Multi-regional economic recovery simulation using an Adaptive Regional Input-Output (ARIO) framework

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Abstract

The economic repercussions of natural hazards extend beyond immediate damages, impacting more than the directly affected regions through trading ties and interrupted service provisions. The Adaptive Regional Input-Output (ARIO) model has been developed to assess these indirect impacts by considering changes in productive capacity and demand-driven output adjustments. We extend a recently refined ARIO model (R-ARIO) to conduct a multi-regional multi-sector analysis. This extension accounts for the geographical disparities in direct damages and inter-regional economic interactions. To illustrate the effectiveness of this approach, we present a case study of the 2011 Tohoku earthquake and assess its economic impacts across 13 prefectures in the East-Japan region. The paper further compares the outcomes of single- and multi-regional analyses to showcase the effect of inter-regional trading ties on economic resilience. Additionally, trade-offs involved in selecting the study area boundary for the multi-regional analysis are discussed.

Keywords: Indirect economic impacts, disaster resilience, Adaptive Regional Input-Output (ARIO) model, multi-regional analysis, regional seismic risk, post-earthquake recovery

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1. Introduction

Natural hazards pose significant challenges to societies around the world. Their economic implications can reverberate long after their immediate physical consequences. The direct economic impacts of natural hazards are readily visible and quantifiable, including damage to housing, transportation networks, utilities, and productive assets. Indirect impacts, or higher-order impacts, can stem from the disruption of supply chains, diminished business activities, shifts in demand patterns, and various other economic factors. These consequences are often more complex to quantify and comprehend, as they involve cascading effects throughout the interconnected economic systems [1, 2]. The difficulty in estimation is further compounded by the fact that the economy can undergo both gains and losses as it adjusts to these disruptions. For instance, the 1994 Northridge earthquake, with a direct loss of $41.8 billion (in 1994 dollars) [3], caused extensive damage to business sites, interruptions of utility services, and employee inaccessibility. Moreover, the disruption to the transportation system impeded customer access and shipments of supplies and output, affecting both the demand and supply sides of the economy. Estimated losses from business interruption exceeded $6.5 billion (in 1994 dollars) [4].

Indirect economic impacts transcend the boundaries of immediately affected regions. The increasing globalization and interconnectedness of economies have amplified the cascading effects of disasters, as disruptions in one region can transmit shocks through supply chains to other regions. For example, the 2019 Midwest floods in the United States disrupted the local crop production and transportation infrastructure, eventually causing a surge in global food prices [5]. These inter-regional impacts are characterized by spillover effects and feedback effects [6]. Spillover effects refer to the repercussions on the producers of supplies that normally flow into the affected region where the demand is curtailed by the shock. Conversely, feedback effects capture the downstream impacts that the output of the shocked region has on the economic activities of other regions. As a result, a localized disaster can have significant implications for regional economies, emphasizing the need for collaborative and coordinated efforts to analyze the effects and respond to such events.

Understanding the economic impacts of natural hazards is crucial for effective risk management, policy formulation, and resource allocation. It enables decision-makers to assess the cost-effectiveness of preventive measures, develop strategies for disaster recovery, and prioritize investments in resilience-building initiatives. Several families of macroeconomic models, including Input-Output (I/O) models and Computable General Equilibrium (CGE) models, have been developed and applied for natural hazard economic impact analysis [7, 8]. While the I/O models primarily focus on inter-sectoral linkages, the CGE models consider the interactions between different economic agents, such as households, firms, and government, and their responses to the shock. Although regional risk assessments still lack a standardized practice for quantifying indirect losses [9, 10], the Adaptive Regional Input-Output (ARIO) model, an extension of the I/O model, has been gaining popularity in recent years [e.g. 11, 12]. The model not only retains the strengths of I/O models by explicitly reflecting sectoral interdependencies and capturing demand-driven changes in output but also incorporates some of the advantages of CGE model such as adaptive behaviors and supply constraints [8, 10, 13]. In its recent development, the R-ARIO model [14] improves the ARIO model by (i) incorporating dynamic reconstruction rates based on sector-specific empirical reconstruction processes, (ii) separating housing losses from productive capital losses as exogenous demand, and (iii) modeling sector-specific adaptive behavior and inventory mechanics for recovery.

Most of the macroeconomic models were originally developed by treating the study areas as a single entity. Lacking spatial explicitness, these models assume uniform perturbation effects and perfect resource allocation across all regions, which neglects geographically concentrated risks and cross-regional interdependencies [15]. Although some macroeconomic models have been extended to consider multi-regional impacts by accounting for specific regional characteristics and their connections [e.g. 16, 17, 18], the R-ARIO model does not yet address inter-regional interactions and their effect on indirect impact estimates. Moreover, there lacks a detailed investigation into the trade-offs between single- and multi-regional analysis.

This paper addresses the gap in the current literature by extending the R-ARIO model to perform multi-regional multi-sector analysis. We present the methodology for preparing the multi-regional economic structure data required for the analysis and the incorporation of regional dimensions into the modeling process. By applying the approach to a case study of the 2011 Tohoku earthquake, we assess the economic impacts in 13 prefectures in the East-Japan region and evaluate spatial variation in economic resilience. Furthermore, we conduct a comparative analysis between single-regional and multi-regional approaches to demonstrate the effect of considering the geographical heterogeneity of impacts and economic ties between various regions. In addition, we perform a sensitivity check to illustrate trade-offs for the selection of the study area boundary for the multi-regional analysis.

2. Existing models to estimate indirect economic impact

The two most common families of macroeconomic models for simulating indirect economic losses of a disaster event are Input-Output (I/O) models and Computable General Equilibrium (CGE) models. These models offer insights into the economic mechanisms that generate indirect impacts and can help to identify the critical sectors for effective mitigation strategies.

I/O modeling was first developed by Leontief [19] to assess the interdependence of industries in an economy. It establishes a system of linear equations that describe how an industry's product is distributed across the entire economy based on the trade flows between various sectors captured in the surveyed input-output table [20]. I/O models have been widely applied to study the impact of disasters on production and trade flows due to their relative simplicity and the ability to evaluate the propagation of disruptions among sectors [21, 22, 23]. However, standard I/O models have limitations in capturing several economic mechanisms that can affect the estimated disaster impacts. These models do not account for factors such as price fluctuations influencing the demand for intermediate and final goods, supply-side shocks, technological advancements, the potential for input and import substitution, adaptive behavior, and other forms of economic resilience during recovery. Additionally, I/O models rely on a constant linear structure, which may oversimplify the complex nonlinear economic processes that underlie the impacts of disasters [9].

CGE models offer a more flexible framework than I/O models, by accounting for economies of scale and nonlinear impact functions. Unlike the I/O models, the CGE models are rooted in general equilibrium theory to depict how various economic agents, including households, firms, and government, interact to achieve market clearing in an economy based on the price mechanism. The models accommodate supply constraints, input and import substitutions, and adaptive behaviors of economic agents in response to flexible prices. They have found applications in analyzing the economic consequences of a wide range of natural hazards [24, 25, 26, 27, 28, 29]. The inherent price flexibility of CGE models makes them more suitable to assess long-term economic impacts. Nevertheless, they may underestimate the true costs of a disaster by allowing for flexibility in short-term responses [30]. Other limitations of CGE models lie in their assumptions regarding perfect competition, rational behavior, and fixed technology [7, 31].

The ARIO model extends standard I/O models to address some of their limitations. This dynamic model, introduced by Hallegatte [13, 32], allows for the simulation of economic activities over a specified time period. The model accounts for direct damage to capital stocks, which leads to a decrease in productive capital within specific sectors and is translated into reconstruction demands assigned to the construction and manufacturing sectors. In its latest development, the refined ARIO model explicitly includes the housing damage in the analysis to account for the additional reconstruction demand from the residential buildings, and the reconstruction demand is aligned with empirically observed recovery rates [14]. Such a shock disrupts the initial economic equilibrium, and the model simulates the dynamic response of the economy as it strives to recover and regain equilibrium. By explicitly incorporating inventories and the recovery capacity of sectors, the ARIO model effectively captures the supply constraints and adaptive behavior exhibited by industries. These methodological enhancements overcome the limitations of linearity found in standard I/O models and enable the integration of additional economic resilience measures into the simulation.

In addition to the input data required by the standard I/O model, which includes economic data obtained from the region's input-output table and the observed or predicted direct loss, the ARIO model further requires the fixed asset value and the recovery curve of each sector to run the analysis. Moreover, five types of user-specified economic behavioral parameters are necessitated for the model to determine the adaptive capacity of each sector during the recovery stage. These parameters include maximum overproduction capacity α^{max}, time to achieve maximum overproduction τ^{α}, target inventory level η, time of inventory restoration τ^{s}, and production reduction parameter (heterogeneity) ψ. The maximum overproduction capacity is the ratio of production increase to pre-disaster production capacity during the short-term non-equilibrium conditions following a disaster. The production reduction parameter or heterogeneity determines how inventory shortages affect production in a sector. It ranges from 0 to 1, where 0 indicates a uniform inventory reduction across all businesses, and 1 indicates that inventory shortages result in a proportional number of businesses running out of inventory in the sector.

The ARIO model then utilizes the input data to assemble the pre-disaster economic equilibrium, apply the direct impacts to the corresponding sectors, and simulate the dynamics of the economic system as it responds to the shocks and strives to regain equilibrium. At each time step, each sector aims to satisfy the demand for commodities and services, but the actual production of these goods and services is subject to both the sector's production capacity and inventories of production inputs. The demand to sector p at the time t, $D_p(t)$, is first calculated by:

$$D_p(t) = \sum_{all\ q} O_{q,p}(t) + C_p(t) + R_p(t) + E_p(t) \tag{1}$$

where

$$\begin{aligned} O_{q,p}(t) &= \text{Orders from sector } q \text{ to sector } p \text{ at time } t \\ C_p(t) &= \text{Total final demand to sector } p \text{ at time } t \\ R_p(t) &= \text{Reconstruction demand to sector } p \text{ at time } t \\ E_p(t) &= \text{Exports of sector } p \text{ at time } t \end{aligned}$$

The production capacity of sector p at time t, $P_p^{cap}(t)$, is constrained by productive capacity and overproduction status:

$$P_p^{cap}(t) = \alpha_p(t) \cdot \left(1 - \frac{L_p(t)}{K_p}\right) \cdot P_p^{ini} + I_p(t) \tag{2}$$

where

$$\begin{aligned} \alpha_p(t) &= \text{Overproduction capacity as the ratio to the pre-disaster production} \\ &\quad\ \text{level of sector } p \text{ at time } t \\ L_p(t) &= \text{Amount of damages to productive capital of sector } p \text{ at time } t \\ K_p &= \text{Pre-disaster fixed asset or productive capital of sector } p \\ P_p^{ini} &= \text{Pre-disaster production (excluding the imports) of sector } p \\ I_p(t) &= \text{Imports of sector } p \text{ at time } t \end{aligned}$$

