A dynamic disastrous CGE model to optimize resource allocation in post-disaster economic recovery: post-typhoon in an urban agglomeration area, China

Hongwei Li¹, Erqi Xu¹∗, Hongqi Zhang¹ and Shuai Zhong¹,²,³,⁴

¹ Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing 100101, People’s Republic of China
² Key Laboratory for Resource Use and Environmental Remediation, Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing 100101, People’s Republic of China
³ Key Laboratory of Carrying Capacity Assessment for Resource and Environment, Ministry of Natural Resources, Beijing 101149, People’s Republic of China
⁴ University of Chinese Academy of Sciences, Beijing 100049, People’s Republic of China

∗ Author to whom any correspondence should be addressed.
E-mail: xueqi@igsnrr.ac.cn

Keywords: dynamic disastrous computable general equilibrium (CGE) model, post-disaster recovery resources, allocation schemes, Super Typhoon Mangkhut, Guangdong Province, China

Abstract
Optimizing the allocation schemes of post-disaster recovery resources can promote the sustainable development of a regional economy. However, previous studies determined the inputs and allocation schemes of recovery resources based on direct economic (DE) loss while neglecting indirect economic (IDE) loss, which restricted economic recovery. This study considered DE and IDE loss, and used a dynamic disastrous computable general equilibrium (CGE) model to simulate multiple scenarios with different inputs and allocation schemes to identify a better economic recovery strategy. Taking Super Typhoon Mangkhut’s landing in Guangdong Province in 2018 as an example, the results showed that the IDE loss had a long-term impact and dynamic accumulation without post-disaster recovery, reaching 15.25 times the DE loss by 2022. In the baseline scenario, the recovery resource inputs, including relief funds, reconstruction funds, and natural disaster commercial insurance, were limited, leading to a cumulative loss recovery rate of less than 2% in 2018–2022. According to our findings, recovery resources needed a 15-fold increase to recover to pre-disaster levels. Considering the impacts of sector connections on IDE loss, six allocation schemes were established based on DE loss, IDE loss, and industrial structure. Compared with the typical allocation scheme based on DE loss, allocating recovery resources according to the diffusion coefficient substantially improved the loss recovery rate and recovery resource utilization efficiency. The dynamic disastrous CGE model conducted multi-scenario simulations to identify the optimal recovery resource allocation scheme that supported rapid and efficient post-disaster economic recovery.

1. Introduction
The frequent occurrence of extreme weather events caused by global warming has a large negative impact on the socio-economic system [1, 2]. Weak awareness of and insufficient investment in disaster prevention, ineffective disaster reduction technology, and urbanization further expand the economic impacts of natural disasters [3, 4]. The frequency of these natural disasters and the high populations and economic concentration in urban regions result in sharp increases of disaster losses, which restricts the sustainable development of urban areas [5–7]. Natural disasters often cause casualties, crop failures, housing destruction, and infrastructure damage, which have major impacts on socio-economic conditions [8, 9]. Direct economic (DE) losses of damaged sectors can affect other industries and even economic
stability, including production, consumption, investment, and employment, resulting in huge indirect economic (IDE) losses [10, 11]. Evidence shows that without post-disaster recovery measures, typhoons will have long-term negative effects on the economy [12]. Therefore, it is necessary to take post-disaster recovery measures to reduce the economic losses caused by typhoons and shorten recovery periods [13, 14].

Econometric models [15], input–output (IO) models [16], and computable general equilibrium (CGE) models [1] are common methods used in the quantitative analysis of post-disaster economic recovery measures. Econometric models cannot describe the interdependence among sectors and regions in disaster recovery, but IO and CGE models can [17–19]. However, IO models can only accelerate recovery by improving production capacity and cannot analyze the impacts of funds or technologies provided by the governments [20]. CGE models consider the economic behaviors of producers, consumers, and governments, and describe the transmission mechanisms of recovery measures in different economic sectors; this overcomes the drawbacks of IO models [21, 22]. Compared with econometric models, CGE models require less data [23]. Furthermore, many regression equations in econometric models can be replaced by equilibrium conditions based on microeconomic theory. CGE models can more easily compare recovery strategies in the same framework [24, 25], making them very useful for the simulation of post-disaster recovery measures [26]. Therefore, this study used a CGE model to simulate the economic impacts of post-disaster recovery measures.

Many researchers have used CGE models to simulate post-disaster economic recovery, and the impacts of these recovery measures vary based on disaster type, including earthquakes [26], hurricanes [27], floods [28], snowstorms [29], and volcanic eruptions [30]. Researchers have analyzed these economic impacts based on the sources and distributions of recovery resources and found that optimizing the recovery scheme can promote recovery [31, 32]. Comprehensive losses from a natural disaster include DE loss and IDE loss, which are also important references for developing a post-disaster recovery strategy [2]. With the rapid development of the socio-economy, the degree of interdependence among various sectors is growing, leading to greater IDE loss from natural disasters [29, 33]. The indirect impacts of natural disasters on the economy are long-term and have a dynamic cumulative effect [34]. However, current post-disaster economic recovery analyses are limited to examining DE loss; they do not consider IDE loss or, especially, the cumulative effects of the two [10]. This approach underestimates natural disaster losses and leads to a reduction in the inputs of recovery resources, which is not conducive to the overall recovery and development of socio-economies [13, 35, 36]. Therefore, it is necessary to consider the DE and IDE losses of natural disasters to determine the necessary recovery resources [37].

DE loss is not only the unique basis for estimating recovery resources but also the only standard currently used for resource allocation [1]. Recovery resource allocation is the key to ensuring stability and promoting economic recovery and development in disaster areas [26]. However, using a single allocation model leads to an inefficient allocation of recovery resources, which makes post-disaster decision-making difficult in diverse situations. How to make full use of various resources to help the affected economies recover quickly and efficiently has become an urgent problem for local governments [38]. Therefore, it is necessary to reasonably allocate recovery resources under the guidance of a sustainable development strategy and on the premise of fully considering the recovery needs of damaged sectors to promote the overall recovery of the post-disaster economy. Economic loss is an important basis for allocating recovery resources [13, 34]. Aside from DE loss, IDE loss and comprehensive economic loss should also be included in the allocation criteria of recovery resources. Given the increasing interdependence among sectors, recovery resource allocation tends to the sectors that have a greater driving effect on economic development, promoting rapid economic growth [39, 40]. Because there are limited resources for post-disaster recovery, how to coordinate economic loss and industrial structure characteristics to explore the optimal resource allocation strategy is of great significance to effective recovery.

This study used a dynamic disastrous CGE model to measure IDE loss while considering DE loss and economic structure. The authors carried out a multi-scenario simulation of different inputs and allocation schemes for recovery resources to identify the optimal recovery strategy and improve the post-disaster economic loss recovery rate. Super Typhoon Mangkhut, which landed in Guangdong Province, China, in 2018, was selected as the research object to test the model. Our results provide flexibility for decision-making in different disaster situations and have important implications for government decision-makers creating recovery policies that reduce economic losses from natural disasters.

2. Materials and data

2.1. Case introduction
Super Typhoon Mangkhut (hereafter Mangkhut) was the strongest typhoon to land in China in 2018. According to statistics from the Ministry of Emergency Management, Mangkhut affected 835 towns and villages of 21 cities and 3.07 million people in Guangdong Province. Furthermore, 1441 houses were seriously damaged, the affected crop area reached 0.23 million hectares, and the tangible assets
Figure 1. Tangible assets losses as a result of Super Typhoon Mangkhut in Guangdong Province.

losses amounted to US$1.99 billion (figure 1). In response to Mangkhut, Guangdong Province issued a typhoon red warning signal and launched the provincial level IV disaster relief emergency response. According to regulations of Guangdong Province on issuing early warning signals of hidden meteorological disasters, suspending classes and stopping work, business, and production are required. For the first time in years, Guangdong Province took the above measures to deal with the typhoon, which had a significant impact on the economy and provided the basic data for this study.

