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ARTICLE

Assessing the Regional Economic Ripple Effect of Flood Disasters Based on a Spatial Computable General Equilibrium Model Considering Traffic Disruptions

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Abstract
With growing regional economic integration, transportation systems have become critical to regional development and economic vitality but vulnerable to disasters. However, the regional economic ripple effect of a disaster is difficult to quantify accurately, especially considering the cumulated influence of traffic disruptions. This study explored integrating transportation system analysis with economic modeling to capture the regional economic ripple effect. A state-of-the-art spatial computable general equilibrium model is leveraged to simulate the operation of the economic system, and the marginal rate of transport cost is introduced to reflect traffic network damage post-disaster. The model is applied to the 50-year return period flood in 2020 in Hubei Province, China. The results show the following. First, when traffic disruption costs are considered, the total output loss of non-affected areas is 1.81 times than before, and non-negligible losses reach relatively remote zones of the country, such as the Northwest Comprehensive Economic Zone (36% of total ripple effects). Second, traffic disruptions have a significant hindering effect on regional trade activities, especially in the regional intermediate input—about three times more than before. The industries most sensitive to traffic disruptions were transportation, storage, and postal service (5 times), and processing and assembly manufacturing (4.4 times). Third, the longer the distance, the stronger traffic disruptions' impact on interregional intermediate inputs. Thus, increasing investment in transportation infrastructure significantly contributes to mitigating disaster ripple effects and accelerating the process of industrial recovery in affected areas.

Keywords Economic ripple effect · Floods · Spatial computable general equilibrium model · Supply chain damage · Traffic disruption

1 Introduction

As regional economic linkages strengthen, disaster impacts are no longer limited to areas directly affected by event shocks (Ham et al. 2005). They spread to industries in non-affected areas via interregional industrial linkages and disruption of transportation infrastructure (Tirasirichai and Enke 2007), resulting in supply bottlenecks and regional ripple effects that are wider in scope and longer in time (Okuda and Kawasaki 2022) but more difficult to evaluate accurately. Assessing disaster-related economic losses as comprehensively as possible is essential for analyzing disaster risks, identifying vulnerable regional industries, and developing post-disaster industrial recovery strategies (Pörtner et al. 2022).

The input-output (IO) model has been widely used to analyze regional economic ripple effects (Galbusera and Giannopoulos 2018; Yang, Wang, et al. 2022; Jiang et al. 2023), but also criticized for lacking economic resilience (Rose 2004; Miller and Blair 2009) and supply-side price feedback (Bachmann et al. 2014). Scholars have tried to address these drawbacks in recent studies by combining the model with computable general equilibrium (CGE) characteristics, such

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as the adaptive regional IO model (ARIO), which considers inventories for additional production system flexibility (Hallegatte 2008, 2014; Wu et al. 2012); multiregional impact assessment model (MRIA), which considers inefficient production technologies (Koks and Thissen 2016); hypothetical extraction method (HEM), which supposes that a certain industry is no longer operational (Dietzenbacher et al. 2019; Xia et al. 2019); and random-utility-based multi-regional IO model (RUBMRIO), which increases elastic trade coefficients considering transportation service level of regions (Zhao and Kockelman 2004; Bachmann et al. 2014). These additional considerations have improved the economic system's resilience and offset part of disasters' negative effects; nevertheless, high uncertainties remain (Wouter Botzen et al. 2019).

The CGE model, which incorporates the price mechanism and the substitution relationship of commodities, is nonlinear compared to the IO model and is considered a flexible approach in regional economic modeling (Kajitani and Tatano 2018; Zhou and Chen 2021). Rose and Guha (2004) emphasized the importance of applying the CGE model to disaster loss assessment. Although CGE models are generally considered more suitable for long-term events, in applying the model to the 2011 Great East Japan Earthquake, Kajitani and Tatano (2018) found that short-term disasters (that is, those lasting several months) can be successfully studied by setting low elasticity of substitution and strict macro closure. Further, because more attention has been paid to risk transmission between regions, spatial computable general equilibrium (SCGE) models have been gradually developed and applied (Carrera et al. 2015). Hitherto, the SCGE model has been widely adopted for the industrial economic analysis of different disaster types, such as earthquakes (Tatano and Tsuchiya 2008; Kajitani and Tatano 2018; Shibusawa 2020), floods (Carrera et al. 2015; Haddad and Teixeira 2015), storm surges (Cui et al. 2018), and pandemics (Rose et al. 2021). Currently, researchers are conducting state-of-the-art SCGE analysis of disasters' regional economic ripple effects. Additionally, since the CGE model strictly follows microeconomic theory to set agent rules, it can better express interaction behaviors among agents (Robson et al. 2018), facilitating the model's extension; for example, it can be used to consider intertemporal dynamics to study post-disaster recovery (Xie et al. 2018; Walmsley et al. 2022) and coupled with traffic models to study traffic disruption impact (Koike et al. 2012; Tatano and Tsuchiya 2022).

Economic linkages between different regions depend on the terms of trade communication undertaken by the transport network (Candelieri et al. 2019). Particularly, transportation systems are highly susceptible to most disaster shocks and have difficulty recovering (Wen et al. 2014). Regarding post-disaster transport disruption, some studies have simply regarded transportation as the damaged sector and introduced its direct losses into models as the shock input (Yu et al. 2013; Tan et al. 2019), while others have tried to integrate transportation behavior into SCGE models (Tatano and Tsuchiya 2008; Koike et al. 2015). The latter is more consistent with how a real economic system operates, but incorporating transportation into SCGE models still faces some challenges (Tavasszy et al. 2011; Van Truong and Shimizu 2017). The most common modeling approach is incorporating transportation costs into SCGE models, which falls into four categories: the iceberg assumption (quantity-based approach), marginal transport cost (price-based approach), accessibility index, and transport capital stocks (Shahrokhi Shahraki and Bachmann 2018). Regarding model application, studies have examined the integration of transport and CGE models in road congestion (Anas 2020), infrastructure investment (Hansen and Johansen 2017), and transport planning (Robson et al. 2018). However, in disaster assessment and management, the integration of traffic disruption and CGE models is still being explored, and the iceberg assumption and marginal transport cost methods are most common (Shahrokhi Shahraki and Bachmann 2018). The iceberg assumption refers to the melting that occurs as an iceberg moves and assumes the quantity of transported goods that "melts" during transportation as a transport cost (Samuelson 1952; Tatano and Tsuchiya 2008; Bröcker et al. 2010). Furthermore, some scholars have expressed transportation cost as the marginal cost added to goods (Ueda et al. 2001; Koike et al. 2012; Koike et al. 2015), similar to tariffs. To determine the transportation marginal cost rate, some studies take traffic distance as the main factor (Horridge 2012; Rokicki et al. 2021), while others consider more complex modeling methods. For instance, Koike et al. (2015) comprehensively considered travel time, time value, and travel cost to calculate increased post-disaster transportation costs. Tatano and Tsuchiya (2008) included both freight and passenger transport, using transit time and monetary value to adjust transport costs after infrastructure damage. Tirasirichai (2007) and Enke et al. (2008) estimated increased travel cost by combining information about damaged highway bridges with that of travel time and travel distance values. Wei et al. (2022) calculated freight costs based on vehicle operating costs, driver wages, and benefits and estimated time costs based on increasing commuting time, simulating the reduction in labor endowment efficiency.

In model coupling, choosing the correct transportation cost specification is critical but challenging (Van Truong and Shimizu 2017). Accurately obtaining data for each industry constitutes an enormous workload, and data availability limitations must be considered. However, for the CGE model, this problem seems to be resolved: all model prices are simulated and compared to the benchmark price (Hosoe et al. 2010), and agent behaviors are based on utility and

