

# 1                   **Macroeconomic models for predicting indirect impacts of disasters: A review**

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## 7                   **ABSTRACT**

8                   Interdependencies between critical infrastructures and the economy amplify the effects of damage caused  
9 by disasters. The growing interest in impacts beyond physical damage has spurred a surge in literature on  
10 economic modeling methodologies for estimating indirect economic impacts of disasters. In this review,  
11 we present a framework for categorizing modeling approaches that assess indirect economic impacts across  
12 natural hazards and anthropogenic disasters such as cyber attacks. We first conduct a comparative analysis of  
13 macroeconomic models, focusing on the approaches capturing sectoral inter-dependencies. These include the  
14 Leontief Input-Output (I/O) model, the Inoperability Input-Output Model (IIM), the Dynamic Inoperability  
15 Input-Output Model (DIIM), the Adaptive Regional Input-Output (ARIO) model, and the Computable  
16 General Equilibrium (CGE) model and its extensions. We evaluate their applicability to disaster scenarios  
17 based on input data availability, the compatibility of model assumptions, and output capabilities. We also  
18 reveal the functional relationships of input data and output metrics across economic modeling approaches  
19 for inter-sectoral impacts. Furthermore, we examine how the damage mechanisms posed by different types  
20 of disasters translate into model inputs and impact modeling processes. This synthesis provides guidance  
21 for researchers and practitioners in selecting and configuring models based on specific disaster scenarios. It  
22 also identifies the gaps in the literature, including the need for a deeper understanding of model performance  
23 reliability, key drivers of economic outcomes in different disaster contexts, and the disparities in modeling  
24 approach applications across various hazard types.

## 25                   **INTRODUCTION**

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

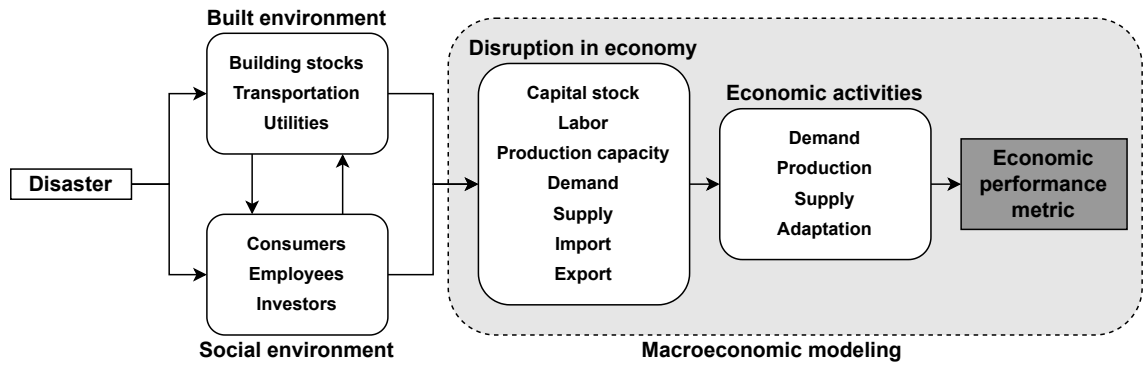
31 Historically, disaster loss estimation focused on quantifying physical damage and was primarily led by  
32 engineers (Rose, 2009). In recent decades, the rising interest in the impacts of disasters beyond physical  
33 damage has led to an evolving understanding and definition of disaster economic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

43 On the economic side, distinctions are drawn between stocks and flows (Rose, 2004). Stocks represent  
44 quantities at a specific time, while flows are time series data that represent the outputs of stocks over time.  
45 Direct stock losses result from property damage and direct flow losses stem from business interruptions by  
46 the hazard itself, such as factory shutdowns following an earthquake (Brookshire et al., 1997; Rose, 2004).  
47 Indirect stock losses are secondary direct losses per the National Research Council (1999) definition, while  
48 the indirect flow losses arise from disruptions in successive rounds of suppliers and customers, such as  
49 reduced supplier orders or consumer spending.

50 Terminological inconsistencies exist in the literature regarding the classification of economic impacts.  
51 Some earlier studies differentiate economic impacts beyond physical damage by defining business-to-business  
52 interactions as indirect effects and customer-to-business interactions as “induced effects” (Miller and Blair,  
53 1985; Miyazawa, 2012). Rose (2004) further proposed the term “higher-order effects” to describe all flow  
54 losses of interdependent activities, capturing both the ripple effects due to economic interdependencies and  
55 other market responses such as price changes. In this review, we follow the broader definition from the

56 National Research Council (1999) that categorizes all economic impacts beyond direct losses as “indirect  
 57 impacts”.

58 We summarize a general framework for indirect economic impact modeling from the engineering per-  
 59 spective in Figure 1. This framework highlights the critical interfaces that need to be considered in the  
 60 analysis. A disaster first directly impacts the built and social environment. These direct impacts cause  
 61 disruptions to one or more economic system components, triggering a ripple effect within the interdependent  
 62 economic system, and resulting in indirect impacts. While macroeconomic modeling navigates the evolving  
 63 dynamics within the economic system, understanding the interface between hazards, physical environments,  
 64 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.

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

75 disaster scenarios based on their impact on modeling inputs.

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

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

## 92 **OVERVIEW OF MODELING APPROACHES**

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

### 98 **Input-Output Models**

99 The I/O model is a widely-used framework that describes how an industry's products are distributed  
100 across all sectors of the economy through trade flows captured in the surveyed Input-Output tables (Leontief,  
101 1944, 1986). The I/O formulation comprises a system of linear equations that quantitatively describe  
102 inter-sectoral trade flows. The capability to assess demand-driven changes in sectoral output makes I/O  
103 models applicable to economic assessment studies of disaster-induced shocks (Kelly, 2015). One of the key

104 advantages of I/O models lies in their ability to evaluate the propagation of disruptions across different sectors,  
105 providing valuable insights into economy-wide interdependencies (Rose, 2004; Okuyama, 2007). Moreover,  
106 I/O models offer a clear distinction between direct and indirect impacts, enhancing the understanding of the  
107 ripple effects of a shock to a specific sector (Kelly, 2015).

108 However, I/O models suffer from three main limitations (Rose, 2004; Okuyama, 2007; Botzen et al.,  
109 2019). Notably, they do not account for price fluctuations, which can influence the demand for intermediate  
110 and final goods, and potentially alter the economic landscape after disasters. Moreover, supply-side shocks,  
111 technological advancements, and the potential for input and import substitution are not fully considered in  
112 the model, which may not adequately capture adaptive behavior and other forms of economic resilience  
113 that can manifest during the recovery process. Additionally, I/O models assume linearity between input and  
114 output. This can result in an oversimplified representation of the complex dynamics of the economy.