The optimal production, P_p^{opt}, is further capped by the demand at the same time t:

$$P_p^{opt} = \min(P_p^{cap}(t), D_p(t)) \tag{3}$$

Additionally, the supply constraint is taken into account to determine the actual production at time t, $P_p^a(t)$, by considering the required inventories of its inputs, $S_{q,p}^r(t)$. This is calculated as the amount of input q necessary to meet the local production level of sector p during the period when the inventory q can last:

$$S_{q,p}^r(t) = \begin{cases} \eta_q \cdot (P_p^{cap}(t) - I_p(t)) \cdot A_{q,p} & \text{if } D_p(t) > P_p^{cap}(t) \\ \eta_q \cdot D_p(t) \cdot \frac{P_p^{cap}(t) - I_p(t)}{P_p^{cap}(t)} \cdot A_{q,p} & \text{if } D_p(t) \leq P_p^{cap}(t) \end{cases} \tag{4}$$

where

$$\eta_q = \text{Target inventory level of sector } q$$
$$A_{q,p} = \text{Number of units of input (in \$) from sector } q \text{ required to produce a \$1 unit of sector } p$$

The maximum possible production of sector p given the actual inventory level of input q, $P_{q,p}^{max}(t)$, is then reduced proportionally if the required inventories are not met when taking into account the inventory heterogeneity effect:

$$P_{q,p}^{max}(t) = \begin{cases} (P_p^{cap}(t) - I_p(t)) \cdot \min\left(1, \frac{S_{q,p}(t)}{\psi_q \cdot S_{q,p}^r(t)}\right) + I_p(t) & \text{if } D_p(t) > P_p^{cap}(t) \\ \min\left(D_p(t) \cdot \frac{P_p^{cap}(t) - I_p(t)}{P_p^{cap}(t)} \cdot \min\left(1, \frac{S_{q,p}(t)}{\psi_q \cdot S_{q,p}^r(t)}\right) + I_p(t), D_p(t)\right) & \text{if } D_p(t) \leq P_p^{cap}(t) \end{cases} \quad (5)$$

where

$$S_{q,p}(t) = \text{The actual inventory level of input } q \text{ for sector } p \text{ at time } t$$
$$\psi_q = \text{Production reduction parameter (heterogeneity) of sector } q$$

The actual local production is governed by the most limiting supply in the production process:

$$P_p^a(t) = \min(P_{q,p}^{max}(t), \text{ for all } q) \quad (6)$$

When demand from a sector exceeds its production, the production is distributed proportionally to partially meet the inter-sector orders, total final demand, reconstruction demand, and exports. The order for the next time step from sector q to sector p, $O_{q,p}(t + \Delta t)$, is then updated based on the current status:

$$O_{q,p}(t + \Delta t) = A_{p,q} \cdot P_q^a(t) + \frac{1}{\tau^s(p)} \cdot (S_{p,q}^t - S_{p,q}(t)) \quad (7)$$

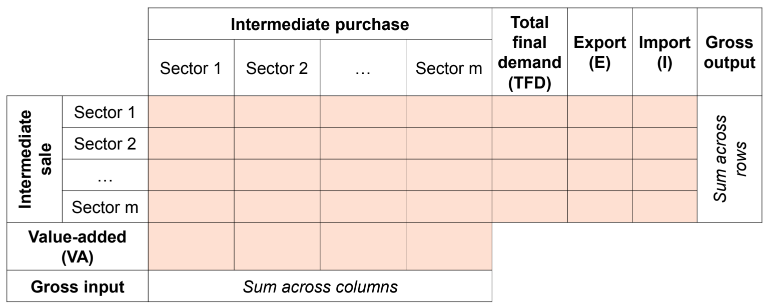
where
$S_{p,q}^t$ = The target inventory level of input q for sector p

Finally, the value added for sector p at each time step t, $VA_p(t)$, is computed and recorded as:

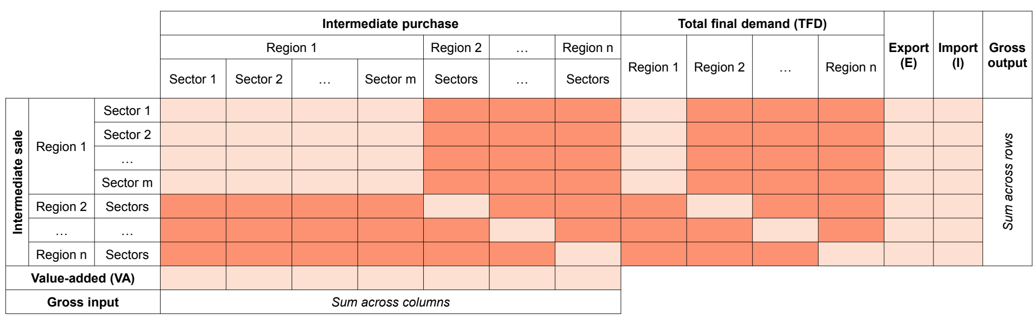
$$VA_p(t) = P_p^a(t) - I_p(t) - \sum_{all\ q} A_{q,p} \cdot P_p^a(t) \quad (8)$$

Although the ARIO model has demonstrated several advantages in simulating post-disaster economic recovery and evaluating indirect economic impacts, many of its applications have been focused on the single-regional analyses [10, 11, 32], where the study area is treated as a single unified economic region. This implicitly assumes that the disruptions caused by a disaster event have a uniform effect throughout the entire region and perfect coordination among all sub-regions can be achieved to optimize the use of limited available resources during the recovery stage. These assumptions are not appropriate for large study areas characterized by spatial variations in both direct damages and economic structures. They also prevent the model from considering indirect economic impacts outside of the study area. Moreover, each sub-region typically has a distinct cross-regional transaction relationship with others. Therefore, spatially explicit analysis is a critical consideration when simulating the economic aftermath of major disasters on a large scale.

Multi-regional analysis has been developed and applied in the form of various macroeconomic models. For example, the Multiregional Input-Output model (MRIO) is an extension of the basic I/O model and has been used in various studies [e.g. 16, 33, 34]. The Multiregional Inoperability Input-Output Model (MRIIM) [15] is the multi-regional extension of the Inoperability Input-Output Model (IIM) that evaluates the inoperability or level of dysfunction of economic systems. Multiregional Impact Assessment (MRIA) model [35] extends the I/O framework to further consider the supply-side disruption and substitution effects. On the CGE side, the Spatial CGE [17] and The Enormous Regional Model (TERM) [36] have also been developed to address inter-regional interdependencies. Nevertheless, these models mostly retain the limitations of their corresponding model family. Recently, there have also been a few attempts to apply the ARIO model in the multi-regional context for disaster impact analysis. These include applying multi-regional extensions of the ARIO model to assess the economic consequences of coronavirus disease 2019 (COVID-19) lockdown [18], wildfire [37], and rainstorm [38] scenarios. Additionally, Krichene et al. [39] expanded the ARIO model to conduct firm-level analyses. While it provides insight into post-disaster economic dynamics at a finer resolution, it requires extensive firm-level input-output data, which may not be readily available in other regions, thereby limiting its generalizability to different case studies. Our paper contributes to the literature by proposing a methodology to evaluate the multi-regional indirect economic impacts of the earthquake scenario at the sector level using the ARIO framework. Our method improves from the past multi-regional ARIO analysis by further accommodating the discrepancies in the recovery capacities between different sectors and explicitly considering the reconstruction demand from the housing sectors, which typically constitutes a significant portion of direct losses in earthquake scenarios. To address the increase in computational costs with refined resolution, we present a process to extract the input information for the regions of interest from an extensive dataset.



(a)



(b)

Figure 1: Structure of (a) single-region input-output table for m sectors, and (b) inter-regional input-output table for n regions with m sectors in each region. The red cells are the annual monetary values from the survey. In the inter-regional input-output table structure, the darker red cells represent the new features that do not present in the single-region input-output table.

3. Extended R-ARIO model for multi-regional analysis

In this section, we extend the R-ARIO model by accounting for the multi-regional dimension of the direct damages, economic structure, and sector interaction. The enhancement is achieved in two main stages. First, the raw data for the multi-region multi-sector economy is preprocessed to provide the necessary information about the entire economy. Second, the R-ARIO model is adapted to consider the preprocessed multi-regional input and geographical constraints of demand and resource distributions. Figure 2 shows an overall workflow of the proposed model.

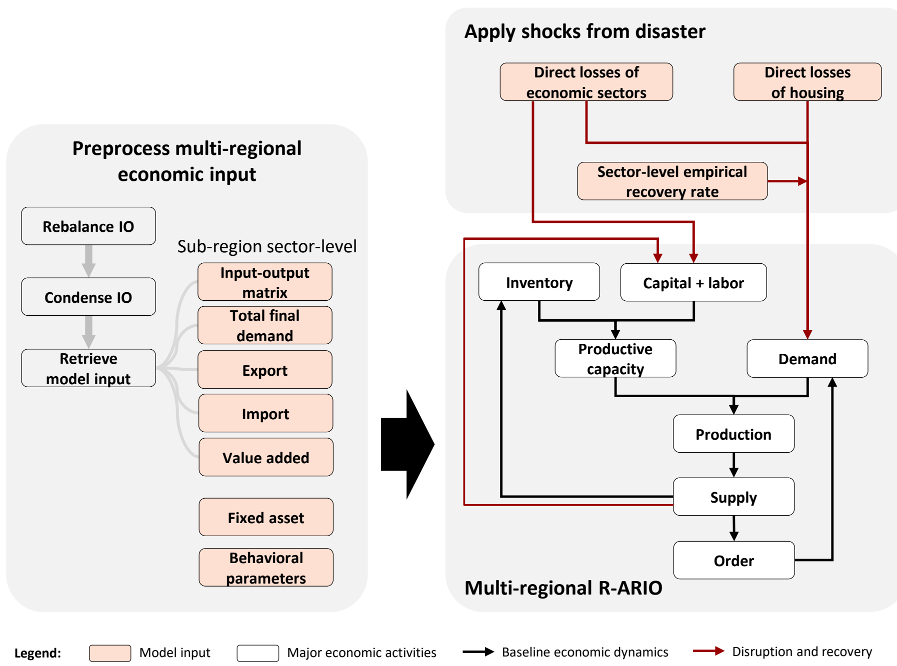


Figure 2: A schematic diagram for the workflow of the extended R-ARIO model for multi-regional analysis.

3.1. Preprocessing input data for multi-regional R-ARIO model

Similar to the original R-ARIO model, the required input data for the multi-regional analysis comprises pre-disaster economic data, damage to fixed assets, and recovery trajectories of all sectors in all regions. Specifically, the pre-disaster economic data encompasses the annual input-output relationship between sectors from multiple regions, value-added, total final demands, fixed assets, exports, and imports. Most of them can be derived from the input-output table.

Input-output tables describe the flows of products within and between industries and consumers for a certain country or region [40, 41]. In a typical input-output table structure (Figure 1a), the upper left quadrant of the table presents the intermediate transfer of goods from industries to either their own or other industries. The upper right quadrant contains the total final demand and export. The bottom left quadrant shows the primary input factors. While one approach is to include both value added and imports in this quadrant, a more common practice is to consider imports as a column in the upper right quadrant or combine them with exports to create a net export field (e.g. Organisation for Economic Co-operation and Development (OECD), Bureau of Economic Analysis (BEA) in the US, and Ministry of Economy, Trade and Industry (METI) in Japan). To construct the input-output tables, the essential information are typically sourced from social accounting data. This data is systematically collected on a regular basis through periodic censuses or surveys. For example, the US national input-output tables are periodically generated from the US National Economic Accounts compiled by the US Department of Commerce [42]. Constructing input-output tables can be complex and resource-intensive due to limited data availability and inconsistent information. As a result, various techniques have been introduced to harmonize data for the creation of survey-based input-output tables [42].

