Direct and Indirect Economic Losses Using Typhoon-Flood Disaster Analysis: An Application to Guangdong Province, China

Zhuoqun Gao 1, R. Richard Geddes 2 and Tao Ma 1,3,*

1 School of Management, Harbin Institute of Technology, Harbin 150001, China; hitgzq@outlook.com
2 College of Human Ecology, Cornell University, Ithaca, NY 14850, USA; rrg24@cornell.edu
3 State Key Laboratory of Urban Water Resource and Environment, Harbin 150001, China
* Correspondence: matao@hit.edu.cn

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Abstract: Guangdong Province is one of China’s largest and most developed regions. It is home to more than 113 million people and features unique geographical and climatic characteristics. Typhoons that pass through often result in heavy rainfall, which causes flooding. The region’s risk of typhoon and flood disasters, and the resulting indirect economic impacts, have not been fully assessed. The purpose of this paper is to introduce a method for assessing the spatial and temporal cumulative risk of typhoon-induced flood disasters, and the resulting indirect economic impacts, in order to deal with the uncertainty of disasters. We combined an analytic hierarchy process (AHP) and spatial analysis using a geographic information system (GIS) to produce a comprehensive weighted-risk assessment from three different aspects of disaster, vulnerability, and resilience, with 11 indicators. A new method for computing risk based on spatial and temporal cumulative patterns of typhoon-induced flood disasters was introduced. We incorporated those direct impacts into a computable general equilibrium (CGE) model to simulate indirect economic losses in alternative scenarios according to different risk levels. We found that the risk in the coastal area is significantly higher than that in the northern mountainous area. The coastal areas of western Guangdong, Pearl River Delta, and Chaoshan Plain face the greatest risk. Our results indicate that typhoon and flood disasters have negative effects on the real GDP, residents’ income, consumption, and several other macroeconomic indicators. We found differing disaster impacts across industrial sectors, including changes in the output, prices, and flow of labor among industries. Our estimates provide scientific support for environmental planning, spatial planning, and disaster-risk management in this important region. They are also of reference value for the development of disaster management strategies in similar climatic regions around the world.

Keywords: typhoon flood disaster; risk assessment; spatial and temporal cumulative risk; CGE; economic impact

1. Introduction

Economic losses caused by natural disasters have increased from USD 14 billion annually in 1985 to more than USD 140 billion in 2014 [1]. The effects of such disasters have also changed radically over time. Fatalities from natural disasters are declining, while the destruction of infrastructure and other economic assets is growing [2]. Governments are taking more active measures throughout the entire disaster life cycle [3]. Researchers have shifted from focusing on individual disasters to assessments of scenarios that acknowledge the likelihood of cascading hazards. They also examine multiple hazards that intersect in either temporal or spatial dimensions, creating an ever-larger
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disaster [1]. Therefore, it is very important to analyze the comprehensive economic impact of the whole disaster life cycle.

The average sea level along the coast of China rose at an average rate of 3.4 mm per year from 1980 to 2019, which was higher than the global average. In 2019, the sea level was 72 mm higher than the average in China, ranking third since 1980 (Ministry of Ecology and Environment of the People’s Republic of China, 2020). Global warming and other factors are driving sea-level rise, aggravating coastal storm surges, flooding, and other adversities. Typhoons generate high-intensity rainfall, which causes flooding. The effects of rain and flooding are largely inseparable. To analyze the indirect economic impact of typhoons and induced flood disasters, we combine the risk and direct impact of those effects to simulate more complex and realistic scenarios in this paper. A proper assessment of typhoon-disaster risk and the economic impact will improve decision making and enhance resilience to such threats in the future [4].