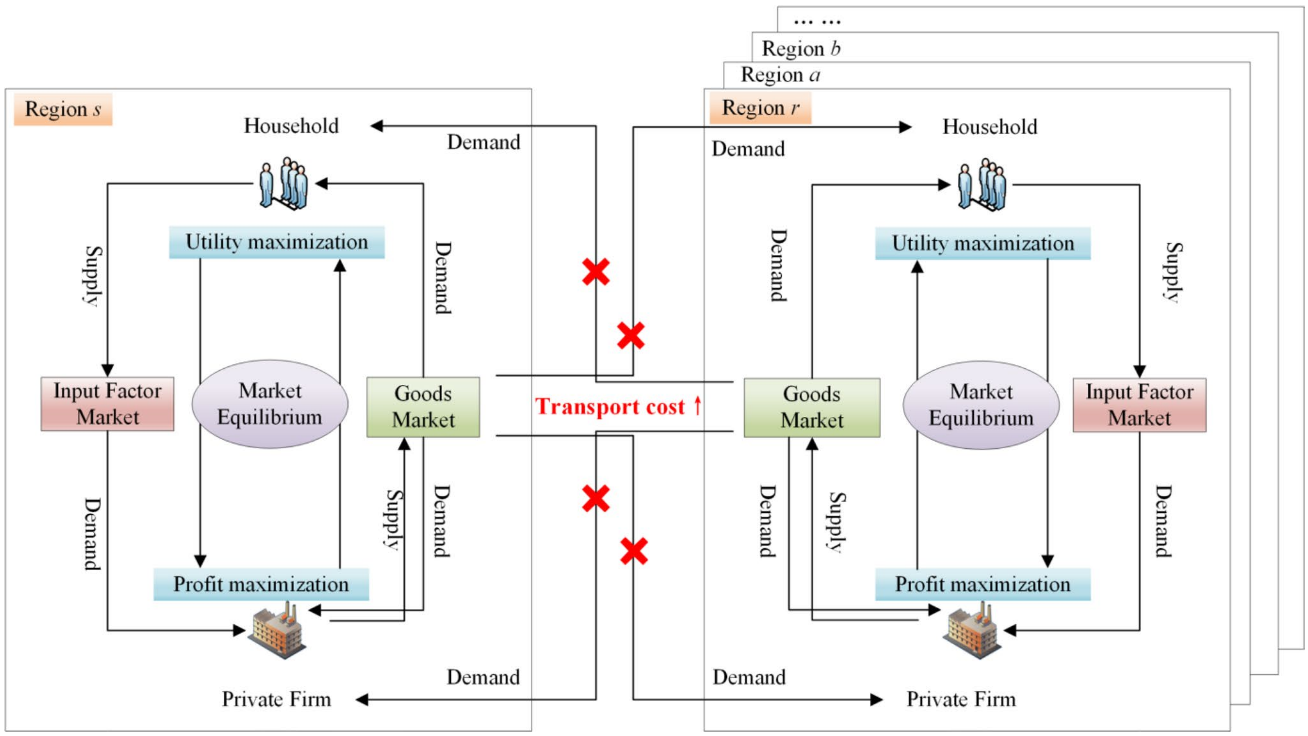


Fig. 1 Structure of the social economic system

production functions to make an optimal decision based on relative prices (Robson et al. 2018). Thus, accurately calculating actual transportation costs of various industries, which is difficult, is unnecessary. Further, most correlated costs increase with transportation distance, such as communication, service, fuel, freight volume, and inventory costs (Haddad and Hewings 2004; Bröcker et al. 2010; Rokicki et al. 2021). Additionally, setting new traffic times, time values, and other factors will also have redundant effects. The CGE model contains much exogenous substitution parameters, which causes certain uncertainties (Hosoe et al. 2010). To avoid more uncertain factors, fewer exogenous variables should be chosen. Using transportation distance as the primary consideration can avoid any unnecessary double-counting impact and industry heterogeneity issues.

Considering the above, we constructed an SCGE model in the context of traffic network disruptions following a disaster, which is a major innovation for the comprehensive assessment of post-disaster economic losses. Additionally, we investigated industries that are more sensitive to traffic disruption factors to provide a theoretical basis for enterprise decision makers to increase inventory and find necessary backup suppliers. The rest of the article is organized as follows. Section 2 introduces a traffic disruption parameter to reflect disaster-related disruption of transportation infrastructure. Section 3 presents modeling issues associated with the disaster setting and transportation disruption costs, and applies the model to a case study in Hubei, China. Section 4 discusses the impact of the marginal rate of transport costs on regional intermediate input. Finally, in Sect. 5, the findings are evaluated, and conclusions are drawn.

2 Spatial Computable General Equilibrium (SCGE) Model Considering Traffic Disruption Costs

Based on the single-region CGE model, the SCGE model adds an interregional trade link module to reflect real-world economic exchanges (Fig. 1). However, after a disaster shock, the disruption of transportation infrastructure often hinders economic exchanges between regions (the line marked with a red cross in Fig. 1), resulting in disaster ripple effects. The main assumptions in this model are:

(1) Private firms produce goods from intermediate inputs (from all regions and different industries) and factor inputs (capital and labor), following profit maximization under Leontief production techniques.
(2) The government, organizations, residents, and other consumers are combined and collectively called the "final consumer," following utility maximization subject to budget constraints.

(3) The model mainly analyzes highway transportation mode without considering railways, waterways, and other transportation.
(4) The economic zone is taken as the smallest unit, and only traffic disruption between regions is considered, disregarding the impact of intra-regional traffic disruption.

To incorporate traffic disruption impact into the SCGE model, we add post-disaster marginal transportation cost to commodity prices. Regarding the specific transmission mechanism, due to transportation infrastructure interruption, the additional transportation cost rate increases post-disaster, resulting in the increase of commodity prices in the place of production during the transportation process and correspondingly higher commodity prices in places of consumption. This price increase means that the share of interregional commodity trade will change (in the traditional SCGE model, the share is fixed and calculated based on the IO table (Hosoe et al. 2010)), which, in turn, affects the supply network of interregional industrial intermediate inputs. Comparing the model equilibrium results of whether commodity prices increase the cost rate of traffic disruption, we can quantitatively evaluate the regional economic ripple effect. Additionally, our SCGE model adopts strict short-term closure in the market equilibrium module, considering the post-disaster characteristics of labor price rigidity, underemployment, and capital shortage (Kajitani and Tatano 2018).

2.1 Production Module

The production module describes the production behavior of firms. Each firm maximizes its profit and produces the final commodity in three stages.

Stage 1: Intermediate input composite goods are compounded from the intermediate inputs from various regions using constant elasticity of substitution (CES) production technology to consider interregional substitutions.
Stage 2: The capital and labor factors form a composite factor using the Cobb-Douglas production function.
Stage 3: Composite elements and intermediate input composite goods are combined to generate the final product using Leontief production technology.

[Stage 1]

$$PTI_{ij}^{s} \cdot TI_{ij}^{s} = \min \sum_{r \in S} (1 + t^{rs}) P_i^r \cdot x_{ij}^{rs}, \tag{1}$$

$$s.t.\ TI_{ij}^{s} = \theta_{ij}^{s} \left[\sum_{r \in S} \beta_{ij}^{rs} \cdot x_{ij}^{rs\,\frac{\sigma_i - 1}{\sigma_i}} \right]^{\frac{\sigma_i}{\sigma_i - 1}}, \tag{2}$$

where x_{ij}^{rs} is the intermediate input i from region r to industrial sector j; P_i^r is the supply price of commodity i in region r; t^{rs} is the transportation cost rate from region r to s, which will increase due to the disruption of transport infrastructure under the disaster shock scenario;TI_{ij}^{s} is the total regional intermediate input composite goods under the Armington assumption (Armington 1969); PTI_{ij}^{s} is the unit cost of the regional intermediate input of composite goods; Fig. 2 shows the process of commodity price changes after the disaster; θ_i is a scale parameter of the CES function; β_{ij}^{rs} is a share parameter of the CES function; and σ_i is an elasticity of substitution parameter. By solving Eqs. 1 and 2, PTI_{ij}^{s} and x_{ij}^{rs} can be obtained as follows:

$$PTI_{ij}^{s} = \frac{1}{\theta_{ij}^{s}} \left[\sum_{r \in S} \beta_{ij}^{rs\,\sigma_i} \cdot (1 + t^{rs})^{1-\sigma_i} \cdot P_i^{r\,1-\sigma_i} \right]^{\frac{1}{1-\sigma_i}}, \tag{3}$$

$$x_{ij}^{rs} = \theta_{ij}^{s\,\sigma_i - 1} \left[\frac{\beta_{ij}^{rs} \cdot PTI_{ij}^{s}}{(1 + t^{rs}) \cdot P_i^r} \right]^{\sigma_i} \cdot TI_{ij}^{s}, \tag{4}$$

[Stage 2]

$$PV_j^s \cdot V_j^s = \min_{l_j^s, k_j^s} (w_j^s \cdot l_j^s + r_j^s \cdot k_j^s), \tag{5}$$

$$s.t.\ V_j^s = \eta_j^s \cdot l_j^{s\,\alpha_j^s} \cdot k_j^{s\,1-\alpha_j^s}, \tag{6}$$

where r, s are region suffixes ($s, r \in S$, $S = \{1, 2, \cdots, m\}$); i, j are the industrial sector suffixes ($i, j \in N$, $N = \{1, 2, \cdots, n\}$); l_j^s is the labor input of sector j in region s; k_j^s is the capital input of sector j in region s; w_j^s is the wage of labor; r_j^s is capital rent; V_j^s is the value-added; PV_j^s is the unit cost of the composite factor; α_j^s is the share parameter; and η_j^s is the scale parameter. Then, l_j^s, k_j^s, and PV_j^s can be obtained as follows:

$$l_j^s = \frac{\alpha_j^s}{w_j^s} \frac{1}{\eta_j^s} \left(\frac{w_j^s}{\alpha_j^s} \right)^{\alpha_j^s} \left(\frac{r_j^s}{1 - \alpha_j^s} \right)^{1-\alpha_j^s} \cdot V_j^s, \tag{7}$$

$$k_j^s = \frac{1 - \alpha_j^s}{r_j^s} \frac{1}{\eta_j^s} \left(\frac{w_j^s}{\alpha_j^s} \right)^{\alpha_j^s} \left(\frac{r_j^s}{1 - \alpha_j^s} \right)^{1-\alpha_j^s} \cdot V_j^s, \tag{8}$$