2.2. A dynamic CGE model

The Guangdong Province dynamic disastrous (GDD) CGE model was composed of six modules—the production, trade, household, government, closure, and recovery and dynamic modules (figure 2)—and its specific structure was shown in appendix A. The GDDCGE model in this study was based on the General Algebraic Modelling System (v25.1.3) software, which converts the mathematical formula into computer language for modeling and simulation analysis [1].

The economic impacts of disaster losses and recovery measures were set as the loss and recovery of capital stock, respectively [26, 41]. In this study, DE loss was defined as the sum of tangible asset losses and direct business interruption losses [10, 36]. According to the statistics from the Ministry of Emergency Management, Mangkhut caused a tangible asset losses of the primary industry in Guangdong Province that reached US$0.89 billion. As tangible assets losses in other industries still lack data, this study did not consider them. Direct business interruption losses refer to the production losses caused by business interruption in secondary and tertiary industries because of the direct impact of typhoons, such as strategic shutdowns before and during disasters [35, 42]. In response to Mangkhut, Guangdong Province suspended school, work, business, and production for about one day to reduce the impact of the disaster. Therefore, the daily average gross domestic product (GDP) of the secondary and tertiary industries in Guangdong Province in 2017 was taken as the direct business interruption losses (table B.1). In the GDDCGE model, DE loss was measured by capital stock impact to simulate the indirect impact of Mangkhut in 2018.
Post-disaster recovery measures include government natural disaster relief funds (hereafter ‘relief funds’), post-disaster reconstruction funds, and natural disaster commercial insurance. Relief funds are generally provided by local governments and are mainly used to maintain the normal lives of affected residents and to repair or rebuild damaged houses, which speeds up the recovery of consumer demand. Reconstruction funds and natural disaster commercial insurance can restore the damaged capital stock across sectors. According to China’s post-disaster recovery practice, damaged houses should be completely repaired or rebuilt at the end of the disaster year. Therefore, relief funds can recover some of the capital stock losses of the disaster year (2018, in this study). Reconstruction funds and natural disaster commercial insurance are invested during the disaster year (2018) and form capital stock in the second year (2019).

The GDDCGE model assumed that labor and technology had progressive and fixed growth rates (equations (1) and (2)). The capital stock accumulated and tended toward sectors with high yields (equations (3) and (4)). In the dynamic module, the study set a capital depreciation rate of 0.05 for each sector and adopted recursive dynamics (equation (5)) [28, 43]:

\[ L_{S_{t+1}} = (1 + \gamma) \times L_{S_t} \]  
(1)

\[ \varphi_{t+1} = (1 + \sigma) \times \varphi_t \]  
(2)

\[ \alphaINV_i = \frac{INVZ_i}{\sum_{i=1} INVZ_i} \times \left( \frac{PK_i}{\sum_{i=1} (PK_i \times KS_i)} \right)^{0.5} \]  
(3)

\[ INV_i = \alphaINV_i \times INV \]  
(4)

\[ K_{i,t} = (1 - \delta) \left( K_{i,t-1} - \text{Dam}_{i,t-1} \right) + INV_{i,t-1} + RC_{\text{relief},i,t-1} + RC_{\text{fund},i,t-1} + RC_{\text{insurance},i,t-1} \]  
(5)

where, \( \gamma \) denotes the growth rate of labor, \( \sigma \) denotes the growth rate of total factor productivity, \( \alphaINV_i \)
denotes the investment allocation rate for sector $i$, $\text{INV}_t$ denotes the investment of sector $i$ in the base period, $\text{INV}_i$ denotes investment of sector $i$, $\delta_i$ denotes the depreciation rate of capital, $K_{i,t}$ denotes the capital of sector $i$ in year $t$, $K_{i,t-1}$ denotes the capital of sector $i$ in year $t-1$, $\text{Dam}_{i,t-1}$ denotes the damage of sector $i$ in year $t-1$, $\text{RC}_{\text{relief},i,t-1}$ denotes the relief funds of sector $i$ in year $t-1$, $\text{RC}_{\text{fund},i,t-1}$ denotes the reconstruction funds of sector $i$ in year $t-1$, and $\text{RC}_{\text{insurance},i,t-1}$ denotes commercial insurance claims for natural disasters of sector $i$ in year $t-1$.

### 2.3. The social accounting matrix (SMA) and model parameters

An IO table is a major basis for creating a SAM table. Beginning with the IO table for Guangdong Province in 2017 issued by the Guangdong Provincial Bureau of Statistics, nonproductive accounts were added, including households, local and central government, the rest of China, and the rest of the world. The model assumed that the IO relationships among sectors were stable. Additional statistical data for the construction of the SAM were obtained from the Guangdong Statistical Yearbook 2018, China Statistical Yearbook 2018, Finance Yearbook of China 2018, and China Taxation Yearbook 2018. To remove errors caused by the use of different data sources, the RAS method was used to balance the macroscopic SAM (table B.1). To provide more information about the socio-economic structure of the study area, we divided the activity and commodity account of the macroscopic SAM into 40 sectors (table B.1) to obtain the microscopic SAM.

The SAM provided a data set describing all economic indicators in the basic year included in the CGE model. The share parameters in the CGE model were directly calculated by the SAM, including some parameters reflecting the behavior of manufacturers, consumers, and governments. The other elastic parameters in the functions—the linear expenditure system (LES) function, constant elasticity of substitution (CES) function, and constant elasticity of transformation (CET) function—were set based on previous research. The income elasticity in the LES function was set at 0.7 [44], and its Frisch parameter was set as $-2$, according to the affluence of Guangdong Province. The substitution elasticity of labor and capital in the CES production function was used based on the research results of Dong et al [45], Su et al [46], Zhai and Hertel [47]. The substitution elasticity parameters of the CES and CET functions in the trade module were based on the findings of Yuan [48]. The values of the elastic parameters are shown in table D.1.

Because the CGE model relies on various economic assumptions, equilibrium assumptions and closure assumptions, it needs to be verified to ensure its accuracy [49, 50]. First, the SAM constructed in this study reached balance after being adjusted by the SAR method. Second, when the benchmark price was set to 1, the set of solutions reached by solving the benchmark CGE model were the same as the benchmark data. Third, based on the second step, when all benchmark prices were expanded or reduced by a proportion at the same time, the values of all price variables expanded or reduced by the same proportion while the values of all quantitative variables were unchanged. Finally, the uncertainties of exogenous elastic parameters might have affected the simulation results. Therefore, based on the method proposed by Ling et al [34] and Mahmood and Marpaung [51], a sensitivity analysis of these elastic parameters was performed. The results showed that when these elastic parameters increased or decreased by 20%, the rate of change of economic indicators was small (appendix E); this indicated that the simulation results were less sensitive to elastic parameters. To summarize, the GDDCGE model constructed in this study is reliable and can be used for simulation analyses of post-disaster economic recovery policies.

### 2.4. Scenario design

The input and distribution of post-disaster recovery resources have important impacts on economic development [16, 26]. Although increasing recovery resources can restore the damaged capital stock of various sectors, the economic recovery effects need to be quantified. In addition, as the linkages among sectors become closer as a city develops, the economic impact of typhoons often spreads to all sectors [1, 28]. How to efficiently allocate the limited resources among various sectors is of great significance for the rapid recovery of city economies after natural disasters. Therefore, this study analyzed the impact of recovery resource inputs and their allocation on post-disaster economic recovery in a multi-scenario simulation. The natural disaster prevention and mitigation plan in China is generally designed on a five-year basis, mainly because this enhances the pertinence and flexibility of plans. To provide reference for the plan’s formulation and related decision-making, we set the period for the simulation to five years.

Three basic scenarios were established in this study (figure 3): a scenario without a disaster (S0), a scenario with a disaster but without recovery (S1), and a scenario with a disaster and recovery (S2). We collected and reorganized some news about Guangdong Province during the post-disaster recovery stage following Mangkhut. The main post-disaster recovery measures were identified, including providing subsidies to the affected residents, helping the damaged enterprises to resume production, urging insurance compensation, and others. Then, scenario S2 was divided into a relief funds scenario (S2.1), a reconstruction funds scenario (S2.2), a natural disaster commercial insurance scenario (S2.3), and a comprehensive scenario including the above...
three inputs (S2.4). By comparing these scenarios, the influences of the various scales of inputs and recovery strategies on economic recovery can be obtained.