115 Several extensions have been developed based on the I/O framework. The dynamic extensions, such  
116 as Leontief dynamic model (Miller and Blair, 1985) and Sequential Interindustry Model (SIM) (Donaghy  
117 et al., 2007), incorporate the temporal variations of economic activities in the analysis. The Inoperability  
118 Input Output Model (IIM) (Haimes and Jiang, 2001; Haimes et al., 2005) and its dynamic counterpart, the  
119 Dynamic Inoperability Input Output Model (DIIM) (Lian and Haimes, 2006), were developed to assess the  
120 inoperability of critical infrastructure systems, where inoperability is defined as the percentage reduction in  
121 sectoral output from its ideal level. Other extensions integrate I/O framework with linear programming (e.g.,  
122 the Multi-Regional Impact Assessment (MRIA) model (Koks and Thissen, 2016)), nonlinear programming  
123 (e.g. Oosterhaven and Bouwmeester, 2016; Garcia-Hernandez and Brouwer, 2021), or additional features to  
124 introduce case-specific economic constraints and adaptability under disaster-induced disruptions (e.g., the  
125 Adaptive Regional Input-Output (ARIO) model (Hallegatte, 2008; Hallegatte, 2014)). The supply-driven  
126 variation of the I/O model or Ghosh model (Ghosh, 1958) inverses the interpretation of the I/O framework to  
127 represent the relationship between primary inputs and output. However, the Ghosh model has faced criticism  
128 regarding its assumptions of perfect demand elasticity and input substitutability (Oosterhaven, 1988; Gruver,  
129 1989), leading to debates about its plausibility and applicability in real-world scenarios (Oosterhaven, 1989;  
130 De Mesnard, 2009).

## 131 **Computable General Equilibrium Models**

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

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

## 151 **Econometric Models**

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

160 incorporate location-fixed effects and evaluate the lagged effects of disasters through a dynamic assessment  
161 of the disaster-economy relationship (Hsiang, 2010; Felbermayr and Gröschl, 2014).

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

## 166 MODEL COMPARISON

167 This section compares the I/O and CGE model classes on the dimensions of input data requirements,  
168 theoretical assumptions, mathematical formulations, and output metrics. The comparison includes the  
169 Leontief I/O model, IIM, DIIM, ARIO, the basic CGE model, and their extensions. These extensions  
170 include dynamic CGE models, CGE models for open economies, and CGE models incorporating fiscal  
171 elements such as taxes, subsidies, or budget constraints for governments and households. These models and  
172 their variations comprise the vast majority of models in the I/O and CGE classes that are deployed in disaster  
173 impact analysis. Moreover, we link the input data and output metrics of each model with the mathematical  
174 formulation of each model, allowing for an end-to-end model comparison across all four dimensions. We  
175 evaluate how assumptions within each dimension affect the capabilities of each model.

176 Through the comparisons, we aim to guide model construction and cross-model translation of output  
177 metrics. Specifically, by summarizing input data requirements, theoretical assumptions, and output metrics,  
178 we provide a structured framework for selecting appropriate models based on resource availability, the char-  
179 acteristics of disruption mechanisms, and analytical objectives. Furthermore, the mathematical formulations  
180 inform modeling processes, highlighting computational considerations and methodological trade-offs that  
181 influence model applicability and interpretation.

182 We adopt the following definitions for the common terminologies: *intermediate inputs* refer to goods and  
183 services traded between economic sectors; *production factors* refer to capital, labor, and natural resources;  
184 and *commodities* refer to goods, services, and production factors.

### 185 Input Data Requirements

186 Table 1 summarizes model inputs for the considered cases. The I/O table is an essential input for all I/O  
187 models. It comprises the annual monetary values of intermediate inputs trade between sectors, sectoral final  
188 demands, value added, exports, imports, and gross output (Miller and Blair, 1985). While Leontief I/O, IIM,

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

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

189 and DIIM only require intermediate inputs trade matrix and sectoral gross output in their model formulations,  
 190 ARIO model leverages most of the information in the I/O table as various model parameters to construct  
 191 the baseline economic structure. The CGE models require information from the Social Accounting Matrix  
 192 (SAM), which extends the I/O table to include all payments to and from households and the government.  
 193 Open economy models incorporate trade with other regions and require the *trade matrix* in addition to the  
 194 local I/O table or SAM. The trade matrix records the trade of money between each sector of the regional  
 195 economy and the regions outside the focus region. The loss vector describes the direct losses, in monetary  
 196 values, in each sector, and is also a crucial disaster scenario input in all macroeconomic models.

197 The Leontief I/O model requires no additional information for analysis. Instead of using the loss vector  
 198 directly, the IIM requires the perturbation vector, which can be derived by normalizing sectoral losses by their  
 199 respective gross output (Santos and Haines, 2004). The dynamic extension of the IIM model, the DIIM,  
 200 goes a step further by incorporating the time required for each sector to recover from initial inoperability to  
 201 a desired post-recovery state (Lian and Haines, 2006).

202 The ARIO model necessitates more extensive input data. In addition to the elements in the I/O table, the  
 203 loss vector, sectoral recovery rates during recovery, and potentially the trade matrix, ARIO also considers  
 204 sector-specific fixed assets to estimate relative damage to sectoral capital stocks. A key feature of the ARIO  
 205 model is its explicit inclusion of user-defined behavioral parameters that characterize the adaptive capacities  
 206 of each sector. These parameters include overproduction capacity, time to achieve maximum overproduction,

207 target inventory levels, time for inventory restoration, and the production reduction parameter, also referred  
208 to as heterogeneity (Hallegatte, 2014; Issa et al., 2024). Additionally, to model reconstruction efforts during  
209 recovery, the ARIO model incorporates an exogenously defined ratio that determines how reconstruction  
210 demand is allocated across sectors.sectors.

211 At its most basic form, the CGE model further requires information on the elasticities of substitution  
212 between inputs in all activities and between commodities for all households, and baseline prices of com-  
213 modities and production factors. By dividing the entries of the SAM with the respective baseline prices,  
214 modelers derive the baseline quantities and stock of production factors. In addition to the SAM, household  
215 consumption decisions are also based on the elasticity of substitution between consumed goods and services.  
216 Production decisions by firms also require the elasticities of substitution between intermediate inputs and  
217 production factors. Dynamic CGE models require the investment matrix which quantifies the allocation of  
218 savings to all sectors, in monetary values. A CGE of an open economy requires additional information on  
219 inter-regional trade for all commodities, along with baseline import and export prices. The derivation of  
220 traded quantities follows from the division of the entries of the trade matrix with the baseline import and  
221 export prices. The baseline prices can include price markups due to taxes and subsidies.

