Macroeconomic models for predicting indirect impacts of disasters: A review

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ABSTRACT

Interdependencies between critical infrastructures and the economy amplify the effects of damage caused by disasters. The growing interest in impacts beyond physical damage has spurred a surge in literature on economic modeling methodologies for estimating indirect economic impacts of disasters. In this review, we propose a mathematical framework for categorizing modeling approaches that assess indirect economic impacts across natural hazards and anthropogenic disasters such as cyber attacks. We conduct a comparative analysis of macroeconomic models, focusing on the approaches capturing sectoral inter-dependencies. These include the Leontief Input-Output (I/O) model, the Inoperability Input-Output Model (IIM), the Dynamic Inoperability Input-Output Model (DIIM), the Adaptive Regional Input-Output (ARIO) model, and the Computable General Equilibrium (CGE) model and its extensions. We evaluate their applicability to disaster scenarios based on input data availability, the compatibility of model assumptions, and output capabilities. We also reveal the functional relationships of input data and output metrics across economic modeling approaches for inter-sectoral impacts. Furthermore, we examine how the damage mechanisms posed by different types of disasters translate into model inputs and impact modeling processes.

INTRODUCTION

The growing interdependencies of modern infrastructures, coupled with the increasing frequencies of natural hazards (NOAA, 2022) and cyber attacks (Statista, 2021), increase the potential vulnerabilities and consequences to physical and cyber threats (FEMA, 2024) and challenge conventional resilience frameworks (Okuyama and Rose, 2019). Understanding the ripple effects of disastrous events on modern infrastructures and the economy is crucial for guiding resilience interventions and mitigating future economic downturns.

Historically, disaster loss estimation focused on quantifying physical damage and was primarily led by engineers (Rose, 2009). In recent decades, the rising interest in the impacts of disasters beyond physical damage has led to an evolving understanding and definition of disaster economic consequences. From the engineering perspective, the National Research Council (1999) classifies losses into three categories: primary direct, secondary direct, and indirect. Primary direct losses are attributed to the immediate physical destruction resulting from the event itself. Secondary direct losses encompass additional impacts stemming from follow-on physical damage, such as fire damage from gas pipe breakage during an earthquake. Indirect losses are activity-related consequences of the physical destruction caused by the event, which can be further subdivided into short-term and long-term indirect impacts. Short-term indirect impacts encompass factors like reductions in spending, input-output losses for firms, and changes in future production, employment, and income. Long-term indirect impacts involve more enduring effects such as migration patterns, shifts in housing values, and government expenditures.

On the economic side, distinctions are drawn between stocks and flows (Rose, 2004). Stocks represent quantities at a specific time, while flows are time series data that represent the outputs of stocks over time. Direct stock losses result from property damage and direct flow losses stem from business interruptions by the hazard itself, such as factory shutdowns following an earthquake (Brookshire et al., 1997; Rose, 2004). Indirect effects are economic impacts beyond direct damages (Rose, 2009). Indirect stock losses are secondary direct losses per the National Research Council (1999) definition, while the indirect flow losses arise from disruptions in successive rounds of suppliers and customers, such as reduced supplier orders or consumer spending. Rose (2004) further introduced the term higher-order effects to describe all flow losses of interdependent activities, beyond direct and indirect flow losses of the focus activity. The term offers a broader perspective by capturing both the ripple effects, due to economic interdependencies, and other market responses, such as changes in income and spending.

Figure 1 presents a general framework for indirect economic impact modeling from the engineering perspective. This framework highlights the critical interfaces that need to be considered in the analysis. A disaster first directly impacts the built and social environment. These direct impacts cause disruptions to one or more economic system components, triggering a ripple effect within the interdependent economic system, and resulting in indirect impacts. While macroeconomic modeling navigates the evolving dynamics within the economic system, understanding the interface between hazards, physical environments, and the economic system is essential for the model setup.

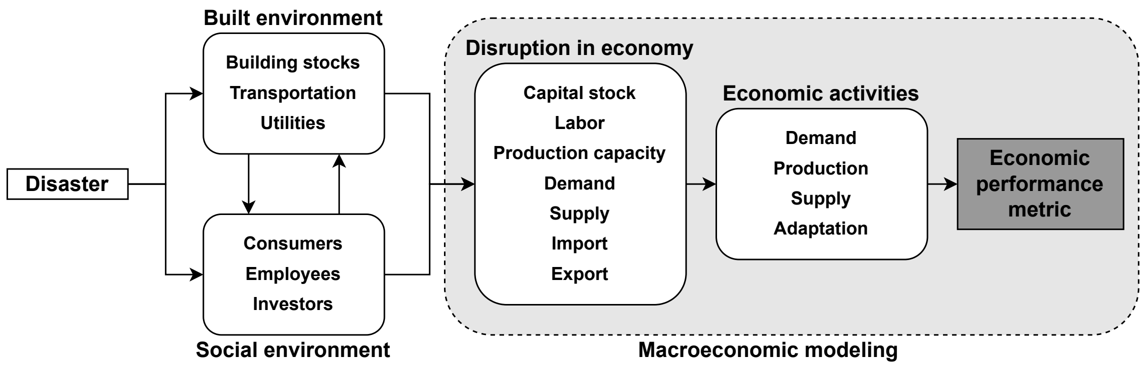

Fig. 1. General framework for indirect economic impact modeling. The light gray box highlights the steps analyzed by macroeconomic models.

Although several reviews have focused on macroeconomic modeling and evaluation of indirect impacts of natural hazards and cyber attacks (e.g. Rose, 2004; Kelly, 2015; Koks et al., 2016; Galbusera and Giannopoulos, 2018; Botzen et al., 2019), they are constrained in at least one of three ways. First, the treatment of the mathematical formulation of each model is limited. Most reviews compare the mathematical formulations at only a high level, if at all, and focus on the qualitative implications of each modeling approach. For example, Rose (2004) considers the appropriate model to study short-term versus long-term indirect economic impacts of a disaster. Second, the reviews describe the differences in input data, mathematical formulations, and output metrics across models at a high level, if at all (e.g. Kelly, 2015; Koks et al., 2016). Third, the existing literature focuses on reviewing modeling approaches and theoretical assumptions (e.g. Galbusera and Giannopoulos, 2018; Botzen et al., 2019), without a systematic review and categorization of disaster scenarios based on their impact on modeling inputs.

This paper aims to advance the existing literature and provide a detailed mathematical framework to categorize approaches that assess inter-sectoral impacts from natural hazards and cyber attacks. Our contribution is three-fold. First, we conduct a comparative analysis of macroeconomic models for disaster impacts, focusing on their assumptions and data requirements. We gauge the applicability of each model to disaster scenarios based on input data availability, the compatibility of model assumptions, and the model outputs' relevance. Second, based on detailed mathematical descriptions, we reveal the relationships between models' inputs and outputs. The relationships give analysts an actionable guide for mapping and comparing inputs and outputs across models. Third, we outline the different sets of damage mechanisms posed by various disasters, and categorize the attributes of disasters that influence model inputs or processes.

The remainder of the paper is organized as follows. First, we review the existing literature and provide an overview of the three major economic modeling approaches in disaster analysis. We then build on the literature review to provide detailed mathematical formulations for the classes of models that address the sectoral interdependencies. Then, we review the literature on the economic impacts of natural hazards and cyber attacks, and characterize how disaster impacts are translated into model inputs across models and disaster types. Based on the review of modeling approaches and economic modeling of natural hazards and cyber attacks, we identify gaps in current approaches and potential future research avenues.

OVERVIEW OF MODELING APPROACHES

There are three broad classes of economic models for assessing indirect impacts: Input-Output (I/O) models, Computable General Equilibrium (CGE) models, and econometric models (Rose, 2004; Galbusera and Giannopoulos, 2018). Understanding the distinct strengths and limitations of each class of models is crucial for selecting a suitable methodology. In this section, we summarize the key features and major developments of each.

Input-Output Models

The I/O model is a widely-used framework that describes how an industry's products are distributed across all sectors of the economy through trade flows captured in the surveyed Input-Output tables (Leontief, 1944, 1986). The I/O formulation comprises a system of linear equations that quantitatively describe inter-sectoral trade flows. The capability to assess demand-driven changes in sectoral output makes I/O models applicable to economic assessment studies of disaster-induced shocks (Kelly, 2015). One of the key advantages of I/O models lies in their ability to evaluate the propagation of disruptions across different sectors, providing valuable insights into economy-wide interdependencies (Rose, 2004; Okuyama, 2007). Moreover, I/O models offer a clear distinction between direct and indirect impacts, enhancing the understanding of the ripple effects of a shock to a specific sector (Kelly, 2015).

However, I/O models suffer from three main limitations (Rose, 2004; Okuyama, 2007; Botzen et al., 2019). Notably, they do not account for price fluctuations, which can influence the demand for intermediate and final goods, and potentially alter the economic landscape after disasters. Moreover, supply-side shocks, technological advancements, and the potential for input and import substitution are not fully considered in the model, which may not adequately capture adaptive behavior and other forms of economic resilience that can manifest during the recovery process. Additionally, I/O models assume linearity between input and output. This can result in an oversimplified representation of the complex dynamics of the economy.

Several extensions have been developed based on the I/O framework, including the Leontief dynamic model (Miller and Blair, 1985), the Inoperability Input Output Model (IIM) (Haimes and Jiang, 2001; Haimes et al., 2005), the Dynamic Inoperability Input Output Model (DIIM) (Lian and Haimes, 2006), the Multi-Regional Impact Assessment (MRIA) model (Koks and Thissen, 2016), and the Adaptive Regional Input-Output (ARIO) model (Hallegatte, 2008; Hallegatte, 2014). The concept of inoperability of an economic sector is defined as the percentage of output reduced from the ideal output and is the main focus of the analysis in IIM models. The Leontief dynamic model, DIIM, and ARIO models incorporate the additional time dimension of economic activities, while the MRIA model further considers geographic heterogeneities in activities and impacts. The supply-driven variation of the I/O model or Ghosh model (Ghosh, 1958) inverses the interpretation of the I/O framework to represent the relationship between primary inputs and output. However, the Ghosh model has faced criticism regarding its assumptions of perfect demand elasticity and input substitutability (Oosterhaven, 1988; Gruver, 1989), leading to debates about its plausibility and applicability in real-world scenarios (Oosterhaven, 1989; De Mesnard, 2009).