In the multi-regional context, the inter-regional input-output table is sometimes available at the sub-national level, which provides the pre-disaster economic structures both within and between the sub-administrative regions in the nation. An illustration of the inter-regional input-output table structure is shown in Figure 1b. The diagonal sub-matrices in the intermediate supply and demand section summarize the transactions within the regions and the off-diagonal sub-matrices show the transactions between the regions. The columns under the total final demand present the amount of the output to meet the demand of various regions from each sector. Compared with the single-region input-output table structure (Figure 1a), the inter-regional input-output table has additional information as highlighted in the dark red color. First, it contains the input-output relationship between the sectors from different regions. Furthermore, it exhibits the flow of output of each sector to meet the total final demands of other regions. Given the discrepancy in the structure of the two types of input-output tables, additional procedures are required to process the model input from the inter-regional input-output table.

Moreover, the area of interest to investigate the economic impact of the disaster damages may vary on a case-by-case basis, depending on the expected influence extent of the disaster, the stakeholder's interest, and the computational capacity. Thus, the conjunction of study regions may not cover the entire nation, and the economic data of the interested regions will need to be extracted from the raw comprehensive inter-regional input-output table.

We use the following steps to process the raw input-output table: (i) inspection and rebalancing the raw input-output table to achieve economic equilibrium; (ii) condensing the table to an input-output table for all sectors in the study regions, based on the same data structure as the single-region input-output table; and (iii) retrieving model input from the condensed input-output table.

To demonstrate the processing details, we present a simplified example here that extracts the economic information of two regions (Region 1 and Region 2) from a three-region economy (Figure 3). However, the method can be generalized and applied to preprocessing the economic data of a subset of regions from a larger multi-regional input-output table. The case study presented in Section 4 shows the application of the method to extract the information for 13 prefectures in Japan out of an inter-prefecture input-output table for a total of 47 prefectures in the nation.

Data inspection and IO rebalance. Due to the circular flow of economic resources between producers and consumers in an economy, a balance should be achieved between the gross input and gross output for each sector. The gross input and gross output refer to the total amount of inputs and outputs involved in the production process of a sector and are computed from the inter-regional input-output table as:

$$\text{gross input} = \text{intra-regional purchases} + \text{inter-regional purchases} + \text{value added} \tag{9}$$

$$\text{gross output} = \text{intra-regional sales} + \text{aggregated final demand} + \text{net export} + \text{net outflow} \tag{10}$$

where the intra-regional transaction refers to the input and output between the sectors within the same region, and the inter-regional transaction refers to that between sectors from different regions. The net export represents the flows between the survey area defined by the input-output table (Region 1, 2, and 3 in the example) and all the regions outside the survey area. The net outflow summarizes the flows between regions within the survey area (e.g. from Regional 1 to Region 2 and 3 in the example).

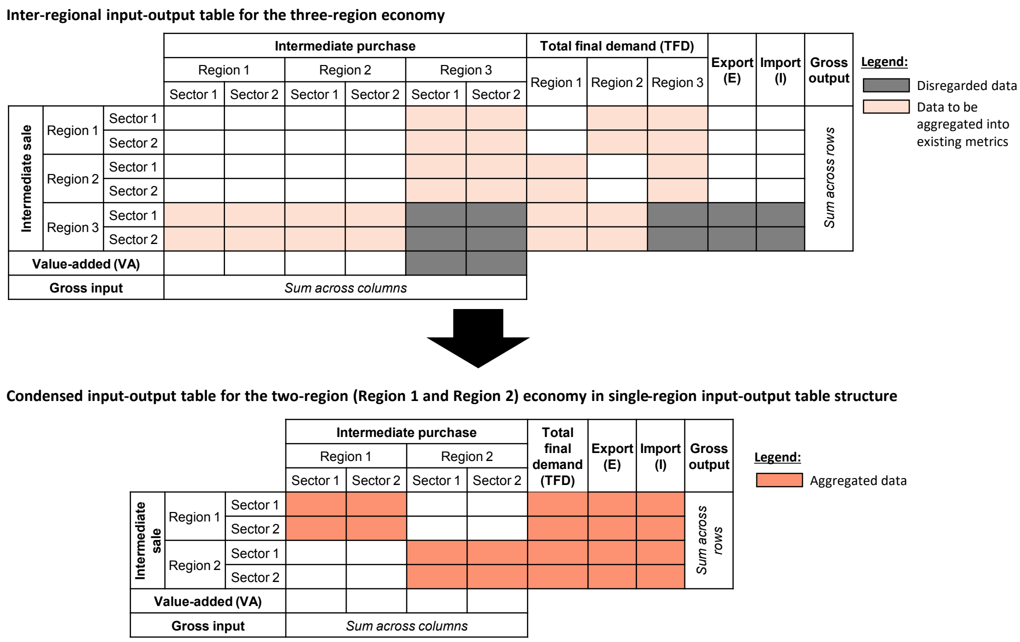


Figure 3: Condensing the inter-regional input-output table for the three-region economy into two-regional (Region 1 and Region 2) input-output table in the form of standard single-region input-output table structure.

The aggregated final demand for sector p in region i, $AFD_i(p)$, is the sum of transaction flows to meet the total final demand, $TFD_{ji}(p)$, for the corresponding sector:

$$AFD_i(p) = \sum_{all\ j} TFD_{ji}(p) \tag{11}$$

The net export for sector p in region i, $NE_i(p)$, is the difference between the export, $E_i(p)$, and import, $I_i(p)$, for the corresponding sector:

$$NE_i(p) = E_i(p) - I_i(p) \tag{12}$$

Similarly, the net outflow for sector p in region i, $NO_i(p)$, is the difference between the outflow, $outflow_i(p)$, and inflow, $inflow_i(p)$, for the corresponding sector:

$$NO_i(p) = outflow_i(p) - inflow_i(p) \tag{13}$$

where $outflow_i(p)$ is the sum of the input from sector p in region i to both sectors and final demands in other regions and $inflow_i(p)$ is the sum of input from the sector p in other regions to region i's sectors and final demand:

$$outflow_i(p) = \sum_{all\ j,\ q} intermediate\ IO_{ij}(p,q) + \sum_{all\ j} TFD_{ij}(p) \tag{14}$$

$$inflow_i(p) = \sum_{all\ j,\ q} intermediate\ IO_{ji}(p,q) + \sum_{all\ j} TFD_{ji}(p) \tag{15}$$

where $intermediateIO$ refers to the intermediate sale and purchase matrix in the input-output table, and $Intermediate\ IO_{ij}(p,q)$ represents the trading flow goes from sector p in the region i to sector q in the region j.

However, a balance between gross input and output in the surveyed input-output table may not be achieved due to inconsistent price accounting among producers [43], discrepancies in the data sources [44, 45], and unavailability of data [45]. An unbalanced input can then cause convergence issues downstream in the ARIO model such that the economic equilibrium is unable to be reached after applying the initial disruption. Therefore, adjustments are necessary to reconcile the input-output data and restore balance before proceeding with subsequent actions.

Various data reconciliation methods have been developed for balancing the input-output table. In this study, we adjust import and export values to rebalance the input-output table, as we have greater confidence in the accuracy of inter-sectoral trading data compared to margin adjustments. However, alternative data reconciliation methods are also available, and the choice should be made by the modelers based on their knowledge and confidence in the data sources. The mathematical methods can be broadly categorized into two groups: the RAS-type cross-entropy methods and quadratic programming (QP)-based methods [46]. The original RAS method, documented in [47], [48] and [49], involves making proportional adjustments to the matrix's columns and rows until the discrepancies in the totals are eliminated. This algorithm has since been expanded into several forms, including three-stage RAS (TRAS) [50], generalized RAS (GRAS) [51], Cell-corrected RAS (CRAS) [52], and Konfliktfreies RAS (KRAS) [53]. These variations address limitations such as considering additional information, handling positive and negative entries, and incorporating arbitrary constraints. On the other hand, the QP method solves the least-squares objective function to resolve conflict in the input data. It was initially proposed and developed by [54], [55], and [56], and was applied to construct an inter-regional input-output (IRIO) model [57]. A recent extension by [46] further enhances its capabilities to handle arbitrary linear constraints and large-scale IO databases. Apart from these mathematical treatments, alternative estimates can also be obtained through the input of local experts and compilers, followed by manual calibration and modifications to ensure consistency [45].

Condense the input-output table of the study regions. The economic data for each individual sector encompasses its interactions with other sectors within the same region, sectors in other study regions, and those outside the study regions. Condensing the input-output table for the study regions (Region 1 and 2 in this example) involves aggregating and rearranging the economic information associated with the local sectors in these regions, while the interactions between sectors outside the study region (Region 3 in this example) are disregarded (Figure 3). During this process, interactions within the same region and across study regions largely remain intact, while interactions with sectors outside the study regions are treated as exports and imports, which are then combined into the relevant metrics. The condensed input-output table is structured according to the format depicted in Figure 1a for ease of information extraction in subsequent steps.

This entire process is illustrated in Figure 4, using a three-region economy example. In more detail, the inflows from the outside regions to the sector p in the study region i are aggregated into the import of the sector:

$$\hat{I}_i(p) = I_i(p) + \sum_{all\ j,\ q} Intermediate\ IO_{ji}(pq) + \sum_{all\ j} TFD_{ji}(p) \qquad \text{for } j \in \{\text{outside regions}\} \tag{16}$$

On the other hand, the outflows from the sector p in the study region i to the outside regions are incorporated into the export of the sector:

$$\hat{E}_i(p) = E_i(p) + \sum_{all\ j,\ q} Intermediate\ IO_{ij}(pq) + \sum_{all\ j} TFD_{ij}(p) \qquad \text{for } j \in \{\text{outside regions}\} \tag{17}$$

Furthermore, the intermediate input-output matrices between the outside regions and the study region i are combined into the region i's intra-regional intermediate input-output matrix. This represents the portion of domestic production that utilizes imported inputs and ensures consistency in the gross input and output levels for sectors within the study region i before and after

