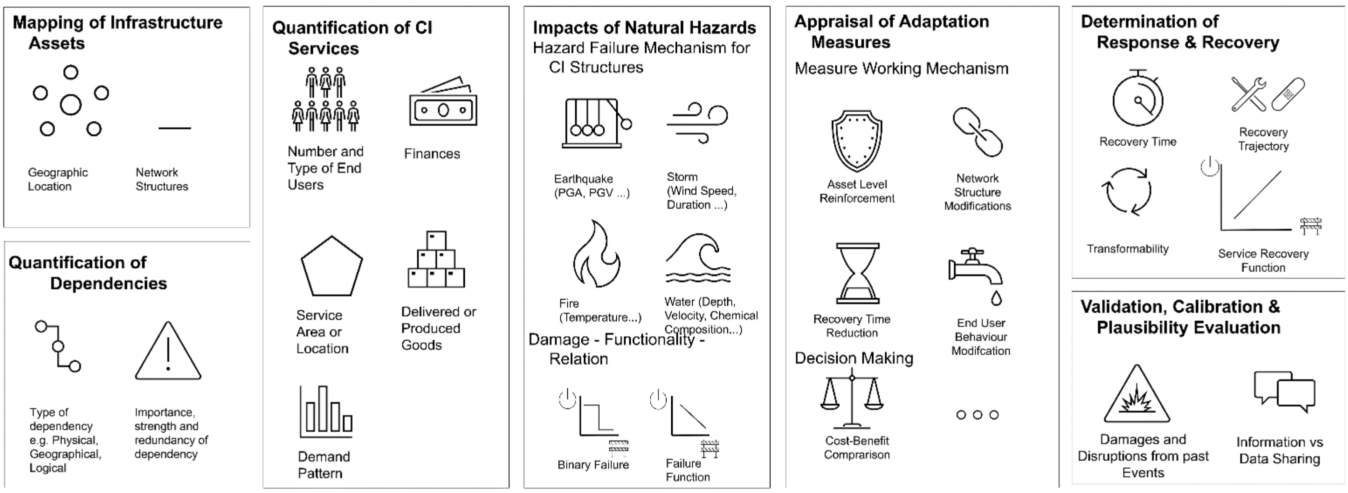

Figure 2: Data types for critical infrastructure network hazard modelling categorised by modelling stages.

availability of such information is highly varied; infrastructure location data may be readily accessible, curated, and openly provided through official (e.g. governmental) sources, as by the *Homeland Infrastructure Foundation-Level Open Data* of the U.S. Department of Homeland Security [17] or by the *Geoportal* of the Swiss Federal Administration [18], the only way to obtain infrastructure data in less affluent regions may be by relying on crowd-sourced mapping platforms, such as OpenStreetMap, with often unknown quality and completeness ratings [19]. Besides regional differences in data availabilities, certain infrastructure sectors are notorious for data scarcity: road infrastructure, for instance, is relatively well mapped and available [20] because the availability of its location is a prerequisite for its usage. Many subterrain components tend to have mapping gaps, which impedes large-scale risk analysis, as is common in the water sector [21]. Further data scarcity concerns arise from resolution issues, that is, when detailed sub-components of infrastructure networks are required for analyses, as opposed to a more simplistic reliance on high-level components. For instance, when representing the power grid through different types of power plants, substations, transformers, high- and medium-voltage transmission lines, power towers, low-voltage distribution lines, poles, etc., instead of simply mapping the most important transmission lines and plants. In the case of missing data sources, workarounds are applied depending on the model purpose. In case a model is generated to develop and test a modelling framework, for example, the generation of synthetic infrastructure data has been used among others in [22,]23], machine-learning-based inference of infrastructure data for the global power transmission grid [24], or even omission from the scope of study [21].