Computable General Equilibrium Models

A CGE model expands the traditional I/O framework to incorporate the response of all sectors and consumers to changes in the prices of commodities in the economy. A CGE comprises cost-minimizing firms, utility-maximizing households, and lump-sum payments by the government. An equilibrium of a CGE is a vector of prices and quantities of commodities that clear all markets (Shoven and Whalley, 1984). The CGE framework accommodates substitution between inputs in production activities and goods consumed by households; supply constraints; substitution between imports, exports, and domestic production; and savings, investment, and borrowing decisions (Hosoe et al., 2010; Lofgren et al., 2002; Capros et al., 2013). Extensions of the standard CGE incorporate technological detail and the response of multiple agents within individual sectors (Böhringer and Rutherford, 2008; Böhringer and Rutherford, 2009).

Some assumptions underpinning CGEs may not hold when applied to disaster disruption. First, assuming perfectly competitive markets, cost-minimizing firms and utility-maximizing households, always at equilibrium, do not necessarily hold under critical conditions (Rose, 2004). Disasters often damage infrastructures and cause supply shortages and service interruptions, causing the supply of goods and services to be voluntary or driven by government interventions. Firms and households may also purchase certain goods and services based on their immediate needs and not based on relative prices. Second, in the immediate aftermath of a disaster, substitution between consumed goods and services may not be possible (Rose and Guha, 2004). Understanding the post-disaster response of agents remains a challenge. Finally, the multiple physical and economic inter-dependencies in a CGE can hinder the decomposition of total impacts into indirect impacts, making it difficult to identify drivers of indirect impacts (Rose and Liao, 2002).

Econometric Models

In contrast to I/O and CGE models that are based on economic theory, econometric models use historical data to estimate the economic impacts based on regressions of region characteristics and disaster indicators, such as level of educational attainment, financial system development, number and types of disasters, direct damages, and fatalities (Albala-Bertrand, 1993; Noy, 2009). These models provide correlations between disasters and economic outcomes. Early studies (e.g. Skidmore and Toya, 2002) conduct cross-sectional regressions by analyzing a broad range of regions and controlling for regional characteristics such as baseline income, educational level, and trade openness. However, these models can be susceptible to omitted variable bias (Raddatz, 2009). Thus, more recent research has shifted to panel or longitudinal analyses, which can incorporate location-fixed effects and evaluate the lagged effects of disasters through a dynamic assessment of the disaster-economy relationship (Hsiang, 2010; Felbermayr and Gröschl, 2014).

Nevertheless, the focal point of econometric models is typically the effects of disasters on economy-wide growth rather than sectoral economic activity and inter-sectoral effects (Kelly, 2015). Moreover, these empirical analyses are often constrained by data availability (Botzen et al., 2019; Kelly, 2015). Given these limitations, we omit them from furher review here.

MODEL COMPARISON

This section compares the I/O and CGE model classes on the dimensions of input data requirements, theoretical assumptions, mathematical formulations, and output metrics. The comparison includes the Leontief I/O model, IIM, DIIM, ARIO, the basic CGE model, and their extensions. These models and their variations comprise the vast majority of models in the I/O and CGE classes and are widely deployed in disaster impact analysis. Moreover, we link the input data and output metrics of each model with the mathematical formulation of each model, allowing for an end-to-end model comparison across all four dimensions. We evaluate how assumptions within each dimension affect the capabilities of each model. Through the

TABLE 1. Required inputs for Leontief I/O, IIM, DIIM, and CGE models for indirect economic impact analysis.

Model Inputs	**Leontief I/O**	**IIM**	**DIIM**	**ARIO**	**CGE**
I/O matrix	✓	✓	✓	✓	✓
Social Accounting Matrix (SAM)				✓	✓
Baseline prices of commodities					✓
Elasticities of substitution (firms and households)					✓
Behavioral parameters				✓	
Fixed assets				✓	
Model Inputs for Model Extensions					
Trade matrix	✓	✓	✓	✓	✓
Export subsidies/import tariffs					✓
Elasticities of substitution (imports and exports)					✓
Investment matrix					✓
Taxes and subsidies					✓
Disaster Scenario Inputs					
Loss vector	✓	✓	✓	✓	✓
Perturbation vector		✓	✓	✓	✓
Recovery rate			✓	✓	✓
Reconstruction demand distribution				✓	

comparisons, we aim to guide model construction and cross-model translation of output metrics.

We adopt the following definitions for the common terminologies: *intermediate inputs* refer to goods and services; *production factors* refer to capital, labor, and natural resources; and *commodities* refer to goods, services, and production factors.

Input Data Requirements

Table 1 summarizes model inputs for the considered cases. The *I/O* matrix is an essential input for all models and comprises the intermediate sales between sectors and gross sectoral output (Miller and Blair, 1985). Open economy models incorporate trade with other regions and require the *trade matrix* in addition to the I/O matrix. The *trade matrix* records the trade of money between each sector of the regional economy and the regions outside the focus region. The *loss vector* describes the direct losses, in monetary values, in each sector, and is also a crucial disaster scenario input in all macroeconomic models. The Leontief I/O model requires no additional information for analysis.

The IIM further requires the *perturbation vector*, which is the direct loss, normalized by the gross output (Santos and Haimes, 2004). The dynamic extension of the IIM model, the DIIM, goes a step further by incorporating the time required for each sector to recover from initial inoperability to a desired post-recovery state (Lian and Haimes, 2006).

The ARIO model necessitates more extensive input data. In addition to the I/O matrix, and potentially the trade matrix, ARIO also considers sector-specific inputs for value-added, total final demand, imports, exports, and fixed assets. The additional inputs are available in the SAM[1]. Moreover, the ARIO model explicitly incorporates a set of user-defined *behavioral parameters* that characterize the adaptive capacities of each sector. These parameters include overproduction capacity, time to achieve maximum overproduction, target inventory levels, time for inventory restoration, and the production reduction parameter, also referred to as *heterogeneity* (Hallegatte, 2014; Issa et al., 2024).

At its most basic form, the CGE model requires information from the SAM, the elasticities of substitution between inputs in all activities and between commodities for all households, and baseline prices of commodities and production factors. The SAM reports monetary values in a calendar year and extends the I/O matrix to include all payments to production factors, such as labor and capital, as well as payments to and from households and the government. By dividing the entries of the SAM with the respective baseline prices, modelers derive the baseline quantities and stock of production factors. In addition to the SAM, household consumption decisions are also based on the elasticity of substitution between consumed goods and services. Production decisions by firms also require the elasticities of substitution between intermediate inputs and production factors. Dynamic CGE models require the *investment matrix* which quantifies the allocation of savings to all sectors, in monetary values. A CGE of an open economy requires additional information on inter-regional trade for all commodities, along with baseline import and export prices. The derivation of traded quantities follows from the division of the entries of the trade matrix with the baseline import and export prices. The baseline prices can include price markups due to taxes and subsidies.

From the comparison, ARIO and CGE models are relatively more data-intensive. Although a substantial portion of the input data is systematically collected through periodic censuses and surveys, some necessitate additional effort for acquisition. Specifically, the ARIO model requires a nuanced understanding of the regional economic capacities and organizational structures gleaned from prior disaster responses to determine the behavioral parameters (Hallegatte, 2008). In the case of CGE models, the calibration of elasticities of substitution can require additional panel data (Németh et al., 2011) and technological data (Balistreri and Brown, 2023) among others. Moreover, when considering disaster scenario inputs, assumptions may be

[1]In the ARIO literature, these additional inputs are available in the I/O table. It is a matrix comprising annual inter-sectoral sales, final demand, and value added, which contains a subset of information in a SAM of CGE models. To reconcile between the different input matrices, in this paper we adopt the following convention: The 'I/O matrix' records the dollar value of annual sales between sectors. The SAM refers to the matrix recording annual value added, final demand from households, the government, and for investment, and taxes, if applicable, in addition to inter-sectoral sales.

imperative owing to the unavailability of empirical data, *e.g.,* for *recovery rates* and the distribution of *reconstruction demand* in ARIO (Markhvida and Baker, 2023) and substitution elasticities in a CGE (Rose and Guha, 2004).

Theoretical Assumptions

The I/O and CGE model classes rely on different assumptions, which map to their formulation and application. In the Leontief I/O model, disruptions are typically accounted for as changes in demand. The model assesses the overall impact by analyzing the resulting changes in sectoral activity. The relationship between the demand reduction and the changes in sectoral activity is linear, which is determined by the technical coefficients that represent the interdependencies between different sectors. The technical coefficients for each sector are the normalized sales volumes between the focus sector and all other sectors in the I/O matrix, normalized by the total output, in dollar values, of the focus sector. A key assumption in the Leontief I/O model is that the technical coefficients remain fixed before and after the disaster, implying that production technology does not adjust following an event during the modeled period. Additionally, the model assumes that inputs remain in fixed proportions to output, which indicates the absence of substitution between different intermediate inputs.

The IIM and DIIM models adopt the same underlying assumptions as the Leontief I/O model. To simulate the dynamic process of the economic sector recovery, the DIIM model requires assumptions for the trajectory of demand and the recovery rate–typically an exponential recovery curve between the initial inoperability state and the final post-recovery inoperability state of each sector. This curve shape was originally chosen by the High-altitude Electromagnetic Pulse (HEMP) Commission (Lian and Haimes, 2006).

The ARIO model shares the assumptions of fixed intermediate input ratios and no input substitutions in sectoral production, but has a different approach for initial economic system disruptions and resulting impacts. ARIO also considers constraints from the production side, such as reduction in productive capacity and lack of inventory of required input. Moreover, ARIO requires additional demand from the sectors responsible for reconstruction. For instance, if direct losses result from damages to buildings and their content, reconstruction demand is allocated to the construction and manufacturing sectors (Hallegatte, 2008; Federal Emergency Management Agency (FEMA), 2022). Although some guidelines or benchmarks exist for the post-disaster distribution of demand from the reconstruction sectors (e.g. Hallegatte, 2008; Markhvida and Baker, 2023), the demand distributions are determined on a case-by-case basis. In addition, ARIO accounts for the adaptation of economic activities, but these adaptations are assumed to be driven by quantities rather than prices. When imbalances in supply and demand occur, ARIO assumes constant adaptation rates to achieve overproduction capacities and restore inventories during the recovery process.

