Review of existing gaps in assessing systemic risk of Critical Infrastructure failure

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Executive Summary

This document provides an overview of the state-of-the-art knowledge in systemic risk assessments, focused on the macroeconomic impacts of critical infrastructure failure. Various macroeconomic impact models, their development, and their applicability to systemic risk assessments are discussed in detail. It satisfies the remit of Task 3.1 within the Work Package 3 (WP3) Multi-hazard Infrastructure Risk Assessment for Climate Adaptation (MIRACA) project. Through this review, we acknowledge that significant research has been done in this field, especially on trade datasets at various scales and the continuous evolution of macroeconomic models over time. However, we find several limitations that will be addressed through MIRACA. To summarize, firstly, we believe that the spatial and economic linkages between the critical infrastructures and economic sectors can be modeled more explicitly. Also, the interdependencies between critical infrastructures are not always fully considered in existing systemic risk assessments. Secondly, there is a data scarcity to model the recovery and adaptive behaviors of economic agents. In addition, systemic risks in a multi-hazard context have not been explored much. Within MIRACA, we attempt to address these drawbacks and extend the boundaries of existing systemic risk assessment research.

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1. Introduction

Critical infrastructures (CI) such as power (energy), transportation, water, and communication systems are designated as lifeline infrastructures (CISA, 2019) that fuel the day-to-day functioning of societies, businesses, and governments (Labaka et al., 2016). During disasters, the significance of infrastructures becomes evident, particularly when a crucial service is disrupted, affecting households, businesses, and other infrastructure systems. This may result in far-reaching consequences for both the economy and society (Dawson et al., 2018). For example, the eruption of Iceland's Eyjafjallajökull volcano in 2010 caused a week-long suspension of Europe's civil aviation, disrupting the transportation of perishable goods and causing substantial revenue losses in the services industry (Alexander, 2013). Similarly, Hurricane Ian in 2022 devastated the power systems in Florida. Four million people were left without power (DiSavino, 2022) and it took nine days post-landfall to restore the grid (FEMA, 2023). Unfortunately, such impacts are projected to worsen on a global scale in the future. Studies indicate that climate change disruptions to critical infrastructure within Europe alone could increase by tenfold by the year 2100 (Forzieri et al., 2018). To mitigate future risks to critical infrastructure, it is essential to have a profound understanding of disaster risk to develop robust adaptation strategies.

Dawson et al. (2018) identified three broad classifications of critical infrastructure risk assessments: (i) asset-level (risk to a single asset) (ii) network-level (risk at a single network level) and (iii) system-level risk assessments. Prior to understanding systemic risk, we first define 'system' as a set of individual elements that exist in relationship with one another and produce properties that can only be ascribed to the whole (Westra & Zscheischler, 2023). In other words, interaction/dependencies between the elements of a system lead to additional higher-order effects (Barabási & Albert, 1999), which emerge only when studied holistically as systems and not as individual elements. Systems exist in a hierarchy and the complexity of the systems increases when moved up the hierarchy, where the system's properties depend more on the organization of the elements rather than the actual properties of the isolated elements (Hochrainer-Stigler, 2020). A hierarchy of systems in the context of CI is shown in Fig.1. In general, systemic risk arises out of complex-cascading effects between the interconnected elements (Hochrainer-Stigler, 2020). Helbing (2013) defines systemic risk as 'the risk of having not just statistically independent failures, but interdependent, so-called cascading failures in a network of N interconnected system components'. The failure or perturbations in one of the infrastructures can cascade into its dependent infrastructures and economic

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sectors leading to a complete system failure e.g., the 2003 Northeast America Blackout (Anderson et al., 2007). In this deliverable, we refer to systemic risk as the risk associated with the top-level systems in the hierarchy (see Fig.1.) such as economic (supply-chain disruptions) impacts (Koks, 2022). The rest of the document focuses on the impacts of natural hazards caused by CI failure resulting in business downtime and supply-chain disruptions.

Complexity

MIRACA	Systems in hierarchy	Examples
Systems	Supply-Chain relationship between different economic sectors.	Input – Output (I-O) tables, Supply – Use tables (SUT).
Networks	Individual CI networks; Interdependent CI networks, CI and business networks.	power distribution network, transportation network, a combined network of power and transportation network elements reflecting the interdependencies, a network of business assets, and CI elements connected via service areas.
Assets	CI assets; Business assets; Households	substations, telecommunication towers, health care facilities, industrial buildings, logistic hubs, residential buildings

Fig.1. *Assets, networks, and systems within MIRACA.*

2. Definitions and Concepts

For MIRACA, we follow the definitions per the 'D1.2-Handbook of Multi-hazard, Multi-Risk Definitions and Concepts' (Gill et al., 2023) of the MYRIAD-EU project. The definitions and concepts are grouped into three major categories namely the hazard definitions, infrastructure definitions, and disaster impact/risk definitions. For definitions, refer to Section 2 of Deliverable 1.1.

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2.1 Classification of disaster impacts

The consequences of disasters can be broadly classified into four groups, based on two different criteria (De Moel et al., 2015; Jonkman et al., 2008). They are (i) direct and indirect impacts and (ii) tangible and intangible impacts. Direct impacts refer to the impacts observed within the spatial extent of the hazard (e.g., damaged buildings within the flooded area), and indirect impacts refer to the consequences outside the hazard extent (e.g., business disruption to a firm because of power failure from a substation being flooded). Tangible refers to the impacts which can be assigned a monetary value (e.g., the damage value of failed components) whereas intangible impacts cannot be monetized (e.g., casualties). One other system of disaster impact classification exists based on the time-dependent nature of the impacts namely the stock and the flow losses (Rose, 2004a). Stock losses refer to the physical damages that occur at the onset of the disaster (at a single point in time), also referred to as asset damages / direct losses. Flow losses are associated with the service disruptions arising out of stock damage which depends on the time of recovery from the disaster, also referred to as indirect losses.

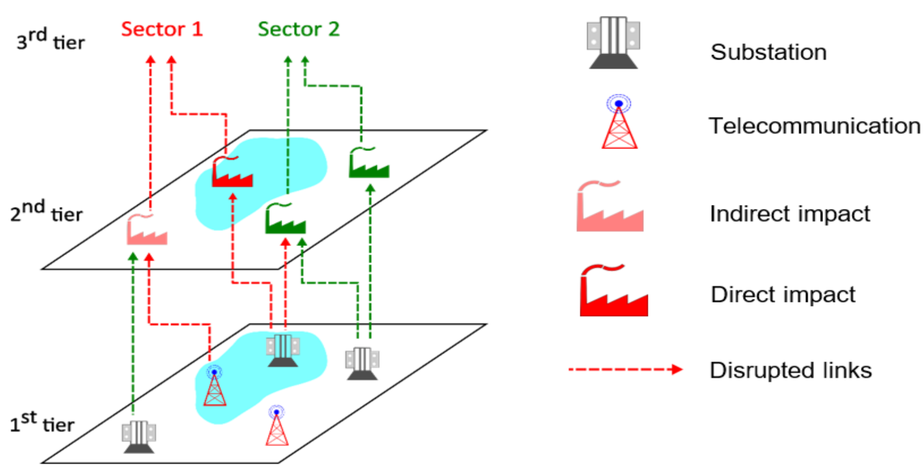

Fig.2. *An explanatory figure to demonstrate the impacts of natural hazards. The blue polygon indicates the spatial extent of a flood event. The substation and the telecommunication tower within the flood extent are non-functional and do not provide their service to the factories (red and partially red) which in turn brings down the production of the economic sectors (Sector 1 in this case). The damaged links are indicated in red dashed lines.*

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Direct losses have been the major interest of the engineering and catastrophe insurance community in the past years. Tools such as fragility (Porter et al., 2007) and vulnerability models (Porter et al., 2001) are used to estimate asset damages. However, reporting only the direct losses in disaster impact analysis ignores the indirect effects (i.e., service disruptions and business downtime) which are found to be substantial (Rose, 2004b). The estimation of indirect losses (e.g., economic impacts) is a more complex analysis compared to that of stock losses because of the underlying interactions and interdependencies between the infrastructures, the business assets, and the economic sectors.