2.2.2. Quantification of Dependencies

Since the seminal work of [1] on the importance of dependencies among critical infrastructures, many frameworks for categorising dependencies have been developed [3, 4]. However, data is needed to identify dependencies in the first place and enable the consideration of potential chain reactions. Empirical approaches have focused on a range of methods such as expert judgement and media coverage [25, 26], yet to date, no comprehensive dependency databases exist which thoroughly document these (cf. [27] for a European-wide effort to build one). The level of detail for such identification efforts is often limited by the resolution at which utility providers share data [28]. Deductions of dependencies often remain at a sectoral scale [29, 30], which does not link appropriately to the resolution of many CIN modelling approaches. Further, quantification of the hence-identified dependencies is often summarised under terms such as 'coupling behaviour' [1] or 'coupling strength'. Ideally, dependencies should incorporate the notion of input quantities at the supporting side which relate to output quantities at the dependent side, and of the degree to which certain impacts on a dependency source propagate down to a dependency target. Quantification efforts have proven to be data-intensive, relying on time-dependent disruption and restoration data [28, 31]. While such coupling behaviours are sometimes implicitly quantified through (lack of) redundancy in the network topology, or through failure tolerance threshold attributes, deterministic and binary dependency formulations still prevail owing to a lack of refined data to capture more elaborate dependency relationships.

2.2.3. Quantification of CI Services

Per definition, CIs provide essential services to a number of end-users, including population, businesses, or other infrastructure. The performance provided by infrastructure can be expressed not only in terms of services but also in terms of goods. However, in the presented work, only services will be mentioned. As CIN modelling is usually concerned with impact estimation, a multitude of data regarding CI services are necessary. First, knowledge about the characteristics of the population, including their number, socio-economic status, and vulnerabilities, served from a particular infrastructure asset is required. Moreover, data on the characteristics of businesses and other infrastructure assets served could also be needed. In the absence of detailed data, a number of substitute techniques are commonly employed, such as the estimation of a service area using geometric methods, for example, Voronoi decompositions or shortest-path algorithms [32 – 35]. Voronoi polygons can also be used for dependency quantification, as in [7]. Other options include the use of surveys [36] or the use of aggregated customer and census data [37]. Additionally, service demand pattern data may also be required for both asset functionality determination and impact estimation [23], especially when examining societal impacts of disruptions [38]. While sufficiently accurate estimations exist for certain CI services, such as water distribution networks [39, 40], they may be more difficult to obtain for other CI services, such as emergency services or the financial sector. CI service data, as defined herein, are usually difficult to obtain either due to legislative restrictions, economic competition, or general absence. Consequently, most studies in the scientific literature resort to a number of assumptions and inference approaches.

2.2.4. Impacts of Natural Hazards

From a CIN modelling perspective, it is important to capture when and how individual infrastructure assets subject to natural hazards fail and translate this direct asset-level failure to system-level indirect failures. It is noted that failure does not necessarily imply a binary state, as is commonly used [41], but can also refer to reduced functionality. Asset damage or failure is a product of complex interactions between the characteristics of the asset and those of the hazard considered [42], making failure identification a data-intensive task. In practice, asset damage is usually linked to certain hazard parameters (e.g. via appropriate curves) according to the type of asset examined. These parameters may vary according to the infrastructure or hazards considered. For example, in the case of flooding, a range of hydrological characteristics can be considered [43], including whether the asset is flooded or not [44], inundation depth [45], water velocity [46], flood duration [47], or water chemical composition, although inundation depth is the most commonly used parameter in practice [48]. In the case of earthquakes, fragility curves linking element damage to ground motion parameters such as peak ground acceleration (PGA), peak ground velocity, and peak ground displacement [49] are commonly employed. Additionally, insights into how damage translates to service or functionality reduction are needed. In addition to the identified hazard failure mechanisms, storms and fires must also be mentioned. Several functionality mechanisms are being considered in practice, such as binary functionality states [50], discrete functionality states [51, 52], or continuous functionality [53]. These mechanisms are infrastructure- and hazard-specific. A binary state realistically represents the failure of electric power assets under a flood scenario, whereas a transportation network requires a continuous functionality representation. Consequential is the consideration of multi-hazards which may further complicate infrastructure response [54]. A simple superposition of the previously mentioned response attributes may not suffice for multi-hazard environments because a compound event could either have more severe impacts on the disruption or also be the same as a singular event. Thus, the disruption functions must be generated individually for each multi-hazard-sector combination. Finally, the exposure to natural hazards may not be described deterministically only, but under consideration of extrinsic uncertainties, for example, meteorologic uncertainties, and intrinsic uncertainties, for example, resulting from a system's inherent variability. Currently, the lack of comprehensive datasets regarding infrastructure failure under a multitude of hazards is a bottleneck for risk and resilience analyses.