CGE models are distinct from I/O models in that prices impact production activities and consumer preferences. A standard CGE model assumes that all sectors are at equilibrium, under perfect competition in every commodity market, and rational agents in every production activity (Rutherford and Schreiber, 2019). The most common production functions in a CGE include the Leontief, Cobb-Douglas, and Constant Elasticity of Substitution (CES) functions (Lofgren et al., 2002). All three exhibit constant returns-to-scale. Household demand is represented through inverse demand curves, which depend on the relative prices of commodities. The derivation of the demand curves is based on the optimal allocation of resources of a representative utility-maximizing agent for each type of household (Hosoe et al., 2010; Lofgren et al., 2002). Trade between regions is based on the relative domestic price of a commodity between two regions (Rutherford and Schreiber, 2019; Lofgren et al., 2002). Finally, the allocation of investment funding between sectors can be exogenous (Lofgren et al., 2002) or based on an investment index (Capros et al., 2013).

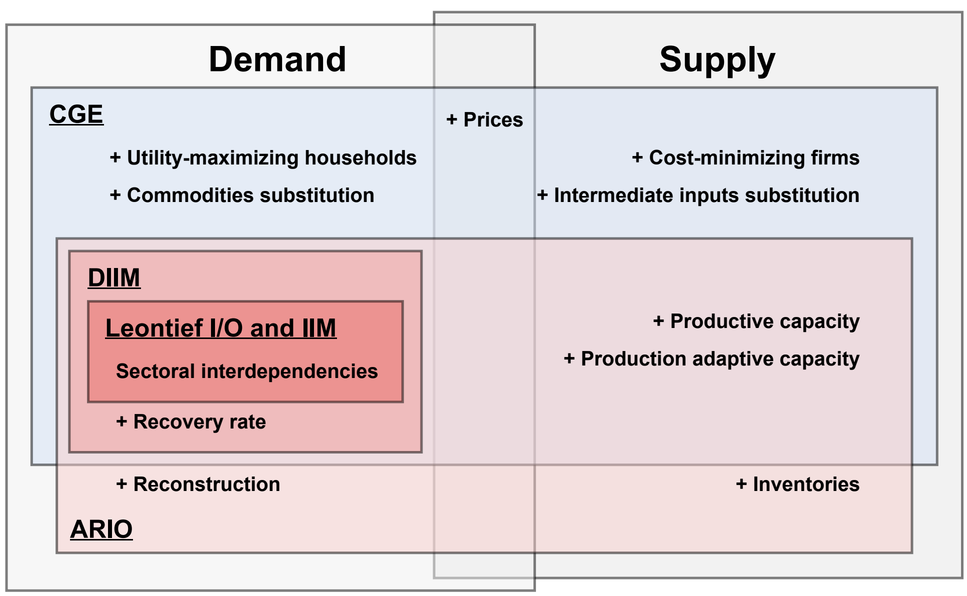

Fig. 2. Overlapping assumptions between Leontief I/O, IIM, DIIM, and CGE models.

We further distinguish between demand- and supply-side assumptions in the Figure 2 Venn diagram. All models in Figure 2 build on the fundamental assumption of fixed production technology (constant technical coefficients) when considering the sectoral interdependencies. However, differences emerge in their treatment of other supply- and demand-side effects.

While most I/O models focus on the demand-side implications, the ARIO model stands apart by also accounting for supply-side factors such as inventories, productive capacity, and production adaptive capacity. This approach leads to a more nuanced representation of the non-linear relationship between direct damages and indirect impacts that exist in reality, in contrast to the simplified assumptions inherent to the Leontief I/O, IIM, and DIIM models which result in a linear relationship.

Moreover, the integration of recovery rates in dynamic models introduces a temporal dimension to the modeling and analysis. In particular, the ARIO model provides a more granular depiction than other I/O models of each sector's state at every time step. By including reconstruction demand, ARIO captures the additional incentives for sectors involved in reconstruction to accelerate production or even engage in overproduction. Meanwhile, it may also reveal potential bottlenecks in the production processes of these critical industries. On the supply side, the role of production adaptive capacity emerges as a crucial determinant, either hindering or facilitating the recovery process based on the assigned values.

The CGE models account for both demand- and supply-side effects. The primary disparity between I/O and CGE models lies in their treatment of price adaptation, substitution between commodities, and associated market adjustments. CGE models assume adaptive behavior across all agents within the economic system. They further account for the substitution of consumed commodities, including intermediate inputs to production and final demand, which mitigates resource shortages. By allowing for such adaptability and optimization by all agents, CGE models tend to forecast economic consequences on the optimistic side (Rose, 2004). However, they typically do not explicitly account for reconstruction demand and inventories as the ARIO model does.

Given the understanding of the behavioral and economic assumptions underpinning the I/O and CGE models, and their potential impacts on assessment outcomes, I/O models may yield a more conservative estimate of indirect impacts compared to CGE models due to their rigidity. Since reaching a market equilibrium following a disaster typically entails a temporal lag, I/O models are better suited for short-term post-disaster impact assessments, while CGE models handle long-term analysis better (Rose and Guha, 2004). The choice of model should, therefore, be guided by the temporal scope and specific analytical objectives of the assessment.

Mathematical Formulations

In this section we compare the fundamental mathematical formulations of the models and discuss their computational requirements. For consistency in presentation across different models, we have adapted some of the notations from their original formulations in Table 2.

TABLE 2. Proposed Leontief I/O, IIM, DIIM, ARIO, and CGE nomenclature, slightly adapted from the original sources to enable consistency across models. For I/O models, it is assumed that each sector produces a single commodity so that $N = M$ for associated variables and parameters.

Definition	Type	Description
$\mathcal{H} = \{1, \dots, H\}$	Set	Set of types of households
$\mathcal{M} = \{1, \dots, M\}$	Set	Set of commodities. When a sector produces a single commodity, this is also the set of sectors
$\mathcal{N} = \{1, \dots, N\}$	Set	Set of activities/sectors when a sector produces multiple commodities
$\mathcal{T} = \{1, \dots, T\}$	Set	Set of time steps
$A \in \mathbb{R}^M \times \mathbb{R}^M$	Parameter	I/O matrix or technical coefficient matrix of input-output coefficients
$\hat{A} \in \mathbb{R}^M \times \mathbb{R}^M$	Parameter	Normalized technical coefficient matrix of input-output coefficients
$b_t \in \mathbb{R}^H \times \mathbb{R}^M$	Parameter	Endowments of commodities of every household at time $t \in \mathcal{T}$
$c_t : \mathbb{R}^M \to \mathbb{R}^N$	Function	Continuous and point-to-point differentiable unit cost functions of operating activities at time $t \in \mathcal{T}$
$\Delta d_t \in \mathbb{R}^M$	Parameter	Total demand reduction compared to baseline at time $t \in \mathcal{T}$
$\hat{d}_t \in \mathbb{R}^M$	Parameter	Normalized total demand reduction at time $t \in \mathcal{T}$
$d_t \in \mathbb{R}^M$	Variable	Total demand at time $t \in \mathcal{T}$
$d_t^X \in \mathbb{R}^M$	Variable	Demand for exports at time $t \in \mathcal{T}$
$d_t^H \in \mathbb{R}^M$	Variable	Demand for households at time $t \in \mathcal{T}$
$d_t^G \in \mathbb{R}^M$	Variable	Demand from the government at time $t \in \mathcal{T}$
$d_t^S \in \mathbb{R}^M$	Variable	Demand from the savings/investment sector at time $t \in \mathcal{T}$
$d_t^+ \in \mathbb{R}^M$	Variable	Reconstruction demand at time $t \in \mathcal{T}$
$\bar{d}_t^H \in \mathbb{R}^H \times \mathbb{R}^M$	Parameter	Baseline demand from every household at time $t \in \mathcal{T}$
$e_n \in \mathbb{R}^M$	Parameter	Vector of 1s when commodity $m \in \mathcal{M}$ is produced by activity $n \in \mathcal{N}$, and 0 otherwise
$f_t : \mathbb{R}^M \to \mathbb{R}^N$	Function	Continuous and point-to-point differentiable production functions of activities at time $t \in \mathcal{T}$
$f_t^S : \mathbb{R}^H \to \mathbb{R}^N$	Function	Capital-updating functions of activities at time $t \in \mathcal{T}$

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Definition	Type	Description
$\Delta k_t \in \mathbb{R}^M$	Variable	Damages to productive capital of sectors at time $t \in \mathcal{T}$
$\bar{k} \in \mathbb{R}^M$	Parameter	Pre-disaster fixed asset or productive capital of sectors
$p_t \in \mathbb{R}^M$	Variable	Wholesale prices of commodities at time $t \in \mathcal{T}$
$p_t^R \in \mathbb{R}^M$	Variable	Retail prices of commodities at time $t \in \mathcal{T}$
$p_t^X \in \mathbb{R}^M$	Variable	Export prices of commodities at time $t \in \mathcal{T}$
$p_t^I \in \mathbb{R}^M$	Variable	Import prices of commodities at time $t \in \mathcal{T}$
$\tilde{p}_t \in \mathbb{R}^M$	Variable/Parameter	International prices of commodities at time $t \in \mathcal{T}$
$p_t^Y \in \mathbb{R}^M$	Variable	Intermediate prices of commodities at time $t \in \mathcal{T}$
$\bar{p}_t^R \in \mathbb{R}^M$	Variable	Baseline retail prices of commodities at time $t \in \mathcal{T}$
$s_t^H \in \mathbb{R}^H$	Variable/Parameter	Savings of households at time $t \in \mathcal{T}$
$t^\theta \in \mathbb{R}^M$	Parameter	Recovery time from inoperability
$v_t \in \mathbb{R}^M$	Variable	Value added of sectors from capital and labor use at time $t \in \mathcal{T}$
$\Delta x_t \in \mathbb{R}^M$	Variable	Reduction in the levels of production compared to baseline at time $t \in \mathcal{T}$
$\bar{x}_t \in \mathbb{R}^M$	Variable	Baseline levels of domestic production of sectors at time $t \in \mathcal{T}$
$\bar{X}_t \in \mathbb{R}^M \times \mathbb{R}^M$	Parameter	Diagonal matrix of baseline levels of production at time $t \in \mathcal{T}$
$\hat{x}_t \in \mathbb{R}^M$	Variable	Normalized reduction in the level of production (*inoperability*) at time $t \in \mathcal{T}$
$\tilde{x}_t \in \mathbb{R}^M$	Variable	Production capacity of sectors at time $t \in \mathcal{T}$
$x_t^I \in \mathbb{R}^M$	Variable	Import of commodities at time $t \in \mathcal{T}$
$x_t^\eta \in \mathbb{R}^M \times \mathbb{R}^M$	Variable	Matrix of maximum possible production of column sectors, accounting for the available inventory of input from row sectors at time $t \in \mathcal{T}$
$x_t \in \mathbb{R}^M$	Variable	Production of sectors at time $t \in \mathcal{T}$
$y_t \in \mathbb{R}^N$	Variable	Level of activities at time $t \in \mathcal{T}$
$z_{nt} \in \mathbb{R}^M$	Variable	Intermediate input commodities demand of activity $n \in \mathcal{N}$ at time $t \in \mathcal{T}$
$\alpha_t^X \in \mathbb{R}^M$	Variable	Overproduction capacity ratio of sectors at time $t \in \mathcal{T}$
$\alpha^S \in \mathbb{R}^M$	Parameter	Savings/investment allocation coefficients
$\beta \in \mathbb{R}^M$	Parameter	Target inventory level of commodities
$\gamma^\eta \in \mathbb{R}^M$	Parameter	Rate to restore inventory of commodities
$\eta_t \in \mathbb{R}^M \times \mathbb{R}^M$	Variable	Matrix of actual inventories of input from row sectors for production of column sectors at time $t \in \mathcal{T}$
$\tilde{\eta}_t \in \mathbb{R}^M \times \mathbb{R}^M$	Variable	Matrix of required inventories of input from row sectors to meet the optimal production of column sectors at time $t \in \mathcal{T}$