Fig.2. presents a demonstration of the stock and flow losses. Consider the real-world economic system to be three-tiered. The first and the base tier consist of critical infrastructures which supply their services to beneficiaries such as households and factories, which form the second tier. The third tier comprises the macro-economic sectors which build upon the products and services supplied to it from the second tier e.g., the manufacturing sector relying on automobile production factories. Let us assume that during a flood event, a substation, a telecommunication tower, and an industrial building (red) were flooded. The physical damage to the components (and the associated repair/replacement cost) of the above-mentioned assets fall under the category of stock losses. Service disruptions from the telecommunication and power infrastructure will disrupt business activities in factories which further affects the corresponding economic sector. The economic sectors interact among themselves through demand and supply chains (e.g., the manufacturing sector depends on the mining sector for iron ores) causing a greater ripple effect (not depicted in Fig.2.). As the system recovers with time, the business activities and the system bounces back to the business-as-usual state. Such losses that occur as a result of service disruption from stock damage and prolong for a while are examples of flow losses. In addition, although being outside the flood extent, the industrial building in partially red shade suffers business downtime because of service disruption. This is an example of indirect impact. The above-mentioned impact propagation from power infrastructure disruption to loss in production of businesses, and hence reduced output of the sector affects the supply side of the economy. This is termed as supply-side impact. On the other hand, after disasters, the consumption pattern of people (and businesses) might shift resulting in demand changes e.g., an increase in demand for reconstruction and health care sectors. This contributes to the demand-side impact.

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The impacts of disasters on economies can also be categorized along a temporal dimension as short-run and long-run effects. Short-run impacts generally include near-term fluctuations in economic activities (positive and negative responses) depending on the nature of the disaster and recovery efforts. For example, disruptions in the flow of goods and services, shifts in demand and supply, and increased demand for reconstruction activities can be interpreted as short-term effects that persist from months to a few years after the disaster. Long-run impacts, however, refer to sustained effects on economic growth, and structural changes, often arising from major catastrophes. Smaller and localized events like minor floods may not significantly alter long-term growth patterns, whereas larger-scale disasters of high intensity such as earthquakes, hurricanes, or tsunamis can have lasting consequences e.g., the 1995 Kobe Earthquake in Japan inflicted substantial changes in the economic structure of Kobe economy (Okuyama, 2014).

2.2 CI recovery and business downtime

As shown in Fig.2., hazards affect the critical infrastructures and the business simultaneously. Even the business that lies outside of the hazard extent might be affected by service disruptions from CIs or the lack of inputs from other businesses that are directly affected by the hazard. This leads to business downtime i.e., the time taken by business to recover from the shock. Downtime of businesses is one of the major drivers of macroeconomic impacts of disasters (higher order effects) e.g., downtime of automobile firms reduces the supply of the manufacturing sector to other economic sectors. Studies have shown that the macroeconomic impacts are highly sensitive to the recovery duration and the recovery paths (Koks et al., 2016; Koks & Thissen, 2016). However, there is no common agreement on how the economy revives after disasters (Li et al., 2013), which forces the impact modelers to assume the recovery duration and recovery paths. Chang (2010) discussed three definitions of recovery such as returning to pre-disaster conditions, attaining what would have occurred ‘without’ the disaster, and reaching a stable state different from the above. Also, downtime is a function of direct damage to the business e.g., the higher the damage to the buildings in which the business operates, the higher its repair time. This section presents some of the available restoration/downtime models of critical infrastructures and businesses.

Karagiannis et al. (2017) provided a detailed report on the power grid recovery after earthquake and flood hazards. The study discussed various factors that resulted in increased recovery of assets e.g., damage to heavy equipment, poor access to the

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damaged areas, and foundation failures. The results of the study suggested that the restoration time of power grids is in the range of one day to three weeks, however high impact events can delay the restoration in the scale of months e.g., hurricane-driven floods. He & Cha (2018) proposed a graph theory-based framework to model the recovery of interdependent infrastructure networks. The methodology is based on the Dynamic Inoperability Input-Output model (refer to Section 3.5.1) (Lian & Haimes, 2006) by modeling the interdependencies at the facility level (e.g., communication towers, power substations). The recovery time of critical infrastructure assets were estimated as a function of its damage/loss ratio (FEMA, 2003). Graph theory metrics such as the size of the largest cluster, and network efficiency were used to measure the operability of the interconnected infrastructure system. Mitoulis et al. (2021) proposed a restoration model for bridges subjected to floods. Experts were asked to fill out a questionnaire with the minimum (structural restoration time) and maximum (traffic reinstatement) time required for twenty-three possible restoration works on bridges after flooding. Some of the restoration tasks include re-alignment of bearings, debris removal, and so on. The dependence of the restoration time on the severity of damage was captured using weighing factors for each damage state. Using this data, the study arrived at traffic restoration models for bridges with varying damage levels and foundation types, which are greatly useful in understanding the macroeconomic impacts of transportation network failures. Researchers have also worked on alternate approaches to model the restoration of critical infrastructures. For example, Román et al. (2019) developed a methodology based on satellite nightlight data to understand the recovery of power infrastructures. In the absence of utility data, such openly available data is quite promising. The recovery of the power infrastructure at any time is quantified as the ratio of radiance before the hurricane to the radiance at that instant of time. This method was applied to Puerto Rico after Hurricane Maria. The results revealed that the rural households (i.e., with lesser density of houses) suffered a lag in restoration compared to the urban areas.

In the past, business recoveries had been studied using post-disaster surveys and engineering-based approaches. Few of the selected business downtime studies are discussed in detail. Yang et al. (2016) proposed a probabilistic methodology for estimating business interruption losses in economic sectors. The authors collected data on business downtime estimates after the Tokai heavy rains in Japan in 2000. The firms were broadly segregated into two major sectors, manufacturing (which includes raw materials, processing, assembly, and livelihood) and non-manufacturing sectors (whole-sale-retail, construction, and services). The methodology utilized two unique models

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namely the functional fragility curves (FFC) and the accelerated failure time model (AFT) to estimate business downtime losses. FFC linked the hazard intensity (e.g., inundation depth) to the production loss (% of production reduced). On the other hand, AFT estimated the exceedance probability of a recovery time, given an inundation depth. Combining these models provided business downtime (BI) loss estimates. The authors clearly stated that BI losses are no replacement for macroeconomic impacts, but rather the repair times obtained should be combined with macroeconomic analysis.

Liu et al. (2022) collected a time series of data on post-disaster recovery after the Great East Japan Earthquake in 2011. The recovery data consisted of production levels at days 1, 14, 31, 61, and 184 (6 months) after the disaster. The study showed two important conclusions. Firstly, the firms contributing to manufacturing sectors recovered faster than their counterparts (i.e., non-manufacturing e.g., services). Secondly, the recovery of the firms depended on the financial conditions/constraints after the post-disaster recovery. For, the firms with loan applications rejected and delayed insurance claims had prolonged recovery periods. In a similar study, Liang et al. (2023) collected recovery data from small businesses from 39 counties after 2017 Hurricane Harvey. The survey was conducted online and the responders (620 respondents) were primarily the decision-makers of the firms. The study provided an arrival rate function that gives the fraction of firms back to the pre-disaster level after a certain time. The firms that suffered major building damages took longer to recover back. For example, only 9% of the businesses with building damages resume operations within 3 months. Also, the arrival rate of resilient firms (firms with flood barriers, emergency generators, etc.) was faster than their counterparts.

Conducting surveys and interviews to understand the recovery of businesses may not always be a feasible option. In addition, they are time-consuming and costlier. For such scenarios, alternate methods exist. Olmez & Deniz (2023) applied an assembly-based approach (engineering–based) to model the vulnerability of industrial buildings in Turkey. An industrial building is disassembled into its components that are vulnerable to floods. The failure state of the components is identified by comparing the capacity of these components against flood actions (e.g., inundation depth, flood velocity) and the actual flood loads on the components. Depending on the damage to the components, a repair time is allotted based on a repair cost and time database e.g., RS means (RSMeans, 2013) provided the time required to repair the component. The accumulation of repair times of the components gives an estimate of the total repair time required by the industrial building. The study provided time-element vulnerability curves (i.e., the curves relating the inundation depth with repair times) under slow-rise and flash flooding

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scenarios. Eyre et al. (2020) used Facebook posts of businesses as a proxy to identify their downtime after a disaster. Businesses post advertisements on their Facebook pages. After a disaster, the social media activity of these businesses decreased which returned to its normal trend after recovery. This approach was validated against hazard events in Nepal (2015 Gorkha Earthquake), Mexico (2017 Chiapas Earthquake), and Puerto Rico (Hurricane Maria 2017). Sousa et al. (2022) developed a comprehensive framework for the assessment of indirect economic losses based on the impact of business interruption and interdependency between the different economic sectors. The proposed framework was applied to the precast reinforced concrete buildings in Portugal highlighting the importance of considering indirect losses in the seismic risk assessment of industrial buildings. The estimation of the indirect losses was carried out based on the procedure described in HAZUS (FEMA, 2003), following principles of input-output flow (Galbusera & Giannopoulos, 2018), but adjusted to the Portuguese reality based on indicators collected from the Portuguese Statistical Office (http://www.ine.pt/).