2.2.5. Determination of Response & Recovery

Modelling the response and recovery process of interdependent CIs naturally relies on most of the aforementioned data to represent the interdependent infrastructure system itself, yet requires various additional data: component repair times [55]; quantitative relationships between the repair state of components and service provision levels [56]–conceptually the inverse of the damage-functionality relationship mentioned above–; data on response actions including work capacities and repair priorities or the rerouting of CI supply flows [57]. This refers to the transformability of infrastructure assets under the stress of natural hazards. Frequently used component repair time tables are partly available through the technical manuals of FEMA's Hazus Program [58] or from ATC-13 data [59] for a wider range of buildings pertaining to different social function classes. Such tables deliver a partial insight into the infrastructure components covered and may not always be directly transferable to regions other than the US for which they were designed. Given the complexity of the task, many recovery studies tend to remain at the sectoral level rather than at infrastructure component levels and do not incorporate the multitude of uncertainties involved in these processes [60].

2.2.6. Appraisal of Adaptation Measures

Commonly, the viability of adaptation measures is evaluated by trading off benefits against costs, which require data on either side and at various scales of a network. Multi-criteria analyses and most commonly, cost-benefit analyses are performed for many types of hazards and individual infrastructure sectors [61 – 63]. As measures may act on different aspects of the risk chain, such as reducing a component's vulnerability or exposure to a certain hazard, or on the hazard intensity itself, data are needed to parametrise the working mechanism and hence quantify risk aversion benefit adequately. Evaluating measures with regard to their co-benefits and costs in other CI sectors requires adequate parameterisation of the above-mentioned dependency relationships. The latter is particularly crucial when evaluating the effects of system-level adaptation measures [56]. These measures, for instance, aim at enhancing resilience through modifying dependency relationships instead of fortifying individual components. Examples of system-level adaptation measures are increasing redundancies, reducing failure propagation behaviour, etc.), or modification of end-user demands and response capacities. Drawing on the level of destruction and disruption from real-world extreme events, it may however be concluded that the performance of adaptation measures is still rarely evaluated at a system level, nor do measures tend to target system-level adaptation [55].

2.2.7. Validation, Calibration & Plausibility Evaluation

In the context of modelling CI responses under hazard scenarios, studies have focused on collecting field data from past events. Such data might include print-media and social media or infrastructure and disruption damage and disruption reports of past events [35], utility providers' service outage statistics and restoration timelines [28, 64], and reports of response measures taken [65]. Methodologies that require data collected from expert and stakeholder elicitation processes may also be employed [66]. It is important that these datasets are of sufficient quality in terms of reliability, consistency, completeness, and detail, which in turn requires additional verification.

Table 1: Three exemplary case studies using CIN modelling featuring a wide range of model purposes, system boundaries, and outputs. Those case studies serve for the further examination of data scarcity implications on modelling qualities.

Case Study Area	Case Study I. - European continent	Case Study II. - Accra, Ghana	Case Study III. - Mozambique
Model Purpose	Continental level **earthquake risk-assessment**; identification of **vulnerable** hotspots; quantification of **interdependency**-induced vulnerability	Identifying **flood risk** for critical infrastructures in Accra including a benefit analysis of **potential CI measures**	Evaluate several **adaptation measures** to reduce **healthcare access disruptions** in the face of wind & flood **multi-hazard** events
System Boundary	Spatial: **Continental** level (Europe); CI sectors: **energy, gas, water, telecommunication**	Spatial: **catchment** area of the Odaw river and four surrounding catchments, CI sectors: **energy, water, telecommunication, healthcare, emergency services**	Spatial: **Country** level; CI sectors: **roads, power, telecommunication, education & healthcare**;
Output	Network fragility **curves**; **Geographical** distribution of disruptions and of **affected** population	**Area** of disrupted CI users per sector, **number and time of disrupted CI users** per year and sector, a **comparative overview** of the previous point for **potential CI measures**	Number of **avoided user-disruptions**, incl. co-benefits on other types of service disruptions (power outages, education disruptions, ..)
Target Group	Decision makers; Academics	**Decision makers** from public administration and **CI operators**	Academics; UN Habitat & Ministry of Health

In general, there is a lack of established CI model validation approaches in the scientific literature, and validation of CI models is rarely comprehensive due to the unavailability of relevant, homogeneous data.