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Definition	Type	Description
$\eta_t^O \in \mathbb{R}^M \times \mathbb{R}^M$	Variable	Matrix of target amount of input from row sectors to replenish the inventories of column sectors at time $t \in \mathcal{T}$
$\theta \in \mathbb{R}^M$	Parameter	Production adjustment rate or interdependency recovery rate of the levels of activity
$\Theta \in \mathbb{R}^M \times \mathbb{R}^M$	Parameter	Diagonal matrix of interdependency recovery rate of levels of activity
$\pi_t : \mathbb{R}^M \rightarrow \mathbb{R}^N$	Function	Unit profit functions of operating activities at time $t \in \mathcal{T}$
$\tau^I \in \mathbb{R}^M$	Parameter	Taxes or subsidies on imports
$\tau^R \in \mathbb{R}^M$	Parameter	Retail taxes or subsidies on commodities
$\tau^X \in \mathbb{R}^M$	Parameter	Taxes or subsidies on exports
$\tau^Y \in \mathbb{R}^M$	Parameter	Taxes or subsidies on intermediate inputs
$\phi_n \in \mathbb{R}^M$	Parameter	Output ratios for a unit of activity $n \in \mathcal{N}$
$\Phi \in \mathbb{R}^M \times \mathbb{R}^N$	Parameter	Output ratios matrix for a unit of every activity in the economy
$\psi \in \mathbb{R}^M$	Parameter	Production reduction parameter (heterogeneity)
$\mathbf{1}_W \in \mathbb{R}^W$	Parameter	Vector of all 1s with dimensions $W \in \mathbb{N}$, for any W (depending on the respective operation)
$\mathbf{0}_W \in \mathbb{R}^W$	Parameter	Vector of all 0s with dimensions $W \in \mathbb{N}$, for any W (depending on the respective operation)

Leontief I/O. The Leontief I/O model is a static model, *i.e.,* comprises a single time step. The model estimates the economic impact of a disaster by analyzing how changes in demand propagate across all economic sectors. It comprises a balancing Eq. (1) that computes the change in production, $\Delta x \in \mathbb{R}^M$, from the change in demand from all sectors, $\Delta d \in \mathbb{R}^M$, compared to baseline production and demand respectively, where the I/O matrix, or *technical coefficient matrix*, $A \in \mathbb{R}^M \times \mathbb{R}^M$ captures the inter-dependencies between all sectors of an economy[2] (Lin et al., 2017):

$$\Delta x = (I - A)^{-1} \Delta d \tag{1}$$

IIM. The IIM is also a static model and is built based on similar principles as the Leontief I/O model. Instead of absolute changes in supply and demand, in an IIM the changes in supply and demand vectors are

[2]For ease of notation, we drop the t index in the static Leontief I/O and IIM models. The Leontief I/O and IIM models in the reviewed literature assume that each sector produces a single commodity. Therefore, $\mathcal{M}$ denotes both the set of commodities and sectors.

normalized using the baseline supply and demand respectively (Haimes and Jiang, 2001; Santos and Haimes, 2004). We denote the diagonal matrix of baseline levels of commodities by $\bar{X} = \text{diag}\left(\{\bar{x}_m\}_{m\in\mathcal{M}}\right)$. Then, the normalized change in demand, or *perturbation* in demand, $\hat{d} \in \mathbb{R}^M$, is[2]:

$$\hat{d} = \bar{X}^{-1}\Delta d \tag{2}$$

The normalized change in sectoral production is referred to as the *inoperability* vector, $\hat{x} \in \mathbb{R}^M$:

$$\hat{x} = \bar{X}^{-1}\Delta x \tag{3}$$

By definition, inoperability of a sector is a continuous variable $\hat{x}_m \in [0, 1]$, where $\hat{x}_m = 0$ signifies a fully operable state and $\hat{x}_m = 1$ indicates complete inoperability for each sector $m \in \mathcal{M}$.

Similarly to the Leontief I/O model, a normalized technical coefficient matrix, $\hat{A} \in \mathbb{R}^M \times \mathbb{R}^M$, accounts for the need of every sector of commodities from all other sectors to produce a unit output:

$$\hat{A} = \bar{X}^{-1}A\bar{X} \tag{4}$$

An IIM comprises a balancing equation which computes the change in sectoral supply from the change in demand from all sectors:

$$\hat{x} = (I - \hat{A})^{-1}\hat{d} \tag{5}$$

Both the Leontief I/O and IIM models comprise a system of linear equations. Solving for a vector x that satisfies equations (1), for Leontief I/O models, and (5), for IIM models, requires relatively little computational power and can be easily implemented in most computing languages.

DIIM. The DIIM model is an extension of the IIM that incorporates the evolution dynamics of the levels of activity and demand in the economy in future time steps, *i.e.*, $t \in \mathcal{T} = \{1, \ldots, T\}$ (Lian and Haimes, 2006). The production adjustment rate, or *interdependency recovery rate*, θ_m is introduced to represent the ability of a sector to adjust its output in response to an imbalance in supply and demand. Under the assumption of exponential recovery, the interdependency recovery rate of each sector $m \in \mathcal{M}$ is derived as[3]:

$$\theta_m = \frac{1}{t_m^{\theta}} \cdot \ln\left[\frac{\hat{x}_{m0}}{\hat{x}_{mt_m^{\theta}}}\right] \cdot \left(\frac{1}{1 - \hat{A}_{mm}}\right) \tag{6}$$

The resilience coefficient, also known as the *recovery coefficient matrix*, is constructed as:

$$\Theta = \operatorname{diag}\left(\{\theta_m\}_{m\in\mathcal{M}}\right) \in \mathbb{R}^M \times \mathbb{R}^M \tag{7}$$

In a DIIM, the inoperability vector evolves over time and depends on the recovery rate of all sectors. Therefore, the balancing Eq. (5) of an IIM becomes (Lian and Haimes, 2006):

$$\hat{x}_{t+1} = \hat{x}_t + \Theta\left[\hat{A}\hat{x}_t + \hat{d}_t - \hat{x}_t\right] \tag{8}$$

The model is posed as a linear time-varying dynamical system (Khalil, 2002). The solution of the DIIM follows an iterative procedure, where the state variables at time $t+1$ are computed given the solution of the previous time step t, over a time horizon starting from a given initial state. However, due to the relatively small set of variables involved and the limited computational resources for each time step, formulating and implementing the model from scratch in most computing languages is straightforward.

ARIO. The ARIO model provides a more detailed simulation of economic recovery by incorporating adaptation and productive constraints over time. Specifically, ARIO models inventories of sectors, which allows them to maintain stocks of commodities. During each time step, sectors aim to satisfy the demand for goods and services. However, actual production is constrained by the sector's production capacity and available inventories of production inputs. The original version of the ARIO model (Hallegatte, 2008; Hallegatte, 2014) did not distinguish between local production and imports when computing the production capacity and supply. Nevertheless, recent model developments have addressed this concern by separately accounting for the constraints and adaptability of local production and imports(Issa et al., 2024)[4].

The demand vector, $d_t \in \mathbb{R}^M$ at time $t \in \mathcal{T}$, is first determined as the sum of orders by all sectors; demand from export; demand from households, the government and the savings/investment sector; and demand for

[3]The DIIM model in the reviewed literature assumes that each sector produces a single commodity. Therefore, $\mathcal{M}$ denotes both the set of commodities and sectors.