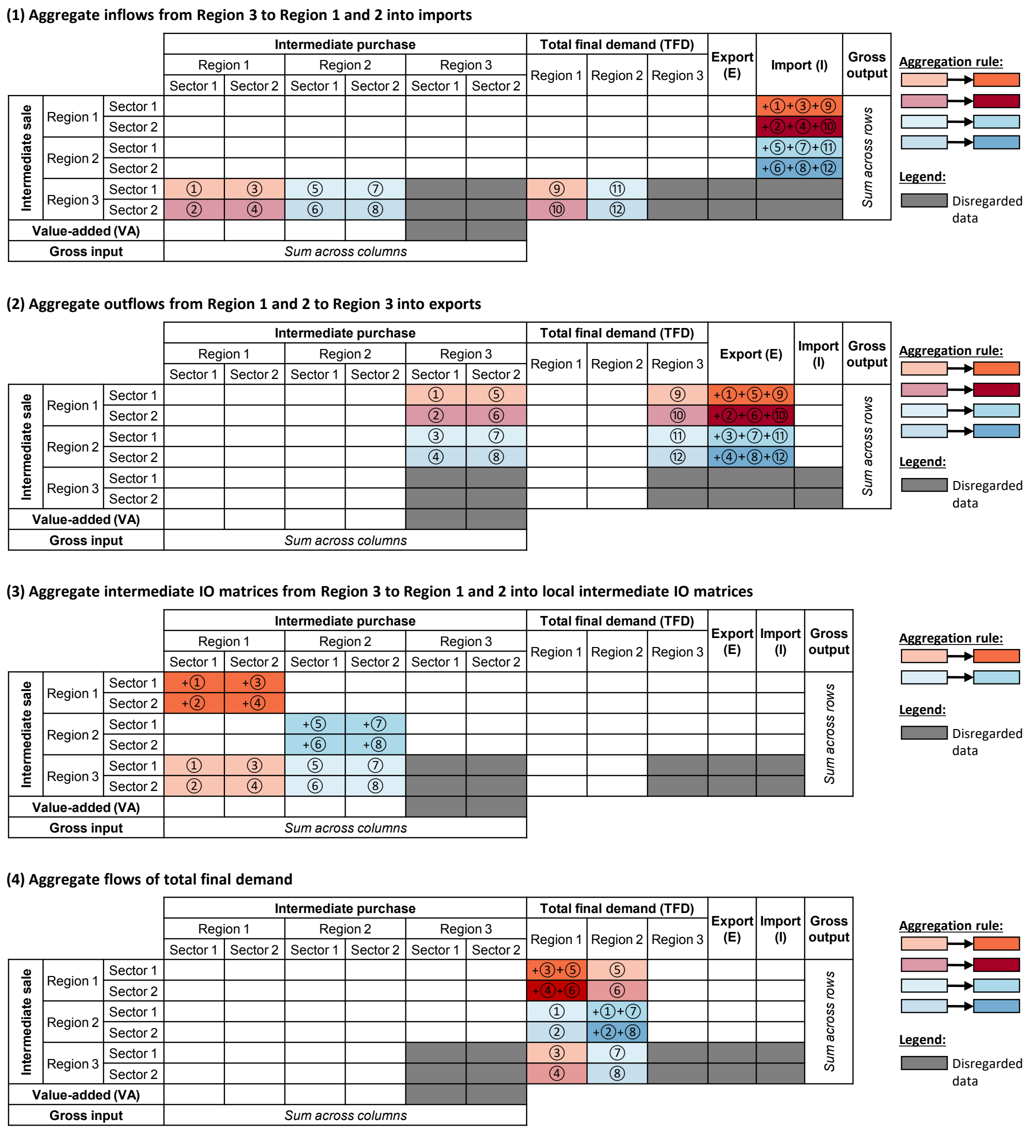


Figure 4: Step-by-step demonstration of condensing the inter-regional input-output table for the three-region economy into two-regional (Region 1 and Region 2) input-output table in the form of standard single-region input-output table structure.

condensing:

$$\widehat{Intermediate\ IO}_{ii} = Intermediate\ IO_{ii} + \sum_{all\ j} Intermediate\ IO_{ji} \qquad \text{for } j \in \{\text{outside regions}\} \tag{18}$$

Lastly, the inflows from the outside regions to directly meet the total final demand of the study region i as well as the outflows from the region i that directly fulfill the total final demand of the other study regions are consolidated into region i's total final demand. This consolidation represents the production of the sector that is utilized to meet the aggregated total final demand within the study area boundary:

$$\begin{aligned} T\hat{F}D_i &= TFD_{ii} + \sum_{all\ \ j} TFD_{ji} + \sum_{all\ \ k} TFD_{ik} \\ &\text{for } j \in \{\text{outside regions}\} \text{ and } k \in \{\text{other study regions}\} \end{aligned} \tag{19}$$

Retrieve model input from the condensed input-output table. The condensed input-output table constructed for the study regions represents the economic composition of a unified economy, encompassing all local sectors within these regions. From the condensed input-output table, we obtain economic input data including the intermediate input-output matrix, total final demand, export, import, and value-added for these sectors. This information is subsequently utilized for conducting a multi-regional R-ARIO analysis.

3.2. Model process

The model takes the processed economic data to establish the pre-disaster economic equilibrium and the supply flow based on the input-output relationship. The direct damages from the disaster are implemented as shocks to the economic system that simultaneously reduce the productive capacity and increase the reconstruction demand of the corresponding sectors. Unlike economic sectors, housing does not directly participate in production activities; however, housing damages are explicitly accounted for in the model by introducing additional reconstruction demand. Lastly, the recovery trajectories of sectors and housing are used to derive the reconstruction demand rate at different recovery stages for each sector during the simulation.

Due to the added regional dimension of the economic sectors in the multi-regional analysis, we adjust the model to reflect regional constraints in the economic recovery process. As the reconstruction efforts are primarily localized, with imported materials if necessary, we allocate the reconstruction demand from each sector to the construction and manufacturing sectors within the same region. These demands can subsequently propagate to other sectors and regions through the input-output dynamics within the economic system. Additionally, in this study, we assume that inventories of the same sector from different regions cannot substitute for each other as input for production. However, our model also provides an option to allow perfect substitution of input from different regions. Modelers can choose either option based on the characteristics of their study areas.

The multi-regional R-ARIO model then adopts a similar workflow as the single-region R-ARIO model (Section 2 and [14]) with the economic input data obtained from Section 3.1 for a large set of region-specific economic sectors. At each time step of the model, sector interactions occur simultaneously within the same region and across different regions, in accordance with their input-output relationship. The available inventories are first used by sectors during the production phase to fulfill various demands, including total final demand, intermediate consumption, exports, and post-earthquake reconstruction. The production level of each sector is further constrained by both the production capacity and inventories. Subsequently, orders are placed on the other sectors to replenish the inventories for future production. Meanwhile, sectors adapt their maximum inventory levels and production capacities to facilitate a faster recovery, based on their individual recovery capacities. This iterative process recurs throughout the modeled recovery period. As reconstruction demand is progressively satisfied and sector-specific productive capacity rebounds, the economy regains stability by reverting to the pre-disaster equilibrium.

4. Case study of the 2011 Tohoku earthquake

To illustrate the method and its potential insights, we consider the 2011 Tohoku earthquake damage and economic impacts that occurred in 13 prefectures in the East-Japan region (Figure 5a). We first simulate the economic recovery of the regions after the earthquake, and then discuss the comparison between single- and multi-regional analyses and the selection of study area boundary for multi-regional analysis.

4.1. The Tohoku Earthquake

The Tohoku earthquake, also known as the Great East Japan earthquake, occurred in northern Honshu, Japan, on 11 March 2011. With a magnitude of M_w 9.1, it was the largest earthquake experienced by Japan in recorded history. The shaking was experienced by most of Japan, and the coast experienced a tsunami with a maximum height of nearly 40 m. The earthquake and tsunami brought about tremendous damages and losses to a massive

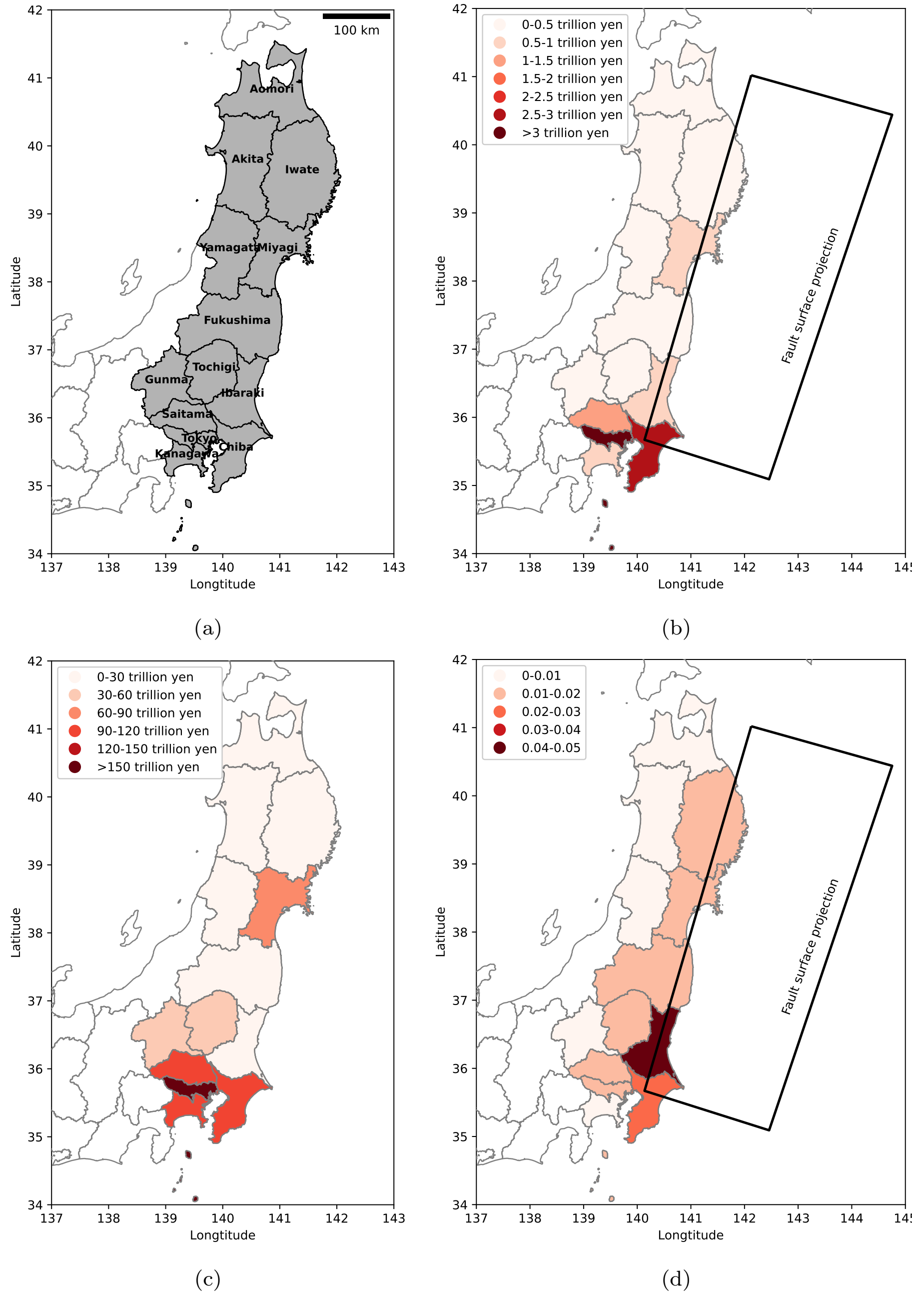


Figure 5: Spatial distribution of (a) prefectures, (b) direct damages from Tohoku earthquake, (c) fixed assets, and (d) direct damages as a fraction of prefectural fixed assets from Tohoku earthquake in the East-Japan region.

area, causing over 15,900 deaths, 3,100 missing, and 6,000 injuries [58]. In this study, we consider the direct losses as the damages to the physical capital caused by the earthquake ground motions. Due to a lack of data, the damages caused by secondary hazards, such as the tsunami and the failure of the Fukushima Dai-ichi Nuclear Power Plant, are not accounted for. Based on the insurance data, the direct losses in the East-Japan region from the earthquake are estimated as 17.8 trillion Yen (in 2011 currency). Although direct damages are spread over the entire East-Japan region, the majority of these losses are concentrated in Tokyo and Chiba in terms of monetary values (Figure 5b). Additionally, Ibaraki and Chiba experience the highest percentage of damage relative to fixed asset values (Figure 5d).