Data Scarcity Influencing CIN Model Characteristics

3.1. Introduction of Case Studies with Varying Model Purposes

Three specific case studies are introduced which represent the experience of the authors and will be used to discuss the effect of data scarcity on CIN models. The CIN model case studies are defined by four model characteristics, as shown in Table 1:

The first case study briefly summarised in Table 1 concerns a continental-level earthquake risk assessment for Europe with the aim of to identify vulnerable geographical hotspots and to quantify the vulnerabilities that are induced by dependencies between CI sectors. Similar case studies have been presented in the scientific literature [67]. While CI networks are represented at an asset level, simplifications regarding the detailed structures of the various networks are made. Similar simplifications are made regarding the ways in which the various CI sectors are connected and how their disruptions influence the population.

The model purpose of the second case study is to identify the flood risk as population time disrupted per year for CIs next to other tangible flood consequences, such as economic damage and endangered populations. The analysis is based on a CIN model based on [68] and is additionally used to compare the benefits of potential mitigation measures and allow for improved decision making. The specific model purpose of flood risk management could be generalised by being applied to other natural hazards such as droughts, storms, and bushfires. Thus, the generalised model purpose would be defined as *hazard risk management*. In terms of abstraction from the real complexity of CIN, this type is more differentiated with regard to the sectors than the first case study, but has a smaller spatial boundary.

The third case study is a sectoral adaptation study designed to decrease healthcare access disruptions across the population in the face of multi-hazard (particularly strong winds and flooding) events [69]. The analysis is based on an integrated natural hazard risk and CIN modelling approach [35] and evaluates five adaptation measure packages, which are either focused on resilience-enhancing measures to a single CI type, target multiple CIs at once, or modify the dependency relationships among CIs. While real-world data are used to map the interdependent CI systems and hazards, the stylised parameterisation of adaptation measures exemplifies trade-offs and benefits of component level against system-level measure packages to prevent service disruptions.

3.2. Repercussions of Data Scarcity for Every Modelling Stage in the presented Case Studies

Exemplifying the introduced modelling stages (cf. section 2.1) and data requirements (cf. section 2.2) on the presented case studies (cf. section 3.1), Table 2 briefly illustrates typical repercussions of data scarcity for the corresponding three generalised model purposes. Table 2 does not claim that these specific repercussions always occur for the associated generalised model purpose types. It merely serves to highlight that this is one of the possible repercussions that can occur and suggests a way of expressing repercussions for a model. For brevity, only one instance of lacking data and its consequence for the modelling process is discussed per stage and case study. Additionally, it is noted that the three given model purpose types are not a complete picture of all possible model purpose types, but only three possibilities. A brief overview is given in Table 2 for every modelling stage. In the asset mapping stage, all case studies receive incomplete or partial information about specific CI sectors. This leads to a coarse representation of the network and its sectoral hierarchy, as well as higher uncertainty of the results. In the stage of dependency quantification, the general issue is missing information about dependencies. This materialises in assumptions that need to be made and overlooked redundancies that should not be disregarded. For the stage of quantification of CI services, the level of detail of the input that is necessary for specific model purposes is a challenge. Additional challenge is to retrieve the same metric for different CI sectors, resulting in challenges for the comparability of scenario calculations.

For all case studies, different problems occur in the stage of natural hazard and operational limits, and the types of challenges are determined by the model characteristics. The first case study mentions that no functionality-impact relation is available for earthquakes. The second case study is missing sector-specific flood-

Table 2: Repercussions of data scarcity in every modelling stage, illustrated for three different model purposes, generalised from exemplary case study experiences in Table 1.