[4]The formulation in this paper is based on the updated ARIO model in Issa et al. (2024)

reconstruction[5]:

$$d_t = \mathbf{1}_M^T z_{mt} + d_t^X + d_t^H + d_t^G + d_t^S + d_t^+ \tag{9}$$

The production capacity, $\tilde{x}_{mt} \in \mathbb{R}$, of sector $m \in \mathcal{M}$ at time $t \in \mathcal{T}$, is constrained by productive capital, the overproduction status, and demand:

$$\tilde{x}_{mt} = \min\left\{\alpha_{mt}^X \cdot \left(1 - \frac{\Delta k_{mt}}{\bar{k}_m}\right) \cdot \bar{x}_m + x_{mt}^I,\ d_{mt}\right\} \tag{10}$$

In ARIO, the inventories of sectoral inputs can contribute to the existing production capacity of sector $m \in \mathcal{M}$. The required inventories of sector $m' \in \mathcal{M}$ to achieve $\tilde{x}_{mt}$, $\tilde{\eta}_{m'mt} \in \mathbb{R}$, is:

$$\tilde{\eta}_{m'mt} = \begin{cases} \beta_{m'} \cdot \left(\tilde{x}_{mt} - x_{mt}^I\right) \cdot A_{m'm}, & \text{when } d_{mt} > \tilde{x}_{mt} \\ \beta_{m'} \cdot d_{mt} \cdot \frac{\tilde{x}_{mt} - x_{mt}^I}{\tilde{x}_{m't}} \cdot A_{m'm}, & \text{when } d_{mt} \le \tilde{x}_{mt} \end{cases} \tag{11}$$

The maximum possible production, $x_{m'mt}^{\eta} \in \mathbb{R}$, updates the production capacity of sector $m \in \mathcal{M}$ to account also for the inventories of each input from sector $m' \in \mathcal{M}$:

$$x_{m'mt}^{\eta} = \begin{cases} x_{mt}^I + \left(\tilde{x}_{mt} - x_{mt}^I\right) \cdot \min\left\{1,\ \frac{\eta_{m'mt}}{\psi_{m'} \cdot \tilde{\eta}_{m'mt}}\right\}, & \text{when } d_{mt} > \tilde{x}_{mt} \\ \min\left\{d_{mt} \cdot \frac{\tilde{x}_{mt} - x_{mt}^I}{\tilde{x}_{mt}} \cdot \min\left(1,\ \frac{\eta_{m'mt}}{\psi_{m'} \cdot \tilde{\eta}_{m'mt}}\right) + x_{mt}^I,\ d_{mt}\right\}, & \text{when } d_{mt} \le \tilde{x}_{mt} \end{cases} \tag{12}$$

The production of sector $m \in \mathcal{M}$ at time $t \in \mathcal{T}$ is governed by the most limiting inventory in the production process:

$$x_{mt} = \min\left\{x_{m'mt}^{\eta}, \quad \forall m' \in \mathcal{M}\right\} \tag{13}$$

If the actual production fails to satisfy the demands of certain sectors, the production is distributed proportionally to meet a portion of the demand of the corresponding inter-sector orders, total final demand (from households, the government, and the savings/investment sector), reconstruction demand, and exports. The orders to sector $m \in \mathcal{M}$ for the next time step $t^+ = t + \Delta t$ from all sectors, $z_{mt^+} \in \mathbb{R}^M$, are then updated based on the current level of production and inventories:

$$z_{mt} = Ax_t + \operatorname{diag}\left(\left\{\left(\gamma_m^{\eta}\right)^{-1}\right\}_{m \in \mathcal{M}}\right) \cdot \left(\eta_{mt}^O - \eta_{mt}\right) \tag{14}$$

[5] The ARIO models in the reviewed literature assume that each sector produces a single commodity. Therefore, $\mathcal{M}$ denotes both the set of commodities and sectors.

Finally, the value added for sector m at time step t, $v_t \in \mathbb{R}^M$, is computed as:

$$v_t = x_t - x_t^I - A^T x_t \tag{15}$$

The above computations iteratively update the status of each sector at each time step until economic metrics, such as value added and inventories, converge to to constant levels, and equilibrium between demand and production is restored.

Code to implement both the original and refined models are available (Markhvida et al., 2020; Issa et al., 2024). The computational requirements of the model are influenced by factors such as the number of sectors and analytical time steps. It can increase significantly when conducting fine-grained multi-regional analysis (Zhu et al., 2024). Therefore, it is essential to consider the computational resources available and optimize the model implementation accordingly to ensure efficient execution.

CGE. A CGE extends the I/O framework to account for the impact of prices $p_t \in \mathbb{R}^M$ on production activities $y_t \in \mathbb{R}^N$ and consumer preferences at each time step $t \in \mathcal{T}$. In each sector, a representative firm minimizes the cost of producing a unit,

$$\min_{z_{nt}} \; p_t^T z_{nt}, \qquad s.t. \;\; f_{nt}(z_{nt}) \cdot e_n = \phi_n \quad (\pi_{nt}) \tag{16}$$

where $\phi_n \in \mathbb{R}^M$ is the vector of amounts of commodities produced for each unit of activity. Specifically, for an activity producing multiple commodities, the entries of ϕ_n sum to one and indicate what percentage of the revenues of the respective activity are associated with the different commodities. Moreover $n \in \mathcal{N}$, $\pi_{nt} \in \mathbb{R}$ is the dual of the production function constraint, and $e_n \in \mathbb{R}^M$ is a vector with entries of 1 for commodities produced by activity $n \in \mathcal{N}$, and 0 otherwise. The sum of all entries of ϕ_n is equal to one. Problem (16) is convex when functions f_{nt} are convex. Hence, finding a minimizer of (16) is equivalent to solving for a point that satisfies the first-order optimality conditions of (16) (Boyd and Vandenberghe, 2004). The optimal primal variables (z_{nt}^*) are the optimal amounts of inputs needed for the production of sector $n \in \mathcal{N}$. The manipulation of the first-order optimality conditions can reveal additional information for each sector. Specifically, by applying Shephard's Lemma to the first-order optimality conditions of (16), we can derive (Mathiesen, 1985):

$$c_{nt}(p_t) = f_{nt}(p_t), \quad \pi_{nt}(p_t) = c_{nt}(p_t) - \phi_n^T p_t, \qquad \forall n \in \mathcal{N},\ t \in \mathcal{T}, \tag{17}$$

where $c_{nt} : \mathbb{R}^M \to \mathbb{R}$ is the unit cost function, *i.e.,* the cost of producing a unit out of sector n's activities as a function of all input prices; and $\pi_{nt} : \mathbb{R}^M \to \mathbb{R}$ is the unit profit function, *i.e.,* the profit from selling a unit out of sector n's activities as a function of all input prices.

The above manipulation can also reveal the demand quantities as a function of commodity prices:

$$z_t(p_t) = \left(\frac{\partial c_t(p_t)}{\partial p_t}\right) y_t, \quad x_t(p_t) = \left(\frac{\partial \pi(p_t)}{\partial p_t}\right) y_t, \qquad \forall t \in \mathcal{T}, \tag{18}$$

where $\frac{\partial c_t(p_t)}{\partial p_t} : \mathbb{R}^M \to \mathbb{R}^M \times \mathbb{R}^N$ is the matrix of demand for intermediate input $m \in \mathcal{M}$ from sector $n \in \mathcal{N}$, based on the commodity prices $p_t \in \mathbb{R}^M$; and $\frac{\partial \pi_t(p_t)}{\partial p_t} : \mathbb{R}^M \to \mathbb{R}^M \times \mathbb{R}^N$ is the matrix of supply of commodity $m \in \mathcal{M}$ from sector $n \in \mathcal{N}$, based on the commodity prices $p_t \in \mathbb{R}^M$. The total intermediate demand ($z_t(p_t) \in \mathbb{R}^M$) and supply ($x_t(p_t) \in \mathbb{R}^M$) from all sectors is the product of the intermediate input and output matrices with total production across sectors ($y_t \in \mathbb{R}^N$). Details on the derivations and the economic intuition behind each term are available in Mathiesen (1985) and Böhringer and Rutherford (2008).

The equivalent of a technical coefficient matrix of a CGE model is a matrix which depends on prices: $A := \frac{\partial c_t(p_t)}{\partial p_t} \in \mathbb{R}^M \times \mathbb{R}^N$. The equivalence is clear when the production function is linear. In that case, the matrix $\frac{\partial c_t(p_t)}{\partial p_t}$ does not depend on prices.

Demand and production in CGEs are functions of commodity prices, and can be parameters in Leontief I/O models, IIMs, DIIMs, and ARIO. However, to highlight the equivalence between models, in what follows we will abuse the notation mildly and maintain the same symbols. Instead, where applicable, we will indicate the dependence on prices.

Households own endowments of commodities $b_{ht} \in \mathbb{R}^M$, including capital and labor, from which they accrue income. Household demand for each household $h \in \mathcal{H}$ at time $t \in \mathcal{T}$, $d^H_{ht}(p_t) \in \mathbb{R}^M$, depends on the relative prices of commodities. The aggregate demand from all households, the government, and the savings/investment sector is:

$$d_t(p_t) = \mathbf{1}_H^T d_t^H(p_t) + d_t^G(p_t) + d_t^S(p_t) \tag{19}$$

For ease of notation, let $\Phi = \{\phi_n\}_{n\in\mathcal{N}} \in \mathbb{R}^{M\times N}$ be the matrix of output commodity ratios for all activities. In its most compact form, following Böhringer and Rutherford (2008) and Rutherford and Schreiber (2019), an equilibrium of a CGE is a vector $(p, y) \in \mathbb{R}^M \times \mathbb{R}^N \times \mathbb{R}^T$ which satisfies the following conditions:

- No profit condition for all activities: Producers need to recover their cost via sales. The cost includes value-added, therefore, the revenues should not exceed the cost, otherwise there will exist income in the economy that is not allocated to any activity or agent[6],

$$\pi_t(p_t) = c_t(p_t) - \Phi^T p_t \geq 0, \qquad \forall t \in \mathcal{T} \tag{20}$$

- No excess demand condition for all commodities: Production should suffice to cover the demand in the model, otherwise prices adjust to ensure this condition,

$$\mathbf{1}_H^T b_t + \left(\frac{\partial \pi_t(p_t)}{\partial p_t}\right)^T y_t - d_t(p_t) \geq 0 \qquad \forall t \in \mathcal{T} \tag{21}$$

- Non-negativity conditions: Positive prices and quantities,

$$p_t \geq 0, \qquad y_t \geq 0 \qquad \forall t \in \mathcal{T} \tag{22}$$

- An operating activity incurs no losses: This condition ensures that if the production (y_t) is positive, then the respective active fully retrieves their cost via sales. If this is not the case and the cost is higher than the revenues, see equation (20), then, the respective production y_t should be zero,

$$\left(c_t(p_t) - \Phi^T p_t\right)^T y_t = 0, \quad \forall t \in \mathcal{T} \tag{23}$$

- Market clearing of a commodity: Given equations (21)-(22), this set of constraints ensures that supply exactly matches demand for a commodity, otherwise, the respective price becomes zero:

$$\left(\mathbf{1}_H^T b_t + \left(\frac{\partial \pi_t(p_t)}{\partial p_t}\right) y_t - d_t(p_t)\right)^T p_t = 0, \quad \forall t \in \mathcal{T} \tag{24}$$

We can rewrite conditions (20)-(24) as a Mixed Complementarity Problem comprising two types of

[6]Since CGEs capture all payments across the economy, therefore there can not exist income that is not allocated to an activity or agent.

conditions (Mathiesen, 1985). First, a set of *zero profit* conditions (25) ensure that all payments for the commodities produced by an activity suffice to cover the cost of the activity. Second, a set of *market clearing* conditions (26) ensure that the supply of each commodity suffices to cover the demand of the commodity.

$$0 \le c_t(p_t) - \Phi^T p_t \qquad\qquad \perp\ y_t\ \ge 0, \quad \forall t \in \mathcal{T} \tag{25}$$

$$0 \le \mathbf{1}_H^T b_t + \left(\frac{\partial \pi_t(p_t)}{\partial p_t}\right) y_t - d_t(p_t) \perp\ p_t\ \ge 0, \quad \forall t \in \mathcal{T} \tag{26}$$

A CGE can extend to include taxes and subsidies, and their implementation is policy-specific. Examples include the regional retail price of a commodity, p_t^R, equals the wholesale price (p_t) plus a sales tax (τ^R); the export or import price of a commodity, p_t^X or p_t^I, equals the wholesale price plus an export subsidy or import tax (τ^X or τ^I); and the price of intermediate inputs, p_t^Y, equals the wholesale price plus a tax/subsidy (τ^Y) (Rutherford and Schreiber, 2019).