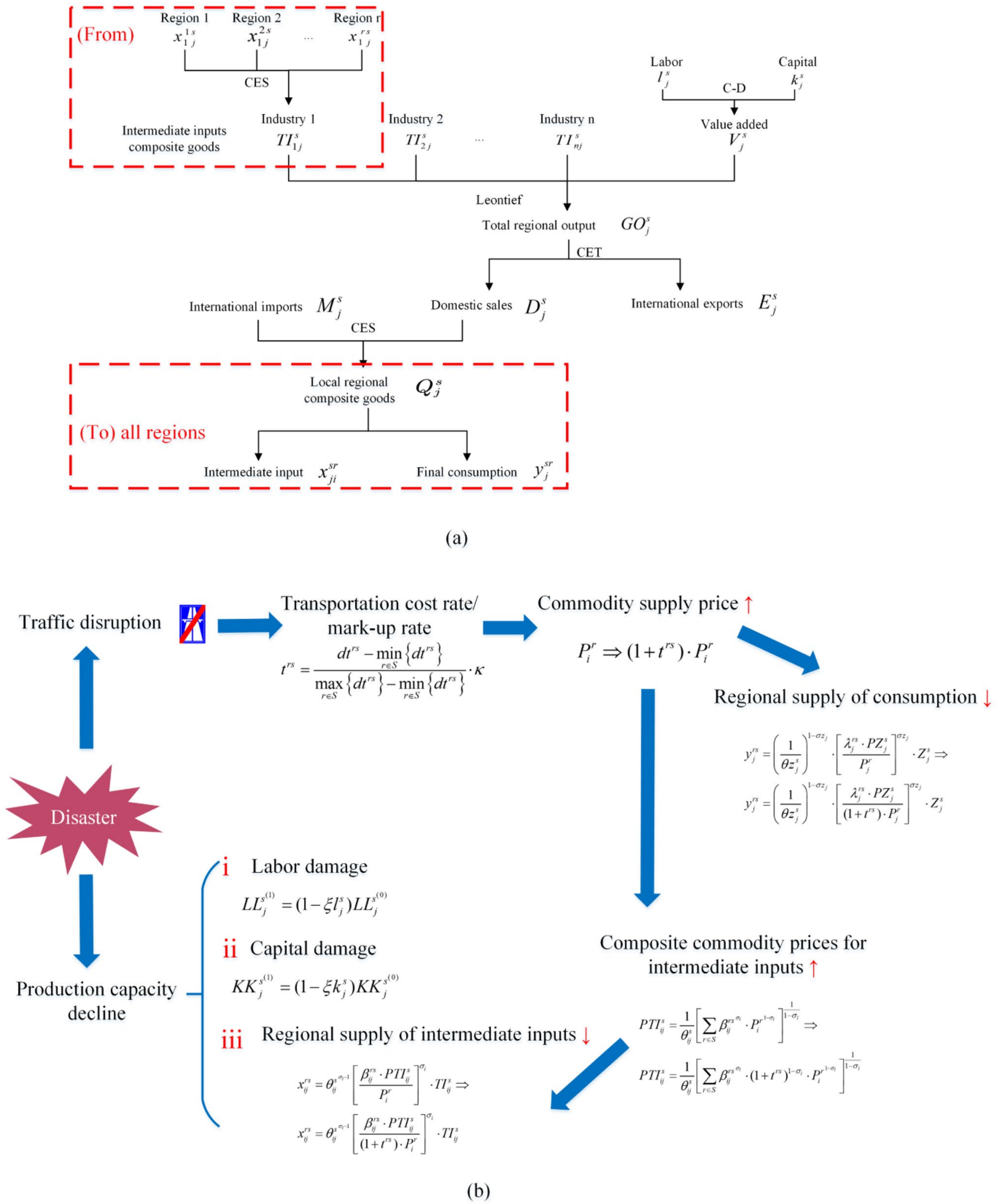


Fig. 2 Diagram of the spatial computable general equilibrium (SCGE) model: **a** Production process and commodity flows; **b** Key equations of SCGE model considering traffic disruption

$$PV_j^s = \frac{1}{\eta_j^s}\left(\frac{w_j^s}{\alpha_j^s}\right)^{\alpha_j^s}\left(\frac{r_j^s}{1-\alpha_j^s}\right)^{1-\alpha_j^s}, \tag{9}$$

[Stage 3]

$$\max_{GO_j^s, V_j^s, TI_{ij}^s} imize\ \pi_j^s = PGO_j^s \cdot GO_j^s - \left(PV_j^s \cdot V_j^s + \sum_i PTI_{ij}^s \cdot TI_{ij}^s\right), \tag{10}$$

$$s.t.\ GO_j^s = \min\left(\frac{V_j^s}{bv_j^s}, \frac{TI_{1j}^s}{a_{1j}^s}, \frac{TI_{2j}^s}{a_{2j}^s}, \cdots, \frac{TI_{nj}^s}{a_{nj}^s}\right), \tag{11}$$

where π_j^s is the profit of firm j in region s; GO_j^s is the total regional output of industry j in region s; PGO_j^s is the supply price of GO_j^s; $a_{1j}^s, \cdots a_{nj}^s$ represent the IO coefficient of intermediate inputs; and bv_j^s is the production capacity rate. By solving Eqs. 10 and 11, TI_{ij}^s, V_j^s, and PGO_j^s are obtained as follows:

$$TI_{ij}^s = a_{ij}^s \cdot GO_j^s, \tag{12}$$

$$V_j^s = bv_j^s \cdot GO_j^s, \tag{13}$$

$$PGO_j^s = \sum_i a_{ij}^s \cdot PTI_{ij}^s + bv_j^s \cdot PV_j^s. \tag{14}$$

2.2 International Trade Module

The international trade module describes the process of combining domestic sales, imported goods, and exported goods before the final consumption module and includes two stages.

Stage 1: Total regional output is divided into domestic sales and exports, using constant elasticity of transformation (CET) function.
Stage 2: The combination of imported goods and domestic sales goods forms local comprehensive commodities, using the CES function.

[Stage 1]

$$\max_{GO_j^s, D_j^s, E_j^s} imize\ \pi 1_j^s = (PD_j^s \cdot D_j^s + PE_j^s \cdot E_j^s) - PGO_j^s \cdot GO_j^s, \tag{15}$$

$$s.t.\ GO_j^s = \theta e_j^s \cdot \left[\delta d_j^s \cdot D_j^{s\frac{\psi_j+1}{\psi_j}} + (1-\delta d_j^s) \cdot E_j^{s\frac{\psi_j+1}{\psi_j}}\right]^{\frac{\psi_j}{\psi_j+1}}. \tag{16}$$

Assume that a virtual firm maximizes its profits by optimizing the volume of exports and domestic sales. In Eq. 15, $\pi 1_j^s$ is the profit of the virtual firm; D_j^s and E_j^s are the respective volumes of domestic sales and exports of industry j in region s; and PD_j^s and PE_j^s are the prices of domestic sales and exports, respectively. In Eq. 16, θe_j^s is a scale parameter of the CET function; δd_j^s is a share parameter; and ψ_j is the elasticity of the transformation parameter. The optimal solution is:

$$D_j^s = \theta e_j^{s^{-\psi_j-1}}\left[\frac{\delta d_j^s \cdot PGO_j^s}{PD_j^s}\right]^{-\psi_j} \cdot GO_j^s, \tag{17}$$

$$E_j^s = \theta e_j^{s^{-\psi_j-1}}\left[\frac{(1-\delta d_j^s) \cdot PGO_j^s}{PE_j^s}\right]^{-\psi_j} \cdot GO_j^s, \tag{18}$$

$$PGO_j^s = \frac{1}{\theta e_j^s}\left[\delta d_j^{s^{-\psi_j}} \cdot PD_j^{s^{1+\psi_j}} + (1-\delta d_j^s)^{-\psi_j} \cdot PE_j^{s^{1+\psi_j}}\right]^{\frac{1}{1+\psi_j}}, \tag{19}$$