3. Macroeconomic impact modeling

Different methods have been widely used to understand the macroeconomic impacts of disasters by economists in the past (Kelly, 2015). They are input-output (I-O), computable general equilibrium (CGE), and econometric methods. I-O and CGE methods have been commonly used to understand supply chain disruptions and the reduction of economic outputs during disasters (Koks et al., 2016). On the other hand, the econometric models use past (historical) data to predict the future impacts of disasters. The rest of the section discusses the I-O, CGE, and econometric methods and relevant studies in detail.

3.1 Traditional Leontief I-O method

I-O methods are based on the analytical framework developed by (Leontief, 1936). I-O models represent the flow of goods and services between different sectors of the economy. Sectors (e.g., manufacturing, agriculture) are the producers of goods in the economy. The produced goods are consumed among the sectors themselves and are supplied to cater to external demands (e.g., household consumptions, government purchases, and exports). Value added represents the additional expenditure to the

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producers (e.g., employee compensation, imported goods, and taxes). The monetary values of these intersectoral transactions are recorded and compiled in a tabular form. A typical input-output table of a two-sector economy resembles Fig.3. Each row represents the distribution of a sector's output and each column represents the distribution of a sector's consumption, to and from different sectors respectively.

The I-O tables are mathematically represented using a system of linear equations $x = Ax + f$. The array x represents the total output of each sector. The matrix A represents the technical coefficients of the inter-sector transactions. Each element A_{ij} represent the value of goods/services from sector i required to produce a unit value output of sector j. The array f represents the final demand for the goods and services of each sector. Subsequently, the relationship between the output vector x and the final demand vector f can be modeled as $x = (I - A)^{-1} \times f$. Here I represents the identity matrix (i.e., a diagonal matrix with all diagonal elements equals 1). The term $(I - A)^{-1}$ is known as the Leontief inverse (or) total requirements matrix, usually represented by the symbol L. The elements of the matrix L_{ij} represent the rate of change in the output of a particular sector x_i to the demand from a sector f_j. Mathematically, it can be represented as $L_{ij} = \partial x_i / \partial f_j$. This formulation facilitates the study of the effect of demand shocks on the output of individual sectors. For a detailed explanation of the I-O formulation, refer to Miller and Blair (2009) .

	Sector 1	Sector 2	Demand	Total Output
Sector 1				
Sector 2				
Value added				
Total Outlays				

Fig.3. *A representative two-sector input-output table (A simplified figure of Figure 1.1 from Miller and Blair (2009))*

3.2 CGE method

CGE methods model the economy-wide linkages between the consumers and the producers and their behaviors (Burfisher, 2016). The term 'computable' refers to the model's capacity to quantify the effects of an economic shock, and the term 'general' refers to the model's wholesome nature to incorporate all the aspects of economic

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activity such as production, consumption, taxes, prices, savings and the term 'equilibrium' refers to the balance of supply and demand. A simplistic representation of a CGE model can be represented by

$$S(P_i, P) = D(I, P) = Q$$

where S represents the supply (production side of the economy) which is a function of the price of inputs P_i and the market price of the commodity P. Similarly, D represents the demand (consumption side of the economy) which is a function of consumer income I and the price of the commodity. The firms produce Q quantities of the commodity such that the market is in equilibrium. Unlike I-O methods, the CGE functions are non-linear and contain elasticity parameters that allow for input substitutions e.g., Cobb and Douglas production functions. The impacts of natural hazards are estimated by quantifying the supply disruptions of goods and services, while in tandem considering the input and import substitution possibilities for the intermediate and final demands (Botzen et al., 2019). The general structure of a CGE model consists of model parameters, variables, and economic equations describing the economic processes. These equations are organized into blocks related to consumption, production, capital and labor, international trade, and taxation. For a detailed description of the CGE models, refer to Burfisher (2016).

3.3 Comparison of I-O and CGE

The I-O and CGE methods have the following major differences in the context of disaster impact analysis (Koks et al., 2016):

Equilibrium: The major difference between the formulation of I-O and CGE methods is that the former does not consider general equilibrium and the latter does. General equilibrium refers to an enclosed economic system in which all produced goods are utilized and all the earned income is expended on various products through savings and investments. The general equilibrium approach provides a comprehensive depiction of the entire economy and takes into account both monetary and non-monetary transactions. Traditional I-O models do not consider all the factors of the economy (e.g., change in price of goods, income).

Substitution Effects: The fixed coefficients of traditional I-O methods do not allow substitution possibilities which is likely to happen in the aftermath of a disaster. For example, after a disaster, producers (industries) tend to substitute their lost inputs from

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new suppliers in unaffected regions i.e., inter-regional substitution. Also, producers can substitute the factors of production such as replacing machinery with manual labor in the event of a power shutdown after disasters. Such substitution effects cannot be modeled using traditional I-O methods. However, CGE models are flexible enough to incorporate substitution effects via elasticity parameters.

Supply-side constraints: I-O models are not equipped to handle supply-side disruptions. The disaster impacts are modeled using simulated reductions on the demand side e.g., (Rose et al., 1997). On the other hand, CGE models can handle reduced production capacities.

Applicability to disaster impacts: Being rigid and linear, I-O-based models don't include the effects of post-disaster resilience measures e.g., substitution of commodities. Hence, they overestimate the disaster impacts. On the other hand, CGE models allow short-term substitution effects which are not relevant in the context of disaster scenarios and may lead to underestimation of losses (Hallegatte, 2014). To summarize, I-O models are considered to reflect the short-term effects of a disaster and CGE models are more equipped to capture the long-term effects (Rose, 2004a). Table 1. provides a summary of the above discussion.

Ease of use: IO models are best known for their simplicity and their capacity to directly depict the economic interconnections among sectors, thereby enabling the derivation of higher-order effects. In contrast, CGE models are more intricate as they consider supply-side effects and offer greater flexibility due to their nonlinearity in inter-sectorial deliveries, substitution effects, and changes in relative prices.

Table 1. *A comparison of I-O and CGE methods. This table is an amalgamation of tables (Table 1) from Balakrishnan et al. (2022) and Koks et al. (2016).*

Attribute	I-O	CGE
Equilibrium condition	Partial	General
Substitution effects	Not possible	Possible
Mathematical model type	Linear	Non-linear
Supply-side disruptions	Not possible	Possible
Time horizon	Short-run	Long-run
Disaster impact estimation	Overestimation	Underestimation

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Model development efforts	Comparatively less	Immense data collection and calibration required

3.4 I-O and CGE-based disaster impact studies

Several studies have used I-O and CGE-based methods to model the impacts of disasters. Some of the selected studies are discussed in detail here.

I-O: Some of the below-selected studies have used extended versions of the traditional I-O methodology e.g., modeling the recovery after disasters (Okuyama, 2004), and extension to other regions (interregional I-O tables (Bouwmeester & Oosterhaven, 2017). Okuyama (2004) used the I-O methodology to understand the impacts of the Great Hanshin Earthquake, in Japan. The I-O table published by the Ministry of International Trade and Industry, Japan was used. After the earthquake, there was an increase in demand in the construction sector (i.e., reconstruction demand). Two distinct scenarios were modeled with and without including reconstruction demand, and positive impacts in gross output were observed when reconstruction demands were taken into account. MacKenzie et al. (2012) studied the effect of the 2011 Japan earthquake on international production sectors. The study proposed a novel formulation to perform multi-regional analysis using I-O tables published by the Organization of Economic Cooperation and Development (OECD, 2011). The study included 18 different countries from Asia and South America which contribute to approximately 66% of Japan's imports. The analysis revealed that Japan's imports increased post-disaster by 10.7% which was able to satisfy 73% of the deficit between demand and production. Okuyama (2014) revealed that disasters not only affect the total economic output after a disaster but also change the economic structure because of recovery and reconstruction activities. As a case study, the study investigated the same after the 1995 Kobe earthquake by decomposition techniques e.g., the total output of Kobe region is decomposed into output for regional final demand and output for exports. A permanent decline in regional output is observed as a result of population decline and loss of lives resulting in demand reduction. Xia et al. (2018) studied the macroeconomic impacts of an extreme heat wave event in Nanjing, China using a supply-driven I-O model. The productivity losses in labor hours induced by the heat waves are translated to its equivalent measure of percentage reduction in value added in the I-O table. The results show that this 14-day event produced an economic loss equivalent to 3.5% of Nanjing's yearly gross value of

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production. Recently, Huang et al. (2022) applied the I-O methodology to evaluate the post-disaster impacts of the 2008 Sichuan earthquake and identified that economically underdeveloped provinces suffered more losses.