Further, we identified the amount of loss recovery that can be achieved with one unit of disaster recovery resources to allocate recovery investments more reasonably. Return on investment (ROI) refers to the ratio of input to total output over a period of time. At present, Guangdong Province only invests in post-disaster recovery resources during the year the disaster occurred, but post-disaster economic recovery takes a long time. Therefore, compared to indicators such as total output and payback period, the ROI is a more suitable measure of recovery resource utilization efficiency across temporal ranges [52]. In this study, the ROI was equal to the ratio of recovery resource inputs to the cumulative reduction in economic loss during the simulation period; the smaller the ROI, the better the economic effect.

To analyze the influence of the scale of inputs, four levels of recovery resources were established. Level 1 was the baseline scenario of recovery resource inputs, and levels 2, 3, and 4 increased from the baseline by 25%, 50%, and 100%, respectively. Referring to the disaster-affected populations and the relief fund standards as outlined in measures of Guangdong Province for the administration of living relief funds for natural disasters, the relief fund for Mangkhut was US$87.30 million; this served as the baseline scenario in S2.1. The Law of the People’s Republic of China on the administration of tax collection and enterprise income tax law provides preferential taxes for enterprises to promote their economic recovery. However, most enterprises refuse to accept these tax credits in order to help government revenues, so that they can be awarded extra financial support from the governments [53]. Therefore, this study assumed 1% of the tax payable for DE loss (approximately US$64.50 million) as the baseline scenario for reconstruction funds (S2.2) [54]. Scenario S2.3 assumed that all sectors had natural disaster commercial insurance. In the baseline scenario, the primary industry’ insurance paid US$63.75 million, which was counted by the Guangdong Banking and Insurance Regulatory Commission. Because few secondary and tertiary industry companies purchase business interruption loss insurance in China [55, 56], this study assumed that insurance could compensate 1% of direct business interruption losses, or approximately US$35.40 million. The baseline scenario for S2.4 (approximately US$250.95 million) was obtained when the baseline scenarios of S2.1, S2.2 and S2.3 were implemented simultaneously.

We considered six allocation schemes of recovery resources in the analysis of the recovery strategies.


| Scenario | Description |
|----------|-------------|
| DE | Distribution according to DE loss |
| IDE | Distribution according to ID loss |
| DE&IDE | Distribution according to the sum of direct and ID loss |
| DC | Distribution according to the diffusion coefficient (DC) (the impact on production demand of each sector when sector \( i \) adds a unit of final product) |
| IC | Distribution according to the inducing coefficient (IC) (the impact on production demand of sector \( i \) when each sector adds a unit of final product) |
| OP | Distribution according to the total output in the IO table (2017) |

(table 1) and applied them to the baseline scenarios in S2.2 and S2.3. The recovery resources provided in different allocation schemes were all less than the DE losses. As the Chinese government’s natural disaster relief funds are earmarked for special use, its distribution scheme is fixed [3]. Therefore, this study does not consider the additional allocation scheme of S2.1.

3. Results

3.1. Economic impact of Super Typhoon Mangkhut in Guangdong Province

This study used the change of GDP (i.e. the sum of total capital income, total labor income and indirect tax income) to characterize the IDE loss (figure 4). Examining the short-term impact of Mangkhut in 2018, compared to the scenario without a disaster (S0), the GDP of Guangdong Province in the scenario with a disaster but without recovery (S1) decreased by 1.01%, which was 3.37 times the DE loss (figure 4(a)). Compared to S0, all sectors in scenario S1 had IDE (figure 4(c)), among which the construction sector (SEC26) suffered the largest loss, reaching US$1296.89 million, while the mining and dressing of metal ores and coal sector (SEC3) had the smallest loss, at US$11.92 million. Sector economic losses caused by Mangkhut also reduced the incomes of governments and residents (figure 4(b)). Compared to S0, the per capita fiscal revenues of the local and central governments in S1 lost 0.99%, which was US$14.10 and US$10.26, respectively. The per capita savings and per capita incomes of residents declined 0.97%, and the per capita income loss of residents was approximately 8.09 times the per capita fiscal income loss of local governments; this demonstrated that typhoons have a clear impact on residents’ property.

In the long term, in the absence of post-disaster recovery measures, the IDE loss caused by Mangkhut in Guangdong Province would continue to expand. By 2022, the cumulative GDP loss reached US$67.61 billion, or 15.25 times the DE loss. Therefore, it is necessary to consider the long-term impacts of IDE loss from natural disasters on regional economic development. The average annual IDE loss rate varied little across sectors, with the public administration and social organizations sector (SEC40) having the highest loss rates (1.01%), and the manufacture of transport equipment sector (SEC17) having the lowest loss rate (0.75%).

3.2. Impact of resource inputs

Using the same allocation scheme, figure 5 illustrated the impacts of different recovery resource inputs on economic recovery. Government natural disaster relief funds were distributed according to the proportion of residents’ consumption (RC) in the relief funds scenario (S2.1). Post-disaster reconstruction funds were allocated according to the proportion of DE loss in the reconstruction funds scenario (S2.2). In the natural disaster commercial insurance scenario (S2.3), insurance claims for the primary industry were paid to SEC1, and the compensation for business interruption insurance was distributed according to the proportion of DE loss in the secondary and tertiary industries. Economic recovery in S2.2 and S2.3 did not begin until 2019 because reconstruction funds and natural disaster commercial insurance could not form capital stock until the year following the disaster. The loss recovery rate of capital stock formed by recovery resources was the highest in the first year and then gradually decreased. Taking scenario S2.1 as an example, the recovery rate of economic loss was 0.43% in 2018 and decreased to 0.32% in 2022 when the inputs in the baseline scenario were valued at US$87.30 million.

With the increase of post-disaster recovery resources input, the economic loss recovery rates increased gradually (figure 5). In the baseline scenario, compared to S1, the cumulative loss recovery rates for S2.1, S2.2, S2.3, and S2.4 were 1.91%, 1.27%, 1.37%, and 4.55%, respectively; the corresponding inputs were US$87.30 million, $64.50 million, $99.15 million, and $250.95 million. When the amount of recovery resources increased to level 4, the cumulative loss recovery rates increased to 3.82%, 2.55%, 2.74%, and 9.10%, respectively. Therefore, economic recovery can be effectively promoted by increasing recovery resources. According to the simulation results, in the comprehensive scenario (S2.4), the economic level of Guangdong Province returned to pre-disaster levels in 2019 when recovery resources increased to US$4.14 billion, which was approximately 16.50 times the input in the baseline scenario. In terms of recovery resource utilization efficiency, the ROI of different resource input scenarios were basically stable (figure 6). When recovery resources increased, the ROI of S2.1, S2.2, and S2.4 decreased slightly, while that of S2.3 increased slightly, but
the range of change was small. Recovery resource utilization efficiency was ranked S2.1, S2.2, and S2.3 in descending order, with ROIs of 6.76%, 7.50%, and 10.72% in the baseline scenarios, respectively.

3.3. Impact of allocation schemes
The economic loss recovery rate varied across allocation schemes (figure 7). In the baseline scenario, when recovery resources were allocated according to...
Figure 6. Return on investment in scenarios with different resource inputs. Level 1 is the basic input, and levels 2, 3, and 4 increase the baseline by 25%, 50%, and 100%, respectively.