4.2. Data description

Most of the required economic input data, with the exception of fixed assets, is obtained from the 2011 Japan inter-prefecture input-output table [59]. This comprehensive data source contains trading statistics for 37 economic sectors in each prefecture of Japan. The sectors are listed in Table 1 following the order shown in the original input-output table, and can be further classified into six industry categories. The input-output table quantifies trading linkages both at the prefecture level (Figure 6) and the sector level (Figure 7) within the East-Japan region. It reveals the trading patterns and relationships among the prefectures. Notably, all prefectures exhibit strong intra-prefecture trading flows, while each prefecture has distinct trading structures with others. Tokyo, Kanagawa, and Chiba demonstrate the most extensive trading connections with other prefectures in the region, both in terms of inflows and outflows. On the other hand, Akita and Yamagata have the least interaction with the other prefectures. Furthermore, the input-output table highlights the economic heterogeneity within each prefecture. Taking Chiba and Tokyo as examples (Figure 7), Tokyo's strongest inter-sector economic ties are primarily concentrated among service sectors, whereas Chiba's economic linkages are more diversified across different types of sectors. These two layers of economic interdependence, both at the prefecture and sector levels, are considered and reflected in the model. Additionally, the input-output table also presents the total annual output for individual industries, and Figure 8 presents the summary for various categories in the regions. In most prefectures, the service sectors achieve the highest production, closely followed by the manufacturing sectors. Tokyo stands out with the highest overall production, primarily driven by its service sectors.

The other required inputs, including the fixed assets (Figure 5c), losses due to damage (Figure 5b), and the damage states of buildings are provided by Sompo Holdings, Inc. based on insurance data. The recovery time of the corresponding buildings is estimated according to HAZUS [60] based on their building occupancy class and comparable damage states. To achieve this, we first compute the average recovery time for each insurance damage state and then map the insurance data categories to the HAZUS-defined categories based on the closest match. In addition, the economic behavioral parameters are determined on a sector-specific basis (Table 2). For details about the parameter selection, see [13] and [14]. These parameters are crucial in capturing the economic recovery capacity and responses of different sectors in the post-disaster context.

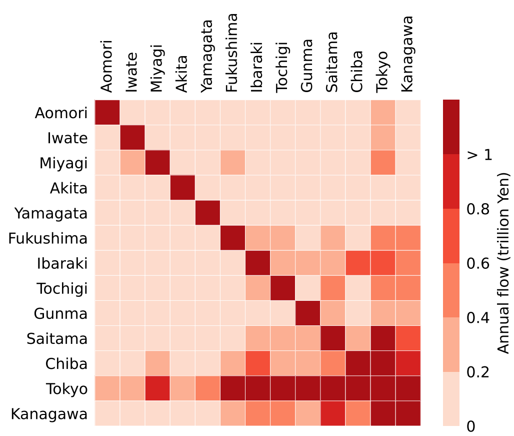
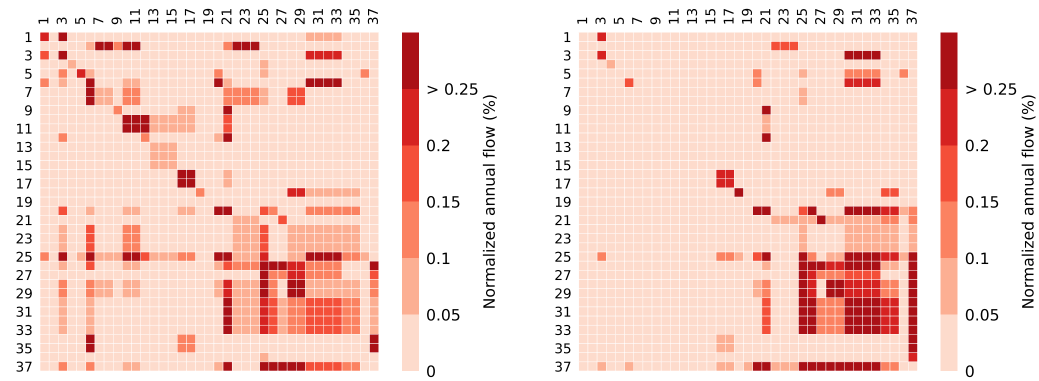


Figure 6: Input-output relationship between 13 prefectures in the East-Japan region, where the rows are selling regions and the columns are buying regions.

Table 1: Economic sectors and assigned categories. The sectors are ordered as per the Japan input-output table.

No.	Sector	Category
1	Agriculture, forestry and fishery	Agriculture, Forestry and Fishery
2	Mining	Mining
3	Beverages and foods	Beverages and Foods
4	Textile products	Manufacturing
5	Pulp, paper and wooden products	Manufacturing
6	Chemical products	Manufacturing
7	Petroleum and coal products	Manufacturing
8	Plastic products and rubber products	Manufacturing
9	Ceramic, stone and clay products	Manufacturing
10	Iron and steel	Manufacturing
11	Non-ferrous metals	Manufacturing
12	Metal products	Manufacturing
13	General-purpose machinery	Manufacturing
14	Production machinery	Manufacturing
15	Business oriented machinery	Manufacturing
16	Electronic components	Manufacturing
17	Electrical machinery	Manufacturing
18	ICT equipment	Manufacturing
19	Transportation equipment	Manufacturing
20	Miscellaneous manufacturing products	Manufacturing
21	Construction	Construction
22	Electricity, gas and heat supply	Utilities
23	Water supply	Utilities
24	Waste management service	Utilities
25	Commerce	Services
26	Finance and insurance	Services
27	Real estate	Services
28	Transport and postal services	Services
29	Information and communications	Utilities
30	Public administration	Services
31	Education and research	Services
32	Medical, health care and welfare	Services
33	Membership-based associations not elsewhere classified (n.e.c.)	Services
34	Business services	Services
35	Personal services	Services
36	Office supplies	Manufacturing
37	Activities not elsewhere classified	Services



(a) (b)

Figure 7: Normalized intermediate input-output relationship across all sectors based on the total intermediate transactions in the region in (a) Chiba, and (b) Tokyo. The rows are selling sectors and the columns are buying sectors. The numbering of the sectors follows Table 1.

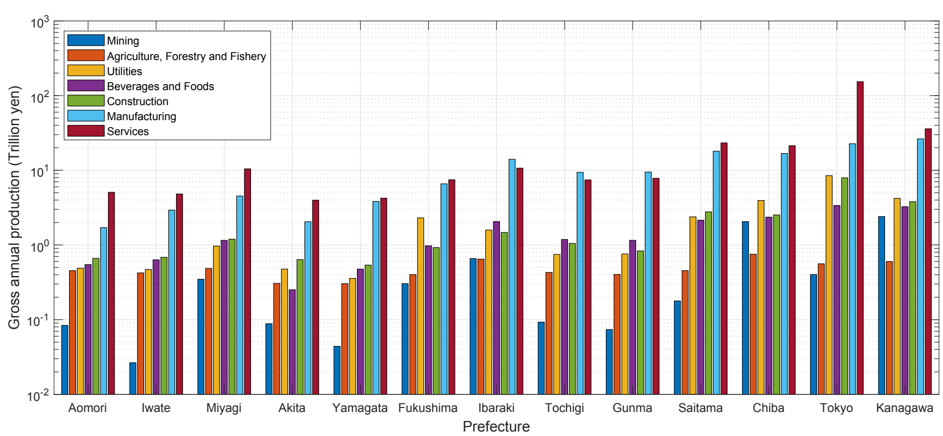


Figure 8: Annual gross output of all sectors in the East-Japan region before the disaster. Data for plotting is retrieved from the 2011 Japan inter-prefecture input-output table in the R-JIP database [59].

Table 2: Economic behavioral parameters for various categories of economic sectors (taken as the mean values suggested in [14]). The construction sector does not have an inventory constraint, so inventory parameters are labeled as n.a. in the table and set to infinity in the model.

Category	τ^{α} **(months)**	α^{max}	τ^{s} **(days)**	η **(days)**	ψ
Agriculture, forestry and fishery	12	1.1	30	90	0.7
Mining	12	1.1	30	90	0.7
Beverages and Foods	6	1.1	30	90	0.7
Manufacturing	6	1.1	30	90	0.7
Construction	12	1.1	n.a.	n.a.	0.7
Utilities	0.5	1.1	2	2	0.7
Services	1	1.1	14	30	0.7

4.3. Modeling assumptions and process

The building stock information is reconciled and aggregated by economic sectors in each prefecture to align with the model resolution. Fixed assets and direct damages at the sector level are determined by aggregating the corresponding building information based on industry types and regions. Due to the lack of empirical data on productive capital recovery, the time to achieve 95% recovery of building stocks in each industry is estimated using HAZUS building recovery times, and a linear recovery curve is assumed [10]. Constant productive capital recovery rates are then determined from the recovery curves and used throughout the recovery simulation. Note that the building stock data provided by Sompo only covers their insured buildings. Therefore, to determine the total assets and losses within the regions, we scale up these figures using estimated ratios of insured buildings to the total number of buildings for individual sectors in each prefecture. The average insurance penetration across all sectors is approximately 20%.

The direct damages from the earthquake are incorporated as reconstruction demand after the event, which is allocated over time based on empirical recovery patterns. It is assumed that 75% of the reconstruction demand, originated from productive assets and housing, is assigned to the construction sector, and the remaining 25% is assigned to manufacturing sectors in the same prefecture [10, 32]. The reconstruction demand for manufacturing sectors is distributed proportionally to the pre-event value added of all manufacturing sectors in the corresponding region. The percentage reduction in production capacity of each sector is determined as the ratio of its direct damages over the fixed asset, which is approximated by the ratio of repair costs over the full replacement cost. Furthermore, the model assumes that the imports remained constant before and after the earthquake for all sectors, reflecting a stable level of external trade throughout the simulation period. Since part of the demand can be met through import substitution during supply shortages, this assumption might result in an overestimation of indirect losses if the study area can increase its imports during recovery, and an underestimation if imports are hindered by earthquake damages.

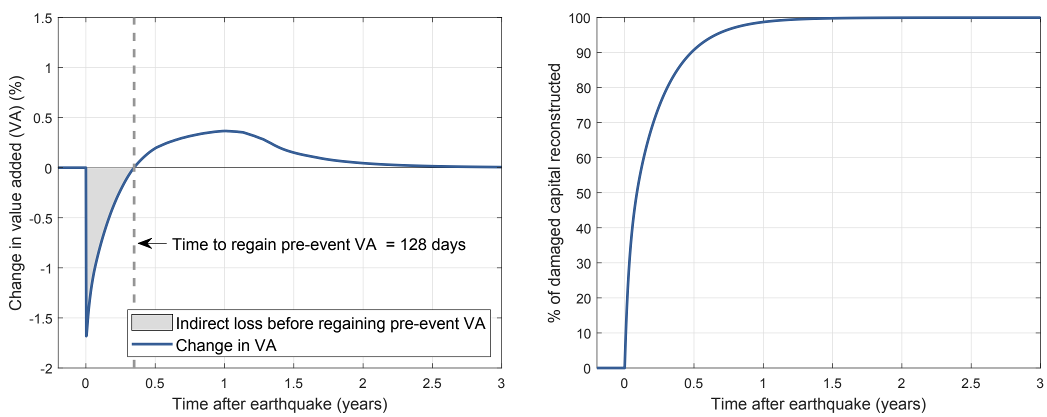
The model simulates the economic activities and recovery process using a time step of one day, and the analysis is run for 10 years starting immediately after the occurrence of the earthquake.