A CGE can also include budget conditions of the government and households. For example, in Eq. (27) each household $h \in \mathcal{H}$ allocate their income, $p_t^T b_{ht} \in \mathbb{R}^H$, to savings, $s_t^H \in \mathbb{R}^H$, or expenditures, $\left(p_t^R\right)^T d_{ht}^H(p_t) \in \mathbb{R}^H$,

$$s_{ht}^H + \left(p_t^R\right)^T d_{ht}^H(p_t) = p_t^T b_{ht}, \qquad \forall h \in \mathcal{H},\ t \in \mathcal{T} \tag{27}$$

Finally, a dynamic CGE includes a mechanism that updates the capital stock (in b_{t+1}) of all activities in each time-step $t \in \mathcal{T}$ based on the savings in the economy by the government and households, *e.g.,*

$$f_t^S\left(s_{ht}^H; \alpha^S, b_{ht}, b_{ht+1}\right) = \mathbf{0}_N \tag{28}$$

The mechanism can be an exogenous allocation of savings, $s_t \in \mathbb{R}^H$, to each activity according to the investment allocation coefficients, $\alpha^S \in \mathbb{R}^N$. Alternatively, the mechanism can be based on economic principles, which would require modeling also the demand and supply for investments, and the capital stock as a variable. Still, we can compute the equilibrium of any CGE via (25)-(26) by substituting the intermediate variables arising from (**??**)-(27), or other features (Böhringer and Rutherford, 2008).

Compared to the other models studied here, the conditions comprising CGE models arise from optimization problems. Depending on the number of features, regional and sectoral disaggregation, and the set of scenarios, CGEs can demand significantly more computational resources. These models are often constructed using specialized software such as General Algebraic Modeling System (GAMS) (Lofgren et al., 2002; McCarl et al., 2014). Note that unlike previous models, which are set up for general analysis and can be applied to any region of interest given the required regional input data, most CGE models are tailored for specific regions, with regional parameters integrated into the model. Adapting or reconstructing the model for a different region can therefore require considerable effort and resources. This regional specificity adds complexity to the modeling process.

Output Metrics

Table 3 summarizes the most commonly-used output metrics across models in the I/O and CGE model classes. The Leontief I/O model quantifies the economic impacts as the change in total sectoral output, which reflects the overall reduction in economic activity across various sectors following a disaster. Additionally, the Leontief I/O model distinguishes cascading losses from total losses, represented as the difference between the reduction in total output and direct losses. Such distinction highlights the additional economic repercussions that arise indirectly from the initial shock. Similarly, the IIM model computes the inoperability of sectors after the disaster. The estimation of output reduction is also possible by multiplying the inoperability ratio with the pre-disaster production levels. The DIIM model determines the trajectory of the sectoral inoperability during the recovery period. For each sector, the integration of the inoperability curves over time yields sectoral output reductions. The ARIO model simulates all economic activities and outputs the value added, demand, and production capacity trajectories during the recovery phase at the sectoral level. The absolute changes in these metrics over time can also be derived as the areas under the respective curves. These metrics reflect shifts in consumer behavior and market dynamics, as well as the ability of industries to meet demand and contribute to economic growth.

A standard CGE quantifies economic impacts primarily through the change in the level of activities or, equivalently, the change in the production of commodities. Depending on the features of a CGE, it can also output changes in domestic production and trade, changes in savings and investment, and changes in household demand. One key application of CGE modeling is the determination of long-term prices of commodities and the Consumer Price Index (CPI) for each household. The CPI reflects changes in the overall cost of living for different segments of the population. Mathematically, the CPI for household h at time t can be calculated as the cost of consumed commodities in a scenario, divided by the baseline cost of household consumption, for each household $h \in \mathcal{H}$ at time $t \in \mathcal{T}$:

TABLE 3. Model outputs of Leontief I/O, IIM, DIIM, ARIO, and CGE for indirect economic impact analysis.

Output	Leontief I/O	IIM	DIIM	ARIO	CGE
Direct model output					
Change in total sectoral output	✓	✓	✓	✓	✓
Change in inoperability		✓	✓	✓	✓
Trajectory of inoperability			✓	✓	✓
Trajectory of demand				✓	✓
Trajectory of production capacity				✓	✓
Trajectory of value added				✓	✓
Trajectory of imports and exports				✓	✓
Trajectory of savings & investment					✓
Trajectory of prices					✓
Changes in income and GDP					✓
Indirect model output					
Cascading losses	✓	✓	✓	✓	
Trajectory of consumer price index					✓
Change in Gini coefficient					✓

$$\mathrm{CPI}_{ht} = \frac{\left(p_t^R\right)^T d_{ht}^{H'}(p_t)\mathbf{1}_M}{\left(\bar{p}_t^R\right)^T \bar{d}_{ht}^H \mathbf{1}_M}, \qquad \forall h \in \mathcal{H},\ \forall t \in \mathcal{T}, \tag{29}$$

where $\bar{p}_t^R \in \mathbb{R}^M, \bar{d}_t^H \in \mathbb{R}^H \times \mathbb{R}^M$ are baseline commodities prices and baseline household demand respectively, and $\mathbf{1}_M$ is a vector of all ones of dimension M. In a CGE model, which is grounded in neoclassical economic theory, market equilibrium for all commodities and factors is ensured through prices. These prices, in turn, influence changes in the Gross Domestic Product (GDP) and the Gini coefficient, a measure of income inequality within a population. Specifically, the Gini coefficient is calculated as the ratio of income held by the top 20% of the population to that held by the bottom 20%. These economic metrics provide insights into the welfare implications of disasters and facilitate the design of targeted interventions to address specific challenges or inequalities within the economy.

Table 4 summarizes the mappings between shared inputs and output metrics across models. The left-hand side includes input and outputs metrics that are consistent across models. The first two rows are demand-related inputs, while the last two rows are output-related metrics. The columns on the right-hand side indicate the mathematical relationships, or mappings, between input and output metrics and model-specific input and output metrics. For example, given the same demand $d_t \in \mathbb{R}^M$ across models, we can run the ARIO and CGE models with the specified demand (last two columns of the first row). The ARIO and CGE models receive demand as an input. However, the Leontief I/O model uses $\Delta d_t = d_t - \bar{d}_t$ as an input. The IIM and

TABLE 4. Mappings of inputs and output metrics across Leontief I/O, IIM, DIIM, ARIO, and CGE models.

Input/Output Metric	Leontief I/O	IIM	DIIM	ARIO	CGE
Demand ($d_t \in \mathbb{R}^M$)	Δd_t	$\hat{d}_t = \bar{X}^{-1}\Delta d_t$	$\hat{d}_t = \bar{X}^{-1}\Delta d_t$	d_t	d_t
Inoperability ($\hat{d}_t \in \mathbb{R}^M$)	$\Delta d_t = \bar{X}\hat{d}_t$	$\hat{d}_t$	$\hat{d}_t$	$d_t = \bar{X}\hat{d}_t + \bar{d}_t$	$d_t = \bar{X}\hat{d}_t + \bar{d}_t$
Sectoral output ($x_t \in \mathbb{R}^N$)	Δx_t	$\hat{x}_t = \bar{X}^{-1}\Delta x_t$	$\hat{x}_t = \bar{X}^{-1}\Delta x_t$	x_t	x_t
Change in sectoral output ($\Delta x_t \in \mathbb{R}^N$)	Δx_t	$\hat{x}_t = \bar{X}^{-1}\Delta x_t$	$\hat{x}_t = \bar{X}^{-1}\Delta x_t$	$x_t = \Delta x_t + \bar{x}_t$	$x_t = \Delta x_t + \bar{x}_t$

DIIM require reformulating the original demand even further into $\hat{d}_t = \bar{X}^{-1}\Delta d_t$ before they can be ran.

EVALUATION OF INDIRECT ECONOMIC IMPACTS FROM DISASTERS

Various disasters exhibit diverse attributes that affect the evaluation of their indirect economic consequences. Understanding the potential impacts and how disasters disturb the behavior of infrastructure and economic systems is essential for the analysis of indirect impacts and identification of the necessary input data. To characterize the application of macroeconomic models to estimations of disaster impacts, we reviewed over 80 case studies within this domain focusing on earthquakes, floods, droughts, heatwaves, wildfires, and cyber attacks (see details in Supplementary Material). The papers were identified and screened by searching a combination of keywords, including "economic loss", hazard type, and economic model names. Among the identified case studies, more than one-third of them focus on flood hazards, and about one-fourth focus on drought hazards, both of which have witnessed a surge in application since the late 2010s. The applications for earthquake hazards comprise approximately one-sixth of the total, with the earliest work dating back to the late 1990s. Conversely, applications for wildfires and heatwaves are relatively new and limited. In this review, each hazard comprises only five papers in their respective fields. In the past decade, there has also been emerging interest in understanding the indirect economic impact of cyber attacks, and 12 relevant application papers are analyzed in this review. In terms of the distribution of macroeconomic model usage across these applications, we observe a mixed use of I/O- and CGE-based models for case studies of earthquake, flood, drought, and heatwave hazards. However, wildfire applications are predominated by CGE models, and most of the cyber attack studies utilize the IIM or DIIM models.