Previous research on the risk of typhoons has focused on its causes. The probability of hazard occurrence and its potential impact are often used to define risk [5]. However, the vulnerability of coastal at-risk areas, especially the built environment [6], and environmental susceptibility to disasters remain under-studied [7]. Mathematical statistics [8], indicator system [9], remote-sensing geographic information systems (GIS) [10], and scenario simulations [11] are the four prevailing methods employed for quantitative disaster-risk assessments [12]. Current disaster-impact analysis typically focuses on modeling physically disruptive events, such as identifying characteristics that affect the probability of structural damage to buildings that suffer flooding and evaluating the economic loss [13]. Typhoon flood disasters and their corresponding direct and indirect economic impacts are poorly understood. There is an analogous lack of economic methods within existing methodologies [14]. Other under-studied yet critical issues include the underlying vulnerability or resilience of socio-economic agents and groups, post-disaster recovery, and issues of financial assistance [15].

Researchers recognize that disasters cannot be handled adequately within the framework of conventional spatial economic models, particularly regarding socio-economic impacts. Common current models include econometric models, input–output models, and social accounting models, among others [15]. These models are based on questionable assumptions for natural phenomena that occur during disasters since they usually reflect stylized and limited aspects of society [16]. Econometric models based on time-series data have the advantage of statistical rigor and accurate predictions. However, they can only provide a rough estimate of a disaster’s overall impact. They rarely include the disaster’s potentially significant ripple effects. Standard input–output (IO) models are static linear and demand driven. They represent a partial economy through sets of interrelationships between producers and consumers, while lacking links between income and consumption. They also exclude the responses to price changes included in the computable general equilibrium (CGE) model. Moreover, traditional IO models are likely to overstate the impact of non-affected regions without considering substitution possibilities between imports from different regions. In contrast, the general equilibrium approach describes a complete economy, accounting for all monetary and non-monetary flows, while linking income and expenditure. The flexibility of both price and replacements is a unique feature of CGE models [17]. However, CGE models may underestimate these effects when there are extreme substitution effects and price changes [16].

Hybrid models have been developed to address some of these shortcomings in conventional models of economic disaster. It was also hoped that hybrids would improve model accuracy while expanding the range of the overall assessment. These hybrids include the adaptive regional input–output (ARIO) model [18], the IO model coupled with a biophysical model [19], and a hybrid dynamic interregional IO model [20]. CGE models have also been extended and further developed in order to make them more suitable for modeling disaster impacts. For instance, regional economic resilience has been added to an advanced CGE model with a recalibrated production function [21]. A spatial CGE model that includes spatial interactions with an interregional, inner-sectoral economy, with all regions connected by transportation networks, has also been developed [22].
A combination of available methods is necessary to properly evaluate the overall impact of a major natural disaster. Indeed, such an approach is critical to meeting the required scope of a disaster assessment [3]. In this paper, we rely on such a combined methodology to simulate economic impacts and include socio-economic resilience within a spatio-temporal risk assessment of a typhoon flood disaster.

First, we specifically combine an analytic hierarchy process (AHP) and spatial analysis through a geographic information system (GIS) to complete a comprehensive weighted assessment of risk. Prior studies have typically taken the city as the smallest unit, despite the fact that economic and social indicators, spatial geographical characteristics, and other indicators are quite different across districts and counties. We refine the spatial unit to the district and county level, which creates a more accurate disaster-risk assessment. We also create a county-level typhoon flood disaster-risk map.

Second, we introduce a method for computing risk with respect to both spatial and temporal cumulative typhoon flood disaster patterns, while further discussing the potential direct impact of different risk levels on various economic production sectors.

Third, we incorporate these direct impacts into a CGE model to simulate indirect economic losses under different risk-level scenarios. This allows us to simulate comprehensive impacts on most sectors and spatial scales at the local level, where disaster directly hits, as well as regional, national, and global levels. Economic impact analysis under different risk levels can better cope with the uncertainty of disaster occurrence. Overall, this study attempts to present a comprehensive and detailed economic impact analysis in terms of the spatial and socio-economic characteristics of a typhoon flood disaster, broadening the scope of the research objects as well as the time range of the disaster impacts. Based on the case study, the results, analysis, and suggestions for disaster management and urban spatial planning are discussed.