4.4. Results and discussion

In this section, we begin by providing a detailed description and interpretation of the model results. Next, we compare the results from the single-region and multi-region analyses, considering both the aggregated and local region levels, to identify differences or similarities in the outcomes. Lastly, we address the selection of the study area boundary and explore how this decision may influence the findings and interpretations of the study.

4.4.1. Model output

The output of the model consists of all quantities computed in Equations (1)-(8), per sector and for each time step. The direct output from the model is at the sector level, but results can be aggregated to assess the overall economic impact and recovery. In this case study, we evaluate the East-Japan region level, the prefecture level, and the sector level. The change in value added over time is chosen as the indicator for post-disaster economic performance.



(a) (b)

Figure 9: Post-earthquake economic performance for East-Japan region over a 3-year recovery period: (a) change in value added, and (b) reconstruction progress.

The overall change in value added for the East-Japan region is shown in Figure 9a. The initial disruption from the direct damage causes an initial drop in the regional value added of about 1.7%, followed by a quick recovery. The economy returns to its pre-earthquake condition in about four months, followed by a growth in value added. Meanwhile, the reconstruction of damaged capital is carried out at a rapid rate after the earthquake (Figure 9b).

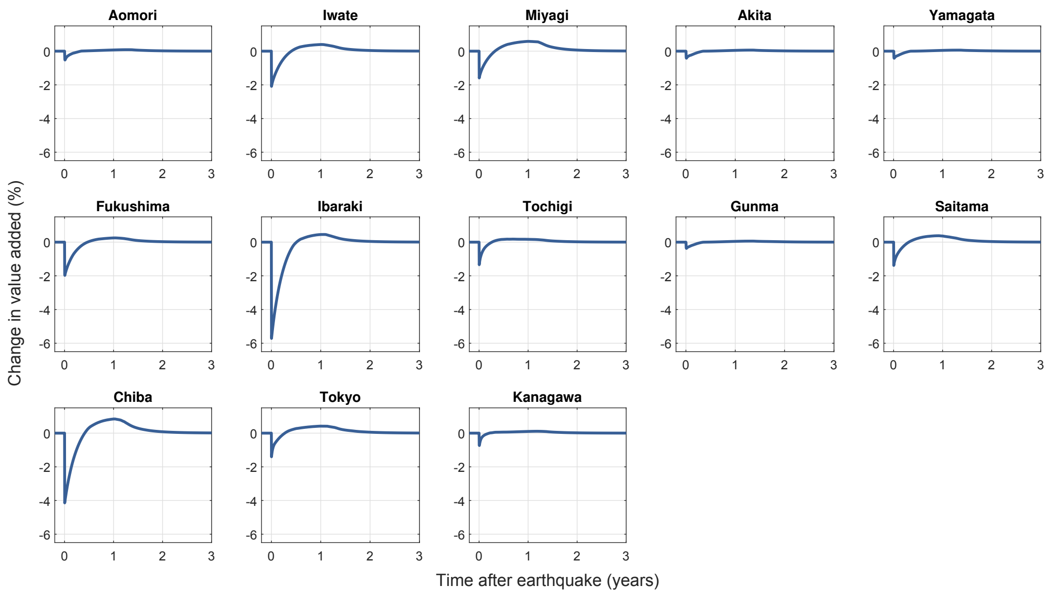


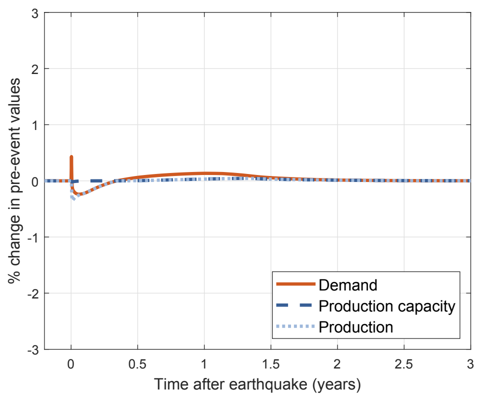
Figure 10: Post-earthquake change in value added at prefecture level over a 3-year recovery period.

The productive capital is restored, and the regional economy regains equilibrium about two years after the earthquake. The resultant total indirect loss from this economic dynamic can be computed as the area under the curve before the pre-earthquake value added level is achieved as it is the maximum deficit the region needs to bear after the disaster. It is estimated to be 0.431 trillion Yen or 0.196% of pre-earthquake annual value added for the East-Japan region in the Tohoku earthquake. This estimate generally matches the statistical data on the actual GDP of the nation, both in terms of timing and magnitude, which shows a decline in GDP of 1.63% in the second quarter of 2011 and a gentle uptick in the third quarter compared to the previous year's values [61]. Kajitani et al. [61] estimate that tsunami losses further reduced the productive capacity of sectors in four coastal prefectures–Iwate, Miyagi, Fukushima, and Ibaraki–by an average of 6% immediately after the event. Additionally, the nuclear evacuation zone had localized impacts on affected businesses. Since our analysis does not account for these factors, which could also affect economic performance beyond earthquake damages, the results are likely to underestimate the actual impacts on these coastal prefectures.

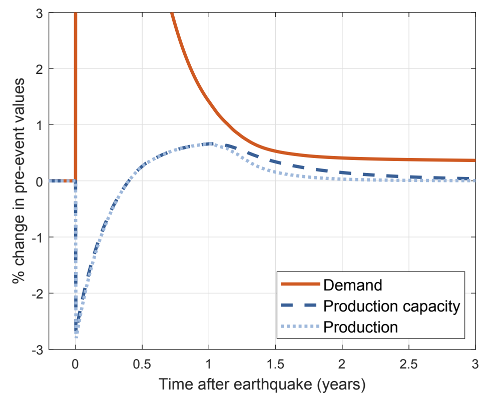
The recovery trajectory of value added for each of the 13 prefectures is summarized in Figure 10. Ibaraki experiences the largest drop in terms of change in value added immediately after the disaster, followed by Chiba. During the economic recovery phase, Chiba achieves the highest positive change in value added, which is followed by Ibaraki and Miyagi. In general, the prefectures that experience a more significant initial drop in value added are more likely to go through a substantial overproduction during the recovery, and vice versa. In addition, prefectures that experience less direct impacts from the earthquake, such as Aomori, Akita, Yamagata, and Gunma, achieve the quickest restoration to economic equilibrium. We further compute the indirect losses across manufacturing sectors by prefecture in terms of changes in value added and compare them with the empirical annual value added fluctuations in the first three years after the disaster provided by Sompo. The comparison shows that Iwate, Miyagi, Fukushima, and Chiba are among the top five most relatively impacted prefectures in both the model results and empirical observations. This indicates that the vulnerable prefectures identified by our model align well with actual observed impacts.

The underlying factors driving the observed economic recovery trends can be investigated by monitoring post-disaster production, production capacity, and demand. Figure 11 illustrates the typical trends observed in the prefectures examined in this case study. During the initial phase of economic recovery, prefectures with minimal direct damages, such as Akita (Figure 11a), experience demand fluctuation (Equation 1) that may govern the production level. Conversely, prefectures with significant direct damages, like Chiba (Figure 11b), generally witness a more pronounced increase in demand, while production is primarily limited by the reduced production capacity (Equation 2). Toward the end of the recovery, production can be governed by the speed of regaining production capacity and meeting local demand. For instance, Kanagawa's production is primarily hindered by production capacity (Figure 11c), whereas Iwate's production is limited by demand (Figure 11d).

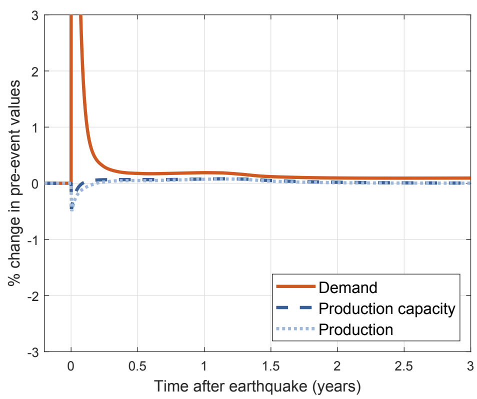
To further evaluate the impacts on the individual sector level, Figure 12 shows the rankings of sectors with the highest direct and indirect impacts in terms of both monetary and relative values. The relative direct impact is the ratio between the damage incurred and the fixed assets, which is also the measure of the percentage reduction in productive capital after the earthquake. The relative indirect impact measures the indirect loss relative to the pre-earthquake annual value added. The bars are colored based on the



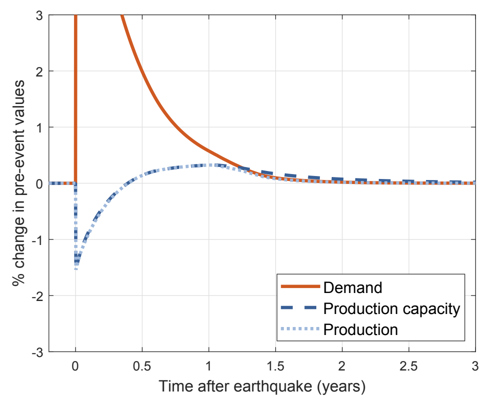
(a) Akita



(b) Chiba



(c) Kanagawa



(d) Iwate

Figure 11: Summary of typical trends in post-earthquake change in demand, production, and production capacity at prefecture level: (a) Akita, (b) Chiba, (c) Kanagawa, and (d) Iwate.