In this section, we present a structured approach to characterize disaster scenarios for economic modeling through two-layer mapping, which corresponds to the first two steps in the general modeling framework shown in Figure 1. The first layer delineates the interface between disasters and the physical environment, identifying the direct impacts induced by each type of disaster. The second layer focuses on the interface between the

TABLE 5. Disaster-direct impact interface: The most common physical disruptions for each disaster type in the literature.

Direct impacts	Earthquake	Flood	Wildfire	Drought	Heatwave	Cyber Attack
Building/physical property damage	✓	✓	✓			
Utility disruptions	✓	✓	✓	✓	✓	✓
Human casualties and displacement	✓	✓	✓		✓	
Transportation disruptions	✓	✓	✓			
Crop yield disruptions		✓	✓	✓	✓	
Port disruptions	✓					
Land inundation		✓				
Physiological strain on workers					✓	
System or data disruptions						✓

physical environment and the economic system to link the physical impacts to potential economic disruptions. Furthermore, we synthesize the general practices of implementing the identified initial disruptions of the economic system into various types of macroeconomic models. Combining the information together, we summarize all potential factors to consider for indirect impact analysis and the translation of non-economic information into economic models tailored to each specific disaster scenario. This not only facilitates horizontal comparisons across a spectrum of disaster applications but also furnishes modelers with an initial checklist of considerations for conducting such analyses.

Interface Between Hazards and Physical Environments

Different types of disasters yield varying direct impacts on physical systems. Table 5 summarizes the most common physical disruptions that have been considered for each type of disaster in the current literature.

Among the range of disasters considered here, earthquakes, floods, and wildfires primarily inflict damage on the built environment, encompassing structures, building contents, and infrastructure (e.g. Sue Wing et al., 2022; Yang et al., 2023; Monge et al., 2023). On the other hand, droughts and heatwaves primarily cause utility disruptions, human casualties, and population displacement (e.g. Wing et al., 2016; Xia et al., 2018; Butry et al., 2019; Yaseen et al., 2020). Specifically, drought events typically lead to water shortages and the loss of hydraulically generated power sources (Martin-Ortega et al., 2012; Boyd and Ibarraran, 2009). For heatwaves, water and power supply are also the two main vulnerable utilities (Disher et al., 2021). Moreover, weather-related disasters, including floods, droughts, wildfires, and heatwaves, often result in agricultural losses, impacting both current crop yields and future harvests, as extensively documented in various studies (e.g. Harris et al., 2002; Wittwer and Griffith, 2011; Borgomeo et al., 2018; Wang et al., 2023). Conversely, a cyber attack is a special case wherein the direct impact predominantly targets the operational functionality

TABLE 6. Direct impact and economic disruption interface: Interpretations of identified direct impacts into economic disruptions, as found in the reviewed literature.

Direct Impacts	Supply-side Economic Disruptions	Demand-side Economic Disruptions
Building/physical property damages	Productive capital loss	Reconstruction demand surge Household demand change
Utility disruptions	Productive capital loss of utility Utility supply reduction	Utility demand surge
Human casualties and displacement	Labor loss	Healthcare demand surge
Transportation disruptions	Labor loss Supply reduction Transportation cost change	Transportation demand change Transportation cost change
Crop yield disruptions	Land productivity loss Land production loss	-
Port disruptions	Import reduction	Export reduction
Land use inundation	Land productivity loss Production stoppage	-
Physiological strain on workers	Labor loss or labor productivity loss	Healthcare demand surge
System or data disruptions	Productivity loss Production stoppage Labor loss due to recovery allocation	Consumer demand reduction

of systems, irrespective of physical damages (e.g. Kelic et al., 2013; Hyatt and Santos, 2022; Eling et al., 2022). However, exceptions apply when a cyber attack targets critical infrastructure, which can result in harm to either the physical system or the operational system (e.g. Martin et al., 2023; Rose et al., 2007).

Certain disasters entail impacts beyond the aforementioned ones. For instance, Wei et al. (2020) considered port disruptions caused by earthquakes, which can damage the critical facilities integral to cargo handling and transportation. Flood events introduce concerns regarding land inundation, which has a time scale attribute and can disrupt routine human activities (e.g. Haddad and Teixeira, 2015; Carrera et al., 2015; Tanoue et al., 2020). Heatwaves, characterized by elevated temperatures, pose a unique threat by inducing physiological strain, thereby diminishing workers' productivity and potentially precipitating health issues (e.g. Xia et al., 2018; Hoffmann, 2019; García-León et al., 2021).

Interface Between Physical and Economic Environments

The influence of direct impacts on the economic system is contingent upon the types of physical systems affected and the characteristics of the direct impacts. Factors such as the role of the damaged system in economic activities and the potential for system recovery can lead to diverse economic repercussions and different considerations in economic impact modeling. Table 6 summarizes how the direct impacts outlined in Table 5 have been considered to affect the economic system in the literature.

Table 6 further distinguishes between supply- and demand-side economic disruptions found in the literature. It shows that most direct impacts are associated with both supply- and demand-side disruptions. On the supply side, the damage or disruption to the built environment can result in loss of productive capital (e.g. Rose and Guha, 2004; Gertz et al., 2019). The impacts on human activities, including *human casualties and displacement*, *transportation disruptions*, and *physiological strain on workers*, can influence the availability of labor, resulting in labor loss (e.g. Mendoza-Tinoco et al., 2017; Kim and Kwon, 2023; Hoffmann, 2019). A special case is *system or data disruptions*, which, while not affecting the total available labor, raises concerns about labor shortage due to increased demand for recovery efforts (Hyatt and Santos, 2022). Another interpretation of impacts associated with *physiological strain on workers* and *system or data disruptions* is the productivity loss, indicating reduced efficiency of labor and/or resources in post-disaster production activities (e.g. García-León et al., 2021; Rose and Chen, 2017; Dieye et al., 2020). Similar concerns also apply to the *crop yield disruptions* and the *land use inundation* (e.g. Horridge et al., 2005; Juana et al., 2014; Haddad and Teixeira, 2015). These three types of supply-side shocks could lead to production reduction for the affected sectors, but *crop yield disruption*, *land use inundation*, and *system or data disruptions* can also result in direct production reduction, since they immobilize the production process (e.g. Bauman et al., 2013; Li et al., 2022; Welburn and Strong, 2022). Another type of supply-side impact is the reduction of supply to the downstream industries. This can be triggered by *utility disruptions* and *transportation disruptions*, which disrupt the supply chain of commodities (e.g. Santos et al., 2014; Shahpari et al., 2022; Wang et al., 2021). Similarly, *port disruptions* affect trade between the studied region and the outside world, leading to reduced imports (Wei et al., 2020). This can cause a shortage in intermediate inputs for production activities or failure to meet consumer demand for final products.

On the demand side, the *building/physical property damages* stimulate reconstruction demand, primarily within the construction and manufacturing sectors (e.g. Okuyama, 2004; Wu et al., 2012; Mendoza-Tinoco et al., 2020). In the meanwhile, the impacts on households can lead to a shift in their consumption patterns and, therefore, the demand for commodities (e.g. Haque and Jahan, 2015; Mendoza-Tinoco et al., 2017). Moreover, *utility disruptions* can lead to the surge in demand by end users. For example, elevated power demand during a heatwave can potentially strain the power network (Liang et al., 2016; Avraam et al., 2023). Negative impacts on humans, including *casualty and displacement* and *physiological strain on workers*, can result in excess emergency visits and hospitalizations (Shahpari et al., 2022; Disher et al., 2021). Conversely, the *system or data disruptions* may induce distrust among previous users, leading to a decline in future consumer engagement with the affected systems (Santos and Haimes, 2004; Gordon et al., 2007). The disruptions in the export supply chain caused by *port disruptions* will also reduce the demand for local production (Wei et al., 2020). The demand for transportation systems may change depending on the purpose of travel. Emergency response and critical supply transport may increase demand on remaining routes, while non-essential trips are likely to decrease in the post-disaster environment (Cho et al., 2001).

Some studies also consider the transportation cost change as the implication of *transportation disruptions* in the economic system (e.g. Cho et al., 2001; Kim et al., 2002; Shibusawa, 2020). Post-disaster transportation prices are determined by the disruption in both supply and demand, and equilibrium is achieved for diminished transportation capacity and modified post-disaster transportation demand. At the post-disaster equilibrium, economic sectors respond to the additional costs caused by strained supply chains and altered production patterns.

Implementation of Disruptions into Macroeconomic Models

The final step of the disaster scenario modeling process is to translate the identified economic impacts of disasters into changes in the corresponding variables and parameters of the macroeconomic models. This step depends on the understanding of the specific channels through which disruptions propagate throughout the economy, the complexity of the model, and the desired granularity of the analysis. Different mechanisms may be employed to capture the nuances of each disruption for different models. Even when using the same model, modelers may opt for different implementations to incorporate additional scenario information, which sometimes may necessitate adaptations of the original model structure.

Table 7 details implementations of the economic disruptions listed in Table 6 found in the reviewed literature for the five macroeconomic models considered in this review. The symbols in Table 7 indicate the existence of matching practice for the corresponding economic models. For demand-side economic disruptions, the majority of models incorporate the impacts as changes in the demand variables of the affected sectors (e.g. MacKenzie et al., 2012; Markhvida et al., 2020; Avelino and Dall'erba, 2019; Bachner et al., 2024; Liang et al., 2016; Shahpari et al., 2022; Santos and Haimes, 2004). The sole exception is for reconstruction demand surge, which can also be interpreted as additional investment in dynamic CGE models (Bachner et al., 2024).

For production-related disruptions, such as *productive capital loss*, *productivity loss*, *labor loss*, and *production loss*, most models implement them as reductions in productive capacity or production factors.

TABLE 7. Model implementation of economic disruptions from the literature.