Model Purpose Type	(A) Hazard Hotspot Assessments	(B) Hazard Risk Management	(C) Sectoral Adaptation
(1) Mapping of Infrastructure Assets	**Network structures** *Only partial information available.* Several assets of the examined networks may be missing or not correctly placed, introducing some uncertainties in the results.	**Network structure of electricity grid** *Only substation information available.* Coarse granularity of electricity sector causes inaccurate results because electricity transformers are not represented.	**Healthcare sites and types** *Many unmapped healthcare sites, unclear service offerings.* Faulty baseline system.
(2) Quantification of Dependencies	**Connections or dependencies between infrastructure** *No information regarding connections.* Assumptions made during this stage introduce some uncertainties in the results.	**Redundant connections in between nodes** *No information about redundancies.* The disruptions in the CIN model will be overestimated due to missing redundancies.	**Dependencies between power network and healthcare network** *No information available regarding the extent of dependency on the power sector.* The disruptions in the CIN model will be overestimated due to overestimation of healthcare site dependencies on the power grid.
(3) Quantification of CI Services	**Population served by each considered asset** *No available information regarding detailed numbers of population served.* Only estimations of population affected are possible.	**Metrics to quantify CI sectors in multi-sectoral network** *Not all sectors give the same metric for CI disruption.* Results of the multisectoral CIN model cannot be compared with each other.	**Socio-economic constraints to access healthcare services.** *No available high-resolution information on who is (financially) able to seek healthcare support.* Over/under-estimation of potentially impacted population.
(4) Impacts of Natural Hazards	**Earthquake damage-functionality relation** *Difficulty in obtaining detailed damage-functionality data for the considered assets.* Binary functionality considered via fragility functions, which may differ from real infrastructure response.	**Water depth-functionality relation** *No data or information for the range of sectors available and the area of interest.* The water depth - functionality relation is set to be binary. Disruptions and their sensitivity might be overestimated.	**Parametrization of combined wind- and flood damage - functionality curves for infrastructures.** *No data on the effect of structural damage onto the functionality of local infrastructures.* Binary and arbitrary damage-functionality thresholds for all infrastructure components may under/-over estimate impacts.
(5) Determination of Response & Recovery	**n/a**	**Recovery time of communication towers** *Sector specific recovery times from other survey areas are extrapolated to unsuitable case study areas.* Availability of spare parts differs in this area due to higher frequency of flooding events. The resilience of this sector is underestimated.	**Clarification on the availability of backup generators for response** *The presence of back-up generator and their associated start-up and run times is not available* Potential damages could be overestimated and potential measures could be suggested that might be in place already.
(6) Appraisal of Adaptation Measures	**n/a**	**Effectiveness of potential measures** *No knowledge about the applicability of a potential measure due to missing information about the technical set up of a CI element.* Measures are tested for effectiveness that might not be feasible at the selected network element.	**Applicability and cost of potential measures** *Unclear (financial) means, cost and local fitness for purpose of certain measures.* Measures may be not implementable, or not as effective as modelled.
(7) Validation, Calibration & Plausibility Evaluation	**Documented failures for similar earthquake scenarios** *No available data at the level of examined detail.* Accurate model validation is not possible.	**Area of disrupted people during historic events** *Not available only individual experiences or anecdotal stories.* No Calibration of model parameters possible.	**Documentation of historic events along the entire impact chain.** *Limited availability of exact hazard footprints, structural damages, functionality failures, service disruptions.* Only anecdotal validation or plausibility valuation, no calibration possible.

depth-functionality relations, and the third case study is missing a combined flood depth and wind speed functionality relation. All missing information results in assumptions that lead to a potential over- or underestimation of the final results. In the response and recovery stage, desired metrics are missing to quantify the recovery after a CI disruption. However, the initial information about the mere presence of emergency structures is also missing, and thus, the response is also not represented appropriately. In the measure appraisal stage, the issue concerns the identification of potential measures alone. However, in case those measures are identified, as in the second case study, the metrics to quantify the potential costs are missing. For all three case studies, the validation stage was strongly influenced by data availability.