CGE: Rose & Liao (2005) used CGE models to estimate the economic impacts of water system disruption after a major earthquake. The novelty of this study is that it linked the resilience (or) post-event adaptation measures (e.g., water conservation, backup supplies) to production function parameters. Tirasirichai & Enke (2007) used CGE models to estimate the indirect economic impacts of bridge damages during an earthquake. The framework was tested within the St. Louis metropolitan area (U.S.A) for a hypothetical earthquake. The effect of bridge damages was converted to increased cost of travel. The modified travel costs were input into the CGE models to estimate the indirect impacts. For this hypothetical scenario, the indirect economic losses were 1.28 times higher than direct losses due to bridge damages. In a very similar study, Tsuchiya et al. (2007) evaluated the economic loss due to highway and railway disruptions combined in Japan using CGE models. Rose et al. (2016) applied CGE models to understand the economic impacts of port disruptions (Port of Los Angeles and Port of Long Beach) due to Tsunamis in California (U.S.A). This study also evaluated different economic resilience measures that can reduce the total impacts by 80 percent. Kajitani & Tatano (2018) applied a CGE model to estimate the short-term economic impacts (in a time scale of months) after a disaster. The elasticity parameters in the model for different sectors (e.g., automobile) are selected based on a calibration process using real-time data after the 2011 Japan earthquake. The selected parameters were either zero or nearly zero (i.e., elasticity equals zero refers to zero substitution possibilities indicating Leontief production function) for all the sectors indicating lesser substitution possibilities in the short term. This reiterates the discussion in section 3.3. CGE models have also been used to understand and quantify the indirect economic impacts of floods. For example, Gao et al. (2020) quantified the effect of a typhoon-induced flood on macroeconomic indicators such as GDP, commodity prices, etc. Also, floods damage the transport infrastructure and increase the cost of commodities. Using a spatial CGE model, Yang et al. (2023) analyzed the economic impacts of flooding-induced traffic disruptions in Hubei province, China. The study revealed that output losses increase by 80% when transport-induced losses are captured. Also, sectors such as storage, transportation, processing, and assembly manufacturing are likely to be more affected. Bachner et al. (2023) used a CGE model to understand the supply chain disruptions due to floods in Austria. The study utilized national datasets that contain the geospatial distribution of

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capital according to industrial sectors, which facilitates the estimation of sector-specific capital damages. The capital damages are negated from the capital accumulation equation of the model via which flood impacts are induced. The results suggested that capital owners and high-income populations are strongly affected in the short term whereas lower-income populations suffer in the long-term due to increased price levels.

3.5 Hybrid models

CGE models represent the true economic system better. However, constructing and calibrating a CGE model requires large amounts of data which may be cumbersome. Also, in developing countries where data availability is limited, the development of a CGE model may be non-viable. On the other hand, I-O models lack the flexibility of the CGE model. Researchers have developed hybrid models that retain the basic definitions and theoretical rules of I-O modeling with added flexibilities of CGE models. Although not a comprehensive review of existing hybrid models, a few representative models and their relevant studies are discussed below.

3.5.1 IIM

The inoperability input-output model (IIM) by Haimes & Jiang (2001) was originally developed to model the interdependencies between critical infrastructures. Later, Lian & Haimes (2006) extended the model to be dynamic (i.e., time-varying impacts with recovery) termed as Dynamic Inoperability Input-Output model (DIIM). The term 'inoperability' refers to the reduced functionality of the system/sector. The interdependencies between the sectors are taken into account via the inoperability indices compiled in an interdependency matrix 'A' (e.g., an element $a_{ji} = 0.3$ indicates Sector j is 30% inoperable if Sector i is 100% inoperable). In its elementary form, the model is a set of differential equations where each equation represents the rate of change of a sector's output with time. The model was demonstrated to estimate the economic losses of a terrorist attack in Virginia. Further, Akhtar & Santos (2013) developed the DIIM model to include the recovery of the workforce. Using DIIM, Thekdi & Santos (2016) studied the supply-chain impacts of port vulnerabilities subjected to hurricanes, terrorist attacks, and labor force strikes. Recently, Chen et al. (2022) applied DIIM to understand the costs of power outages in China. Being used widely in several studies, the model still holds several limitations. The mathematical framework of this

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model relies on interdependency and other similar (capital coefficient matrix, industry resilience coefficient matrix) matrices. Deriving the elements of these matrices is a complex task with huge uncertainties. Secondly, the model ignores the geo-spatial connectedness between infrastructures and businesses. Also, the model is not flexible enough to take into account the adaptive behaviors of economic agents such as overproduction, substitution effects, etc.

3.5.2 ARIO

The Adaptive Regional Input-Output (ARIO) model was developed by Hallegatte (2008). This model brought in major novelties which include incorporating production sector capacities and the adaptive behaviors of different economic agents. This model disintegrates the final demand vector of the I-O table into local demand, export demand, and reconstruction demands. Disasters are simulated in the economic system via increased reconstruction demands and reduced production capacities. Different adaptation behaviors are parametrically modeled. First, the model introduces a rationing scheme in the aftermath of a disaster where inter-sector demands are given priority. Secondly, the adaptation behavior of consumers to delay their purchases or export them from external suppliers is taken into account. Finally, the overproduction capacities of sectors and the price changes due to demand surges are also considered. The model was further extended to handle inventory flexibilities by Hallegatte (2014). This model is widely used to understand the economic impacts of disasters. Hallegatte (2008) used ARIO to study the impacts of Hurricane Katrina affecting the state of Louisiana. Interestingly, the study explores the possible scenarios of scaled-up direct damages of Hurricane Katrina and identifies that indirect losses increase non-linearly with direct losses beyond a threshold (50 billion USD). Zeng et al. (2019) developed a flood footprint assessment model using ARIO to assess the indirect impacts of flood events. Very recently, Hu et al. (2023) used ARIO models to estimate the economic impacts of a flood event combined with export restrictions during a pandemic. However, the model being regional fails to capture the spillover effects of disasters into other regions. Studies have found that multi-regional effects are substantial which not only represent the losses but also the gains in the other regions (Koks & Thissen, 2016; Schulte In Den Bäumen et al., 2015; Wenz et al., 2014). Also, Hallegatte (2008) acknowledges that the parameters of adaptive behaviors are difficult to calibrate. In a recent study, Liu et al. (2023) proposed a multi-regional ARIO model (termed as 'AMRIO') to analyze the indirect economic losses of rainstorm events in China. The model allowed

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inter-regional substitution of products/services from the same industry in other regions. The results indicated a non-linear relationship between direct and indirect economic losses. In addition, the study proved that indirect economic losses of high-impact rainstorm events can be twice that of direct losses. Guan et al. (2020) applied an extended ARIO model to study the supply chain effects of different Covid-19 lockdown scenarios. The lockdown scenarios varied in duration (2,4 and 6 months), strictness i.e., the restrictions applied to transport and labor availability (20%, 40%, 60%, 80%), and spatial spread (e.g., lockdown only in China, only in USA and Europe and all countries). The study used GTAP v10 (Aguiar et al., 2022), a global trade database to model the supply chain transactions between countries. The existing ARIO model is improved further to incorporate substitution of products from the same sector in different regions and the clients are allowed to choose suppliers based on their maximum capacity. The results revealed that the lockdown losses are more sensitive to the duration of the lockdown than the strictness. Also, the impact of the lockdown imposed in Europe and the United States is relatively high. For example, the economic loss of a lockdown scenario only in Europe and the United States (for 6 months, and 80% strictness) is nearly 75% of the loss had the same lockdown conditions been imposed over all countries.

3.5.3 Optimisation approaches

Oosterhaven & Bouwmeester (2016) developed a novel optimization-based methodology to simulate disruptions in the inter-regional I-O tables. The method aims to reduce the information gain between the post and pre-event I-O tables while holding onto the constraints of I-O analysis (e.g., supply equals demand). The methodology was later used by researchers to understand the impacts of trade disruptions between countries (Bouwmeester & Oosterhaven, 2017) and natural hazards (Oosterhaven & Többen, 2017). Koks & Thissen (2016) developed a dynamic Multi-Regional Impact Assessment (MRIA) model to study the economic impacts of disasters on the regional economies of Europe. The model addressed/improved upon three key aspects in the economic impact analysis of disasters. Firstly, the model is multi-regional which enables the study of the impacts outside the disaster-affected region. Also, it allows for substitution possibilities within regions resulting in positive gains if other regions increase their supply to cater to the demands of disaster-hit regions. Secondly, disasters affect the production capacities in the affected region i.e., a supply-side disruption. The model translates the disaster impact analysis into an optimization

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problem to minimize the production values and take in the supply-side and import constraints explicitly. Finally, the model accounts for production inefficiencies through non-demanded byproducts being supplied into the market. This model requires supply-use tables as its inputs (Thissen et al., 2013). The supply table records the value of products supplied into the economy by different economic sectors and imports. The use table records the value of products consumed by different economic sectors, exports, and so on. The model was illustrated by applying it to flood hazard impacts in Rotterdam. Koks et al. (2019) used MRIA to understand the macroeconomic impacts of future flood events in Europe. The indirect losses were segregated into first-order (losses to sectors within disaster-hit regions) and second-order (losses to sectors outside disaster-hit regions) for different climate scenarios. The results of second-order effects indicated positive gains in sectors outside the disaster extent. In another study, Koks et al. (2019) applied the MRIA model to understand the economic impacts of power service disruptions due to flooding in the United Kingdom. The results indicate that losses rise threefold when infrastructure failure is considered in the economic impact analysis. Given the merits of MRIA and its wider use, it can only be used to estimate the short-run economic impacts of disasters. The long-term effects of disasters (e.g., price change of commodities) are out of the scope of MRIA.