2. Methodology

2.1. The Analytic Hierarchy Process (AHP) Method

The AHP method is one of the most commonly applied multiple criteria decision-making techniques [23]. It provides an efficient and effective platform for complex decision-making problems through the use of objective mathematics to quantify complex qualitative problems [24]. Specifically,

\[
A = [a_{ij}]_{n \times n} = \begin{bmatrix}
1 & a_{ij} & \cdots & a_{1n} \\
1/a_{ij} & 1 & \cdots & a_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
1/a_{1n} & 1/a_{2n} & \cdots & 1
\end{bmatrix}
\]

(1)

where \(A\) is the AHP pairwise comparison matrix, and \(a_{ij}\) is the relative importance of element \(i\) to element \(j\). The weight of the element can be calculated from Equation (2):

\[
w_i = \frac{M_i}{\sum_{j=1}^{n} M_j}
\]

(2)

where \(M_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}}\). Furthermore, the consistency ratio should be calculated according to Satty’s definition, which is the consistency index/random index:

\[
CI = \frac{\lambda_{\text{max}} - n}{n-1}
\]

(3)

\[
\lambda_{\text{max}} = \frac{\sum_{j=1}^{n} a_{ii} w_i}{\sum_{i=1}^{n} a_{ii} w_i}
\]

(4)

\[
CR = \frac{CI}{RI}
\]

(5)

Here, CR is the consistency ratio, CI is the consistency index, and \(\lambda_{\text{max}}\) is the largest eigenvalue of the comparison matrix. RI is the average consistency random index [25], shown in Table A1 (see Appendix A).
2.2. Spatial Multi-Criteria Analysis

Spatial multi-criteria analysis comprehensively considers the influence of each factor, weighting the evaluation factors in order to rank or score the overall performance in a spatial manner. The input is a set of standardized and weighted maps with spatial representation of factors. The final map of the overall performance score $u_j$ can be calculated using the formula [26]. The weights ($w_{ij}$) are non-negative and add up to 1, and $v_{ij}$ is the standardized performance score (from 0 to 1) for indicator $x_{ij}$.

$$u_j = \sum_{i=1}^{m} v_{ij} \times w_{ij}$$  (6)

2.3. Mechanism of Spatio-Temporal Risk Accumulation

The path and intensity of a typhoon and its secondary disasters are hard to predict. Information from particular past typhoons provides a poor basis for a phrased policy-making process. We thus introduced the concept of cumulative risk. For disaster-related government policy, the impact of spatial risk is accumulated in a certain period of time; that is, the synthetic spatio-temporal risk index reflects the extent to which potential disaster areas may be affected within a specific period. We analyzed the potential risk and overall impact for the one year covered by the disaster policy.

We report a schematic of spatio-temporal risk accumulation in Figure 1. The blue polyline represents the phased impact on production activities obtained by adding up the number of typhoon flood disaster occurrences. The red polyline shows the actual production impact. In reality, risk is accumulated on both a temporal and spatial scale, as shown in the gradual-change gray area. The red rectangles represent all spatial units with a gradually higher risk level, accumulated in the gray area at the end of the research period.

![Figure 1. Schematic of the spatio-temporal risk accumulation mechanism.](image)

We next introduced scenarios representing different levels of risk. Risk is defined as determining the probability of a system failure and the consequent losses [27]. In the cumulative spatio-temporal risk matrix $R_{ij}$, column $j$ represents scenarios with different risk levels $n$ ($n = j$), which are sorted in descending order. In each column, spatial units are sorted by their risk level in ascending order from 1 to $n$. The number of spatial units with the same risk level of $n$ is represented by the subscript of $k_n$. 
Here, $RI_{ij}$ is the risk of a specific spatial unit $i$ with the risk level of $n$. Furthermore, $i$, $j$, and $n$ are integers, where $j \in [1, n]$, $k_n$ is the number of spatial units with the same risk level of $n$, $\sum_{k=1}^{n} k_x = i$. For example, in the most severe disaster scenario (with the risk level of $n$) for the cumulative period of time, most spatial units are affected by it to different extents, as shown in the first column.