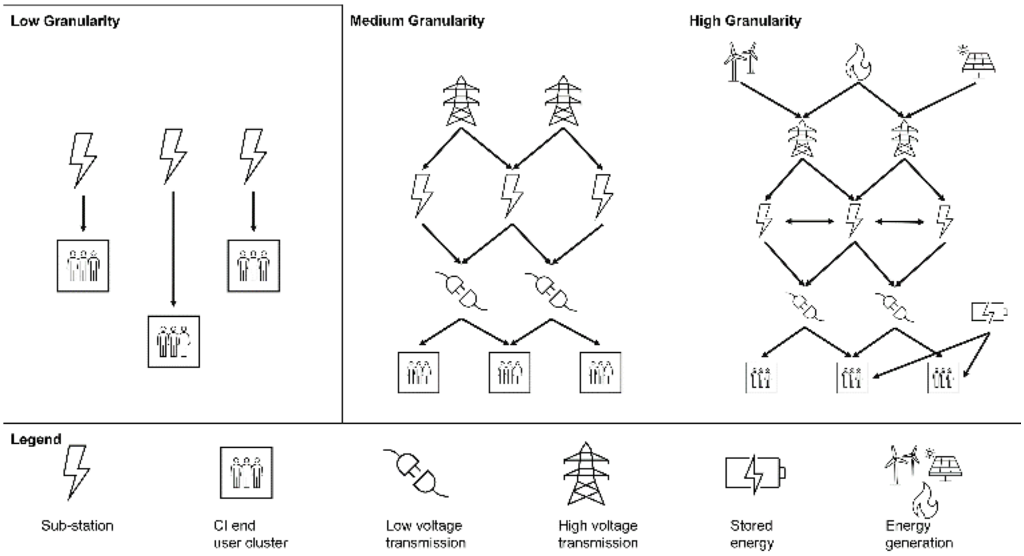

Figure 3: Amount of data and information available affects the resolution (granularity) with which CIs, CI dependencies, and services can be modelled.

3.3. *Influence of data scarcity on CIN model characteristics*

As the compilation in Table 2 illustrates, the absence of data impacts model inputs and potential outputs. This invariably affects a range of model characteristics, which should be carefully evaluated under consideration of the model's purpose to critically reflect its fitness for the intended purpose. Without a claim of completeness, a few crucial model characteristics and the implications of data scarcity on those are discussed below, extending the mathematically driven characteristics of networks as introduced by [70].

The *granularity* describes how fine or coarse a network model resembles the details of CI supply systems. Figure 3 illustrates one possible scale from low to high granularity for the electricity sector. The figure does not depict the exclusive approach to coarse granularity; for instance, dynamics encompassed by coarser granularity can also be cross-sectoral. Granularity is intricately linked to the accuracy and complexity of CIN models. Invariably, the amount of data and information available influences how accurate and complex a model can be and how granular it may or should be resolved. The granularity is adjusted on a precision scale according to the model objectives. Thus, models of type A tend to attain their model purpose using coarser granularity than models of type C, which generally may require finer granularity. When comparing the examples in cell 1A and 1C, Table 2 is also underlined.

Another CIN model characteristic linked to granularity and accuracy is the *ability to resemble chain reactions*. The German Federal Office of Civil Protection and Disaster Assistance (BBK) suggests a scale of three types

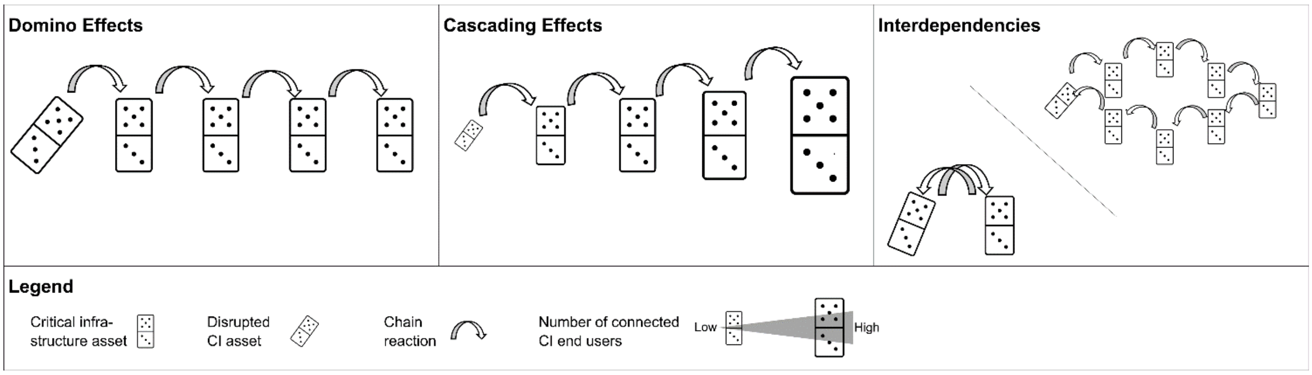

Figure 4: Types of failure mechanisms or chain reactions that can propagate through disrupted CINs adapted from the definitions in [69]. Depending on data availability, different failure mechanisms/chain reaction types may be captured.

of chain reactions, as shown in Figure 4 [71]. The first type of chain reaction refers to the *domino effect*, where disruptions are propagated through critical infrastructure assets through their dependencies. *Cascading effects* describe a type of chain reaction similar to the domino effect, but underline the progressive consequences of the disruption. The last type of chain reaction features *interdependencies*, which refer to mutual reliance or connections between different CI assets. Depending on the granularity as well as the level of detail of dependency information, those different chain reaction levels are representable in CIN models. Table 2 introduces in cell 2A the fact that all of those dependencies had to be assumed and thus have a lot of uncertainty. Thus, the resemblance of chain reactions might be inaccurate.