Figure 7. Cumulative loss recovery rates and returns on investment for allocation schemes in the baseline scenario in S2.2 (a) and S2.3 (b), 2018–2022.

the DC, S2.2 and S2.3 had the largest cumulative loss recovery rates, reaching 3.15% and 2.33%, respectively; their recovery resource utilization efficiency were the highest, with ROIs of 3.03% and 6.29%, respectively. Therefore, it is necessary to consider increasing recovery resources in sectors with a higher DC to improve recovery resource utilization efficiency. In S2.2 and S2.3, the allocation schemes with the lowest loss recovery rates and recovery resource utilization efficiency were related to DE loss and IDE loss, with cumulative loss recovery rates and ROIs of 1.27%/1.36% and 7.50%/10.81%, respectively. The loss recovery rate and recovery resource utilization efficiency of the allocation schemes were ranked in the following order, from largest to smallest: DC, IC, OP, IDE, DE&IDE, and DE in S2.2 (figure 7(a)) and DC, IC, OP, DE, DE&IDE, and IDE in S2.3 (figure 7(b)). During post-disaster recovery, the appropriate allocation scheme can be selected according to the recovery resource types and target need.

The loss recovery rate of each sector varied by allocation scheme (figure 8). When recovery resources were allocated according to the DC in S2.2 and S2.3, the cumulative loss recovery rate of most sectors was the largest among all allocation schemes; only the recycling and disposal of waste (SEC21) was the smallest, reaching −0.03% and 0.57%, respectively. When recovery resources were allocated according to the DC and the IC, the cumulative loss recovery rates of the sectors changed greatly, and the trend was similar, while there were few differences in the other distribution methods. Using the DC and IC, the manufacture of communication, the computers and other electronic equipment (SEC19; S2.2) and the manufacture of food and tobacco (SEC5; S2.3) were the sectors with the highest cumulative loss recovery rates, and SEC21 (S2.2 and S2.3) had the lowest cumulative loss recovery rate. The results showed that the cumulative loss recovery rates of sectors varied by recovery resource type and allocation scheme. Therefore,
it is necessary to focus on the sectors with lower loss recovery rates to promote economic recovery.

3.4. Impact on macroeconomic indicators
Aside from the interactions among sectors, the GDCCGE model can also analyze the incomes and expenditures of residents and governments (figure 9). Compared with S1, due to the input of post-disaster recovery resources, residents’ incomes, government revenues, and government consumption increased, while residents’ consumption decreased and gradually returned to the pre-disaster level in S2.2 and S2.3. The higher the cumulative loss recovery rate of the allocation scheme, the larger the rate of change of the macroeconomic indicators. The post-disaster recovery resources promoted the production activities of all sectors, which increased residents’ incomes and government revenues. Using the DC, residents’ incomes and government revenues increased by 3.16% for both in S2.2, and they increased by 2.33% and 2.34%, respectively, in S2.3. Compared with S0, the per capita consumption of residents increased by US$0.46 for ensuring normal living needs without recovery investments in S1. When post-disaster recovery resources were invested, the local and central governments increased consumption to provide material support, which reduced the consumption of residents. Using the DC, residents’ consumption decreased by 2.85% and government consumption increased by 3.16% in S2.2; in S2.3, the corresponding changes were 7.52% and 2.23%. To summarize, post-disaster investment exerts positive effects on the recovery of incomes and government revenues. The basic quality of life of residents after the disaster still needs attentions.

4. Discussion
4.1. Multi-scenario simulation of post-disaster recovery resources
Rapid and effective post-disaster recovery is the key to ensuring economic recovery and social stability in disaster areas [14, 26]. Previous studies have determined the inputs and allocation schemes of recovery resources using one variable, typically DE loss, which led to insufficient input of recovery resources and low of recovery resource utilization efficiency [26, 28]. Considering the comprehensive economic loss and sector linkages, this study enriched the criteria for inputs and allocation schemes of recovery resources.
By comparing and analyzing multi-scenario simulation results, the optimal strategy of economic recovery was identified; this was an important reference for improving the economic recovery rate of Guangdong Province.

In our study, Mangkhut had a long-term negative impact on economic development and dynamic accumulation [11, 12]. Post-disaster recovery resources had a positive impact on economic recovery [28, 58], and the cumulative loss recovery rate of the baseline scenario in S2.4 (comprehensive scenario) was 4.55% from 2018 to 2022. Moreover, when recovery resources were increased to level 4 in S2.4, the loss recovery rate reached 9.10%. That is, increasing post-disaster recovery resources improves the loss recovery rate, which is consistent with the findings of previous research [40, 59]. When recovery resources are limited, we need to innovate allocation scheme to improve recovery resources utilization efficiency [41]. We found that the loss recovery rate and recovery resource utilization efficiency of the DC in S2.2 and S2.3 was higher compared to the DE. The sectors with a large DC have a strong driving effect on the production of other related sectors. When the recovery resource allocation tended to these sectors, the radiation effect stimulated the economic recovery of other sectors. Therefore, in future post-disaster recovery, more attention should be paid to sectors with a high DC.

Compared to S0, the per capita fiscal revenues of local governments in S1 declined 0.99%, which was US$14.10. Local government’s fiscal revenues were less damaged by Mangkhut, which did not affect the overall post-disaster recovery process of Guangdong Province [26]. In the post-disaster recovery stage, the revenues and consumption levels of local governments improved continuously; this not only allowed governments to maintain their operation, but also ensured social stability and residents’ emotional stability [16, 54]. In terms of social activities, residents’ consumption was mainly concentrated in education (SEC37), health, social security and social welfare (SEC38), culture, sports and recreation (SEC39), and public administration and social organizations (SEC40) in the post-disaster stage. But residents’ consumption before the disaster was mainly concentrated in farming, forestry, animal husbandry and fishery (SEC1), manufacture of food and tobacco (SEC5), transport, storage and postal services (SEC28), and hotels and catering services (SEC29), indicating that Mangkhut created inconveniences for local people to obtain clothing, food, housing, and transportation and it reduced their quality of life temporarily [35, 60]. Therefore, to ensure the normal lives of the affected residents, the local government should carry out post-disaster recovery measures in a timely fashion [3, 26, 61]. Still, the above cannot cover all the social impacts of post-disaster recovery measures, and
how to establish a complete social impact analysis still needs to be studied.

4.2. Optimizing the resource allocation strategy for economic recovery

During post-disaster recovery, the fairness of the allocation of recovery resources should be considered along with recovery resource utilization efficiency and the loss recovery rate [62]. However, Guangdong Province only realized the fairness of allocation, that is, it allocated recovery resources according to DE loss, resulting in low loss recovery rate in the baseline scenarios. When the baseline input increased to US$4.14 billion, the economic level of Guangdong Province returned to pre-disaster levels in 2019. However, it is difficult for local finances to bear such a high level of post-disaster recovery resources.

This study innovated allocation schemes to achieve a higher loss recovery rate and recovery resource utilization efficiency using limited recovery resources. The results showed that the loss recovery rate and recovery resource utilization efficiency were the highest when recovery resources favored the sectors with a higher DC. As both relief funds and reconstruction funds come from government finances, their amount and use are greatly limited, while natural disaster commercial insurance is more flexible [63]. To ensure fairness, S2.1 should continue to be used to maintain the normal lives of affected residents and to repair or rebuild damaged houses. S2.2 should be allocated according to DE loss to recover production in damaged sectors, and S2.3 should use the allocation scheme that can improve the loss recovery rate and recovery resource utilization efficiency. Business interruption insurance is an important part of natural disaster commercial insurance, which plays an important role in ensuring the stable development of enterprises and promoting post-disaster economic recovery [64]. Business interruption insurance, as an additional policy of enterprise property insurance, composes a very small share of the insurance market in China and fails to fully stabilize enterprise production and operations [65]. With frequent typhoons, reasonable shutdowns are an effective response measure, but this causes huge losses to all industries. However, the scope of liability of business interruption insurance in China is confined to the loss of profit caused by material loss, and it does not compensate for the business interruption losses caused by government administrative orders [66].