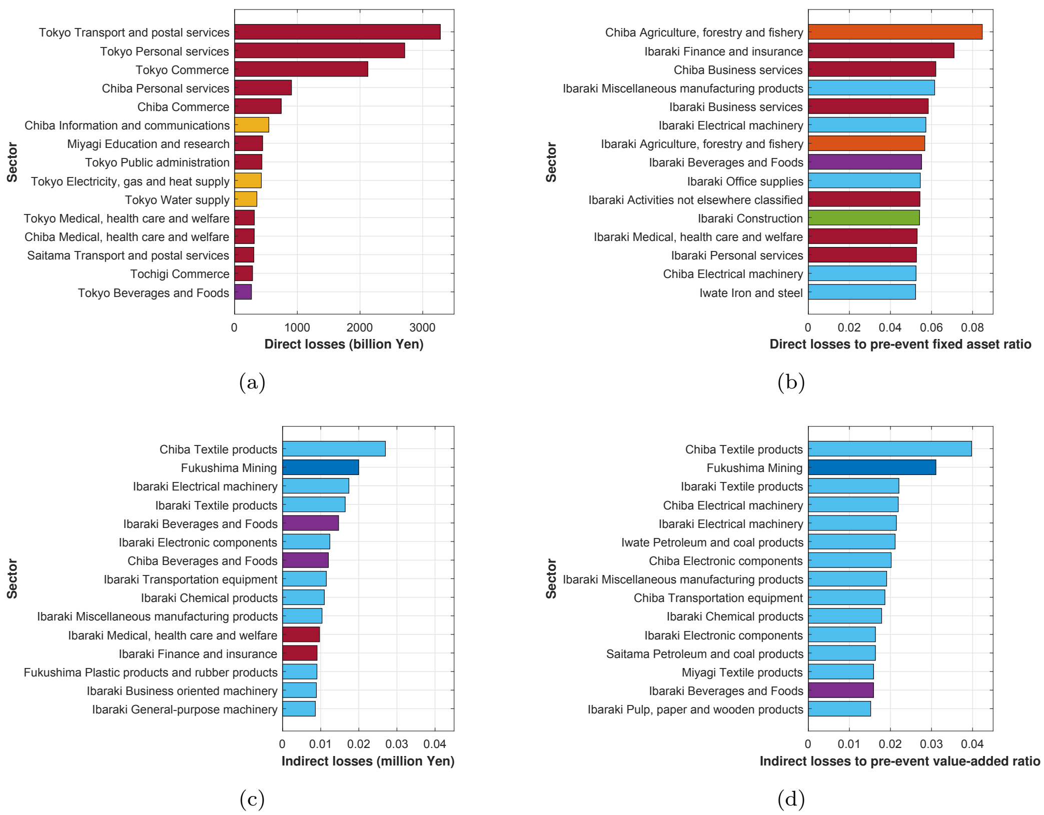
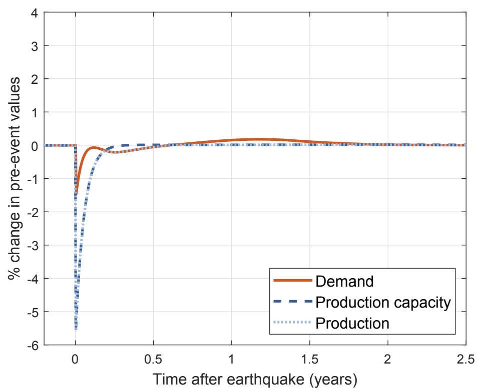


Figure 12: The top 15 sectors in the East-Japan region with the highest (a) direct losses, (b) direct losses as a fraction of pre-disaster fixed assets, (c)indirect losses, and (b) indirect losses as a fraction of pre-disaster value added. The color coding of the bars corresponds to the sector categories shown in Figure 8.

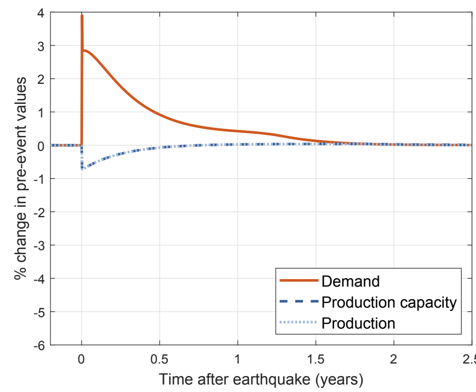
sector categories shown in Figure 8. The sectors with the greatest direct losses are concentrated in Tokyo and Chiba, while the sectors with the greatest indirect losses, relative direct impacts, and relative indirect impacts are predominantly located in Chiba and Ibaraki. This highlights the substantial economic consequences faced by these prefectures. The sectors with the largest direct losses are mostly service sectors, and the sectors with the largest relative direct impacts include a diverse range of industries. However, the manufacturing sectors (textiles, mining, machinery) predominantly bear the brunt of the highest relative indirect impacts. Notably, none of these sectors appear on the lists of top direct loss and relative direct impacts, indicating a complex relationship between direct and indirect impacts.

Figure 13 shows the drivers of performance for the selected sectors in the aforementioned lists. Although the Agriculture, Forestry and Fishery sector in Chiba (Figure 13a) experiences the largest initial reduction in productive capacity, it rapidly regains production capacity due to a quick restoration of destructed capital, driven by the sector's high reconstruction demand rate. Additionally, the demand for the sector stabilizes quickly after the disaster. Therefore, its value added achieves an early return to the pre-earthquake equilibrium, resulting in a small relative indirect loss. In contrast, the Textile Products sector in Chiba (Figure 13b) experiences a smaller initial reduction in production capacity and a large increase in demand following the earthquake. However, its production capacity recovery is slower, leading to a more substantial relative indirect impact. Similar trends in demand and production are observed for the Electrical Machinery sector in Ibaraki (Figure 13d), which suffered both significant relative direct and indirect losses. The Mining sector in Fukushima (Figure 13c), on the other hand, illustrates that a post-disaster reduction in demand can lead to a high relative indirect impact, despite a small relative direct impact. These patterns emphasize the intricate interactions between sectors in determining demand dynamics and their subsequent effects. Apart from these factors, other factors, such as the breakdown between domestic production and imports, may also influence the changes in sector-level value added.

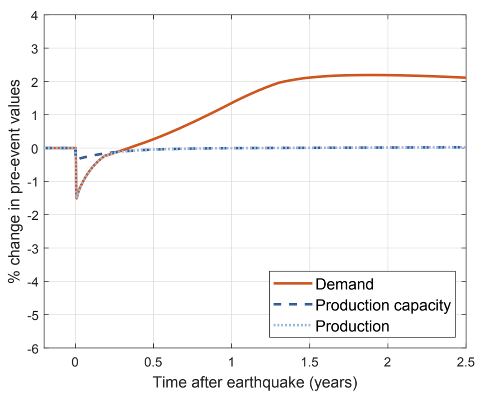
To validate the model performance, we further compare the sectoral model results with the empirical observations provided by Kajitani et al. [61]. We find alignment between the modeled and observed recovery times for most service and manufacturing sectors. However, our model does not further differentiate recovery capacities within the manufacturing sector category to capture the slower recovery observed in the steel and refinery sectors



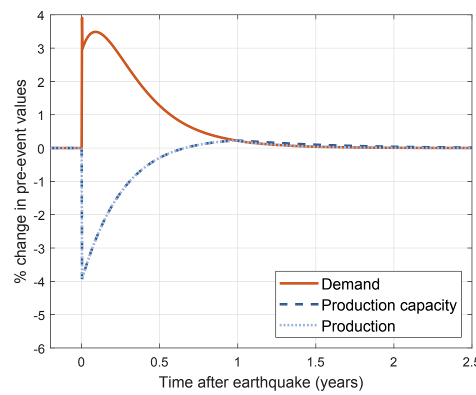
(a) Chiba Agriculture, forestry and fishery



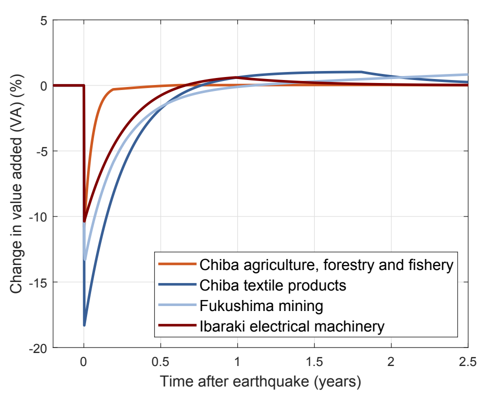
(b) Chiba Textile products



(c) Fukushima Mining



(d) Ibaraki Electrical machinery



(e) Change in value added for the four sectors

Figure 13: Summary of typical trends in post-earthquake change in demand, production, and production capacity at sector level: (a) Chiba Agriculture, forestry and fishery, (b) Chiba Textile products, (c) Fukushima Mining, (d) Ibaraki Electrical machinery, and (e) the corresponding changes in value added for these four sectors.

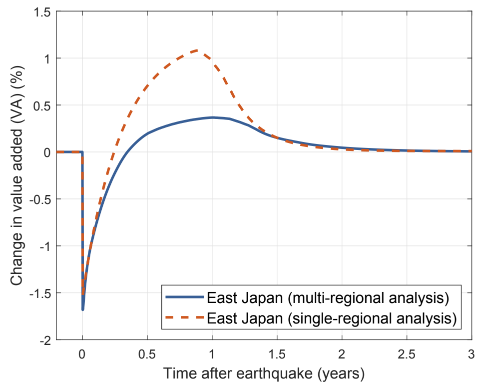


Figure 14: Post-earthquake change in value added for East-Japan region over a 3-year recovery period from multi- (blue solid line) and single-regional (red dashed line) analysis.

after the disaster, which were also severely impacted by tsunami damages.

4.4.2. Comparison between single-regional and multi-regional analysis

Compared to prior single-regional analyses, the multi-regional analysis framework proposed here considers the heterogeneity in direct disaster impacts and recovery capacity across different regions. To quantify the difference such a refinement makes to the results, we perform single-regional analyses on both aggregated East-Japan region and individual prefectures for this case study. For the aggregated East-Japan region single-regional analysis, the initial damages and economic activities in various prefectures are combined (while maintaining the 37 distinct economic sectors). The direct losses incurred by a given sector in different prefectures are added up, and the single-region input-output table for the entire East-Japan region is constructed by aggregating flows corresponding to the same types of sectors from different prefectures in the inter-regional input-output table. Subsequently, the economic recovery is simulated for each of these sectors of the entire region without further disaggregation into prefectures. For individual prefectures, the single-regional analysis is conducted based only on the damages that occurred within the prefecture, assuming a constant level of imports from outside regions.

Figure 14 compares results from the single- and multi-regional analysis results for the aggregated East-Japan region. The single-regional analysis simulates a slightly less severe drop immediately after the earthquake (1.5% versus 1.7%) and a greater overproduction during the later recovery phase.

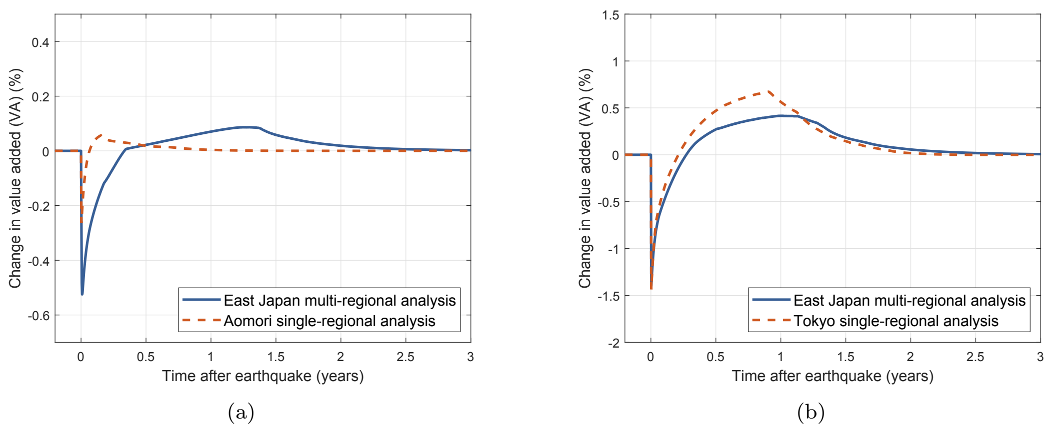


Figure 15: Post-earthquake change in value added over a 3-year recovery period from single- and multi-regional analysis for: (a) Aomori, and (b) Tokyo.