222 From the comparison, the construction of ARIO and CGE models are relatively more data-intensive.  
223 Although a substantial portion of the input data is systematically collected through periodic censuses and  
224 surveys, some necessitate additional effort for acquisition. Specifically, the ARIO model requires a nuanced  
225 understanding of the regional economic capacities and organizational structures gleaned from prior disaster  
226 responses to determine the behavioral parameters (Hallegatte, 2008). In the case of CGE models, the calibra-  
227 tion of elasticities of substitution can require additional panel data (Németh et al., 2011) and technological  
228 data (Balistreri and Brown, 2023) among others. Moreover, when considering disaster scenario inputs,  
229 assumptions may be imperative owing to the unavailability of empirical data, *e.g.*, for recovery rates and the  
230 distribution of reconstruction demand in ARIO (Markhvida and Baker, 2023) and substitution elasticities in  
231 a CGE (Rose and Guha, 2004).

## 232 **Theoretical Assumptions**

233 The I/O and CGE model classes rely on different assumptions, which map to their formulation and  
234 application. In the Leontief I/O model, disruptions are typically accounted for as changes in demand. The  
235 model assesses the overall impact by analyzing the resulting changes in sectoral activity. The relationship

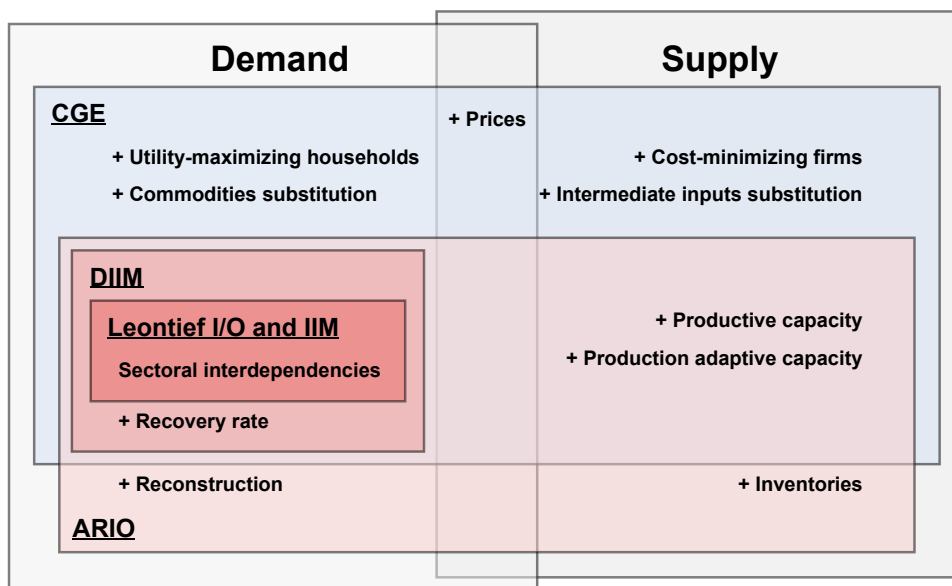
236 between the demand reduction and the changes in sectoral activity is linear, which is determined by the  
237 technical coefficients that represent the interdependencies between different sectors. The technical coeffi-  
238 cients for each sector are the normalized sales volumes between the focus sector and all other sectors in  
239 the I/O matrix, normalized by the total output, in dollar values, of the focus sector. A key assumption in  
240 the Leontief I/O model is that the technical coefficients remain fixed before and after the disaster, implying  
241 that production technology does not adjust following an event during the modeled period. Additionally, the  
242 model assumes that inputs remain in fixed proportions to output, which indicates the absence of substitution  
243 between different intermediate inputs.

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

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

261 CGE models are distinct from I/O models in that prices impact production activities and consumer  
262 preferences. A standard CGE model assumes that all sectors are at equilibrium, under perfect competition  
263 in every commodity market, and rational agents in every production activity (Rutherford and Schreiber,  
264 2019). The most common production functions in a CGE include the Leontief, Cobb-Douglas, and Constant  
265 Elasticity of Substitution (CES) functions (Lofgren et al., 2002). All three exhibit constant returns-to-scale.

266 Household demand is represented through inverse demand curves, which depend on the relative prices of  
 267 commodities. The derivation of the demand curves is based on the optimal allocation of resources of  
 268 a representative utility-maximizing agent for each type of household (Hosoe et al., 2010; Lofgren et al.,  
 269 2002). Trade between regions is based on the relative domestic price of a commodity between two regions  
 270 (Rutherford and Schreiber, 2019; Lofgren et al., 2002). Finally, the allocation of investment funding between  
 271 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, ARIO, and CGE models.

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

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

281 Moreover, the integration of recovery rates in dynamic models introduces a temporal dimension to the

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

288 The CGE models account for both demand- and supply-side effects. The primary disparity between  
289 I/O and CGE models lies in their treatment of price adaptation, substitution between commodities, and  
290 associated market adjustments. CGE models assume adaptive behavior across all agents within the economic  
291 system. They further account for the substitution of consumed commodities, including intermediate inputs  
292 to production and final demand, which mitigates resource shortages. By allowing for such adaptability and  
293 optimization by all agents, CGE models tend to forecast economic consequences on the optimistic side (Rose,  
294 2004). However, they typically do not explicitly account for reconstruction demand and inventories as the  
295 ARIO model does.

296 Given the understanding of the behavioral and economic assumptions underpinning the I/O and CGE  
297 models, and their potential impacts on assessment outcomes, I/O models may yield a more conservative  
298 estimate of indirect impacts compared to CGE models due to their rigidity. Since reaching a market  
299 equilibrium following a disaster typically entails a temporal lag, I/O models are better suited for short-term  
300 post-disaster impact assessments, while CGE models handle long-term analysis better (Rose and Guha,  
301 2004). The choice of model should, therefore, be guided by the temporal scope and specific analytical  
302 objectives of the assessment.