We should therefore pay more attention to business interruption insurance, improve its coverage, and clarify its underwriting scope, which is an inevitable requirement to ensure the rapid economic recovery of all sectors [67]. First, the use of business interruption insurance should be maximized. Guangdong Province has the most frequent typhoon landings and the most developed economy in China. Frequent shutdowns create numerous restrictions on the economic development of Guangdong Province, making business interruption insurance necessary to maintain the production and operation of each sector. Guangdong Province could conduct a pilot project in the coastal areas most affected by typhoons to assess the feasibility of the approach. Second, business interruption insurance coverage in sectors with a large DC must be improved. In the current economic structure of Guangdong Province, the sectors with a larger DC are concentrated in the secondary industry, mostly equipment manufacturing, which is the core of the industry (figure 10). Moreover, the sectors with a large DC also have a large IC. Therefore, after resuming production through business interruption insurance, the double-high sectors can boost the economic recovery of other sectors through their industrial links. Third, local governments must take more responsibility in promoting the development of business interruption insurance. Because a shutdown is an important strategy for local governments to deal with typhoons, and the effects of typhoon landings are uncertain, it is difficult for insurance companies to fully bear these risks.

4.3. Limitations and future research

Different disaster loss shocks were simulated in the GDDCGE model to obtain different IDE losses. China's statistics on tangible assets losses caused by natural disasters are vague, making it difficult to cover all sectors. Therefore, this study only considered the tangible assets losses in the primary industry and ignored other sectors. When simulating the loss impacts of typhoons, the lack of tangible assets loss data in the secondary and tertiary industries may have resulted in the underestimation of comprehensive loss. The question of whether the simulation results for the post-disaster recovery resources change if there is enough data on tangible assets losses requires further investigation. In addition, the CGE model is not only a macro model, which makes it difficult to describe the micro part of the economic system, but also a counterfactual model, which cannot be verified by the data [26, 50]. We only considered the impacts of natural disasters and recovery investments in the model, so the results can only provide reference for post-disaster recovery in the future [2, 68]. However, the effects of these measures still needs to be verified in practice.

The method and allocation schemes in this study can be applied to other provinces or countries to determine the basic direction of post-disaster recovery from a macro perspective. If the economic and natural disaster loss data are sufficient, the dynamic disastrous CGE model can also be used to simulate...
The post-disaster economic recovery of cities or even counties, obtaining a more detailed and targeted post-disaster recovery strategy. Integrated assessment models are used to evaluate the DE losses due to long-term climate change [69, 70]. Climate change scenarios only consider temperature and precipitation, which can be applied to low-temperature disasters, high-temperature disasters, droughts, and floods [2, 71]. However, the DE losses of typhoon disasters are often the result of the joint action of multiple factors, such as precipitation, wind, and storm surge. Therefore, if the relationship between typhoon variables (frequency, intensity etc) and DE loss, or recovery measures and recovery investments, can be constructed through other models or methods, the GDDCGE model can simulate and analyze the post-disaster economic recovery under the long-term impact of climate change with different strategies, thereby supporting local governments.

An additional scenario based on the impacts of climate change is established (S3; table 2). Although fewer typhoons are now hitting China’s southeast coast, their intensity has increased as a result of climate change and is expected to continue to increase in the future [72]. Using the function of typhoon intensity grade and DE loss rate constructed by Yin et al [73], this paper predicted the DE losses with the increase of typhoon intensity based on the Mangkhut and then executed our dynamic disastrous CGE model. When the typhoon intensity of Mangkhut increased by 50%, the DE loss rate was 3.7 times that of Mangkhut. To minimize the impact of the assumption on future economic evolution, we assumed that this typhoon landed in Guangdong Province in 2018 and caused a DE loss of about US$16.41 billion [74, 75]. The cumulative IDE loss of the typhoon was about US$246.04 billion, as assessed by the GDDCGE model from 2018 to 2022. The recovery resource inputs of S3 were about US$0.85 billion, which was twice the baseline scenario of the recovery resources input in S2.4. The results showed that the largest cumulative loss recovery rate was 8.45% when reconstruction funds and natural disaster commercial insurance were allocated.

Table 2. Description of post-disaster economic recovery in S3. RC, DE, IDE, DC, IC, and OP, respectively, indicate that recovery resources are allocated according to the proportion of residents’ consumption, DE loss, IDE loss, DC, IC, and total output.

| Scenario   | Allocation scheme | S.1 | S.2 | S.3 | Scenario   | Allocation scheme | S.1 | S.2 | S.3 |
|------------|-------------------|-----|-----|-----|------------|-------------------|-----|-----|-----|
| S3-DE      | RC                | DE  | DE  |    | S3-DC      | RC               | DC  | DC  | DC  |
| S3-IDE     | RC                | IDE | IDE |    | S3-IC      | RC               | IC  | IC  | IC  |
| S3-DE&IDE  | RC                | DE&IDE | DE&IDE |    | S3-OP      | RC               | OP  | OP  | OP  |

Figure 10. Ranking of DC and IC in sectors.
based on the DC, which proved the effectiveness of the model (figure 11).

5. Conclusion

In this study, we innovated standards for setting the inputs and allocation schemes of post-disaster recovery resources; we use the dynamic disastrous CGE model to conduct multi-scenario simulations. When there were no post-disaster recovery measures, the IDE loss caused by Mangkhut in Guangdong Province broadened. By 2022, the cumulative GDP loss reached US$67.61 billion, approximately 15.25 times the DE loss. At present, Guangdong Province's recovery resources inputs and allocation schemes are not ideal for post-disaster recovery. In the baseline scenario, compared to S1, the cumulative loss recovery rates of S2.1, S2.2, and S2.3 were 1.91%, 1.27%, and 1.37%, respectively. The simulation results for the allocation schemes showed, with under the condition of limited recovery resources, the loss recovery rate and recovery resource utilization efficiency were highest when recovery resources were allocated according to the DC. Compared to the DE loss, the loss recovery rate of the DC in S2.2 and S2.3 increased by 147.82% and 70.40%, and the recovery resource utilization efficiency increased by 59.65% and 41.79%, respectively. According to this study, the best comprehensive post-disaster economic recovery scenario was when S2.1 maintained the normal lives of affected residents on the basis of relief fund standards, and when S2.2 and S2.3 allocated recovery resources based on the DC. Our results demonstrate the importance of increasing recovery resources and optimizing their allocation schemes to improve post-disaster economic recovery.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Acknowledgments

This work was supported by the National Key R&D Program of China (2017YFC1503003, 2018YFC1508801) and Youth Innovation Promotion Association CAS (2021052).

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Equation system of the GDDCGE model

The GDDCGE model was composed of the production, trade, household, government, closure, and recovery and dynamic modules, whose structure is described in figure 2. This appendix illustrates the specific features of the GDDCGE model [1, 49].

A.1. Production module

With the constraints of existing production technology, manufacturers determine the optimal inputs according to the principle of cost minimization. This module adopted two layers of a nested structure. On the left side of the top layer, labor ($L$) and capital ($K$) were combined with added value ($Q_{V_i}$) by the CES
production function (equation (A.1)). On the right side of the top layer, raw materials (QM_i) were combined with intermediate input (QX_i) by the Leontief function (equation (A.2)). On the bottom layer, the Leontief function was used to synthesize intermediate input and added value into the total output of each department (QX_i) (equations (A.3) and (A.4)).

$$QV_i = \varphi_i^{LK} \times \left( \beta_{L,i} \times L_i^{\frac{1}{\gamma_i}} + \beta_{K,i} \times K_i^{\frac{1}{\gamma_i}} \right)^{\frac{\gamma_i}{\gamma_i - 1}}$$  \hspace{1cm} (A.1)

$$QM_{c,j} = \sum_{c=1}^{n} a_{c,i} \times QM_i$$  \hspace{1cm} (A.2)

$$QV_i = \text{iva}_i \times QX_i$$  \hspace{1cm} (A.3)

$$QM_i = \text{ima}_i \times QX_i$$  \hspace{1cm} (A.4)

where, \( L_i \) denotes the labor in sector \( i \). \( K_i \) denotes the capital in sector \( i \). \( QV_i \) denotes the added value in sector \( i \). \( QM_{c,j} \) denotes the intermediate input of sector \( i \), which provided by sector \( c \). \( QM_i \) denotes the intermediate input of sector \( i \). \( QX_i \) denotes the total output of sector \( i \). \( \varphi_i^{LK} \) denotes the efficiency parameter of sector \( i \). \( \varepsilon_i^{LK} \) denotes the substitution elasticity of labor and capital in sector \( i \). \( \beta_{L,i} \) and \( \beta_{K,i} \) denote the share coefficients of labor and capital in sector \( i \), meeting \( \beta_{L,i} + \beta_{K,i} = 1 \). \( a_{c,i} \) denotes the consumption coefficient of sector \( c \) to sector \( i \). \( \text{iva}_i \) denotes the added value rate of sector \( i \). \( \text{ima}_i \) denotes the intermediate input rate of sector \( i \).