[Stage 2]

$$\max_{Q_j^s, M_j^s, D_j^s} imize\ \pi 2_j^s = PQ_j^s \cdot Q_j^s - (PM_j^s \cdot M_j^s + PD_j^s \cdot D_j^s), \tag{20}$$

$$s.t.\ Q_j^s = \theta m_j^s\left[\delta m_j^s \cdot M_j^{s\frac{\sigma m_j-1}{\sigma m_j}} + (1-\delta m_j^s) \cdot D_j^{s\frac{\sigma m_j-1}{\sigma m_j}}\right]^{\frac{\sigma m_j}{\sigma m_j-1}}. \tag{21}$$

Similar to Stage 1, in Eq. 20, $\pi 2_j^s$ is the profit of the virtual firm; Q_j^s are the local composite commodities of industry j in region s, which are transported to various regions for intermediate inputs and final consumption; and PQ_j^s is the price of local composite commodities. In Eq. 21, θm_j^s is a scale parameter of the CES function; δm_j^s is a share parameter; and σm_j is the elasticity of substitution. The optimal solution is:

$$M_j^s = \theta m_j^{s^{\sigma m_j-1}}\left[\frac{\delta m_j^s \cdot PQ_j^s}{PM_j^s}\right]^{\sigma m_j} \cdot Q_j^s, \tag{22}$$

$$D_j^s = \theta m_j^{s^{\sigma m_j-1}}\left[\frac{(1-\delta m_j^s) \cdot PQ_j^s}{PD_j^s}\right]^{\sigma m_j} \cdot Q_j^s, \tag{23}$$

$$PQ_j^s = \frac{1}{\theta m_j^s}\left[\delta m_j^{s^{\sigma m_j}} \cdot PM_j^{s^{1-\sigma m_j}} + (1-\delta m_j^s)^{\sigma m_j} \cdot PD_j^{s^{1-\sigma m_j}}\right]^{\frac{1}{1-\sigma m_j}}. \tag{24}$$

2.3 Consumption Module

The consumption module describes the final consumer's consumption behavior. Each consumer can freely buy products under income constraints to achieve maximum utility, as follows:

$$U^s = \left(\sum_{j \in N} \mu_j^s \cdot Z_j^{s\,\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \tag{25}$$

$$s.t. \sum_{j \in N} PZ_j^s \cdot Z_j^s = I^s, \tag{26}$$

where U^s is the utility of the final consumer in region s; Z_j^s is the total demand of commodity j of the final consumer; μ_j^s is the share parameter of commodities ($\sum_{j \in N} \mu_j^s = 1$); ρ is the elasticity of substitution parameter; PZ_j^s is the unit cost of Z_j^s; and I^s is the income of the final consumer. Solving Eqs. 25 and 26, the optimal volume of each commodity is obtained as follows:

$$Z_j^s = \left(\frac{\mu_j^s}{PZ_j^s} \right)^{\rho} \cdot \frac{I^s}{\sum_{j \in N} \mu_j^{s\rho} \cdot PZ_j^{s\,1-\rho}}. \tag{27}$$

Additionally, the substitution relationship between the goods in various regions is described by the CES function:

$$PZ_j^s \cdot Z_j^s = \min \sum_{r \in S} (1 + t^{rs}) \cdot P_j^r \cdot y_j^{rs}, \tag{28}$$

$$s.t. \, Z_j^s = \theta z_j^s \left(\sum_{r \in S} \lambda_j^{rs} \cdot y_j^{rs\,\frac{\sigma z_j - 1}{\sigma z_j}} \right)^{\frac{\sigma z_j}{\sigma z_j - 1}}, \tag{29}$$

where y_j^{rs} is the quantity of goods consumed from region r to s; θz_j^s is a scale parameter; λ_j^{rs} is a share parameter ($\sum_{r \in S} \lambda_j^{rs} = 1$); and σz_j is an elasticity of substitution parameter. By solving Eqs. 28 and 29, y_j^{rs} and PZ_j^s are obtained as follows:

$$y_j^{rs} = \left(\frac{1}{\theta z_j^s} \right)^{1-\sigma z_j} \cdot \left[\frac{\lambda_j^{rs} \cdot PZ_j^s}{(1 + t^{rs}) \cdot P_j^r} \right]^{\sigma z_j} \cdot Z_j^s, \tag{30}$$

$$PZ_j^s = \frac{1}{\theta z_j^s} \left[\sum_{r \in S} \lambda_j^{rs\,\sigma z_j} \cdot (1 + t^{rs})^{1-\sigma z_j} \cdot P_j^{r\,1-\sigma z_j} \right]^{\frac{1}{1-\sigma z_j}}. \tag{31}$$

The income of the final consumer comes from labor wages, capital rent, and regional transfer payments:

$$I^s = \sum_{j \in N} (w_j^s \cdot l_j^s + r_j^s \cdot k_j^s) - TP^s, \tag{32}$$

where I^s represents the income of final consumer in region s, and TP^s is the regional transfer payment.

2.4 Market Equilibrium Module

The market equilibrium module includes three parts: international market equilibrium conditions, commodity, and factor market equilibrium conditions.

2.4.1 International Market Equilibrium Conditions

The small-country assumption is adopted in the model, that is, both import and export prices of goods are exogenous. Further, the economic system must be balanced in terms of international payments, that is, the total inflow of currency must equal the total outflow. Thus,

$$PE_j^s = EXR \cdot PWE_j^s, \tag{33}$$

$$PM_j^s = EXR \cdot PWM_j^s, \tag{34}$$

$$\sum_{j \in N} PWE_j^s \cdot E_j^s + SF^s = \sum_{j \in N} PWM_j^s \cdot M_j^s, \tag{35}$$

where PWE_j^s is the export price in international currency; PWM_j^s is the import price in international currency; EXR is the exchange rate; and SF^s is the foreign savings in international currency.

2.4.2 Commodity-Market Equilibrium Conditions

Commodity market-clearing conditions aim at the equilibrium of supply and demand of composite commodities in the local market, which is formulated as:

$$Q_j^s = \sum_{r \in S} \sum_{i \in N} x_{ji}^{sr} + \sum_{r \in S} \sum_{j \in N} y_j^{sr}. \tag{36}$$

2.4.3 Factor Market Equilibrium Conditions

In normal periods, factor market equilibrium conditions mean that the capital factor can move freely within industrial sectors and the labor factor can move freely among regions, which is given as:

$$\sum_{j \in N} k_j^{s(0)} = \sum_{j \in N} KK_j^{s(0)}, \tag{37}$$

$$\sum_{s \in S} l_j^{s(0)} = \sum_{s \in S} LL_j^{s(0)}, \tag{38}$$

where suffixes $^{(0)}$ and $^{(1)}$ are added to distinguish the pre-disaster variables from post-disaster. $KK_j^{s(0)}$ and $LL_j^{s(0)}$ are the initial endowments of capital and labor in normal periods, respectively.

During a disaster period, the capital and labor endowments suffer from shocks (Kajitani and Tatano 2018). Under the disaster shock scenario, the model assumes that labor prices are rigid downwards, unemployment will occur, and capital will be fully utilized but will not allow movement among sectors over a short period of time post-disaster. The equilibrium conditions can be set as:

$$(w_j^{s(1)} - w_j^{s(0)})(l_j^{s(1)} - LL_j^{s(1)}) = 0, \text{ where } w_j^{s(1)} \geq w_j^{s(0)}, l_j^{s(1)} \leq LL_j^{s(1)}, \tag{39}$$

$$k_j^{s(1)} - KK_j^{s(1)} = 0, \tag{40}$$

$$KK_j^{s(1)} = (1 - \xi k_j^s) KK_j^{s(0)}, \tag{41}$$

$$LL_j^{s(1)} = (1 - \xi l_j^s) LL_j^{s(0)}, \tag{42}$$

where $KK_j^{s(1)}$ and $LL_j^{s(1)}$ are the respective endowments of capital and labor after a disaster, and ξk_j^s and ξl_j^s are the respective damage ratios of capital and labor.

3 Application to a Flood Disaster in Hubei Province, China

This section describes the study's case background, data sources, and disaster shock settings.

3.1 Case Background

An unexpected heavy rainstorm affected Enshi City, Hubei Province, on 17 July 2020, causing a 50-year return period flood disaster. A total of 471,656 people in 88 villages and towns in eight prefectures were affected by the disaster, and 51,997 people were evacuated. The flood caused the collapse of 1372 houses and serious damage to 1221 houses; the affected crop area was 17,693 ha. According to official statistics, the direct economic loss was RMB 2338.23 million yuan (USD 339 million).[1] Inaccessible roads caused by traffic disruptions further affect industrial supply chain recovery after disasters. According to the survey data, road restoration typically takes seven days but can take up to 30 days for severely damaged roads.

3.2 Data Sources

The main dataset used in this study is the interregional IO table of China for 2017, which includes 31 provinces (except for Hong Kong, Macao, and Taiwan) and 42 industrial sectors and was based on data from the National Statistics Bureau (Zheng et al. 2021). The interregional IO table reflects the technology and industrial structure of regional production and clearly shows the productivity flow relationship among different regions. To facilitate model construction and accelerate data iteration, we merged the original 42 industrial sectors into 10 (Table 1) and highlighted the manufacturing industry, referring to Yang et al. (2016).