The estimated indirect loss is 0.352 trillion yen from the single-regional analysis, slightly smaller than the 0.431 trillion yen from the multi-regional analysis. Despite the proximity in these indirect loss estimates in this case, single-regional analysis tends to underestimate the indirect negative economic impacts of the disaster, because it assumes a uniform distribution of damage and recovery across the sub-regions for each sector, whereas, in the multi-regional analysis, the regional variation is modeled. Thus, the multi-regional approach accounts for varying degrees of productive capital damage across different sub-regions, including the most severe reductions, which is likely to trigger a more substantial initial impact on the region's value added. Moreover, there is a higher chance the regional economic recovery could be bottlenecked by certain vulnerable sectors within specific sub-regions at some point of time, which can impede the overall recovery process. In addition, the multi-regional analysis surpasses the single-regional analysis with the ability to provide a more granular depiction of impact and unveil sub-regional intricacies (e.g. as shown in Figure 10).

We next consider the set of analyses considering damage to only a single prefecture. The results fall into two distinct groups. For prefectures that are less directly damaged during the disaster, such as Aomori (Figure 15a), the single-regional analysis projects less significant indirect impacts on the regional economy, which is reflected by both a shallower initial reduction in the value-added and a gentler overproduction afterward. For more significantly damaged prefectures like Tokyo (Figure 15b), however, the opposite effects

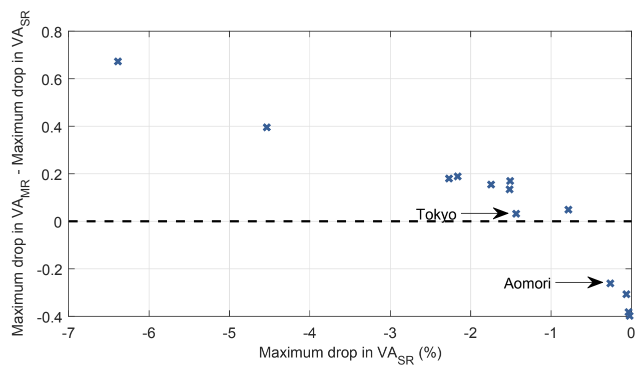


Figure 16: Difference of maximum drop in value added during the simulated recovery between multi-region analysis (VA_{MR}) and single-regional analysis (VA_{SR}) for each of the 13 prefectures in the East-Japan region.

are observed. This trend can also be visualized in Figure 16, which plots the differences in the maximum drop of value added in the multi-regional analysis versus that in the single-regional analysis. When the maximum decrease in value added in the single-region analysis is close to 0, the indirect impacts for these regions are estimated to be less severe in the single-regional analysis. For prefectures experiencing a larger maximum drop in value added in the single-region analysis, the difference in the results between the multi- and single-regional analysis flips to be positive, suggesting the overestimated impacts from the single-regional analysis. This reflects the major limitation of the single-regional analysis when applied to a large study area that arises from the isolated analysis for the study region. As a result, it ignores both the enhanced resilience introduced by the trading linkages with the outside world for the regions that are badly damaged and the increased vulnerability posed by the same ties to the less directly impacted regions.

4.4.3. Selection of the scope of analysis area

One challenge for the regional economic impact analysis is that the definition of the geographic extent of the cascading impacts is not intuitive and involves uncertainties, which leads to the question of how to define the study area boundary. As the model assumes a fixed level of imports before and after the disaster, the study region is isolated from the rest of the world in the analysis, which may neglect some critical linkages between the regions within and outside the study boundaries. This might affect the simulated recovery within the study area or fail to capture the cascading impacts extending be-

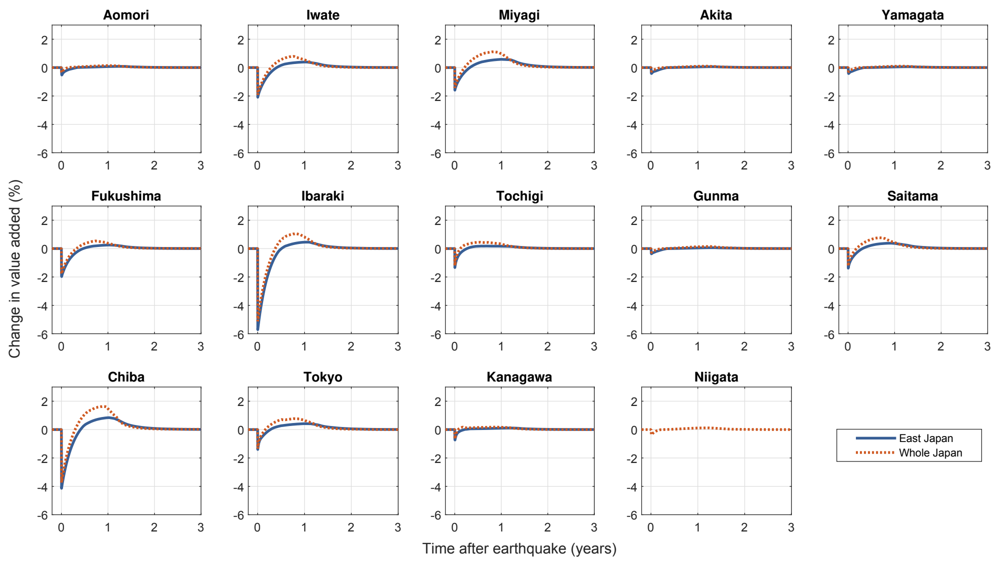


Figure 17: Post-earthquake change in value added at prefecture level over a 3-year recovery period from multi-regional analysis for East-Japan region only and the entire nation.

yond the defined regions. On the other hand, defining an excessively large study area increases the required input data and computational costs. To assess the effect of using different scopes of the analysis region, we conduct the multi-regional analyses of the case study earthquake considering analysis areas of the 13 prefectures in East Japan and all 47 prefectures in Japan, and the results from the two analyses are compared.

Figure 17 shows the simulated change in value added at the prefecture level from the two analyses. The figure contains the results for all prefectures within the East-Japan region and one example prefecture, Niigata, which falls outside the scope of the previous study boundary. Based on the plots, the estimated economic recovery trends are almost the same for the 13 prefectures in the East-Japan region that are directly damaged during the earthquake, except that the maximum drop in value added is slightly less and overproduction in the late-recovery stage is slightly higher when prefectures that are not directly impacted are also considered in the analysis. Moreover, when the analysis takes into account the undamaged prefectures, the value added for those regions experiences a slight reduction immediately after the event, followed by a rapid recovery. This minor discrepancy may result from the contribution of resilience from the overproduction capacity outside the study area and the economic linkages between the damaged and undamaged prefectures. This also suggests that the majority of the influence on the regional economic recovery in this case comes from the regions that are directly impacted by the disruption. The overall indirect losses are 0.431 trillion yen and 0.351 trillion yen from the analysis considering the East-Japan region and the entire Japan region respectively. The estimated impacts closely align between the two analyses, and therefore defining the study boundary based on the area of direct damages might be an appropriate option in this case. However, the analysis considering the entire Japan also outputs the indirect impacts to the undamaged regions, although they are relatively small compared to those in the East-Japan region. If these results are of interest to the decision-makers, the larger study scope should be considered for the analysis.

5. Conclusion

This study extended the refined Adaptive Regional Input-Output (R-ARIO) model framework to simulate the multi-regional economic recovery process from disaster disruptions, providing a more realistic and nuanced assessment of economic impacts on a large study area. The proposed model takes into account the geographical heterogeneity in both direct damages and economic activities. The direct losses in each region and their economic sector are captured separately and translated into the reduction in productive capital and post-disaster reconstruction demand. The interactions between various economic sectors within or outside the same region during the recovery are then simulated, subject to constraints from the trading structure, demand, productive capital, and available supply. To facilitate implementation, this paper also provides a detailed workflow for extracting the trading structures specific to the regions of interest from a raw inter-regional input-output table.

The model was demonstrated using a case study of the 2011 Tohoku earthquake. The magnitude and duration of indirect economic impacts of the earthquake were estimated using simulation at three different resolutions, the East-Japan region as a whole, prefecture level and sectoral level. The peak reduction in value added for the East-Japan region is about 1.7% happens immediately after the earthquake, and the total indirect loss in the region amounts to 0.43 trillion Yen or 0.2% of the region's pre-earthquake annual value added. This trend generally matches with the observed economic reality after the earthquake. The variation of recovery and indirect impacts across different prefectures and sectors were also examined to identify the vulnerable areas in the system during the impact propagation and recovery. Notably, Ibaraki and Chiba experience the most significant relative indirect economic impacts among all 13 prefectures in the East-Japan region. The study also highlights that sectors experiencing substantial relative indirect impacts do not necessarily incur high direct losses. In this particular scenario, manufacturing sectors emerge as the dominant contributors to the list of sectors with the largest relative indirect impacts. In addition, the model simulates the evolution in demand and production during recovery, which reveals cases when production is restricted by demand, production capacity, or supply. These constraints vary across different sectors and prefectures, implying the need for tailored resilience tactics in each case.

Moreover, the comparison between single- and multi-regional analysis was presented to illustrate the effect of inter-regional trading ties on the resilience of the regional economy. For regions with higher direct impacts, the multi-regional analysis predicts smaller indirect impacts than the single-regional analysis since the multi-regional analysis captures the mitigating effects arising from the increased trade with less affected regions. For low-impacted regions, the indirect impacts are elevated due to their interdependence with more disrupted regions. Furthermore, a single-regional analysis conducted over a large study area tends to underestimate the indirect economic impacts faced by the region. Lastly, the trade-off for the selection of the study area boundary for the multi-regional analysis was discussed. It is shown that using the area of direct damages as the study boundary provides a fair estimation compared to the analysis done with a larger study area. However, more information about the cascading impacts to undamaged regions can be obtained from the latter option with the expense of demanding additional input data and computations.

The proposed model provides a baseline scenario where the post-event resource distribution follows the inter-regional trading relationship, without assigning priority to meet the excess local demand. Additionally, the model predicts that the economy will return to the pre-disaster equilibrium, which may not fully capture the long-term post-disaster conditions. Future studies could consider incorporating additional factors to account for potential shifts in the economic landscape following a disaster. Moreover, the scarcity and coarse resolution of post-disaster regional economic data present challenges for model validation. Improved management and accessibility of future post-disaster economic information could facilitate the advancement of simulation methods in this domain.

In conclusion, the presented model is most applicable to assess the economic resilience of multiple regions subject to a widespread initial shock. It can help decision-makers to evaluate the extent and duration of the initial and cascading disruptions to the economic activities as well as identify the critical or vulnerable linkages and components in the economic system during the recovery stage. Consequently, the model results can inform the development of resilience investments and risk management strategies, such as strategic resource allocation to vulnerable sectors, enhancing the robustness of businesses pre-disaster, and strengthening the resilience of inter-regional supply chains.

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Conflict of interest

The authors declared that they have no potential conflicts of interest concerning the research, authorship, and/or publication of this paper.

Supporting Information

Code implementing the proposed model is available at: https://github.com/tingerzhu/MR-ARIO. The damage and economic datasets used in this study were provided by Sompo. The 2011 Japan inter-prefecture input-output table was originally available in the R-JIP database (https://www.rieti.go.jp/jp/database/r-io2011/index.html) and preprocessed by Sompo to ensure its compatibility with other data in terms of the sector definition.

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