A.2. Trade module

The trade module described the commodity trading process. This module adopted two layers of a nested structure with the CET function to describe the distribution of outputs. On the first layer, the outputs were the optimal combination of domestic sale and export sale (equation (A.5)) that maximized revenue; on the second layer, the domestic sale consisted of Guangdong Province’s sales and the rest of China (equation (A.6)). The Armington hypothesis was used to describe the incomplete substitution between imported supply and domestic supply. A two-layer nested structure with the CES function was used to synthesize the supply. On the first layer, the supply was the optimal combination of domestic products and export products (equation (A.7)) that minimized costs; on the second layer, the domestic products consisted of Guangdong province’s supply and the rest of China (equation (A.8)):

$$QX_i = \varphi_i^{NEX} \times \left( \beta_{E,i} \times QE_i^{\frac{\gamma_i}{\gamma_i - 1}} + \beta_{NX,i} \times QNX_i^{\frac{\gamma_i}{\gamma_i - 1}} \right)^{\frac{\gamma_i}{\gamma_i - 1}}$$  \hspace{1cm} (A.5)

$$QNX_i = \varphi_i^{NNE} \times \left( \beta_{NI,i} \times QNI_i^{\frac{\gamma_i}{\gamma_i - 1}} + \beta_{NE,i} \times QNE_i^{\frac{\gamma_i}{\gamma_i - 1}} \right)^{\frac{\gamma_i}{\gamma_i - 1}}$$  \hspace{1cm} (A.6)

$$QX_i = \varphi_i^{NQ} \times \left( \beta_{E,i} \times QE_i^{\frac{\gamma_i}{\gamma_i - 1}} + \beta_{QX,i} \times QNX_i^{\frac{\gamma_i}{\gamma_i - 1}} \right)^{\frac{\gamma_i}{\gamma_i - 1}}$$  \hspace{1cm} (A.7)

$$QNX_i = \varphi_i^{NN} \times \left( \beta_{NI,i} \times QNI_i^{\frac{\gamma_i}{\gamma_i - 1}} + \beta_{NE,i} \times QNE_i^{\frac{\gamma_i}{\gamma_i - 1}} \right)^{\frac{\gamma_i}{\gamma_i - 1}}$$  \hspace{1cm} (A.8)

where, \( QX_i \) denotes the total output of sector \( i \). \( QE_i \) denotes the export of sector \( i \). \( QNX_i \) denotes the domestic output of sector \( i \). \( QN_i \) denotes the output of Guangdong Province in sector \( i \). \( QNE_i \) denotes the output of other domestic provinces in sector \( i \). \( \varphi_i^{NEX}, \varphi_i^{NNE}, \varphi_i^{NQ}, \varphi_i^{NN} \) denote the efficiency parameter of sector \( i \). \( \varepsilon_i^{NEX} \) denotes the substitution elasticity of export and domestic output in sector \( i \). \( \varepsilon_i^{NNE} \) denotes the domestic output elasticity of export and domestic output in sector \( i \). \( \varepsilon_i^{NQ} \) denotes the output elasticity of export and domestic output in sector \( i \). \( \varepsilon_i^{NN} \) denotes the import elasticity of export and domestic output in sector \( i \). \( \beta_{E,i} \) and \( \beta_{NX,i} \) are the share coefficients of export and domestic output in sector \( i \), meeting \( \beta_{E,i} + \beta_{NX,i} = 1 \). \( \varepsilon_i^{NEX}, \varepsilon_i^{NNE}, \varepsilon_i^{NQ}, \varepsilon_i^{NN} \) denote the share coefficients of export and domestic output in sector \( i \), meeting \( \beta_{E,i} + \beta_{NX,i} = 1 \).
A.3. Household module
The household module mainly discussed the residents’ income and expenditure decision. The income of residents came from labor income (LS), capital income (KS), and transfer payment (TRI) from local governments (equation (A.9)). Residents’ expenditure consisted of deposits (HS), personal income tax (DTAX), and consumption (CH) (equations (A.10)–(A.12)):

\[
Y = PK \times KS + PL \times LS + TRI \quad (A.9)
\]
\[
HS = mps \times (1 - ty) \times Y \quad (A.10)
\]
\[
DTAX = ty \times Y \quad (A.11)
\]
\[
PC_i \times CH_i = PC_i \times muh_i + alphH_i \times \left( CHZ - \sum_{i=1}^{n} PC_i \times muh_i \right) \quad (A.12)
\]

where, LS denotes labor income. KS denotes capital income. TRI denotes the local government transfer payments to residents. HS denotes household savings. DTAX denotes individual income tax to the government. CH denotes consumption expenditure. Y denotes the total income of residents. PK denotes the price of capital. PL denotes the price of labor. mps denotes the marginal savings rate of residents. ty denotes the individual income tax rate of residents. PC_i denotes the consumer price of sector i. muh_i denotes the living consumption of sector i. alphH_i denotes the marginal consumption of residents for sector i. CHZ denotes the total consumption in the base period.

A.4. Government module
The government module described the revenues and expenditures of local and central governments. The local governments levied value-added tax (GLTV A) and personal income tax (GLDTAX), and received central government subsidies (TRIL) (equation (A.13)). The central government levied value-added tax (GCTVA), customs tax (GCTAX), and personal income tax (GCDTAX), and received the local governments’ fiscal revenue (TRIC) (equation (A.14)). In terms of expenditure, the local governments handed over fiscal revenue to the central government (TRIC) (equation (A.15)), transferred payment to residents (TRI), saved (SLG) (equation (A.17)), and consumed (LCG) (equation (A.16)). The central government allowed (TRIL) (equation (A.19)), saved (SCG) (equation (A.18)), and consumed (CCG) (equation (A.16)):

\[
TAXRL = GLTV A + GLDTAX + TRIL \quad (A.13)
\]
\[
TAXRC = GCTVA + GCTAX + GCDTAX + TRIC \quad (A.14)
\]
\[
LCG = alphl \times TAXRL \quad (A.15)
\]
\[
CCG = alphc \times TAXRC \quad (A.16)
\]
\[
SLG = mpl \times TAXRL \quad (A.17)
\]
\[
SCG = mpc \times TAXRC \quad (A.18)
\]
\[
TRIL = tril \times TAXRC \quad (A.19)
\]
\[
TRIC = tric \times TAXRL \quad (A.20)
\]

where, GLTV A denotes value-added tax to the local government. GLDTAX denotes individual income tax to the local government. GCTVA denotes value-added tax to the central government. GCDTAX denotes individual income tax to the central government. GCTAX denotes tariff to the central government. TRIL denotes the central government subsidies to the local government. TRIC denotes the local government subsidies to the central government. TRI denotes the local government transfer payments to residents. SLG, SCG denotes the savings of the local and central government. LCG, CCG denotes the consumption of the local and central government. alphl, mpl, tric denotes local government consumption rate, savings rate and transfer rate to the central government. alphc, mpc, tril denotes central government consumption rate, savings rate and transfer rate to the local government.