### 303 **Mathematical Formulations**

304 In this section we compare the fundamental mathematical formulations of the models and discuss their  
305 computational requirements. For consistency in presentation across different models, we have adapted some  
306 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
$\mathcal{M} = \{1, \dots, M\}$	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/Variable	I/O coefficient matrix or technical coefficient matrix
$\hat{A} \in \mathbb{R}^M \times \mathbb{R}^M$	Parameter	Normalized technical coefficient matrix or allocation coefficient matrix
$b_t \in \mathbb{R}^H \times \mathbb{R}^M$	Parameter	Endowments of commodities of every household at time $t \in \mathcal{T}$
$c_t : \mathbb{R}^M \rightarrow \mathbb{R}^N$	Function	Continuous and point-to-point differentiable unit cost functions of operating activities at time $t \in \mathcal{T}$
$\pi_t : \mathbb{R}^M \rightarrow \mathbb{R}^N$	Function	Continuous and point-to-point differentiable unit profit 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 $t \in \mathcal{T}$
$d_t \in \mathbb{R}^M$	Parameter/Variable	Total demand at time $t \in \mathcal{T}$
$d_t^+ \in \mathbb{R}^M$	Variable	Reconstruction demand 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 $n \in \mathcal{N}$ , activities at time $t \in \mathcal{T}$
$\Delta k_t \in \mathbb{R}^M$	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 $t \in \mathcal{T}$
$t^\theta \in \mathbb{R}^M$	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 ( <i>inoperability</i> ) at time $t \in \mathcal{T}$
$\tilde{x}_t \in \mathbb{R}^M$	Variable	Production capacity of sectors at time $t \in \mathcal{T}$

*Continued on next page*

Definition	Type	Description
$x_t^\eta \in \mathbb{R}^M \times \mathbb{R}^M$	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 $t \in \mathcal{T}$
$\beta \in \mathbb{R}^M$	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 $t \in \mathcal{T}$
$\eta_t^O \in \mathbb{R}^M \times \mathbb{R}^M$	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
$\phi_n \in \mathbb{R}^M$	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)

307 **Leontief I/O.** The Leontief I/O model is a static model, *i.e.*, comprises a single time step. The model  
308 estimates the economic impact of a disaster by analyzing how changes in demand propagate across all  
309 economic sectors. It comprises a balancing Eq. (1) that computes the change in production,  $\Delta x \in \mathbb{R}^M$ ,  
310 from the change in demand from all sectors,  $\Delta d \in \mathbb{R}^M$ , compared to baseline production and demand  
311 respectively, where the I/O coefficient matrix, or *technical coefficient matrix*,  $A \in \mathbb{R}^M \times \mathbb{R}^M$  captures the

312 inter-dependencies between all sectors of an economy<sup>1</sup> (Leontief, 1986):

$$313 \quad \Delta x = (I - A)^{-1} \Delta d \quad (1)$$

314 **IIM.** The IIM is also a static model and is built based on similar principles as the Leontief I/O model.  
 315 Instead of absolute changes in supply and demand, in an IIM the changes in supply and demand vectors are  
 316 normalized using the baseline supply and demand respectively (Haimes and Jiang, 2001; Santos and Haimes,  
 317 2004). We denote the diagonal matrix of baseline levels of commodities by  $\bar{X} = \text{diag}(\{\bar{x}_m\}_{m \in \mathcal{M}})$ . Then,  
 318 the normalized change in demand, or *perturbation* in demand,  $\hat{d} \in \mathbb{R}^M$ , is<sup>1</sup>:

$$319 \quad \hat{d} = \bar{X}^{-1} \Delta d \quad (2)$$

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

$$321 \quad \hat{x} = \bar{X}^{-1} \Delta x \quad (3)$$

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

324 Similarly to the Leontief I/O model, a normalized technical coefficient matrix,  $\hat{A} \in \mathbb{R}^M \times \mathbb{R}^M$ , accounts  
 325 for the demand-side interdependencies by quantifying how the inoperability of one sector propagates to  
 326 others. The normalization results in a coefficient matrix structurally resembling the *allocation coefficient*  
 327 *matrix* used in the supply-side I/O model:

$$328 \quad \hat{A} = \bar{X}^{-1} A \bar{X} \quad (4)$$

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

$$331 \quad \hat{x} = (I - \hat{A})^{-1} \hat{d} \quad (5)$$

332 Both the Leontief I/O and IIM models comprise a system of linear equations. Solving for a vector  
 333  $x$  that satisfies equations (1), for Leontief I/O models, and (5), for IIM models, requires relatively little

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<sup>1</sup>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.

334 computational power and can be easily implemented in most computing languages.

335 **DIIM.** The DIIM model is an extension of the IIM that incorporates the evolution dynamics of the levels of  
 336 activity and demand in the economy in future time steps, *i.e.*,  $t \in \mathcal{T} = \{1, \dots, T\}$  (Lian and Haimes, 2006).  
 337 The production adjustment rate, or *interdependency recovery rate*,  $\theta_m$  is introduced to represent the ability  
 338 of a sector to adjust its output in response to an imbalance in supply and demand. Under the assumption of  
 339 exponential recovery, the interdependency recovery rate of each sector  $m \in \mathcal{M}$  is derived as<sup>2</sup>:

$$340 \quad \theta_m = \frac{1}{t_m^\theta} \cdot \ln \left[ \frac{\hat{x}_{m0}}{\hat{x}_{m_t^\theta}} \right] \cdot \left( \frac{1}{1 - \hat{A}_{mm}} \right) \quad (6)$$

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

$$342 \quad \Theta = \text{diag} (\{\theta_m\}_{m \in \mathcal{M}}) \in \mathbb{R}^M \times \mathbb{R}^M \quad (7)$$

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

$$345 \quad \hat{x}_{t+1} = \hat{x}_t + \Theta [\hat{A}\hat{x}_t + \hat{d}_t - \hat{x}_t] \quad (8)$$

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

351 **ARIO.** The ARIO model provides a more detailed simulation of economic recovery by incorporating  
 352 adaptation and productive constraints over time. Specifically, ARIO models inventories of sectors, which  
 353 allows them to maintain stocks of commodities. During each time step, sectors aim to satisfy the demand  
 354 for goods and services. However, actual production is constrained by the sector's production capacity and  
 355 available inventories of production inputs. The original version of the ARIO model (Hallegatte, 2008;

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<sup>2</sup>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.

356 Hallegatte, 2014) did not distinguish between local production and imports when computing the production  
 357 capacity and supply. Nevertheless, recent model developments have addressed this concern by separately  
 358 accounting for the constraints and adaptability of local production and imports (Issa et al., 2024)<sup>3</sup>.