The *communicability* of CIN models describes their ability to transfer the methodology and potential outputs to the desired target group. The absence of information and data often leads to replacement through assumptions and heuristics, which often happen implicitly or may not be closely tracked. More assumptions may lead to lower communicability of how a model is set up and reduce trust in its outputs. This is one factor influencing the process of testing measures in the CIN model environment, as described in Table 2, cell 6B.

The existence of many assumptions due to data scarcity may hamper *the reproducibility* of a modelling approach by other researchers. Furthermore, data availability and assumptions for certain geographic or system boundaries, for which a model was initially designed, may not extend to other regions and systems, limiting its transferability. Some modelling approaches may be more versatile and flexible with respect to underlying premises than others, which feature a higher level of hard-coded assumptions, or which are calibrated against specific, non-widely available datasets.

Discussion & Outlook

Current CIN modelling techniques can already supply advice for consequence assessment and mitigation planning; however, the more accurate, complete, relevant, consistent, and accessible the data, the better the model results. The added value of this work lies in collecting the data requirements of the CIN models. This is achieved through the systematic division of data categories and associated data types based on the modelling stages. Further possibilities of categorisation, for example, based on sectors or importance for models, are conceivable. These new categories have the potential to elicit further data types that have not yet been considered. Therefore, this work does not claim to be a complete collection of data needs, but is intended as a propulsion for the discourse about the data availability of CIN models.

Wording remains a challenge in the field of hazard modelling for CIN models because the two fields of expertise (impact modelling and engineering of CIs) meet and do not share the same established terminology. Although the network models considered in this work have been limited to graph-based CIN models, it remains an issue to identify the right terminology for the interaction of data scarcity and CIN models. The characteristics previously defined are the first approach to describe the interface of those fields under consideration of the capabilities and limitations of CIN models. More efforts need to be invested in defining a generally accepted terminology for a range of network characteristics such as fidelity, granularity, sensitivity, or the representation of cascading effects to close the gap between impact modelling and CIN modelling.

In the context of this work, the category of CIN model purposes has been defined and filled with three examples along a scale from (1) hazard vulnerability hotspot assessment to (2) hazard risk management to (3) sectoral adaptation. These examples seek the representation of network models on a scale comparable to a spatial scale (global, national, regional, and local) suggested by [72] for flood risk assessments, including typical model characteristics for each scale level. In the future, scales like these need to be defined for other CIN model characteristics with a clear division of levels as well. The definition of these levels is not about setting a better or worse value, but about being able to accommodate the subdivisions defined by model purposes and to enable differentiation of the characteristics.

Assumptions made by Cin modellers are one concomitant of data scarcity. These assumptions can be supported by CI operators and scientists alike through expert knowledge. Nevertheless, assumptions influence the network model's characteristics in their performance. Although commonly used in CIN models, current studies often lack sufficient communication or quantification of the uncertainty resulting from assumptions, unlike other fields in which such practices are more prevalent [73]. A range of possibilities are available to modellers to quantify or counter uncertainties, beginning with uncertainty analysis [74], sensitivity analysis, anecdotal verification with expert knowledge, or at least an overview of made assumptions, as done in [35]. It must, however, be noted that uncertainty and sensitivity analyses often in turn also rely on more input data, for instance, for validation and setting of plausible bounds for the tested parameters as an input. It remains an open question on how to validate, verify, or make plausibility checks appropriately. These checking processes can be done in many possible ways, from surveys validating each asset and its characteristics, to the validation of small representative units of a network, to the anecdotal validation of individual elements of a CIN, and under consideration of temporal variability of data inputs. It is suggested to further investigate CIN model validation techniques based on specific model purpose types and under consideration of the data needs highlighted in this work.