A.5. Closure module
The closure module included commodity market balance, factor market balance, local and central government revenue and expenditure balance, provincial revenue and expenditure balance, international revenue and expenditure balance, and investment and savings balance.
### Appendix B. Direct economic (DE) loss of sectors

**Table B.1.** Direct economic (DE) loss of sectors in Guangdong Province (unit: million USD, the exchange rate of CNY to USD is 0.15 in 2018).

| ID  | Sectors                                                                 | DE loss  |
|-----|--------------------------------------------------------------------------|----------|
| 1   | Farming, forestry, animal husbandry and fishery                           | 891.00   |
| 2   | Extraction of petroleum and natural gas                                   | 14.55    |
| 3   | Mining and dressing of metal ores and coal                               | 3.00     |
| 4   | Mining and dressing of nonmetal ores and other ores                      | 7.20     |
| 5   | Manufacture of food and tobacco                                          | 74.85    |
| 6   | Textile industry                                                         | 27.45    |
| 7   | Textile, sewing machine and leather manufacturing                        | 83.10    |
| 8   | Wood processing and furniture manufacturing                              | 35.10    |
| 9   | Manufacture of papermaking, printing, cultural, educational and sports articles | 80.25    |
| 10  | Petroleum refining, coking and nuclear fuel processing                    | 32.70    |
| 11  | Chemical products                                                        | 133.95   |
| 12  | Nonmetal mineral products                                                 | 54.30    |
| 13  | Smelting and pressing of metals                                          | 48.75    |
| 14  | Metal products                                                            | 74.55    |
| 15  | Manufacture of general-purpose machinery                                  | 48.75    |
| 16  | Manufacture of special-purpose machinery                                  | 43.95    |
| 17  | Manufacture of transport equipment                                        | 80.25    |
| 18  | Manufacture of electrical machinery and equipment                          | 125.10   |
| 19  | Manufacture of communication, computers and other electronic equipment    | 315.90   |
| 20  | Other manufactures                                                       | 52.50    |
| 21  | Recycling and disposal of waste                                          | 3.30     |
| 22  | Manufacture of metal products, machinery and equipment maintenance        | 73.05    |
| 23  | Production and supply of electric power and heat power                    | 5.40     |
| 24  | Production and supply of gas                                             | 10.05    |
| 25  | Production and supply of water                                           | 124.05   |
| 26  | Construction                                                              | 327.90   |
| 27  | Wholesale and retail trades                                              | 147.90   |
| 28  | Transport, storage and postal services                                    | 69.00    |
| 29  | Hotels and catering services                                              | 156.00   |
| 30  | Information transmission, computer services and software                  | 282.90   |
| 31  | Finance                                                                  | 315.90   |
| 32  | Real estate                                                               | 136.65   |
| 33  | Leasing and business services                                             | 75.75    |
| 34  | Scientific research, technical services and geological prospecting       | 47.10    |
| 35  | Management of water conservancy, environment and public facilities        | 25.20    |
| 36  | Services to households and other services                                 | 63.15    |
| 37  | Education                                                                 | 121.20   |
| 38  | Health, social security and social welfare                                | 78.45    |
| 39  | Culture, sports and recreation                                           | 18.30    |
| 40  | Public administration and social organizations                            | 126.90   |
### Appendix C. SAM in GDDCGE model

Table C.1. The macro social accounting matrix of Guangdong Province in 2017 (unit: million USD, the exchange rate of CNY to USD is 0.15 in 2017).

| Factors          | Activities | Commodities  | Labor | Capital | Households | Government | Rest of the World | Rest of China | Investment | Total         |
|------------------|------------|--------------|-------|---------|------------|------------|-------------------|---------------|------------|---------------|
| Activities       | —          | 38,427.76    | —     | —       | —          | —          | —                 | —             | —          | 38,427.76     |
| Commodities      | 25,130.75  | —            | —     | —       | 5161.82    | 1670.08    | 6721.60           | 9099.06       | 6002.40    | 53,785.70     |
| Factors          | 6528.39    | —            | —     | —       | —          | —          | —                 | —             | —          | 6528.39       |
| Capital          | 5114.88    | —            | —     | —       | —          | —          | —                 | —             | —          | 5114.88       |
| Households       | —          | —            | 6528.39| 5114.88 | —          | —          | 523.94            | —             | —          | 12,167.22     |
| Government       | 1653.74    | 446.18       | —     | —       | 158.09     | 295.90     | —                 | 751.67        | —          | 3305.57       |
| Rest of the World| —          | 4601.31      | —     | —       | —          | —          | —                 | —             | —          | 4601.31       |
| Rest of China    | —          | 10,310.45    | —     | —       | —          | —          | —                 | —             | —          | 10,310.45     |
| Investment       | —          | —            | —     | 6847.31 | 815.66     | 2120.29    | 1211.39           | —             | —          | 6754.07       |
| Total            | 38,427.76  | 53,785.70    | 6528.39| 5114.88 | 12,167.22  | 3305.57    | 4601.31           | 10,310.45     | 6754.07    | 140,995.35    |
Appendix D. Parameters in production and trade modules

Table D.1. Values of elastic substitution parameters in production and trade modules.

| Sectors                                           | $\varepsilon_{LK}^i$ | $\varepsilon_{NXE}^i$ | $\varepsilon_{NNE}^i$ | $\varepsilon_{NNI}^i$ | $\varepsilon_{NQI}^i$ |
|---------------------------------------------------|----------------------|------------------------|-----------------------|-----------------------|-----------------------|
| Farming, forestry, animal husbandry and fishery    | 1.937                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Extraction of petroleum and natural gas            | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Mining and dressing of metal ores and coal         | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Mining and dressing of nonmetal ores and other ores| 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Manufacture of food and tobacco                    | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Textile industry                                  | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Textile, sewing machine and leather manufacturing  | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Wood processing and furniture manufacturing        | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Manufacture of papermaking, printing, cultural, educational and sports articles | 3.161 | −4.0 | −4.0 | 3.0 | 3.0 |
| Petroleum refining, coking and nuclear fuel processing | 3.161            | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Chemical products                                  | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Nonmetal mineral products                          | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Smelting and pressing of metals                    | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Metal products                                     | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Manufacture of general-purpose machinery           | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Manufacture of special-purpose machinery           | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Manufacture of transport equipment                 | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Manufacture of electrical machinery and equipment  | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Manufacture of communication, computers and other electronic equipment | 3.161 | −4.0 | −4.0 | 3.0 | 3.0 |
| Other manufactures                                 | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Recycling and disposal of waste                    | 3.161                | −4.0                   | −4.0                  | 3.0                   | 3.0                   |
| Manufacture of metal products, machinery and equipment maintenance | 3.161 | −4.0 | −4.0 | 3.0 | 3.0 |
| Production and supply of electric power and heat power | 4.442              | −0.5                   | −0.5                  | 0.9                   | 0.9                   |
| Production and supply of gas                       | 4.442                | −0.5                   | −0.5                  | 0.9                   | 0.9                   |
| Production and supply of water                     | 4.442                | −0.5                   | −0.5                  | 0.9                   | 0.9                   |
| Construction                                       | 1.953                | −3.8                   | −3.8                  | 3.0                   | 3.0                   |
| Wholesale and retail trades                        | 1.902                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Transport, storage and postal services             | 3.704                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Hotels and catering services                       | 2.078                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Information transmission, computer services and software | 2.140             | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Finance                                            | 2.140                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Real estate                                        | 2.140                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Leasing and business services                      | 2.140                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Scientific research, technical services and geological prospecting | 2.140 | −3.0 | −3.0 | 2.0 | 2.0 |
| Management of water conservancy, environment and public facilities | 2.140 | −3.0 | −3.0 | 2.0 | 2.0 |
| Services to households and other services          | 2.140                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Education                                          | 2.140                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Health, social security and social welfare         | 2.140                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Culture, sports and recreation                     | 2.140                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |
| Public administration and social organizations      | 2.140                | −3.0                   | −3.0                  | 2.0                   | 2.0                   |

Appendix E. Sensitivity analysis

This study took the scenario with a disaster but without recovery (S1) as an example to test the elastic parameters in the production module and trade module. The results showed that when these elastic parameters increased or decreased by 20%, the rate of change of related economic indicators was small (table E.1). Therefore, simulation results of the GDGCCGE model established in this study were less sensitive to elastic parameter values, indicating that the model was reliable.
Table E.1. Sensitivity analysis.