Based on the theoretical expected loss of a flood introduced by U.S. Army Corps of Engineers (1996) [28],

$$E(x) = \int_{-\infty}^{\infty} x \frac{dF(x)}{dx} dx$$

where $E(x)$ is the expected annual flood damage, $x$ represents a random variable representing the amount of loss with the probability of occurrence equal to $f(x)dx$, and $F(x)$ is the loss cumulative distribution function. We defined the expected cumulative spatio-temporal risk as $E'(x, y)_j$ with the risk level of $j$ as below:

$$E'(x, y)_j = \sum_{y=1}^{n-j+1} \sum_{k=j}^{n} y \times k_x$$

Here, $E'(x, y)_j$ is the sum of the elements of the $j$ column of the matrix $RI_{st}$.

### 2.4. Computable General Equilibrium Model for Guangdong Province

The computable general equilibrium (CGE) model is widely used in economic impact and policy analysis. It is constructed based on the traditional Walras paradigm and can be described as a system of simultaneous non-linear equations of the real economy. In the regional CGE model of this study, mainland China was divided into two regions: Guangdong Province and the other provinces of China. The model contains 42 production sectors, an enterprise sector, a sector of the rest of the world, a sector of the other provinces, central and local government sectors, and a household sector. Factors of labor and capital are assumed to be used for production. The main model structure includes six modules, shown in Figure 2. Due to the openness of the regional economy, regional trade consists of trade between the rest of the regions of China and foreign countries.

In the trade module, the imperfect substitution between commodities produced domestically and imported commodities is described as the constant elasticity of substitution (CES) function, according to the Armington assumption. The constant elasticity of transformation (CET) function is used to estimate the substitution relationship between exports and domestic products. Among them, the ratio of the quantity of commodities consumed in the research province to the commodities traded to other provinces in China is obtained through data calibration in the base run. In the production
module, the production process is divided into two stages. In the first stage of production, factors of capital and labor are combined into the composite factor (value added) using the Cobb–Douglas (C–D) production function. In the second stage, the gross domestic output is determined by the CES function, where the composite factor is combined with the composite commodity. For disaster research, we assumed that labor and capital stock could not move from one region to another in the period, and that labor was in a full employment condition. Moreover, the composite commodity was derived from all kinds of intermediate inputs in the form of a Leontief function.

**Figure 2.** Overall structure of the computable general equilibrium (CGE) model.

From the two aspects of supply and demand, this CGE model describes the open economic activities in the product market. The supply system consists of the producer's behavior equations in demanding factor inputs and supplying products. The model follows the small country assumption in foreign trade: when the economy is so small that it does not have a significant impact on the rest of the world, even when engaged in an extreme activity such as export dumping [29]. We assumed that import and export prices quoted in foreign currency terms were given exogenously. The demand system that describes the total consumption demand of goods includes the consumption demand of
households and local and central governments, the intermediate input, and the investment demand. In market equilibrium, the total supply is equal to the total demand, and the region’s commodity demand and commodity supply in other regions have formed regional flows of commodities.

In addition, households are endowed with capital and labor. The income of the household includes returns on factors of production, enterprise transfer payments, and government transfer payments, which are used for investment, consumption, or savings after paying income taxes. Households maximize CES-type utility through consumption under budget and commodity price constraints. Furthermore, three balances of investment saving, government budget balance, and the balance of payments are obtained in the model. The exchange rate and foreign capital inflow are exogenous. The structure of the model is shown below.

2.5. Data Acquisition

The data used in this research were derived from a wide variety of fields, including meteorology, hydrology, geography, topography, and socio-economic statistics. The meteorological data of Guangdong Province were obtained from the National Meteorological Information Center (CMABST data) from 2010 to 2018 [30], which provided the location and intensity of tropical cyclones every six hours in the Northwest Pacific Ocean, as well as the Guangdong Provincial Marine Disaster Bulletin from 2010 to 2018 [31]. Data on tropical cyclones at the level of a super typhoon, severe typhoon, typhoon, and severe tropical storm 3 to 6 are analyzed in this study, according to the classification of the National Standard for Tropical Cyclone Classification issued by the China Meteorological Administration (GB/T 19201–2003). Other infrastructure, land use, and water system data were selected from OpenStreetMap [32]. Digital elevation model data were taken from NASA Shuttle Radar Topography Mission (SRTM) Version 3.0 (90 m resolution) [33]. Provincial social accounting matrix data (2012) were derived from the Centre for Economic Systems Simulation Research. Annual average rainfall data and other socio-economic statistical data were derived from the 2018 Guangdong Statistical Yearbook and 2018 Guangdong Statistical Yearbook on Agriculture [34]. The values of the elasticity of substitutions were set by econometric estimations, which are listed in Table A7.