According to differences in regional industries and the tightness of regional economic integration, we divided the 31 provinces into nine regions, as illustrated in Fig. 3. Hubei is at the center of the eastern region and is an important transportation hub. Additionally, Hubei Province contains China's important industrial cluster development bases for automobile production, food and textile processing, the steel and petrochemical industry, and electronic information technology, among others. Thus, analyzing the impact of the disaster in Hubei on the regional industrial production supply chains nationwide has great practical significance.

3.3 Disaster Setting

This section describes this study's disaster settings, including labor and capital impacts and methods for linking transportation network disruptions to the model.

3.3.1 Labor and Capital Impact Setting

Typically, disasters affect labor and capital endowments, thereby hindering firms' production process (Yang, Chen, et al. 2022). We set the labor loss rate at 5.20% based on the entire province's labor productivity from the Statistical Bulletin of National Economic and Social Development of Hubei Province, 2020.[2] Table 2 shows the industry loss ratio and business interruption time (number of working days closed). The data were derived from previous field survey conducted by our research group in June 2021. Unstructured interviews and questionnaire surveys were adopted to obtain relevant damaged enterprise data, such as submergence depth and duration, asset loss rate, and business interruption time. A total of 399 questionnaires were collected, and 365 samples were finally obtained by

[1] USD 1 = RMB 6.8974 in 2020.

[2] http://tjj.hubei.gov.cn/.

Table 1 Merged industrial sectors

No.	Reclassified sector	Symbol	Detailed division
1	Agriculture	Agr	Agriculture, forestry, animal husbandry, and fishery
2	Mining	Min	Mining and washing of coal
			Petroleum and natural gas extraction
			Metal ore mining
			Non-metal mineral mining
3	Livelihood-related manufacturing	Lman	Food product manufacturing and tobacco processing
			Textiles
			Apparel, leather, fur, down, and related products
			Sawmills and furniture
			Other manufacturing machinery, scrap, and waste
4	Raw materials manufacturing	Rman	Papermaking and paper products
			Petroleum processing, coking, and nuclear fuel processing
			Chemical industry
			Nonmetallic mineral products
			Metal smelting and pressing
			Metal products
5	Processing and assembly manufacturing	Pman	General purpose machinery
			Special purpose machinery
			Transport equipment
			Electric equipment and machinery
			Communications equipment, computers, and other electronic equipment manufacturing
			Instruments and meters
			Metal products, machinery, and equipment repair services
6	Production and supply of electric power, gas, and water	Ene	Production and supply of electric power and heat
			Production and supply of gas
			Production and supply of tap water
7	Construction and real estate	Con	Construction
			Real estate
8	Trade, catering, and accommodation	Acc	Wholesale and retail trade services
			Accommodation and food serving services
9	Transportation, storage, and postal service	Tra	Transport, storage, and postal services
10	Integrated services	Svc	Telecommunication, computer services, and software
			Finance
			Rental and business services
			Residential services and other social services
			Scientific research and technical services
			Comprehensive technical services
			Water, environment, and public facilities management
			Education
			Health, social security, and welfare
			Cultural, sporting, and recreational services
			Public management and social organization

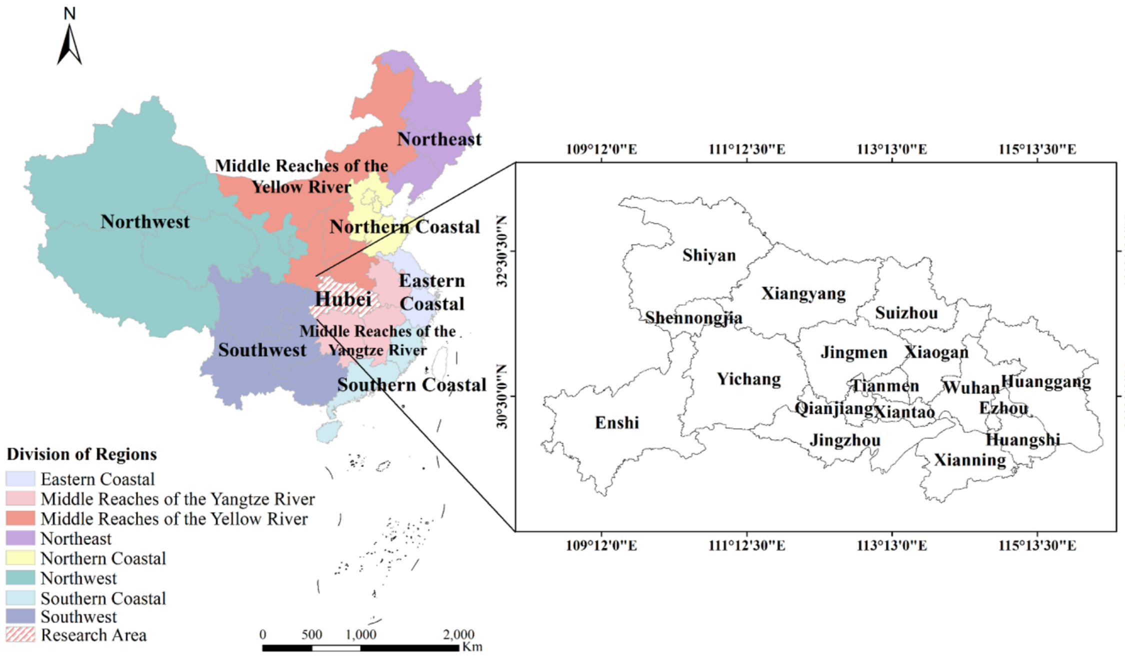


Fig. 3 Division of regions and map of the research area

Table 2 Industrial loss ratio and business interruption time according to the surveys

Symbol	Industrial sector	Loss ratio (%)	Business interruption time (days)
Agr	Agriculture	10	90
Min	Mining	10	30
Lman	Livelihood-related manufacturing	20	30
Rman	Raw materials manufacturing	20	30
Pman	Processing and assembly manufacturing	20	30
Ene	Production and supply of electric power, gas, and water	20	15
Con	Construction and real estate	10	45
Acc	Trade, catering, and accommodation	30	21
Tra	Transportation, storage, and postal service	20	10
Svc	Integrated services	10	26

Source Field survey by the research group in June 2021.

eliminating invalid samples such as missing values and outliers. Then, the industry loss ratio was converted to a yearly scale through the business interruption time in Eq. 43:

$$Loss\ ratio\_capital_j = Loss\ ratio_j \times \frac{BIT_j}{248}, \tag{43}$$

where subscript j is the industrial sector suffix; BIT_j is the business interruption time; and 248 is the number of legal working days in 2020.

3.3.2 Transportation Network Disruption Setting

The disruption of transportation networks due to disasters often interrupts industrial supply chains. In the model, the exogenous variable t^{rs} increases, representing the cost increase rate (mark-up rate) of goods transported from region r to region s after a disaster (Koike et al. 2015). We set the cost increase rate t^{rs} based on transportation distance between regions (previous research in general mainly focused on highways (Tirasirichai and Enke 2007; Tatano and Tsuchiya 2008; Bachmann et al. 2014)), as transportation distance is a major factor for modeling transport

Table 3 Cost increase rate of transport between each region and Hubei

Symbol	Region	Distance (km)	t^{rs}
HB	Research area (Hubei Province)	–	0
NE	Northeast economic zone	2,095.83	0.09648
NC	Northern coastal comprehensive economic zone	1019.23	0.04692
EC	Eastern coastal comprehensive economic zone	687.40	0.03164
SC	Southern coastal comprehensive economic zone	1112.43	0.05121
YE	Comprehensive economic zone in the middle reaches of the yellow river	908.80	0.04183
YZ	Comprehensive economic zone in the middle reaches of the yangtze river	357.60	0.01646
SW	Southwest comprehensive economic zone	1160.04	0.05340
NW	Northwest comprehensive economic zone	2172.36	0.1

costs (Haddad and Hewings 2004); industry inconsistency is not an issue. Considering the study area is Hubei Province, we only focused on the disruption of transportation between other regions and Hubei. First, we queried the universal transportation distance between each province and Hubei using Baidu Maps,[3] a common software for intelligent route planning and navigation. Each provincial capital, usually a center for population agglomeration and economic development, was selected as the start and end of a given journey. The average transportation distance between all provinces in each economic region and Hubei was then calculated (Table 3). Finally, the distance was standardized and the cost increase rate of transport between each region and Hubei was calculated as:

$$t^{rs} = \frac{dt^{rs} - \min_{r \in S}\{dt^{rs}\}}{\max_{r \in S}\{dt^{rs}\} - \min_{r \in S}\{dt^{rs}\}} \cdot \kappa, \tag{44}$$

where dt^{rs} is the actual distance between regions r and s (Hubei Province), and κ is the marginal rate of transport cost, which is also called the parameter of elasticity of substitution and is equal to 0.1 based on Koike et al. (2015). Post-disaster transport network disruption increases inter-regional trade's transport costs, regarded as the price markup of goods (Horridge 2012; Rokicki et al. 2021), and ultimately updates the supply share parameter between regional markets, which is usually fixed in the traditional SCGE model (Ando and Meng 2009).