3.5.4 ABM based approaches

Agent-based modeling (ABM) approaches simulate the behavior of individual economic agents to assess the macro-level economic impacts. General equilibrium models (e.g., CGE based) assume that the agents optimize rationally whereas ABMs take into account the agent's heuristic behavior to make decisions and other boundary constraints (Poledna et al., 2023). Few such agent-based modeling approaches are discussed here. Acclimate is a multi-regional dynamic model to model the economic disruptions of the global supply-chain network using EORA input-output tables (Lenzen et al., 2012). The first version of the model was developed by Bierkandt et al. (2014). The model considers the behavior of economic agents from both the production and the consumption sides. External perturbations to the production side of an economic sector are forced via a parameter 'production ratio' which then is used to reduce the production output of the economic sectors. Both production and consumption sides are coupled with their pre-disruption storage capacities. An added novelty of this model is that it includes the time delay induced by the transport of goods. Subsequently, Wenz et al. (2014) modified the model to include demand-induced backward dynamics which

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was not available in ARIO. The earlier 'production ratio' was revised to 'target product ratio' which encompasses the aspects of overproduction and demand redistribution. Further, Otto et al. (2017) reformulated the production level of firms by assuming an optimized profit maximization scheme. The authors demonstrated the model (and its subsequent developments) for a hypothetical production loss in Japan's manufacturing sector. However, the model does not allow for substitution of goods for production. Also, the parameters of agent's behavior (e.g., assumed storage capacities of production sites) and the supply and demand redistribution patterns after disasters are yet to be backed up by studies and data for more precise loss estimates. Willner et al., (2018) applied the Acclimate model to simulate the global economic risks of future flooding events. Flood hazard maps are overlaid with population maps to identify the fraction of the affected population. The population affected is used as a proxy to estimate the reduction in production capacities (i.e., perturbation to the Acclimate model). The study identified that the total economic loss will increase by 17% in the next 20 years and also emphasized that balanced trade relations are essential for economic resilience against future climate events. Poledna et al. (2023) proposed an ABM model for small economies (at a national level) by utilizing data from national accounts, sector accounts, I-O tables, and census data. The behavior/decision of the agents (e.g., firms) is assumed to depend on the economic growth rate and inflation. The developed model was applied to understand the economic impacts (e.g., GDP, unemployment rate) of Covid 19 lockdown in Austria. The model estimated that the real GDP will decrease by 6 percent points and the unemployment rate will increase by 2.4 percent points. Also, Bachner et al. (2023) utilized the model by Poledna et al. (2023) to estimate the economic impacts of flood events of different return periods in Austria.

3.5.5 Comparison of hybrid models

While all the above-mentioned models share the common goal of estimating the economic impacts of a disruption, the outcomes of these models may vary significantly. For example, Koks et al. (2016) performed a quantitative comparative study of three different models ARIO, MRIA, and IEES (CGE-based), and evaluated the national-level economic losses of flooding scenarios in Italy. The results suggest that, for a given region, the difference between the loss estimates can vary up to a factor of seven depending on the model used and the recovery path. In most cases, the difference between MRIA and IEES (CGE-based) model loss estimates was less. However, the ARIO model overestimated the losses because of its linear nature and limited substitution

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characteristics from other regions. In another study, Bachner et al., (2023) performed a multi-model analysis (a CGE based and an ABM-based model) to estimate the economic impacts of floods in Austria. The results of the CGE model and ABM model were leading to different conclusions. For example, for a 1 in 1000-year flood event, the CGE model estimated a reduction in GDP of about 2 % while on the other hand ABM model estimated a GDP growth. The study argued that CGE models assume all production factors are used optimally and hence the reconstruction activities had to be compensated by reduction of other activities in the economy. These results highlight the importance of understanding the model assumptions and the uncertainties around the economic impact estimates.

3.6 Econometric methods

Econometric models use past (historical) data to understand the impacts of disasters using regression analysis. A simplistic representation of an econometric model is shown via equation $Y = aX + b$, where Y, the dependent variable represents the economic measure of interest (e.g., gross domestic product (GDP), GDP per capita, GDP growth rate, per capita income) and X, the independent variable represents a measure of disaster intensity such as the number of disasters in a year, the direct damages, the number of casualties, the physical hazard intensities such as wind speed for hurricanes (Botzen et al., 2019). The coefficients a and b describes the nature of relationship between the economic measure and the disaster intensity and are one of the main outcomes of the analysis. Datasets such as EM-DAT (CRED, 2023) by the Center for Research on the Epidemiology of Disasters (CRED) and NatCatService (Munich Re, 2010) by MunichRe are available to estimate these coefficients. However, this method is statistically rigorous (Balakrishnan et al., 2022) and is focused on the impacts on economic growth (i.e., long-run impacts) rather than the short-term economic output (Cavallo et al., 2013). Few of the pieces of literature in econometric studies are discussed in detail.

Skidmore & Toya (2002) used the EM-DAT (CRED, 2023) dataset to study the relationship between disasters and the long-term economic growth of 89 countries over 30 years from 1960-1990. The study identified a positive correlation between the number of disasters and economic growth, indicating that disasters increase the GDP growth rates. Moving further, the analysis segregated the disasters and identified that climatic disasters are positively correlated and geological disasters are negatively correlated with economic growth. The authors justified that the disasters catalyze the

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process of updating new technologies and thus result in positive economic growth. However, the disaster intensity measures from EM-DAT (CRED, 2023) are well correlated well with the GDP per capita (dependent variable of the analysis), because the disaster losses are greater in developed countries (Botzen et al., 2019). Future studies used physical intensities of hazards that are not subjected to this endogeneity bias. Felbermayr & Gröschl (2014) created a database of disaster events named 'GeoMet' where disasters were represented with physical intensities using geophysical and meteorological information. For example, the intensities of earthquake events were measured on the Richter scale and hurricanes with wind speeds. The study revealed that disasters have negative impacts on economic growth and also identified that the top one percent of worst disasters reduce the GDP per capita by 6.83 percentage points (arithmetic difference between percentages).

Considerable interest had been shown in the past to understand the impacts of individual hazards on short and long-term economic growth (e.g., the impacts of hurricanes on economic growth). Hsiang (2010) studied the economic impacts of increasing surface temperatures in twenty-eight Caribbean countries. The study reported that total production in agricultural sectors and non-agricultural sectors reduces by 0.1% and 2.4% respectively per degree (°C) rise in temperature. The study argued that increasing temperatures affect the labor forces via thermal stress which in turn can be attributed to the economic costs of climate change. Strobl (2011) introduced a hurricane disruption index by combining the damages, wind speed estimates, and exposure. The analysis suggested that the worst hurricane scenarios could bring down the county's annual growth rate by 3.04 percentage points, which is nearly twice the county-level average growth rate. In addition, the study claimed that hurricanes being spatially very limited do not have a great impact on the long-run national growth rates. However, Hsiang & Jina, (2014) rejected the hypothesis that disasters increase growth or disaster losses disappear in the long run. They studied the GDP growth rates of the countries exposed to tropical cyclones between the period 1950-2008. The study identified that hurricanes indeed affect long-term economic growth e.g., a 90th percentile hurricane event can reduce the per-capita income by 7.4% even after two decades. Dottori et al. (2018) evaluated the losses (human losses, direct damages, and indirect losses) from flooding at different levels of warming (1.5°C, 2°C, 3°C) at the continental scale. The indirect losses were estimated using a global econometric model MaGE (Fouré et al., 2013). The model is recursive with time i.e., the economic impacts of a particular year will be reflected in its economic performances in the subsequent years. The study identified that advanced economies such as Japan

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and North America are less affected whereas the highly populated countries like China would suffer greater indirect losses. In addition, the ratio of direct to indirect losses increases with warming e.g., indirect losses can be twice the direct losses with 3°C of warming. However, the study did not account for the ripple effects of international trade in its analysis. Hu et al. (2019) evaluated the flood impacts on the Chinese manufacturing sector via firm-level econometric analysis. Empirical data on labor productivity (i.e., the ratio of revenue to the number of employees) was collected from approximately 400 thousand firms over 8 years. A regression analysis combining the flood hazard and labor productivity data revealed that Chinese manufacturing firms are subjected to a 28.3% percent output reduction on average after a flood event. The results of this econometric analysis were then fed into a Leontief I-O-based macroeconomic model to estimate the total output losses (12.3 % annual loss) in the Chinese economy.