3. Case Study

3.1. Study Area

We focused on China’s Guangdong Province. Guangdong is an economic mega-province featuring a population of about 113 million. Located in the south of China (see Figure 3), it covers a land area of approximately 179.7 thousand km² and features a coastline of 4114.3 km. Guangdong’s geomorphic types are complex and diverse. The southern area is covered by easily flooded plains housing the bulk of Guangdong’s massive population.

Guangdong belongs to East Asia’s monsoon region and is prone to meteorological disasters, including rainstorms, floods, and tropical cyclones. It ranks first among all Chinese provinces in terms of the number of typhoons making landfall in China each year. Precipitation from July to September is mainly brought on by typhoons [35]. Unsurprisingly, Guangdong’s direct economic losses from marine disasters are also the highest in China, accounting for about 90% of all Chinese typhoon-related economic losses (2018 Guangdong Provincial Marine Disaster Bulletin). However, the data fluctuate greatly. Storm surges account for 99.9% of total losses from marine disasters over time, as shown in Figure 3 below.
The statistical data of marine disasters include storm surges, ocean waves, red tides, coastal erosion, sea water intrusion, soil salinization and salt tide intrusion, etc.

3.2. Risk Analysis

3.2.1. Establishment of the Indicator System

Tropical cyclones, also called typhoons, are intense circular storms characterized by high winds and heavy rainfall. The storm’s location is the only technical difference between a typhoon and a hurricane. Typhoons typically combine three specific hazard types: heavy winds, rainfall, and flooding. We analyzed the combined risk of these three hazards.

Extensive literature suggests alternative risk-assessment indicators, including risk as a function of hazard, exposure, and vulnerability [36]. Other common indicators utilized for various research purposes include (i) hazard, threat, and uncertainty; (ii) uncertainty, elements at risk, and community perception; (iii) frequency, consequences, and preparedness; (iv) likelihood and exposure to hazard; (v) probability, vulnerability, and social factors; (vi) probability and impact; and (vii) expected loss [37]. To summarize, in an ideal disaster-risk management plan, both a hazard (i.e., the probability of occurrence) and vulnerability (i.e., loss, impact, or consequences) analysis are conducted [38]. The most standard risk formula is expressed as [5]:

\[ R = H \times V \]  

where \( R \) is the risk, \( H \) is the hazard, and \( V \) is the vulnerability. From an economic and disaster-management perspective, an area’s response-and-recovery capacity is also a critical part of the disaster-risk function. We thus added a “resilience” indicator, as shown in Equation (11):
where risk (R) is a weighted result of the disaster hazard (H), vulnerability (V), and resilience (RE).

We used the AHP method introduced in Section 2.1 to calculate the joint contribution of these indicators. Figure 4 below offers a schematic representation of our risk-assessment approach with specific criteria and their elements. The gray elements contribute to the reduction of risk.

![Figure 4. Hierarchy of the typhoon flood risk multi-factor assessment system.](image)

Disaster criteria include three elements: typhoon frequency, water density, and mean annual rainfall. Typhoon frequency reflects the occurrence possibility and the destruction intensity grade of a typhoon disaster. Water density refers to the density of the main rivers in the study area. The water density and mean annual rainfall elements show the likelihood and severity of potential rainstorm and flood disasters.

The vulnerability criterion consists of four elements: elevation, slope, population density, and production land. The elevation and slope are used to reflect the topography of a disaster-prone environment, while the population density is a proxy for the likely impact on the labor input into production. Production land includes industrial land and agricultural land, which measure the impact on industrial and agricultural production, respectively.