3.4 Case Study Results

This section presents case study results, focusing on traffic disruption's impact on regional output and regional intermediate input post-disaster.

3.4.1 Traffic Disruption Impact on Regional Output Loss

By assessing disasters' regional ripple effects, we captured and quantified cross-regional and cross-industry loss. Figure 4 shows the production output loss for other regions, GO_j^s, in two cases: increased traffic disruption costs (Fig. 4a) and no traffic disruption costs (Fig. 4b). Considering traffic disruption costs, other regions' total ripple effects caused by Hubei's flood disaster is RMB 446.9 billion yuan (USD 64.8 billion), approximately 1.81 times the total ripple effects without traffic disruption costs.

In Fig. 4, darker colors equal greater decline in regional output value. Comparing the two scenarios, the non-negligible output loss gaps are extremely prominent in the country's remote zones, such as NW (46 times). On the one hand, the remote areas' economic development is highly dependent on transportation. On the other hand, pillar industries in NW, such as the aerospace industry, energy and chemical industry, and automobile manufacturing, are more susceptible to traffic disruptions. Thus, the results show that the outputs of *Lman* and *Tra* in NW significantly decline after increasing traffic disruption costs. Considering traffic disruption costs, the drop value of production output generally shows an increasing trend with increasing distance, centered on Hubei Province. Particularly, NW's output loss reaches RMB 161.5 billion yuan (USD 23.4 billion, 36% of the total regional economic ripple loss), and SC's output loss reaches RMB 111.7 billion yuan (USD 16.2 billion, 25% of the total regional economic ripple loss).

Further, the reasons for the decline of production output value in different regions were analyzed. Figure 5 shows the contributions of different production output loss by sector in different regions. Based on economic development and distance from the affected area (Hubei), other regions are divided into developed areas, areas close to Hubei, and remote areas. Major causes include factor damage, the

[3] https://map.baidu.com.

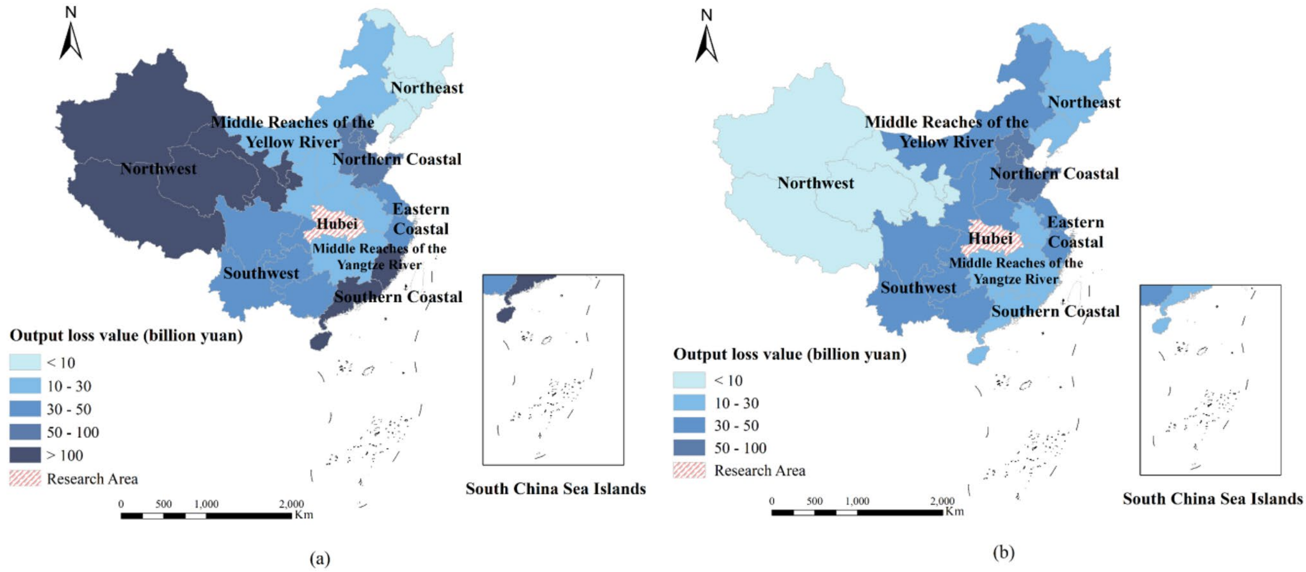
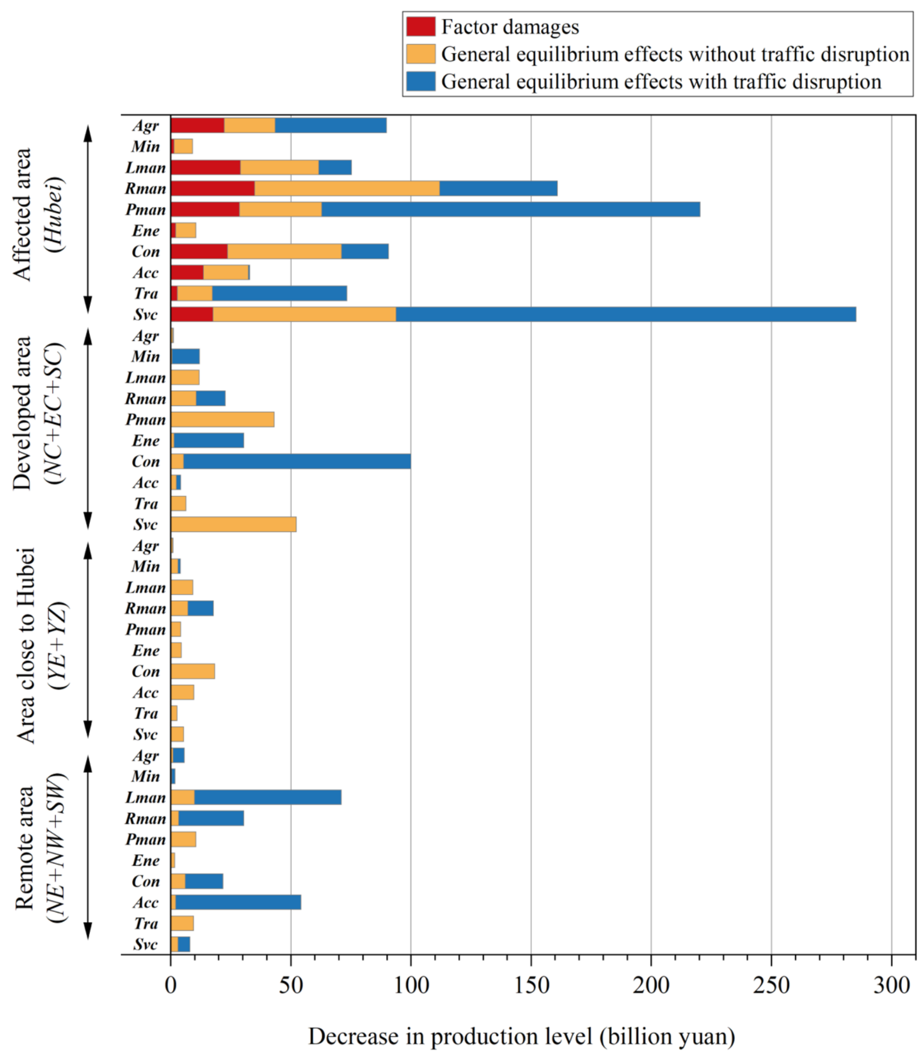


Fig. 4 Output loss for other regions in two cases: **a** Scenario considering traffic disruption costs; **b** Scenario without traffic disruption costs

Fig. 5 Production output loss in each region classified by damage source (see Table 1 and Table 3 for sector and region abbreviations)