Communication and the expressed quantification of uncertainties have the potential to enhance trust in CIN model results and, consequently, strengthen CIN modelling methods as a whole. When it comes to presenting the results, uncertainties must be communicated appropriately to establish trust with the intended recipients and allow for robust decision-making [75]. In the case studies presented, CI stakeholders, particularly CI operators, were involved as recipients, or the least CI operators were key partners in the development and implementation of measures. In any case, trust is significant in ensuring sufficient eagerness. Early and ongoing participation of CI stakeholders in the process of CIN hazard assessments can be beneficial in all stages of the modelling process [26, 56]. Not only will this create a greater identification in the potential results but also has a huge potential of acquiring qualitative information or sometimes even quantitative information, in perspective: data. Limited resources for the participation of critical infrastructure stakeholders and the acquisition of input data should be adapted to the model purpose intended to be addressed with a model. It is important to ensure that all other model characteristics are aligned with the needs of the affected CI stakeholders to enable mutual benefits.

An issue that persists and needs to be addressed in participatory settings is the way data is conveyed or provided. A range of options have been tested by the US Federal National Laboratories (for example, Sandia Lab, Los Alamos Lab, Idaho National Laboratories, etc.), but the knowledge is not publicly accessible for security reasons. Opposite to these options is the openness to share most of its infrastructure data, as done in New Zealand for example [76]. Therefore, it seems that the willingness to share data varies a lot and discussion is ongoing. The question remains whether the sharing of data or information itself is proven to cause more disruptions in CIN due to physical or cyber-attacks compared to disruptions from natural hazards that cannot yet be recorded or recorded inadequately due to a lack of data exchange.

Although some data sources were compiled in this study, gaps remain. One suggestion is to collect more impact data in the direct aftermath of disaster events, either in person or through social media. Another suggestion is to establish platforms for CIN datasets accessible for research, including a range of prerequisites from users and providers: (1) consideration of previously defined data types needed, (2) awareness of the level of detail that needs to be published if this data is used by CIN modellers, and (3) sensibility for privacy of CI users. Despite the strong case for more and better data and information in CIN modelling, it is paramount to critically reflect on the need for complexity and detail, depending on the purpose for which a model is built. In many cases, the unavailability or inaccessibility of very detailed data does not hamper the purpose of the developed CIN models. Whether a model aims to create new knowledge (models for understanding) or to create new capabilities within its user space (models for action) may require different levels of upfront data availability, since in the latter scenario users may provide those themselves on-the-fly, as deemed necessary. Further, societal context and ethical uncertainties may influence data requirements - some societies and studied problems may require higher levels of resolution and certainty to justify action than others.

Conclusion

CIN modelling offers approaches to better assess and manage natural hazards. Data inputs limit and determine the value of CI modellers' "offerings" to specific assignments. This study identifies overarching similarities in the modelling process, defines eight stages, and associates each stage with data types. The typification of those data needs has been documented, and the potential data sources for all data types are pinpointed, or if unavailable, gaps are identified. Three purpose-driven classes of CIN models have been distinguished, setting it apart from the pure size-driven classification (e.g. local, regional, national, global). For the model purpose type, case studies of CIN models have qualitatively shown the influence of data scarcity and the resulting assumptions at each modelling stage.

This work increased the level of understanding regarding CIN modelling and the difficulties faced by both CI operators and CI modelling experts alike. The modelling stages and data types defined enhance the possibility of communicating about data needs and assumptions in participatory settings. On the other hand, an orientation is provided for network modellers at an early stage of a model setup, including potential data sources. Additionally, CIN modellers are encouraged to disclose uncertainties in their methods by delivering examples on how data scarcity influences network characteristics. In the end, this contribution advances the potential of CIN models to be utilised mutually by research and practice.

The work provided enhances CIN modelling techniques by clearly outlining their data needs based on modelling workflow stages and provides a literature review that identifies potential data sources or examples in practise or research. Ultimately, this leads to the enhancement of analyses and evaluation methods for resilience-based planning of urban environments under consideration of CI services. The purpose of CIN models needs alignment with CI stakeholders and needs to go hand in hand with the model purpose and the model characteristics to influence data availability positively.

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Relevance to Resilience

Impacts on critical infrastructure assets cascade through their dependencies on other CI assets. CI network modelling methods are viable tools to consider these cascading effects.

When addressing the resilience of an infrastructure, it is essential to consider the dependencies within a network. Different measures, each with a variety of operating principles, must be tested for their potential to increase resilience. Critical infrastructure network modelling methods have proven to be valuable tools for quantifying CI response, reconstruction, protection, and adaptation measures.

This work contributes to unlocking the potential of CIN modelling methods by classifying and identifying data needs and discussing the implications of data scarcity on model performance.

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