In the context of disasters and other external shocks, resilience refers to the ability of individual or production sectors to adapt and return to the baseline performance [39,40]. Based on prior literature [12], we chose the road density, other infrastructure density, and GDP per capita as indicators of resilience. Road density and other infrastructure represent the ability of emergency response to maintain production factor flows, transfer to alternative production factors, and maintain transportation and production in order to mitigate disaster impacts. Other infrastructures in our study include railways, bus stops, and other transport infrastructures. GDP per capita represents the economic resilience [41], which indicates recovery capability.

3.2.2. Risk Mapping and Evaluation
While standardizing for positive and negative indicators (see Figures 5–7), we analyzed the overall risk and mapped a spatial analysis using GIS (see Figure 8). We used the AHP method to determine the weights. The judgement matrix and consistency ratio of AHP methodology are shown in Tables A2–A5. Specifically, the overall flood risk map was generated using the summation of three weighted composite criterion maps of disaster, vulnerability, and resilience. We constructed these by overlaying the 10 weighted standardized maps of elements on each criterion map.

Figure 5. Criterion of vulnerability: (a) elevation, (b) population density, and (c) slope.
Figure 6. Criterion of resilience: (a) GDP per capita, (b) road density, and (c) infrastructure density.

Figure 7. Criterion of disaster hazard: (a) annual average rainfall, (b) typhoon frequency, and (c) water density.
Figure 8. Overall typhoon flood disaster-risk map.

The estimates show that the comprehensive disaster risk of a typhoon in the southern coastal area of Guangdong is significantly higher than that in the northern mountainous area. The coastal areas of western Guangdong, Pearl River Delta, and Chaoshan Plain are high-risk areas. At the county level, the first-level risk areas include Xuwen County and Leizhou City of Zhanjiang City, and the second-level risk areas include Suixi County of Zhanjiang City, Yangxi County of Yangjiang City, Doumen District of Zhuhai City, Taishan City of Jiangmen City, Wuchuan City of Zhanjiang City, Dianbai District, and Gaozhou City of Maoming City.

3.2.3. Spatio-Temporal Risk and Scenario Settings

Using the methodology introduced in 2.3 based on historical data of typhoon flood disasters in Guangdong Province, the cumulative spatio-temporal risk matrix $R_{st}$ is shown below:
RI_{st} = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
2 & 1 & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
3 & 2 & 1 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
4 & 3 & 2 & 1 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
5 & 4 & 3 & 2 & 1 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
6 & 5 & 4 & 3 & 2 & 1 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}.
\tag{12}

For agricultural direct economic impact assessment in scenarios with six risk levels, affected area, disaster area, and low-yield area were defined by the decrease in crop production due to natural disasters by 10\%, 30\%, and 80\%, respectively, in the Chinese meteorological disasters almanac (2014). The crop yield loss percentage was simplified as below:

\[
\text{Proportion of crop yield loss} = \frac{\text{Affected area} \times 0.1 + \text{disaster area} \times 0.2 + \text{low - yield area} \times 0.7}{\text{Total sown area of crops}} \times 100\% \tag{13}
\]

According to the six risk scenarios’ settings, we set the spatial units (districts and counties) corresponding to the affected area, disaster area, and low-yield area, respectively. Based on the cultivated land area of the crops in each spatial unit, we calculated the overall loss of agriculture production in Guangdong Province.

To assess the industrial and service direct impact based on the risk level of each county, the cumulative number of days of production suspension was calculated in each scenario. Furthermore, according to the output value of the industries in each county, the overall impact of production suspension of Guangdong Province was calculated. Scenarios of different levels of risk are shown below (see Figure 9).
3.3. Results of Economic Impact Analysis

From the differences of the changes in these macroeconomic indicators (Table 1) compared to the baseline scenario (without any disaster), scenarios under the relatively mild disaster impacts show a small amount of growth. Although disasters cause economic losses, they also expand the demand of sectors and then eventually promote economic growth. However, in the more serious disaster scenarios, due to the periodic stagnation of production, the changes of various economic indicators show a downward trend.