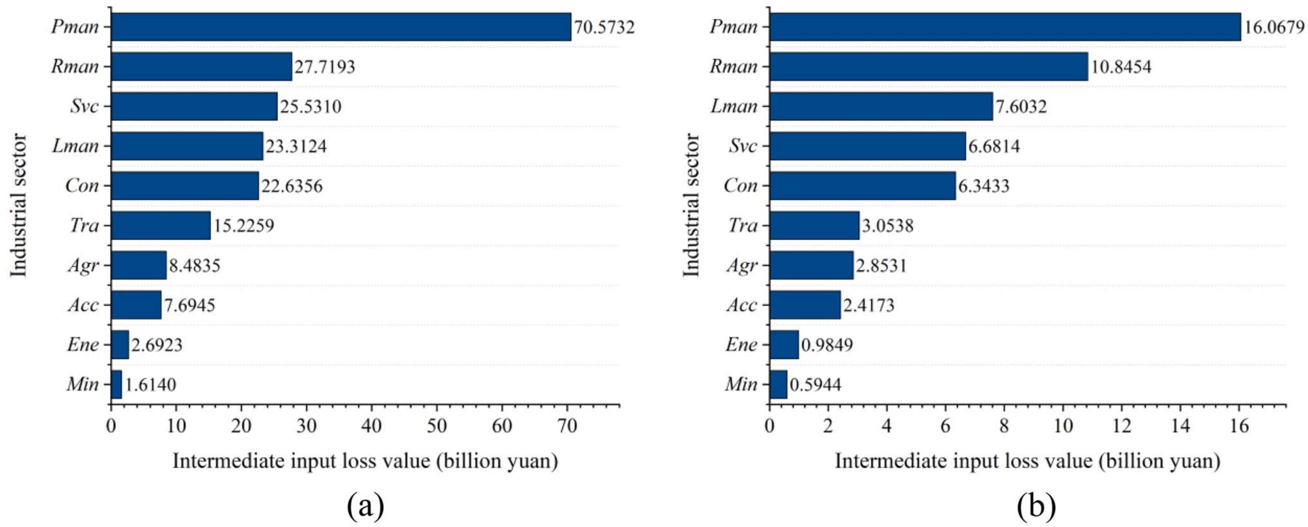


Fig. 6 Intermediate input loss value from other regions to various industries of Hubei **a** considering traffic disruption costs and **b** without traffic disruption costs

general equilibrium effect, and traffic disruption damage. Factor damage is exogenously set as a shock in Hubei Province (red bars). General equilibrium effects are incremental effects calibrated by the SCGE model without traffic disruption costs (yellow bars). Traffic disruption damage comprises the incremental effects calibrated by the SCGE model considering traffic disruption costs (blue bars).

Hubei Province is the most directly affected area, with three major impacts. Among the non-affected regions, the developed areas (economically developed coastal regions) suffer more general equilibrium effects due to their closer economic ties to Hubei. Additionally, traffic disruption damages are greater in developed and remote areas, while regions close to Hubei suffer less traffic disruption damages. Additionally, output losses do not increase in all industrial sectors affected by traffic disruption damages (see the blue bars with zero values in Fig. 5, especially in regions close to Hubei). The mechanism is as follows: traffic disruption costs affect product prices, which in turn affect the optimal distribution of products in non-affected areas, and is ultimately reflected in increased or unchanged outputs in some sectors. From the industrial perspective, the outputs of the manufacturing, energy supply, and construction industries are most affected by traffic disruption, as these industries have specific production clusters (usually located in remote zones, such as NW) that are heavily dependent on raw materials, energy supply, and so on. Thus, transportation system disruptions greatly affect these industries' production levels.

3.4.2 Traffic Disruption Impact on Regional Intermediate Input

In the model design, post-disaster, the cost of transportation disruptions increases in the process of the interregional trade module, especially that related to intermediate input (see Sects. 2.1 and 3.3.2). Therefore, we also focused on the change in intermediate inputs from other regions to Hubei Province after the flood disaster, which is also key in affected areas' production and recovery.

Figure 6 shows the total intermediate input loss from other regions to Hubei by sector, calculated by TI_{ij}^{s}. After increasing traffic disruption costs, trade exchanges among regions are blocked. The value of the intermediate input loss from other regions to Hubei increases threefold on average—fivefold in *Tra* and 4.4 in *Pman*. Additionally, regardless of whether traffic disruption costs increase, a larger drop in intermediate input value from other regions to Hubei occurs in manufacturing industries and integrated services. The value of intermediate input loss from other regions to Hubei's *Pman* reaches RMB 70.6 billion yuan (USD 10.2 billion), considering traffic disruptions. Hubei is a large-scale industrial base in China, with developed industries, such as automobile and machinery manufacturing, constituting a large proportion of total provincial GDP. Therefore, it is crucial to reconnect the industrial chain and restore related industries' intermediate input supply post-disaster.

Conversely, the intermediate input loss value in *Min* and *Ene* from other regions to Hubei is the smallest. This is because Hubei is rich in mining, power, and water resources, and these industries have more backward linkages with

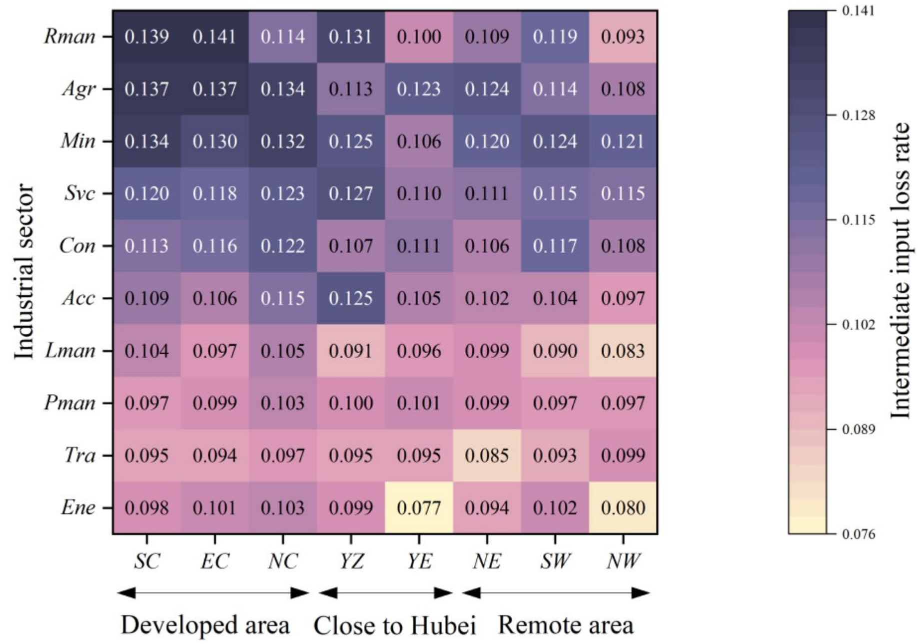


Fig. 7 Intermediate input loss rate from each region to various industries of Hubei without traffic disruption costs (see Table 1 and Table 3 for sector and region abbreviations)

industries within the province than those outside; therefore, the input supply outside the province declines less post-disaster.

3.4.3 Traffic Disruption Impact on Regional Intermediate Input of Each Subsector and Subregion

Figure 7 illustrates the intermediate input loss rate from each region to various industries of Hubei without traffic disruption costs, calculated by $\sum_{i}^{n} x_{ij}^{rs}$. Overall, the average loss rate of the intermediate input from other regions to Hubei is 11%. The proportions of intermediate input loss in *Rman*, *Agr*, and *Min* in Hubei are relatively high—up to 14%. The raw material and mining industries play an important supporting role in post-disaster industrial recovery and are significant driving factors for regional economic development (Li et al. 2021). Therefore, the government should emphasize the coordinated recovery of these industrial supply chains and the transmission risk of the production supply system. The proportions of intermediate input loss in *Ene* and *Tra* are relatively small, and these are the basic industries necessary for normal production and life.

Additionally, developed areas (SC, EC, and NC) have a higher proportion of intermediate input loss to Hubei, likely because of their closer economic ties; therefore, their disaster responses are stronger, in extreme contrast to remote areas, when traffic disruptions are not considered. Figure 8 shows the scenario considering traffic disruption costs. Compared with Fig. 7, the average loss rate of the intermediate input from other regions to Hubei is 38%, which is approximately 3.5 times of that without traffic disruption costs. Figure 8 highlights that *Tra* has the highest intermediate input loss rate—up to 57%—in contrast with Fig. 7. This is because the transportation industry is directly connected to the cost of traffic disruptions: the latter increases and the transport sector's intermediate input decreases as regional trade is disrupted. The next highest are *Svc* and *Pman*, which are Hubei Province's pillar industries. The proportion of intermediate input loss in *Ene* is relatively small, as in the scenario without traffic disruption costs.

Affected by traffic disruptions, the ranking of the proportion of intermediate input loss in different regions also changes. Remote areas (NE, NW, and SW) have a higher proportion of intermediate input loss to Hubei, while the areas close to Hubei (YE and YZ) have a lower proportion. In other words, the longer the distance, the stronger the traffic disruptions' impact on interregional intermediate inputs.

4 Discussion

In this section, we conduct a sensitivity analysis of the marginal rate of transport cost. A marginal transport cost of 0% indicates the transportation network is fully functioning (not damaged); 10%, 30%, or 50% means that the transportation network is subject to varying degrees of damage.