359 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  
 360 from export; demand from households, the government and the savings/investment sector; and demand for  
 361 reconstruction<sup>4</sup>:

$$362 \quad d_t = \mathbf{1}_M^T z_{mt} + d_t + d_t^+ \quad (9)$$

363 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,  
 364 the overproduction status, and demand:

$$365 \quad \tilde{x}_{mt} = \min \left\{ \alpha_{mt}^X \cdot \left( 1 - \frac{\Delta k_{mt}}{\bar{k}_m} \right) \cdot \bar{x}_m + x_{mt}^I, d_{mt} \right\} \quad (10)$$

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

$$368 \quad \tilde{\eta}_{m'mt} = \begin{cases} \beta_{m'} \cdot (\tilde{x}_{mt} - x_{mt}^I) \cdot A_{m'm}, & \text{when } d_{mt} > \tilde{x}_{mt} \\ \beta_{m'} \cdot d_{mt} \cdot \frac{\tilde{x}_{mt} - x_{mt}^I}{\tilde{x}_{m't}} \cdot A_{m'm}, & \text{when } d_{mt} \leq \tilde{x}_{mt} \end{cases} \quad (11)$$

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

$$371 \quad x_{m'mt}^\eta = \begin{cases} x_{mt}^I + (\tilde{x}_{mt} - x_{mt}^I) \cdot \min \left\{ 1, \frac{\eta_{m'mt}}{\psi_{m'} \cdot \tilde{\eta}_{m'mt}} \right\}, & \text{when } d_{mt} > \tilde{x}_{mt} \\ \min \left\{ d_{mt} \cdot \frac{\tilde{x}_{mt} - x_{mt}^I}{\tilde{x}_{mt}} \cdot \min \left( 1, \frac{\eta_{m'mt}}{\psi_{m'} \cdot \tilde{\eta}_{m'mt}} \right) + x_{mt}^I, d_{mt} \right\}, & \text{when } d_{mt} \leq \tilde{x}_{mt} \end{cases} \quad (12)$$

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

$$374 \quad x_{mt} = \min \{ x_{m'mt}^\eta, \forall m' \in \mathcal{M} \} \quad (13)$$

375 If the actual production fails to satisfy the demands of certain sectors, the production is distributed

<sup>3</sup>The formulation in this paper is based on the updated ARIO model in Issa et al. (2024).

<sup>4</sup>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.

376 proportionally to meet a portion of the demand of the corresponding inter-sector orders, total final demand  
 377 (from households, the government, and the savings/investment sector), reconstruction demand, and exports.  
 378 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  
 379 based on the current level of production and inventories:

$$380 \quad z_{mt} = Ax_t + \text{diag} \left( \left\{ (\gamma_m^\eta)^{-1} \right\}_{m \in \mathcal{M}} \right) \cdot \left( \eta_{mt}^O - \eta_{mt} \right) \quad (14)$$

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

$$382 \quad v_t = x_t - x_t^I - A^T x_t \quad (15)$$

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

386 Code to implement both the original and refined models are available (Markhvida et al., 2020; Issa et al.,  
 387 2024). The computational requirements of the model are influenced by factors such as the number of sectors  
 388 and analytical time steps. It can increase significantly when conducting fine-grained multi-regional analysis  
 389 (Zhu et al., 2024). Therefore, it is essential to consider the computational resources available and optimize  
 390 the model implementation accordingly to ensure efficient execution.

391 **CGE** A CGE extends the I/O framework to account for the impact of prices  $p_t \in \mathbb{R}^M$  on production  
 392 activities  $y_t \in \mathbb{R}^N$  and consumer preferences at each time step  $t \in \mathcal{T}$ . Demand and production in CGEs are  
 393 functions of commodity prices, and can be parameters in Leontief I/O models, IIMs, DIIMs, and ARIO. In  
 394 what follows, We highlight the equivalence between models by abusing the notation mildly and maintaining  
 395 the same symbols. Instead, where applicable, we will indicate the dependence on prices.

396 Let  $\Phi = \{\phi_n\}_{n \in \mathcal{N}} \in \mathbb{R}^{M \times N}$  be the matrix of output commodity ratios for all activities,  $\pi_t : \mathbb{R}^M \rightarrow \mathbb{R}^N$   
 397 be the unit profit function,  $c_t : \mathbb{R}^M \rightarrow \mathbb{R}^N$  be the unit cost function of activity  $n \in \mathcal{N}$ , and  $b_t \in \mathbb{R}^M$  be  
 398 the vector of household endowments in year  $t \in \mathcal{T}$ . Intermediate demand of commodities for production  
 399 activities in a CGE is decided based on prices. Therefore, the equivalent of a technical coefficient matrix  
 400 of a CGE model is a matrix which depends on prices:  $A(p_t) \in \mathbb{R}^M \times \mathbb{R}^N$ . In its most compact form,  
 401 following Mathiesen (1985) and Böhringer and Rutherford (2008), an equilibrium of a CGE is a vector

402  $(p, y) \in \mathbb{R}^M \times \mathbb{R}^N \times \mathbb{R}^T$  which satisfies the following conditions:

- 403 • No profit condition for all activities: Producers need to recover their cost via sales. The cost includes  
404 value-added, therefore, the revenues should not exceed the cost, otherwise there will exist income in  
405 the economy that is not allocated to any activity or agent<sup>5</sup>,

$$406 \quad \pi_t(p_t) = c_t(p_t) - \Phi^T p_t \geq 0, \quad \forall t \in \mathcal{T} \quad (16)$$

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

$$409 \quad b_t + A^T(p_t)y_t - d_t(p_t) \geq 0 \quad \forall t \in \mathcal{T} \quad (17)$$

- 410 • Non-negativity conditions: Positive prices and quantities,

$$411 \quad p_t \geq 0, \quad y_t \geq 0 \quad \forall t \in \mathcal{T} \quad (18)$$

- 412 • An operating activity incurs no losses: This condition ensures that if the production ( $y_t$ ) is positive,  
413 then the respective activity fully retrieves their cost via sales. If this is not the case and the cost is  
414 higher than the revenues (see equation (16)), then, the respective production  $y_t$  should be zero,

$$415 \quad \left( c_t(p_t) - \Phi^T p_t \right)^T y_t = 0, \quad \forall t \in \mathcal{T} \quad (19)$$

- 416 • Market clearing of a commodity: This set of constraints ensures that supply exactly matches demand  
417 for a commodity, otherwise, the respective price becomes zero:

$$418 \quad (b_t + A(p_t)y_t - d_t(p_t))^T p_t = 0, \quad \forall t \in \mathcal{T} \quad (20)$$

419 The elasticities of substitution between inputs of production activities appear in the unit cost and unit  
420 profit functions ( $c_t, \pi_t$ ), while the elasticities of substitution between consumed commodities by households  
421 appear in the demand function ( $d_t$ ).