| Module          | Parameters  | Change | GDP          | Central government revenue | Resident income | Resident save |
|-----------------|-------------|--------|--------------|-----------------------------|----------------|--------------|
| Production      | $\epsilon^P$ | +20%   | −0.2971%     | −0.2775%                    | −0.2907%        | −0.2880%      | −0.2880%     |
|                 |             | −20%   | 0.8655%      | 0.8283%                     | 0.8489%         | 0.8351%       | 0.8351%      |
| Trade           | $\epsilon^T$| +20%   | −0.8361%     | −0.8182%                    | −0.8221%        | −0.8033%      | −0.8033%     |
|                 |             | −20%   | 1.6219%      | 1.5838%                     | 1.6037%         | 1.5593%       | 1.5593%      |
|                 | $\epsilon^N$| +20%   | −0.1426%     | −0.1390%                    | −0.1405%        | −0.1371%      | −0.1371%     |
|                 |             | −20%   | 0.5073%      | 0.4946%                     | 0.5008%         | 0.4878%       | 0.4878%      |
|                 | $\epsilon^N$| +20%   | 0.2266%      | 0.2255%                     | 0.2266%         | 0.2299%       | 0.2299%      |
|                 |             | −20%   | −0.2215%     | −0.2172%                    | −0.2179%        | −0.2127%      | −0.2127%     |
|                 | $\epsilon^Q$| +20%   | 0.3031%      | 0.2969%                     | 0.2989%         | 0.2912%       | 0.2912%      |
|                 |             | −20%   | −0.3005%     | −0.2945%                    | −0.2969%        | −0.2887%      | −0.2887%     |

References

[1] Xie W, Li N, Wu J D and Hao X L 2014 Modeling the economic costs of disasters and recovery: analysis using a dynamic computable general equilibrium model Nat. Hazards Earth Syst. Sci. 14 757–72
[2] Zhang H, Liu C and Wang C 2021 Extreme climate events and economic impacts in China: a CGE analysis with a new damage function in IAM Technol. Forecast. Soc. Change 169 120765
[3] Zhang Q, Lu Q B, Zhong D P and Ye X T 2018 The pattern of policy change on disaster management in China: a bibliometric analysis of policy documents, 1949–2016 Int. J. Disaster Risk Sci. 9 55–73
[4] Wang L, Zhou Y, Lei X, Zhou Y and Mao X Z 2020 Predominant factors of disaster caused by tropical cyclones in South China coast and implications for early warning systems Sci. Total Environ. 726 138556
[5] Weinkle J, Landsea C, Collins D, Musulin R and Piellek R 2018 Normalized hurricane damage in the continental United States 1900–2017 Nat. Hazards Earth Syst. Sci. 18 249–276
[6] Yglesias V et al 2021 Risky development: increasing exposure to natural hazards in the United States Earth’s Future 9 e2020EF001795
[7] Liu Y, Zhang Z T, Chen X, Huang C F, Han F and Li N 2021 Assessment of the regional and sectoral economic impacts of heat-related changes in labor productivity under climate change in China Earth’s Future 9 e2021EF002028
[8] Mok J S, Kim S H, Kim J, Cho H, An S U, Choi A, Kim B, Yoon C, Thamdrup B and Hyun J H 2019 Impacts of typhoon-induced heavy rainfalls and resultant freshwater runoff on the partitioning of organic carbon oxidation and nutrient dynamics in the intertidal sediments of the Han River estuary, Yellow Sea Sci. Total Environ. 691 858–67
[9] Xu S, Zhu X L, Helmer E H, Tan X Y, Tian J Q and Chen X H 2021 The damage of urban vegetation from super typhoon is associated with landscape factors: evidence from Sentinel-2 imagery Int. J. Appl. Earth Obs. Geoinf. 104 102536
[10] Carrera L, Stuardi G, Bosello F and Mysiak J 2015 Assessing direct and indirect economic impacts of a flood event through the integration of spatial and computable general equilibrium modelling Environ. Model. Softw. 63 109–22
[11] Elliott R J R, Liu Y, Strobl E and Tong M 2019 Estimating the direct and indirect impact of typhoons on plant performance: evidence from Chinese manufacturers J. Environ. Econ. Manage. 98 102252
[12] Attary N, Cutler H, Shields M and Lindt J W V D 2020 The economic effects of financial relief delays following a natural disaster Econ. Syst. Res. 32 351–77
[13] Wang G, Chen R and Chen J 2017 Direct and indirect economic loss assessment of typhoon disasters based on EC and IO joint model Nat. Hazards 87 1751–64
[14] Ravago M L V, Mapa C D S, Aycardo A G and Abrigo M R M 2020 Localized disaster risk management index for the Philippines: is your municipality ready for the next disaster? Int. J. Disaster Risk Reduct. 51 101913
[15] Stauffer J M, Pedraza-Martínez A J, Yan L and van Wassenhove L N 2018 Asset supply networks in humanitarian operations: a combined empirical-simulation approach J. Oper. Manage. 63 44–58
[16] Li J, Crawford-Brown D, Syddall M and Guan D B 2013 Modeling imbalanced economic recovery following a natural disaster using input-output analysis Risk Anal. 33 1908–23
[17] Xue H, Kumar V and Sutherland J W 2007 Material flows and environmental impacts of manufacturing systems via aggregated input-output models J. Clean. Prod. 15 1349–58
[18] Wang X B, Ge J P, Li J S and Han A P 2017 Market impacts of environmental regulations on the production of rare earths: a computable general equilibrium analysis for China J. Clean. Prod. 154 614–20
[19] Ioza E, Zeller V and Achten W M J 2020 Extreme climate events and economic impacts of a flood disruption of Los Angeles: is your municipality ready for the next disaster? Int. J. Disaster Risk Reduct. 51 101913
[20] Beaussier T, Caurla S, Bellon-Maurel V and Loiseau E 2019 Coupling economic models and environmental assessment methods to support regional policies: a critical review J. Clean. Prod. 216 408–21
[21] Huang H, Roland-Holst D, Wang C and Cai W J 2020 China’s income gap and inequality under clean energy transformation: a CGE model assessment J. Clean. Prod. 251 119626
[22] Rose A and Liao J S Y 2005 Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions J. Reg. Sci. 45 75–112
[23] Zhang R S, Fujimori S and Hanaoka T 2018 The contribution of transport policies to the mitigation potential and cost of 2 °C and 1.5 °C goals Environ. Res. Lett. 13 054008
[24] Clora F, Yu W S, Baudry G and Costa L 2021 Impacts of supply-side climate change mitigation practices and trade policy regimes under dietary transition: the case of European agriculture Environ. Res. Lett. 16 124048
[25] Xie W, Li N, Wu J and Hao X 2015 Disaster risk decision: a dynamic computable general equilibrium analysis of regional mitigation investment Hum. Ecol. Risk Assess. 21 81–99
[68] O’Ryan R, Nasirov S and Alvarez-Espinosa A 2020 Renewable energy expansion in the Chilean power market: a dynamic general equilibrium modeling approach to determine CO₂ emission baselines J. Clean. Prod. 247 119645

[69] Phillips F 2020 The SDG project: a long-term project under technological uncertainty Engineering 6 600–3

[70] Revesz R L, Howard P H, Arrow K, Goulder L H, Kopp R E, Livermore M A, Oppenheimer M and Sterner T 2014 Improve economic models of climate change Nature 508 173–5

[71] Ackerman F and Munitz C 2012 Climate damages in the FUND model: a disaggregated analysis Ecol. Econ. 77 219–24

[72] Lok C and Chan J 2018 Changes of tropical cyclone landfalls in South China throughout the twenty-first century Clim. Dyn. 51 2467–83

[73] Yin J, Dai E F, Wu S H and Pan T 2013 A study on the relationship between typhoon intensity grade and disaster loss in China Geogr. Res. 32 266–74

[74] Halsnaes K, Kuhl J and Olesen J E 2007 Turning climate change information into economic and health impacts Clim. Change 81 145–62

[75] Cui Q, Xie W and Liu Y 2018 Effects of sea level rise on economic development and regional disparity in China J. Clean. Prod. 176 1245–53