Figure 9 illustrates the total intermediate input loss value from all regions to Hubei. With an increase in κ, the intermediate input loss value in various industries also increases. According to the distance between the blocks in the figure, *Pman*, *Rman*, and *Lman* are more sensitive to traffic disruptions. Figure 10 illustrates the marginal rate of transport

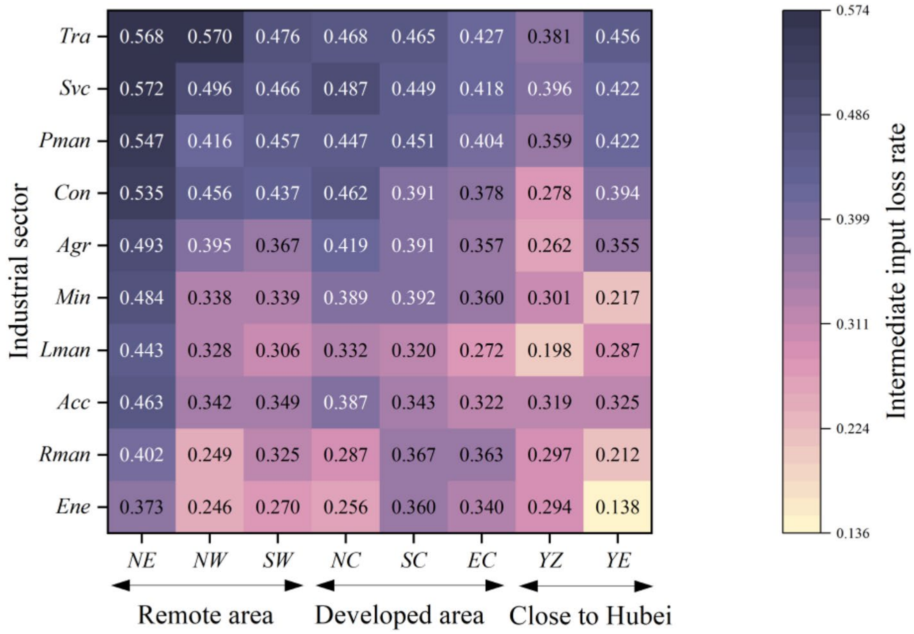


Fig. 8 Intermediate input loss rate from each region to various industries of Hubei considering traffic disruption costs (see Table 1 and Table 3 for sector and region abbreviations)

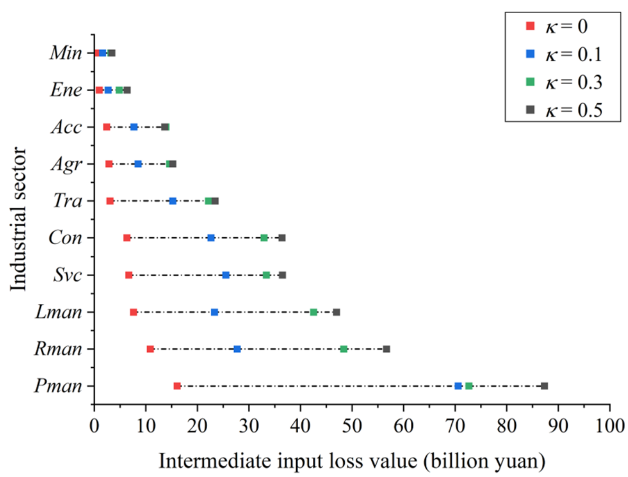


Fig. 9 Impact of marginal rate of transport cost on intermediate input loss value in different sectors (see Table 1 for sector abbreviations)

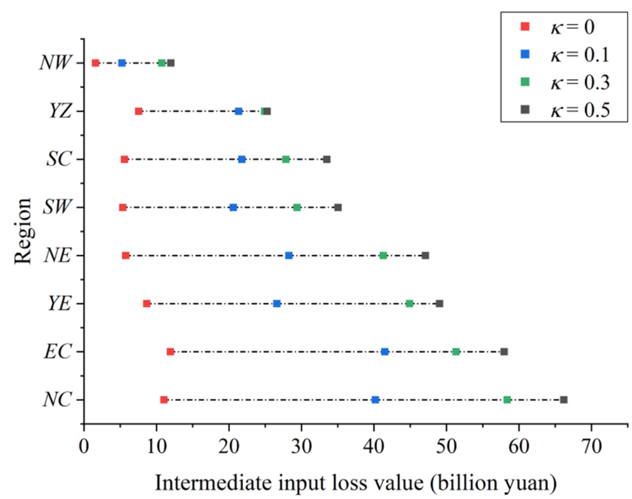


Fig. 10 Impact of marginal rate of transport cost on intermediate input loss value in different regions (see Table 3 for region abbreviations)

cost's impact on the intermediate input loss value in different regions, which increases with an increase in κ. The intermediate input from the eastern regions is more sensitive to traffic disruptions than that from the western remote regions. Moreover, the intermediate input in economically developed areas (NC, EC) is more sensitive to traffic disruptions than that in economically underdeveloped areas. Additionally, there is a critical state for intermediate input loss: as κ increases, the intermediate input loss value increases at a lower rate (the black square is very close to the green square in Fig. 10).

To summarize, the marginal rate of transport costs plays a critical role in regional trade activities. When κ is at 0%, the transport network is fully functioning. Thus, the gaps of intermediate input loss value between the points in Figs. 9 and 10 when marginal rates of transport costs are different, are considered the benefits of disaster prevention investments in the transportation system (Koike et al. 2015). As the marginal rate of transport costs increases, the drop value of the regional intermediate input gradually increases (prevention investment has a bigger impact on intermediate inputs). Notably, the intermediate input loss value does not increase indefinitely but gradually approaches a critical value because limitations in production value and economic structure prevent the intermediate input from declining indefinitely. Additionally, manufacturing industries are more sensitive to traffic disruptions, being more dependent on the supply of raw materials, semi-finished products, and finished products from other regions in the production process. Meanwhile, economically developed regions suffer larger impacts, mainly because they have closer economic ties to the affected area. For example, the automobile manufacturing industry in Hubei is closely related to the automobile manufacturing industry in EC.

5 Conclusion

Transportation infrastructure plays a key role in connecting regional economic exchange, especially under the current structure of regional differences in industrial layout. In disaster research, considering traffic disruption costs in the study of disasters' impact on regional economic ripple effects can provide theoretical support for the rapid and efficient recovery of regional industries, which has practical value and is worth exploring further. This study proposed an SCGE model to study regional ripple effects considering disaster-caused traffic disruption costs and applied the model to a practical case, with the following findings.

First, after increasing traffic disruption costs, the total output loss of non-affected areas is 1.81 times higher than before. Additionally, non-negligible output losses reach rather remote zones of the country, such as the Northwest Comprehensive Economic Zone, which comprises 36% of the total regional ripple loss after increasing traffic disruption costs. Further, developed areas with close economic ties to Hubei are greatly affected by general equilibrium effects, and remote areas are more affected by traffic disruption damage.

Second, traffic disruption significantly hinders regional trade activities, especially in terms of the regional intermediate input, from non-affected to affected areas. After increasing traffic disruption costs, total intermediate input loss is approximately three times higher—five times in transportation, storage, and postal service and 4.4 times in processing and assembly manufacturing.

Third, by comparison, the longer the distance, the stronger the traffic disruptions' impact on interregional intermediate inputs. The intermediate input drop rate is higher in remote areas (for example, Northeast Economic Zone, Northwest Comprehensive Economic Zone, and Southwest Comprehensive Economic Zone). Additionally, economically developed regions cannot be ignored; they have close economic linkages with Hubei Province.

In sum, we applied the SCGE model to show the interregional propagation of economic damage and included transportation disruption costs to more accurately capture the regional economic ripple effect of disasters. Nonetheless, some study limitations must be highlighted. First, the elasticity values of each part of the SCGE model were set based on previous research and the disaster economic theory, which may have led to some bias in the assessment of disaster ripple effects. Elasticity of substitution should be calibrated with more detailed regional empirical studies. Second, we took the economic zone as the smallest unit and only considered traffic disruption between regions, ignoring the impact of intra-regional traffic disruption. This may overlook industry ripple effect loss within the affected area, thereby underestimating disaster impact. Third, we singled out the disruption mode of highway transport, but in reality, firms may choose multi-modal transportation or flexibly change transportation methods, which may have led to disaster loss overestimation to some extent. In the future, the transportation mode selection mechanism can be considered in the model or conducted by coupling with other models, such as the agent-based model. Nevertheless, this study makes a valuable contribution by exploring the integration of transportation system analysis with economic modeling to assess regional economic ripple effects. Further, it enables improved observation of the economic impact path of disaster among various regions and sectors and detection of vulnerable and critical industrial sectors.

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