Economic Disruptions	Model implementations								
	Productive capacity/ production factor	Productivity parameter	Demand (upstream)	Supply (downstream)	Production	Import and export	Inter-regional I/O relationship	Price	Investment
Demand surge or reduction			✻ ○ ● ◇						◇
Productive capital loss	✻ ○ ● ◇		✻	✻	✻ ◇				
Productivity loss		◇							
Labor productivity loss	✻ ◇		✻						
Land productivity loss	◇	◇			◇				
Labor loss	✻ ○ ● ◇				✻				
Land production loss			✻	✻					
Production stoppage	○ ◇		✻	✻	◇				
Supply reduction	○ ◇			●	✻				
Import and export reduction						◇			
Transportation cost change							✻	◇	

✻ Leontief I/O model ○ IIM and DIIM models ● ARIO model ◇ CGE model

This is achieved either by directly reflecting the changes in corresponding variables in the cases of *productive capital loss* and *labor loss* (e.g. Jenkins, 2013; Carrera et al., 2015; Koks et al., 2015; Mendoza-Tinoco et al., 2017; Yaseen et al., 2020); or by converting the initial effects into equivalent changes in productive capacity in the cases of *productivity loss* and *production loss* (e.g. Dieye et al., 2020; Li et al., 2022). Specifically, *productivity losses* are modeled in two distinct ways in CGE models. While some CGE implementations directly reflect the losses to changes in the productivity parameter built into the production function (e.g. Wing et al., 2016; Rose and Chen, 2017; Sawadogo, 2022), other studies assume constant productivity and convert the productivity loss into reductions in the availability of production factors such as labor or land (e.g. Carrera et al., 2015; Hu et al., 2019; García-León et al., 2021). However, when these factors are considered in the basic form of the Leontief I/O model, there are no corresponding variables to reflect supply-side changes directly. Consequently, most implementations account for these disruptions as reduced demand for affected sectors to upstream industries and/or reduced supply to downstream industries (e.g. Kulshreshtha and Klein, 1989; Jonkman et al., 2008; Lin et al., 2012; Haque and Jahan, 2015; Kokaji and Goto, 2022; Welburn and Strong, 2022; Lyu et al., 2023). A few I/O implementations convert the production-related disruptions into final production reductions when incorporating them into the model (e.g. Breisinger et al., 2016; Gao et al., 2020; Li et al., 2018).

The implementation of *supply reductions* can vary, even for the same type of model. Wang et al. (2021) incorporate supply reductions into the ARIO model directly by imposing constraints on the supply between affected sector pairs during simulation. Santos et al. (2014) and Shahpari et al. (2022) model the shortage of water supply in the DIIM and the CGE models, respectively, as the reduction in the productive capacity of water-dependent industries by treating water as one of the intermediate inputs to their production function. Alternatively, Kelic et al. (2013) consider the supply shock resulting from cyber attacks on the oil industry as a reduction in oil production. Besides, *import and export reductions* can be directly reflected in the model by adjusting the value of corresponding import and export variables (Wei et al., 2022). The *transportation cost change* can be directly incorporated into CGE models (Wei et al., 2022), while in Leontief I/O implementations, the corresponding changes in inter-regional input-output relationships are computed to reflect equivalent effects on the trading patterns (Cho et al., 2001; Welch et al., 2022).

Combining Tables 5 – 7, we obtain the most commonly affected economic variables for various disasters as tabulated in Table 8. In this table, we also summarize the distribution of the disaster impacts across industries. Based on the comparison, the implementation of earthquake and wildfire scenarios in the

TABLE 8. Most common economic model implementations of various disaster scenarios from the literature.

Economic model implementations	Earthquake	Flood	Wildfire	Drought	Heatwave	Cyber Attack
Affected sectors	All	All with special concerns for Agriculture	All	Agriculture and water-dependent industries	All with special concerns for Power and Healthcare	ICT, Finance and critical infrastructure
Capital	✓	✓	✓	✓		✓
Labor	✓	✓	✓		✓	
Productivity		✓		✓		✓
Production		✓				✓
Demand (+)	✓	✓	✓	✓	✓	
Demand (-)						✓

reviewed literature exhibit analogous impacts on the economic system, primarily focusing on economic-wide productive capital, labor, and increased demand for reconstruction. Thus, they can adopt a similar scenario modeling design of indirect economic impacts. The flood scenario in the reviewed literature also considers productivity and production losses, especially for the Agricultural sector. Heatwave scenarios in the reviewed literature also induce economic-wide disruptions that mainly stem from shocks on labor, along with increased demand in the power and healthcare sectors. Conversely, droughts and cyber attacks initiate disruptions in specific industries. For drought scenarios, implementations revolve around damaged productive capital and productivity in agriculture and water-dependent sectors, alongside the need for reconstruction. Cyber attacks primarily target industries such as ICT, finance, and critical infrastructure, resulting in reductions in productive capital, productivity, production, and potential demand decline in the targeted sectors.

Additional attributes of the disasters, including their spatial and temporal scales and the likelihood of compounding with other disasters, can also affect the model selection and disaster scenario modeling design. For instance, events that affect large areas, such as major earthquakes or floods, may necessitate a multi-regional analysis to capture the heterogeneity in the spatial distribution of disruptions and regional economies (Crowther and Haimes, 2010; Zhu et al., 2024). Moreover, compared to the relatively short duration of earthquakes, where direct impacts can be imposed at a single point in time, the floods can last for weeks, which can delay the recovery process (Avelino and Dall'erba, 2019; Tanoue et al., 2020). For long-lasting disasters like droughts and heatwaves, the recovery may even coincide with the ongoing impact of the disaster itself (Jenkins, 2013). In such cases, the temporal dimension becomes a crucial consideration for modeling. Dynamic models, which can capture changes over time, can be more appropriate than static ones to account for the evolving nature of the disaster's effects and the recovery process. Last, cyber attacks can compound the impact of other disasters (Avraam et al., 2023). In these scenarios, the analysis needs to consider the potential impacts of both events and requires an integrated modeling approach.

OPPORTUNITIES FOR FUTURE RESEARCH

From this review, we identify several challenges of existing frameworks and opportunities for future research. First, given that different economic models exhibit their own unique strengths and limitations, enhancement of modeling approaches, such as model integration or multi-model analysis, are potential options to reduce biases and improve the robustness of analyses (Young and Holsteen, 2017). Moreover, further analysis of model mechanisms can lead to better understand model performance and reliability. For example, sensitivity analysis can quantify the significance of input data, model parameters, and assumptions in each model. By systematically varying these factors and assessing their impact on model outputs, researchers can gain insights into the sources of uncertainty and potential areas for model refinement.

Another opportunity is to refine the impacts considered in each disaster scenario. First, the two-layer mapping summary presented in Tables 5 and 6 can guide the exploration of links between disasters and environments. For instance, while port disruptions have been considered in earthquake case studies, they may also occur during flood and wildfire scenarios. Additionally, factors such as casualties and population displacement could induce changes in household demand, yet existing case studies often overlook these impacts. Bridging these gaps would enhance our understanding of interactions between disasters and economic systems, and support the development of more realistic models. Second, many existing applications tend to focus solely on specific physical impacts and their immediate implications, potentially overlooking broader economic ramifications of disasters (Martin-Ortega et al., 2012). Developing a rubric outlining factors that drive the economic outcomes in each disaster, or within specific study regions, can overcome the potentially exhaustive nature of factors to be considered for each disaster scenario, and the inherent challenges of data collection.

Our review also underscores the disparity in the number of applications and modeling approaches across various types of disasters. Despite their significance, studies addressing the indirect economic impacts of heatwaves, wildfires, and cyber attacks remain limited in comparison to floods and droughts (Callahan and Mankin, 2022; Bayham et al., 2022; Agrafiotis et al., 2018). This underscores the need for further research and methodological development to comprehensively understand and mitigate the economic ramifications of these less-explored disaster types. Furthermore, studies focusing on wildfires and cyber attacks currently particular economic models. Diversification and exploration of alternative modeling approaches for these disasters are essential for a more robust and nuanced understanding of the economic impacts of disasters.

CONCLUSION

In this review, we synthesize the current state of knowledge on the assessment of indirect economic impacts of disasters by providing a characterization of economic modeling methodologies for indirect impact evaluation. The reviewed models include the Leontief I/O model, the IIM, the DIIM, the ARIO model, and the CGE model along with its extensions. We mapped input data and output metrics across economic modeling methodologies for inter-sectoral impacts. Therefore, this work goes beyond a high-level comparison of economic modeling approaches and contributes to the translation of disaster scenario inputs and output metrics across methodologies.

While basic models require less data and computational resources, more sophisticated models like ARIO and CGEs can produce more diverse economic indicators and analyze a wider range of demand- and supply-side effects. ARIO and CGEs require additional input parameters, such as behavioral parameters and elasticities of substitution, which necessitate further calibration efforts and can be challenging to obtain. On the other hand, ARIO provides more detailed sectoral outputs than other I/O models, including changes in demand, production capacity, and value-added following a disaster. CGE models go even further by analyzing the effects on households, offering insights into the welfare implications of disasters. Moreover, while most I/O models primarily focus on demand-side implications of disaster shocks, ARIO and CGEs also consider supply-side factors like productive capacity, providing a more direct and accurate representation of disaster impacts when these primarily affect the supply side. The key distinction between I/O and CGE models lies in their treatment of market adjustments. The inherent flexibility of CGE models makes them better suited for long-term analysis, whereas I/O models are more appropriate for assessing short-term post-disaster impacts.

By outlining the distinct threats posed by various types of natural hazards and cyber attacks, we revealed how different disasters can be effectively modeled by the macroeconomic models reviewed here. Specifically, we identified commonly used modeling variables to reflect the initial disruptions for different disaster types. Earthquakes, floods, and wildfires share similar modeling implementation, while the other disasters impact distinct combinations of productive capital, productivity, production, and demand. This information can guide modelers in selecting appropriate modeling approaches and collecting necessary data.

Our work establishes the mathematical equivalence of inputs, modeling assumptions, and outputs of existing macroeconomic models, and opens up promising opportunities for future research. Primarily, our work allows for model integration and multi-model analysis based on a harmonized set of inputs and assumptions, similar to the ones conducted for climate policy analysis under the United Nations Intergovernmental Panel on Climate Change (Guivarch et al., 2022). Secondarily, our work allows for revisiting the investigation of the source and significance of modeling uncertainties, refining modeling factors that capture broader economic ramifications, diversifying modeling approaches, and focusing on less-explored disasters like heatwaves, wildfires, and cyber attacks, based on the mathematical equivalences revealed here. These avenues can advance our understanding of disaster indirect economic impacts and improve our capability to effectively manage such crises.

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