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<sup>5</sup>CGEs capture all payments across the economy, therefore there can not exist income that is not allocated to an activity or agent.

422 A CGE can extend to include taxes and subsidies, and their implementation is policy-specific. Examples  
423 include sales taxes, export subsidies, and import tariffs. Moreover, dynamic CGEs include a mechanism  
424 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  
425 economy by the government and households. The allocation of savings can be based on fixed ratios, or an  
426 endogenous mechanism that accounts for the returns on investment.

427 Compared to the other models studied here, the conditions comprising CGE models arise from opti-  
428 mization problems. Depending on the number of features, regional and sectoral disaggregation, and the  
429 set of scenarios, CGEs can demand significantly more computational resources. These models are often  
430 constructed using specialized software such as General Algebraic Modeling System (GAMS) (Lofgren et al.,  
431 2002; McCarl et al., 2014). Note that unlike previous models, which are set up for general analysis and can  
432 be applied to any region of interest given the required regional input data, most CGE models are tailored for  
433 specific regions, with regional parameters integrated into the model. Adapting or reconstructing the model  
434 for a different region can therefore require considerable effort and resources. This regional specificity adds  
435 complexity to the modeling process.

## 436 **Output Metrics**

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

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

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

451 A standard CGE quantifies economic impacts primarily through the change in the level of activities  
 452 or, equivalently, the change in the production of commodities. Depending on the features of a CGE, it  
 453 can also output changes in domestic production and trade, changes in savings and investment, and changes  
 454 in household demand. One key application of CGE modeling is the determination of long-term prices of  
 455 commodities and the Consumer Price Index (CPI) for each household. The CPI reflects changes in the overall  
 456 cost of living for different segments of the population. Specifically, the Gini coefficient is calculated as the  
 457 ratio of income held by the top 20% of the population to that held by the bottom 20% and is a measure of  
 458 income inequality within a population. In the absence of changes in endowments, the Gini coefficient is  
 459 primarily influenced by changes in prices, hence, is reported predominantly by CGEs.

460 In a CGE model, which is grounded in neoclassical economic theory, market equilibrium for all com-  
 461 modities and factors is ensured through prices. These prices, in turn, influence changes in the Gross  
 462 Domestic Product (GDP) and the Gini coefficient. These economic metrics provide insights into the welfare  
 463 implications of disasters and facilitate the design of targeted interventions to address specific challenges or  
 464 inequalities within the economy.

465 To further facilitate cross-model translation of input and output metrics, we summarize the mappings  
 466 between shared inputs and output metrics across models in Table 4. The left-hand side includes input and  
 467 output metrics that are consistent across models. The first two rows are demand-related inputs, while the  
 468 last two rows are output-related metrics. The columns on the right-hand side indicate the mathematical

**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 ( $d_t \in \mathbb{R}^M$ )	$\Delta d_t$	$\hat{d}_t = \bar{X}^{-1} \Delta d_t$	$\hat{d}_t = \bar{X}^{-1} \Delta d_t$	$d_t$	$d_t$
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 ( $x_t \in \mathbb{R}^N$ )	$\Delta x_t$	$\hat{x}_t = \bar{X}^{-1} \Delta x_t$	$\hat{x}_t = \bar{X}^{-1} \Delta x_t$	$x_t$	$x_t$
Change in sectoral output ( $\Delta x_t \in \mathbb{R}^N$ )	$\Delta x_t$	$\hat{x}_t = \bar{X}^{-1} \Delta x_t$	$\hat{x}_t = \bar{X}^{-1} \Delta x_t$	$x_t = \Delta x_t + \bar{x}_t$	$x_t = \Delta x_t + \bar{x}_t$

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 DIIM require reformulating the original demand even further into  $\hat{d}_t = \bar{X}^{-1} \Delta d_t$  before they can be run. An illustrative example is available in Supplemental Materials.

## 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 the 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). These selected natural hazard types encompass geophysical, hydrological, meteorological, and climatological hazard events ([Integrated Research on Disaster Risk, 2014](#)) and may share similar indirect impact mechanisms with other hazards within the same categories. 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 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

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

<b>Direct impacts</b>	<b>Earthquake</b>	<b>Flood</b>	<b>Wildfire</b>	<b>Drought</b>	<b>Heatwave</b>	<b>Cyber Attack</b>
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						✓

492 applications, we observe a mixed use of I/O- and CGE-based models for case studies of earthquake, flood,  
 493 drought, and heatwave hazards. However, wildfire applications are predominated by CGE models, and most  
 494 of the cyber attack studies utilize the IIM or DIIM models.

495 In this section, we present a structured approach to characterize disaster scenarios for economic modeling  
 496 through two-layer mapping, which corresponds to the first two steps in the general modeling framework shown  
 497 in Figure 1. The first layer delineates the interface between disasters and the physical environment, identifying  
 498 the direct impacts induced by each type of disaster. The second layer focuses on the interface between the  
 499 physical environment and the economic system to link the physical impacts to potential economic disruptions.  
 500 Furthermore, we synthesize the general practices of implementing the identified initial disruptions of the  
 501 economic system into various types of macroeconomic models. Combining the information together, we  
 502 summarize all potential factors to consider for indirect impact analysis and the translation of non-economic  
 503 information into economic models tailored to each specific disaster scenario. This not only facilitates  
 504 horizontal comparisons across a spectrum of disaster applications but also furnishes modelers with an initial  
 505 checklist of considerations for conducting such analyses.