4. CI Failure in economic impact analysis

Failure of critical infrastructure systems such as power, transport, water, etc. during disasters results in huge economic losses and disrupts the normal functioning of societies. Understanding the economic impacts of critical infrastructure failure is a complex task in hand because of the underlying interactions between infrastructure and businesses and so the economic sectors. Also, critical infrastructures are interdependent among themselves which elevates the complexity. The following section details a few selected studies that have considered the economic impacts of service disruptions from critical infrastructures particularly focused on energy, transport, port, and water infrastructures.

4.1 Energy

Rose et al. (1997) analyzed the economic impacts of electricity disruption for simulated hypothetical earthquake scenarios in the New Madrid seismic zone, Memphis. This study used a 21-sector I-O table and divided the study area into 36 electric power supply areas (EPSA). EPSA zones were linked to the production sector using the population data per employment in each zone. The failure probabilities of substations (in each zone) were translated to their appropriate production output losses in each sector to perform I-O analysis. The resulting economic impacts do not account for the

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business asset damages (e.g., buildings and factories where businesses are set up) which play a major role in total economic impacts and restoration. Also, the limitations of using a standard I-O model hold (see Section 3.3). Okuyama (2004) considers lifeline infrastructures such as electricity, gas, and sanitary services as separate sectors in the I-O table. The study examined the disruption in other economic sectors given a unit output reduction in lifeline sectors. Coupling the inputs of infrastructures under one sector, however, isn't realistic since different CIs support businesses differently and the impacts of CI failure differ from one another (e.g., the factories are more resilient to telecommunication failure compared to power failure). Moreover, the spatial connections between infrastructures and industries are not taken into account. Anderson et al. (2007) evaluate the economic impacts of the 2003 NorthEast blackout event using the inoperability input-output (IIM) model originally developed by Haimes & Jiang (2001). The developed methodology utilizes the post-disaster data of electricity outages and links the outages to their economic output reduction. In addition to the existing limitations of the IIM model (see Section 3.4), the requirement of post-disaster outage data makes the methodology difficult to apply elsewhere.

Recent studies have started prioritizing the importance of the geospatial spread of infrastructures and their connectedness with economic sectors in their analyses. For example, Garcia Tapia et al., (2019) considered a network graph model (i.e., nodes and edges) of New York City's electrical grid and estimated the economic impacts using a simplistic (reduced GDP contribution of each sector) and rather unconventional approach. The inter-sector higher-order effects were ignored. Koks et al. (2019) developed a framework to understand business disruption losses of power infrastructure failure in the United Kingdom using the MRIA model (see Section 3.4). The results indicate that losses rise threefold when infrastructure failure is considered in the economic impact analysis which supports the need to consider the effect of infrastructure failure in economic impact models. However, the methodology only applies to single infrastructures whose service areas are assumed to be mutually exclusive (i.e., network redundancies cannot be modeled). Also, the connections between infrastructure assets and the beneficiaries (factories, households) were not modeled explicitly.

4.2 Transport

Santos & Haimes (2004) studied the cascading economic impacts of air transportation networks subjected to terror attacks using the IIM model. The results

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indicated that sectors closely associated with air transportation (e.g., tourism, manufacturing, oil and gas) are likely to be more affected. Similar to Okuyama (2004), the study ignored the spatial connectedness of the air transport network and the economic sectors. However, later studies have understood the importance of considering the spatial distribution of transportation networks e.g., (Cho et al., 2015; Wei et al., 2018). In general, the structure of the proposed frameworks in these studies consists of a transportation network model, a cost model, and a macroeconomic impact model. The transportation network model captures the increased travel times (and distances) of freights and passengers caused by the disruption, the cost model estimates price changes of the commodities due to increased travel times (and distances) and the economic impact model takes these price changes as inputs and estimates the ripple effect among the other economic sectors.

Tirasirichai & Enke (2007) evaluated the indirect economic losses of damaged highway bridges subjected to a hypothetical earthquake using a regional CGE model. The study results indicated that the indirect losses are significant compared to the direct losses (i.e., damage cost of the highway bridges). In a similar study, Tsuchiya et al. (2007) analyzed the economic impacts of disrupted highways and railroads due to earthquakes in the Tokai-Tonankai region of Japan. The study models transport distributions of commodity flows and passenger trips, where the former represents the disruption of intermediate inputs to firms and the latter represents the business trips which are accounted as technical knowledge input to firms. Cho et al. (2015) developed a model 'TransNIEMO' by coupling the National Interstate Economic Model (NIEMO) with the highway network in the United States. NIEMO is a multi-regional I-O model with 50 regions (states) and 47 economic sectors. The price increase of delayed transportation of goods was converted to its corresponding reduced demand from the consumers. This study examined different disruption scenarios (e.g., bridge closures, tunnel closures) and identified that the economic impacts were moderate because of the inherent redundancy available in the transportation network.

Colon et al. (2020) performed a criticality analysis (i.e., identifying the important components of a network) of the road network in the United Republic of Tanzania. This study took a modified approach by coupling each transportation network node with nodes of representative firms (of each economic sector) and households. This allows us to map the spatial linkages of supply chain activities at a network level. The results revealed critical roads of the network which are supply-chain specific. Also, the study identified that the indirect economic losses increase non-linearly with the increase in restoration time. The average losses corresponding to a two-week disruption is five

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times higher than that of a week disruption. However, the developed frameworks in the above-mentioned studies are tailor-made to transportation networks and cannot be translated to other infrastructures such as power. International institutions such as the World Bank Group have invested considerable resources to understand the macroeconomic losses of transportation infrastructure failure in developing nations. Oh et al. (2019) studied the criticality, vulnerability, and risk of transportation networks in Vietnam subjected to floods and landslides. Freight flow disruptions affect the supply of inputs to the producers and reduce the demand for unavailable commodities. The resulting macroeconomic losses were estimated using multi-regional economic input-output models proposed by Koks & Thissen (2016). The results indicated that the daily losses to road and rail networks can be up to 1.9 million and 2.6 million USD/day respectively. Also, the expected annual economic losses are likely to increase by 100 percent by 2030. In a similar study, Kesete et al. (2021) analyzed the impact of floods on transportation network in Argentina. The losses due to road failure can be up to 3.8 million USD (for a network disruption of 10 days) which is likely to increase under future climate scenarios. Both the above studies emphasize the importance of targeted adaptation via cost-benefit analysis.

Ports being the crucial channels of regional exports and imports have gained considerable interest in economic impact analysis. Rose & Wei (2013) studied the macroeconomic impacts of a 90-day shutdown of twin ports Beaumont and Port Arthur, Texas. The study applied a combination of demand-driven and supply-driven I-O models. While the demand-driven model was used to capture the demand reduction because of disrupted exports, the supply-driven model was applied to account for the lack of supply from imports to other economic sectors and households. In a similar study, Rose et al. (2016) analyzed the economic impacts of a port disruption using a CGE model at the Port of Los Angeles and Port of Long Beach California subjected to a Tsunami event. The total economic impacts were evaluated as the sum of property damages, impacts from trade disruptions, and evacuation costs. The building and content loss estimation data obtained from Porter et al. (2013) was translated as a percentage reduction of capital stock to be used in the economic impact model. The above two studies also evaluated the effect of alternate resilience measures such as re-routing, redistribution of exports, and so on. The results indicated that the resilience measures can reduce the economic impacts by more than 70%.

Thekdi & Santos (2016) provided a framework to identify the vulnerable economic sectors affected by port disruptions using the DIIM model (see Section 3.5.1). The framework was applied to the Port of Virginia subjected to various sudden onset

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scenarios (e.g., hurricanes, dock worker strikes, and terror attacks). The study provided a decision-making chart based on the economic loss and inoperability of each sector resulting from the port shutdown, from which the vulnerable sectors can be identified. In another study, Verschuur et al. (2022) studied the criticality of ports in international trade and global supply chains. Over 1300 ports across 176 countries were selected for this study. The trade flows between ports were derived from multi-regional input-output tables EORA-MRIO (Lenzen et al., 2017). The study identified critical (important) ports of the network via different metrics such as the ports' contribution to global and regional output, port-level exports, and imports. Also, the study revealed that low-income and small island countries are more dependent on port infrastructures for their trade activities. Very few economic impact studies have managed to consider this linkage between hazard and port downtime. Balakrishnan et al. (2022) proposed a methodology to analyze hurricane-induced port shutdowns and their associated economic impacts. The methodology is divided into two major sections; the first section focuses on the determination of the duration of port shutdown and the second section focuses on the economic impacts. Hurricane parameters such as landfall, distance from the eye, and intensity were used to develop the prediction model for port shutdown. The methodology is applied to the Texas port system and the economic impacts of hurricanes (of different return periods) were estimated. Verschuur et al.
(2023) studied the global trade risks associated with port disruptions from climate extremes (e.g., cyclones, and flooding). The expected annual downtime of ports subjected to operational disruptions and climate extremes (Verschuur, Koks, Li, et al., 2023) was combined with ship movement between ports, their freight flows, and global supply-chain datasets (EORA – MRIO, refer to section 8) to estimate the global trade impacts. The study estimated that the annual loss of port disruptions equals 81 billion USD, where cross-border effects (countries depending on foreign ports for trade) dominate in more than 80% of the countries. Fotopoulou et al. (2022) proposed a methodology for the system-wide seismic risk assessment of port facilities which considers the combined effects of ground shaking and liquefaction as well as various interdependencies among port elements, which affect the port's operation and, consequently, the total risk impact. The systemic risk analysis of the port is carried out using as a performance indicator the reduction in the container and bulk cargo movements affected by the seismic performance of the piers, the waterfront, and container/cargo handling equipment, as well as their interaction with the seismic performance of the electric power system. The methodology, based on either probabilistic or deterministic scenario-based approaches, is demonstrated through an

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application to the Thessaloniki port in Greece. The results of the probabilistic seismic risk assessment are illustrated in terms of annual probabilities of collapse and loss exceedance curves for each port component as well as normalized performance loss for the whole port system for the container and cargo terminal.

4.3 Water Supply

Rose & Liao (2005) analyzed the economic impacts of water supply disruption in the Portland metropolitan area subjected to earthquakes. The study area was divided into nine service areas and coupled with economic sectors using a similar method adopted by Rose et al. (1997). The study used a CGE model where water is considered as a separate input in the firm's production functions explicitly to facilitate the analysis. Also, this formulation allowed us to parametrically model the different resilience measures such as water conservation, substitutability, backup supplies, and so on. In another study, Rose et al. (2011) evaluated the regional economic impacts of water supply disruption in Los Angeles subjected to a Verdugo scenario earthquake. The study identified that the economic losses can be countered up to 90% with appropriate resilience measures.

5. Economic impacts in a multi-hazard context

The impacts of consecutive multi-hazard events differ greatly from impacts that have been analyzed as multiple independent single-hazard events, primarily because of the existing inter-relationships between the hazards, the recovery dynamics, and the economic dependencies (Hochrainer-Stigler et al., 2023). For example, Japan in June 2018 suffered from major flooding and landslide events. Before the complete recovery of the system, two other extreme events followed (a heatwave in July and typhoons in August) within 2 months making the impacts even worse. Conventional impact modeling approaches are not fully equipped to model the above interactions (Argyroudis et al., 2020; Ruiter et al., 2020).

There has not been much attention given to understanding the economic impacts of multi-hazards (Zeng & Guan, 2020). Very few studies exist. For example, Zeng & Guan (2020) proposed a methodology to estimate the indirect economic impacts of a

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hypothetical scenario of consecutive flood events of the same impact, with one week being the occurrence time between these events. The method applied the ARIO model for economic impact analysis. The results indicated that the losses can be twice the losses had they been considered as single disasters. Using a similar methodology, Hu et al. (2023) studied the economic impacts of a flood event and a pandemic (biological hazard) control occurring concurrently. Verschuur et al. (2023) evaluated the trade and economic losses of global port infrastructure subjected to several multi-hazards such as earthquakes, cyclones, floodings, and operational failures. However, this is an asset-level risk analysis and does not consider the interactions between the hazards (e.g., consecutive events, cascading events).

Also, macroeconomic impact models are not intended to provide precise estimates but rather serve as tools for generating preliminary insights into the potential cascading effects of supply-chain disruptions during disasters. These models incorporate various parameters, including the behavioral patterns of economic agents, which vary depending on factors such as the nature of the hazard, its intensity, and regional disparities. The complexities of these models are further amplified in a multi-hazard context, where the spatial and temporal overlap of different hazards introduces additional layers of uncertainty and complexity. Consequently, these models should be interpreted as indicative rather than definitive assessments of disaster impacts.

6. Economic Validation of CI impacts on disasters

Empirical evidence of impacts after disasters is essential for the development and validation of macroeconomic impact models (or any disaster impact models). This includes the data on asset damages (e.g., damage to infrastructure assets, damages to different classes of buildings), service outages experienced by consumers, business downtime, and the recovery of damaged assets and businesses. This data can be used to substantiate the model results/outcomes and also if required, aids in the calibration of relevant model parameters. However, there is limited availability of such validation data (Koks et al., 2022; Verschuur et al., 2020). Further, the task of validating a macroeconomic impact model possesses additional complexities. In most cases, the impact on regional supply chains extends beyond the disaster-hit regions via imports and exports (i.e., multi-regional spillover effects). In addition, the data on the behavior

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of economic agents (producers and consumers), the change in production capacities and demands, the inventory capacities, and, the recovery duration of business assets are either not available or difficult to obtain.

In the past, very few studies have attempted to validate the macroeconomic impact estimate from their models. For example, Kajitani & Tatano (2018) studied the short-run economic impacts of the 2011 East Japan earthquake and tsunami using a CGE model. The study utilized the monthly observed data of the Index of Industrial Production (IIP – a measure of production levels of economic sectors) of manufacturing sectors to validate the results. The model overestimated the production levels in the post-disaster scenario, however, the trend of monthly estimated IIPs is consistent with the observed IIPs spatially (across different regions) and temporally. Alleman et al. (2023) validated a dynamic I-O model which models the supply-chain impacts of the COVID-19 pandemic in Belgium. The model results were validated using different indicators of the economy such as the Gross domestic product, Employment, Business to Business transactions, and Revenue, observed quarterly (for four quarters of the year from 2020-Q2 to 2021-Q1).

In a recent study, Koks et al. (2022) compiled the critical infrastructure impacts of the 2021 mid-July Western European flood event in Germany, Belgium, and the Netherlands. The study provided the first-of-its-kind estimates of infrastructure asset damages and recovery durations for six different infrastructure classes (transport, energy, water, telecommunication, healthcare & education, and solid waste) across the three countries. This can be used as validation material in future CI risk studies. Interestingly, much of the information/data had been compiled via online articles and reports published near the time of the disaster. This method of data collection proved to be efficient and should be applied to future disasters as well by regional agencies and institutions. Particularly, the data on the recovery of infrastructures and businesses is crucial for modeling the macroeconomic impacts of disasters.

7. Uncertainties in CI systemic risk modeling

Understanding the uncertainties involved in a risk analysis is crucial. Uncertainties can emanate from the input data used, selected model parameters, and so on. Broadly, the uncertainties can be classified into two major categories: (i) aleatory (inherent randomness in the system) e.g., future trade flows between different regions and

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sectors, and (ii) epistemic (lack of knowledge/data) e.g., lack of recovery data to quantify the model parameters. Several researchers have emphasized the inclusion of uncertainties in systemic risk assessments. For example, Rose (2004b) stated that using deterministic estimates to discuss the results of risk analysis is an exaggeration of certainty. Such deterministic modeling estimates may lead to faulty policies and decision-making (Santos et al., 2022). This section discusses the uncertainties in systemic risk modeling associated with CI data availability and economic impact model parameters.

Data availability of critical infrastructure asset locations, their specific functions, and interconnections are some of the hindrances in CI risk studies. This has resulted in studies undertaking more simplified approaches to model the CI networks. In recent years, many efforts have been made to improve the data availability of transport and power infrastructure systems. Around 80% of the global road network is available via OpenStreetMap (OSM) (Barrington-Leigh & Millard-Ball, 2017). Similarly, global datasets on power infrastructures are being developed (Arderne et al., 2020). However, there is a severe lack of data availability for certain infrastructures such as water supply systems (Koks, 2022). Economic impact analysis without complete data on CI assets will lead to inaccurate loss estimates. Similarly, the values of the parameters of economic impact models (e.g., elasticity coefficients (CGE), adaptive behavior parameters) sometimes have very little/ no real-time data to be backed up. Studies have attempted to quantify these uncertainties via Monte Carlo simulations and sensitivity analysis. Tirasirichai & Enke (2007) made 1,00,000 iterations of the model with a set of different elasticity coefficients and presented the mean estimates of indirect impacts. Tsuchiya et al. (2007) performed a sensitivity analysis to understand the effect of intra-region commodity transit times on the loss estimates. The analysis revealed that even when the intra-region transit times are doubled, the losses change only by a lesser extent (increases approximately 10%). Similarly, Hallegatte (2008) understood the influence of ARIO model parameters via sensitivity analysis. For example, the overproduction parameters of the model, namely the overproduction capacity and overproduction characteristic time (i.e., the time required to reach the overproduction capacity) were subjected to sensitivity analysis. Four different sets of these parameters were chosen. The effect of overproduction capacity on the output losses was stronger compared to the overproduction characteristic time. With a fifty percent increase in production capacity, the pre-disaster output levels were attained within 2 years, whereas a twenty percent increase in production capacity takes 6 years for the same. However, in the

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range between 3 and 6 months, the overproduction characteristic time did not have a greater effect on the output losses.