### 506 **Interface Between Hazards and Physical Environments**

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

509 Among the range of disasters considered here, earthquakes, floods, and wildfires primarily inflict damage  
 510 on the built environment, encompassing structures, building contents, and infrastructure (e.g. [Sue Wing et al.,](#)  
 511 [2022](#); [Yang et al., 2023](#); [Monge et al., 2023](#)). On the other hand, droughts and heatwaves primarily cause  
 512 utility disruptions, human casualties, and population displacement (e.g. [Wing et al., 2016](#); [Xia et al., 2018](#);

513 Butry et al., 2019; Yaseen et al., 2020). Specifically, drought events typically lead to water shortages and the  
514 loss of hydraulically generated power sources (Martin-Ortega et al., 2012; Boyd and Ibararan, 2009). For  
515 heatwaves, water and power supply are also the two main vulnerable utilities (Disher et al., 2021). Moreover,  
516 weather-related disasters, including floods, droughts, wildfires, and heatwaves, often result in agricultural  
517 losses, impacting both current crop yields and future harvests, as extensively documented in various studies  
518 (e.g. Harris et al., 2002; Wittwer and Griffith, 2011; Borgomeo et al., 2018; Wang et al., 2023). Conversely,  
519 a cyber attack is a special case wherein the direct impact predominantly targets the operational functionality  
520 of systems, irrespective of physical damages (e.g. Kelic et al., 2013; Hyatt and Santos, 2022; Eling et al.,  
521 2022). However, exceptions apply when a cyber attack targets critical infrastructure, which can result in  
522 harm to either the physical system or the operational system (e.g. Martin et al., 2023; Rose et al., 2007).

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

### 530 **Interface Between Physical and Economic Environments**

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

536 Table 6 further distinguishes between supply- and demand-side economic disruptions found in the  
537 literature. It shows that most direct impacts are associated with both supply- and demand-side disruptions.  
538 On the supply side, the damage or disruption to the built environment can result in loss of productive  
539 capital (e.g. Rose and Guha, 2004; Gertz et al., 2019). The impacts on human activities, including *human*  
540 *casualties and displacement, transportation disruptions, and physiological strain on workers*, can influence  
541 the availability of labor, resulting in labor loss (e.g. Mendoza-Tinoco et al., 2017; Kim and Kwon, 2023;

**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

542 **Hoffmann, 2019**). A special case is *system or data disruptions*, which, while not affecting the total available  
543 labor, raises concerns about labor shortage due to increased demand for recovery efforts (**Hyatt and Santos,**  
544 **2022**). Another interpretation of impacts associated with *physiological strain on workers* and *system or data*  
545 *disruptions* is the productivity loss, indicating reduced efficiency of labor and/or resources in post-disaster  
546 production activities (e.g. **García-León et al., 2021; Rose and Chen, 2017; Dieye et al., 2020**). Similar  
547 concerns also apply to the *crop yield disruptions* and the *land use inundation* (e.g. **Horridge et al., 2005;**  
548 **Juana et al., 2014; Haddad and Teixeira, 2015**). These three types of supply-side shocks could lead to  
549 production reduction for the affected sectors, but *crop yield disruption*, *land use inundation*, and *system or*  
550 *data disruptions* can also result in direct production reduction, since they immobilize the production process  
551 (e.g. **Bauman et al., 2013; Li et al., 2022; Welburn and Strong, 2022**). Another type of supply-side impact  
552 is the reduction of supply to the downstream industries. This can be triggered by *utility disruptions* and  
553 *transportation disruptions*, which disrupt the supply chain of commodities (e.g. **Santos et al., 2014; Shahpari**  
554 **et al., 2022; Wang et al., 2021**). Similarly, *port disruptions* affect trade between the studied region and the  
555 outside world, leading to reduced imports (**Wei et al., 2020**). This can cause a shortage in intermediate inputs  
556 for production activities or failure to meet consumer demand for final products.

557 On the demand side, the *building/physical property damages* stimulate reconstruction demand, primarily  
558 within the construction and manufacturing sectors (e.g. **Okuyama, 2004; Wu et al., 2012; Mendoza-Tinoco**

559 *et al.*, 2020). Meanwhile, the impacts on households can lead to a shift in their consumption patterns  
560 and, therefore, the demand for commodities (e.g. Haque and Jahan, 2015; Mendoza-Tinoco *et al.*, 2017).  
561 Moreover, *utility disruptions* can lead to the surge in demand by end users. For example, elevated power  
562 demand during a heatwave can potentially strain the power network (Liang *et al.*, 2016; Avraam *et al.*, 2023).  
563 Negative impacts on humans, including *casualty and displacement* and *physiological strain on workers*, can  
564 result in excess emergency visits and hospitalizations (Shahpari *et al.*, 2022; Disher *et al.*, 2021). Conversely,  
565 the *system or data disruptions* may induce distrust among previous users, leading to a decline in future  
566 consumer engagement with the affected systems (Santos and Haimés, 2004; Gordon *et al.*, 2007). The  
567 disruptions in the export supply chain caused by *port disruptions* will also reduce the demand for local  
568 production (Wei *et al.*, 2020). The demand for transportation systems may change depending on the purpose  
569 of travel. Emergency response and critical supply transport may increase demand on remaining routes, while  
570 non-essential trips are likely to decrease in the post-disaster environment (Cho *et al.*, 2001).

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

### 577 **Implementation of Disruptions into Macroeconomic Models**

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

585 Table 7 details implementations of the economic disruptions listed in Table 6 found in the reviewed  
586 literature for the five macroeconomic models considered in this review. The symbols in Table 7 indicate  
587 the existence of matching practice for the corresponding economic models. For demand-side economic

**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 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

588 disruptions, the majority of models incorporate the impacts as changes in the demand variables of the  
589 affected sectors (e.g. MacKenzie et al., 2012; Markhvida et al., 2020; Avelino and Dall' erba, 2019; Bachner  
590 et al., 2024; Liang et al., 2016; Shahpari et al., 2022; Santos and Haimés, 2004). The sole exception is  
591 for reconstruction demand surge, which can also be interpreted as additional investment in dynamic CGE  
592 models (Bachner et al., 2024).

593 For production-related disruptions, such as *productive capital loss*, *productivity loss*, *labor loss*, and  
594 *production loss*, most models implement them as reductions in productive capacity or production factors.  
595 This is achieved either by directly reflecting the changes in corresponding variables in the cases of *productive*  
596 *capital loss* and *labor loss* (e.g. Jenkins, 2013; Carrera et al., 2015; Koks et al., 2015; Mendoza-Tinoco et al.,  
597 2017; Yaseen et al., 2020); or by converting the initial effects into equivalent changes in productive capacity  
598 in the cases of *productivity loss* and *production loss* (e.g. Dieye et al., 2020; Li et al., 2022). Specifically,  
599 *productivity losses* are modeled in two distinct ways in CGE models. While some CGE implementations  
600 directly reflect the losses to changes in the productivity parameter built into the production function (e.g.  
601 Wing et al., 2016; Rose and Chen, 2017; Sawadogo, 2022), other studies assume constant productivity and  
602 convert the productivity loss into reductions in the availability of production factors such as labor or land (e.g.  
603 Carrera et al., 2015; Hu et al., 2019; García-León et al., 2021). However, when these factors are considered in  
604 the basic form of the Leontief I/O model, there are no corresponding variables to reflect supply-side changes  
605 directly. Consequently, most implementations account for these disruptions as reduced demand for affected  
606 sectors to upstream industries and/or reduced supply to downstream industries (e.g. Kulshreshtha and Klein,  
607 1989; Jonkman et al., 2008; Lin et al., 2012; Haque and Jahan, 2015; Kokaji and Goto, 2022; Welburn and  
608 Strong, 2022; Lyu et al., 2023). A few I/O implementations convert the production-related disruptions into  
609 final production reductions when incorporating them into the model (e.g. Breisinger et al., 2016; Gao et al.,  
610 2020; Li et al., 2018).