The lack of recovery data of economic systems after disruptions increases the uncertainty in impact estimates using dynamic models. For example, Koks & Thissen (2016) observed that the increase in recovery duration can increase economic losses greatly. Recent studies have made progress in quantifying the recovery time of businesses after earthquake and hurricane disruptions e.g., (Liang et al., 2023; K. Liu et al., 2021) Also, the elements of the I-O tables (i.e., the transactions between economic sectors) may be uncertain. Santos et al. (2022) modeled the columns of the coefficient matrix (see Section 3.1) using a Dirichlet distribution. The results were presented using a box and whisker plot indicating the minimum, 25th percentile, 50th percentile, 75th percentile, and maximum economic loss estimates corresponding to each sector. For example, the manufacturing sector had a greater uncertainty around its loss estimates compared to other sectors. From a modeling perspective, this method of presenting results with confidence intervals is valuable, as it highlights the uncertainties arising from different assumptions made within the model. Also, this enables the decision-makers to understand the whole spectrum of anticipated economic losses and frame appropriate policies considering the uncertainties.

8. Data usage for economic impact modeling

The following datasets are required to estimate the macroeconomic impacts of CI due to natural hazards a) asset locations of critical infrastructures (e.g., power substations, railway stations) and business assets (e.g., industrial buildings, mines) b) vulnerability data of assets (i.e., models that estimate the damage to the asset for a given hazard intensity) c) network flow data d) data on flow of goods and services between different economic sectors and e) the recovery data (recovery duration of assets after hazards). Deliverable 1.1 presents a review of the existing exposure data of critical infrastructures and the vulnerability data/studies available for different hazards such as floods, earthquakes, landslides, wildfires, and hurricanes. Deliverable 2.1 reviews different datasets available for CI interdependency modeling. Further, this section focuses on the available multi-regional trade datasets.

Data on the flow of goods and services (e.g., I-O tables, Supply, and Use tables) between different sectors and regions is an essential requirement to perform economic

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impact analysis. They reflect the supply and consumption patterns of economic sectors and other economic agents (e.g., households, and governments). In addition, multi-regional datasets reflect the trade relations and dependencies of economic sectors in different regions. Within MIRACA, the RHOMOLO V4 dataset will be used. It consists of multi-regional supply and use tables for 306 NUTS-2 (Nomenclature of Territorial Units for Statistics application) regions of the European Union. This inter-regional dataset is derived from intercountry Input-Output tables from Eurostat, also popularly referred to as FIGARO tables. Also, input-output datasets are available at a global scale reflecting the inter-sector and intercountry dependencies. For example, the GTAP (Global Trade Analysis Project) dataset consists of multi-regional I-O tables covering 141 countries that contribute to 99.1% of global GDP (96.4% of the world's population). EORA-MRIO is a similar global-level dataset covering 190 countries. The above-mentioned datasets have been widely used in economic impact studies. The following table provides an overview of the datasets discussed above.

Table 2. *A comparison of the existing datasets that describe the inter-sector trade relationships between different regions/countries*

Sl. No	Characteristics	RHOMOLO - PBL	GTAP	EORA-MRIO
1.	Abbreviation	-	Global Trade Analysis Project	Multi-Regional Input Output
2.	Scale	Europe	Global	Global
3.	Sectors	56	65	25
4.	Regions	306 (NUTS-2 regions of EU)	-	-
5.	Countries	28 (one rest of the world)	141	187 / 190
6.	Source	Garcia-Rodriguez et al. (2023)	Aguiar et al. (2022)	Lenzen et al. (2013)

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7.	Latest version	RHOMOLO V4	GTAP v11	Eora26
8.	Base Year	2017	2004, 2007, 2011, 2014, 2017	1990-2022

9. Conclusions and Future directions

In this deliverable (WP3 – D3.1), we conducted an extensive review of systemic risk assessment, particularly focused on the macroeconomic impacts of natural hazards. Different approaches to modeling macroeconomic impacts such as the input-output (I-O) method, computable general equilibrium (CGE) method, hybrid models, and econometric models were discussed along with their relevant studies in tandem. In addition, we reviewed several studies that estimate the macroeconomic impacts of critical infrastructures (e.g., energy and transport), datasets of multi-regional trade, and the uncertainties of macroeconomic impact modeling. Through this review, we acknowledge that a significant amount of research has been undertaken in the development of macroeconomic impact models and multi-regional trade datasets. However, we identify several areas of improvement within the existing frameworks which can be addressed via MIRACA.

The existing frameworks can be improved profoundly by **spatial integration of the critical infrastructures with the macroeconomic models**. A major fraction of the existing economic impact studies do not consider the service disruptions from infrastructure failure during natural hazards. Even if considered, they do not model the spatial (e.g., power systems spatially connected to the factories) and economic (e.g., power system shutdowns resulting in downtime losses in factories) linkages between infrastructures and the economic sectors. For example, most of the studies model economic disruptions via simplified assumptions such as the percent reduction in physical damage equals the percent reduction in output of an economic sector (Rose et al., 2016), the population affected as a proxy (Willner et al., 2018) and so on. As shown in Fig.2., infrastructures back up the business assets (i.e., factories and households) in their day-to-day activities. During natural hazards, these business assets face service disruptions from their supporting infrastructures resulting in downtime. This downtime loss is translated into its corresponding economic sector to which the factory or household contributes. **Within MIRACA**, we plan to focus on modeling this realistic pathway of failure propagation which incorporates the fragility of infrastructures and business assets

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toward natural hazards. However, this requires the development of advanced models (built with modularity) developed over state-of-the-art datasets as discussed in Section 8. We plan to extend the existing MRIA (Koks & Thissen, 2016) macroeconomic model with additional modules that link asset and network-level functionality losses to production losses in sectors. MRIA (refer to Section 3.5.3), an optimization-based approach can be used to estimate both supply and demand side impacts with interregional substitution capabilities. These additional modules will serve the following purposes: (i) spatially connect the critical infrastructure assets with business assets (e.g., factories), (ii) the downtime of the businesses will be linked to the production capacities of the economic sectors.

Critical infrastructures such as **telecommunications, water supply, and health services are not given due importance** in economic impact studies. Very few or no studies exist. For example, in the modern world, infrastructures such as telecommunication are as vital as infrastructures such as power and transport, where internet disruption in days can potentially disrupt business operations in many sectors. Hence, infrastructure owners and governments are in need to understand the systemic risks of such infrastructures. Also, there is a lack of a unified framework to understand the macroeconomic impacts of different infrastructures. **Within MIRACA**, we intend to develop a unified framework that can apply to all infrastructures by linking the infrastructure assets with their economic sectors. Also, the CI interdependency modeling methods developed in WP2 will be used in the framework. The developed framework will be used to estimate the macroeconomic impacts of telecommunication and health service disruptions within use cases 3 and 4.

Next, **the lack of data and unknowns in infrastructure systems, business operations, and recovery prove to be a major hindrance**. Many studies have emphasized that economic impacts are proportional to the recovery duration of the system. However, the lack of recovery data increases the uncertainties in the impact estimates. Similarly, economic impact models have improved significantly to take into account the adaptive behaviors of agents e.g., inventory capacity, rationing the supply. However, they cannot be backed up by real-time data forcing the researchers towards sensitivity analysis (exploring different model parameters and their impacts). Global/national organizations along with economic agencies should increase their efforts to conduct surveys and collect appropriate data on the recovery and adaptive behaviors of business agents in post-disaster scenarios. **Within MIRACA**, we intend to reduce this gap through stakeholder (e.g., KPN) consultation in different use cases. Also, we plan to understand the recovery process at different time scales such as the stagnation period

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after the hazard, the restoration of infrastructure services, and the restoration of businesses.

Finally, with multi-hazard events being more evident, existing frameworks do not consider the **economic impacts of multi-hazard scenarios**. In addition, most of the existing economic impact modeling frameworks are not equipped to handle the model uncertainties inherently (deterministic approaches). **Within MIRACA**, we extend the framework to understand the economic impacts of cascading and consecutive multi-hazard events. Also, we plan to identify the important uncertainties in these frameworks and quantify them. To summarize, this review identified several research gaps in the existing macroeconomic impact modeling frameworks that can be further improved in MIRACA. We believe the improved methods will deliver insightful results to the decision-makers in understanding the macroeconomic impacts of CI failure in Europe.

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