611 The implementation of *supply reductions* can vary, even for the same type of model. Wang et al.  
612 (2021) incorporate supply reductions into the ARIO model directly by imposing constraints on the supply  
613 between affected sector pairs during simulation. Santos et al. (2014) and Shahpari et al. (2022) model the  
614 shortage of water supply in the DIIM and the CGE models, respectively, as the reduction in the productive  
615 capacity of water-dependent industries by treating water as one of the intermediate inputs to their production  
616 function. Alternatively, Kelic et al. (2013) consider the supply shock resulting from cyber attacks on the oil  
617 industry as a reduction in oil production. Besides, *import and export reductions* can be directly reflected

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

<b>Economic model implementations</b>	<b>Earthquake</b>	<b>Flood</b>	<b>Wildfire</b>	<b>Drought</b>	<b>Heatwave</b>	<b>Cyber Attack</b>
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 (-)						✓

618 in the model by adjusting the value of corresponding import and export variables (Wei et al., 2022). The  
619 *transportation cost change* can be directly incorporated into CGE models (Wei et al., 2022), while in Leontief  
620 I/O implementations, the corresponding changes in inter-regional input-output relationships are computed  
621 to reflect equivalent effects on the trading patterns (Cho et al., 2001; Welch et al., 2022).

622 Combining Tables 5 – 7, we obtain the most commonly affected economic variables for various disasters  
623 as tabulated in Table 8. In this table, we also summarize the distribution of the disaster impacts across  
624 industries. Based on the comparison, the implementation of earthquake and wildfire scenarios in the  
625 reviewed literature exhibit analogous impacts on the economic system, primarily focusing on economic-  
626 wide productive capital, labor, and increased demand for reconstruction. Thus, they can adopt a similar  
627 scenario modeling design of indirect economic impacts. The flood scenario in the reviewed literature also  
628 considers productivity and production losses, especially for the Agricultural sector. Heatwave scenarios  
629 in the reviewed literature also induce economic-wide disruptions that mainly stem from shocks on labor,  
630 along with increased demand in the power and healthcare sectors. Conversely, droughts and cyber attacks  
631 initiate disruptions in specific industries. For drought scenarios, implementations revolve around damaged  
632 productive capital and productivity in agriculture and water-dependent sectors, alongside the need for  
633 reconstruction. Cyber attacks primarily target industries such as ICT, finance, and critical infrastructure,  
634 resulting in reductions in productive capital, productivity, production, and potential demand decline in the  
635 targeted sectors.

636 Additional attributes of the disasters, including their spatial and temporal scales and the likelihood  
637 of compounding with other disasters, can also affect the model selection and disaster scenario modeling  
638 design. For instance, events that affect large areas, such as major earthquakes or floods, may necessitate

639 a multi-regional analysis to capture the heterogeneity in the spatial distribution of disruptions and regional  
640 economies (Crowther and Haimes, 2010; Zhu et al., 2024). Moreover, compared to the relatively short  
641 duration of earthquakes, where direct impacts can be imposed at a single point in time, the floods can last  
642 for weeks, which can delay the recovery process (Avelino and Dall’erba, 2019; Tanoue et al., 2020). For  
643 long-lasting disasters like droughts and heatwaves, the recovery may even coincide with the ongoing impact  
644 of the disaster itself (Jenkins, 2013). In such cases, the temporal dimension becomes a crucial consideration  
645 for modeling. Dynamic models, which can capture changes over time, can be more appropriate than static  
646 ones to account for the evolving nature of the disaster’s effects and the recovery process. Last, cyber attacks  
647 can compound the impact of other disasters (Avraam et al., 2023). In these scenarios, the analysis needs to  
648 consider the potential impacts of both events and requires an integrated modeling approach.

## 649 **OPPORTUNITIES FOR FUTURE RESEARCH**

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

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

668 overcome the potentially exhaustive nature of factors to be considered for each disaster scenario, and the  
669 inherent challenges of data collection.

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

## 678 CONCLUSION

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

687 While basic models require less data and computational resources, more sophisticated models like  
688 ARIO and CGEs can produce more diverse economic indicators and analyze a wider range of demand- and  
689 supply-side effects. ARIO and CGEs require additional input parameters, such as behavioral parameters and  
690 elasticities of substitution, which necessitate further calibration efforts and can be challenging to obtain. On  
691 the other hand, ARIO provides more detailed sectoral outputs than other I/O models, including changes in  
692 demand, production capacity, and value-added following a disaster. CGE models go even further by analyzing  
693 the effects on households, offering insights into the welfare implications of disasters. Moreover, while most  
694 I/O models primarily focus on demand-side implications of disaster shocks, ARIO and CGEs also consider  
695 supply-side factors like productive capacity, providing a more direct and accurate representation of disaster  
696 impacts when these primarily affect the supply side. The key distinction between I/O and CGE models lies in

697 their treatment of market adjustments. The inherent flexibility of CGE models makes them better suited for  
698 long-term analysis, whereas I/O models are more appropriate for assessing short-term post-disaster impacts.

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

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

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719 **Glossary**

720 **ARIO** Adaptive Regional Input-Output.

721 **CGE** Computable General Equilibrium.

722 **CPI** Consumer Price Index.

723 **DIIM** Dynamic Inoperability Input Output Model.

724 **GAMS** General Algebraic Modeling System.

725 **GDP** Gross Domestic Product.

726 **HEMP** High-altitude Electromagnetic Pulse.

727 **I/O** Input-Output.

728 **IIM** Inoperability Input Output Model.

729 **MRIA** Multi-Regional Impact Assessment.

730 **SAM** Social Accounting Matrix.

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