### Table 1. Macroeconomic impacts of typhoon flood disasters.

| Variables                          | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 | Scenario 5 | Scenario 6 |
|------------------------------------|------------|------------|------------|------------|------------|------------|
| Real GDP change                    | −2.8017%   | −1.8254%   | −0.9742%   | −0.4681%   | −0.0820%   | −0.0146%   |
| Total household consumption change | −0.7729%   | −0.0203%   | 0.5383%    | 0.6655%    | 0.6884%    | 0.3736%    |
| Household income change            | −2.0977%   | −1.0826%   | −0.1784%   | 0.2516%    | 0.4781%    | 0.2801%    |
| Wage rate of labor change          | −2.3239%   | −1.1149%   | −0.2132%   | 0.2227%    | 0.4561%    | 0.2685%    |
| Local government consumption       | −1.4451%   | −0.9484%   | −0.4946%   | −0.2465%   | −0.0322%   | −0.0057%   |
| Local government income            | −1.7675%   | −0.8343%   | −0.0944%   | 0.2473%    | 0.4211%    | 0.2449%    |
| Central government income          | −1.5487%   | −0.7141%   | −0.0479%   | 0.2593%    | 0.4093%    | 0.2356%    |
| International investment           | −0.5277%   | 0.0662%    | 0.5192%    | 0.6572%    | 0.6507%    | 0.3516%    |

Sectoral changes in the production output, commodity price, and employment of the six scenarios are shown in Figures 10–12. A list of the names of industry sectors (1–42) and commodities (43–84) is shown in Table A6. The results of sectoral changes in the production output, commodity price, and labor input of the six scenarios reveal which industrial sectors are most affected by typhoon flood disasters. From the results of the simulation, we can see that the output of industries shows a decreasing trend, among which the top 10 industries with the largest output reduction are as follows: communication equipment, construction, instrument making, general equipment, special equipment, electrical machinery and equipment, scrap and waste, nonmetallic mineral, metal smelting and rolling, and timber and furniture.

![Figure 10. Simulation result of industry output change.](image-url)
From the change in nominal prices of products in various industries as shown in Figure 11, the prices of most products display a growth trend, among which gas production and distribution has the largest price increase, far exceeding other industries. Although the price of some sectoral products shows a downward trend, such as education, real estate, public and social management, and wholesale and retail trades, other products from service industries also exhibit a decrease in price. The price drop in the service sectors is far greater than in the industrial sectors, among which education displays the biggest drop.

![Commodity price change](image1)

**Figure 11.** Simulation result of commodity price change.

In terms of employment change, the mobility of human capital between industries and the labor in manufacturing industries such as metal smelting and rolling, communication equipment, other nonmetal ore mining, construction, and metal ore mining, as well as service industries such as technical services and wholesale and retail trades, exhibits a trend of transferring to work in other industries after the shock of a typhoon flood disaster.

![Labor input change](image2)

**Figure 12.** Simulation result of labor input change.
4. Discussion and Conclusions

This study introduced a research method for improving the integrity and accuracy of economic disaster impact analysis. It first assessed the comprehensive county-level risk of typhoon-induced flood disasters by a combination of the AHP method and spatial analysis through a geographic information system (GIS) to further carry out comprehensive weighted assessment and cumulative risk analysis. The analysis took typhoon frequency, typhoon rainstorm frequency, drainage density, elevation, slope, land-use type, population density, and urbanization density as the main factors that influence the typhoon flood risk of the research area. It further introduced a mechanism of how risk cumulates on the scale of time and space, known as the expected cumulative spatio-temporal risk, broadening the scope of the research objects and the time range of the disaster impact. Based on the risk analysis, this paper constructed a disaster impact scenario and used the CGE model to simulate the comprehensive economic impact, taking Guangdong Province as an example. Based on the results of the analysis, the following conclusions can be drawn.

We found that the risk in the coastal area is significantly higher than that in the northern mountainous area. Pearl River Delta and Chaoshan Plain are high-risk areas. At the county level, the first-level risk areas include Xuwen and Leizhou of Zhanjiang City, which is a similar result to that obtained by Zhang and Chen in spatial risk analysis [12]. The high-risk area has high values for disaster and vulnerability indicators such as typhoon frequency, water density, annual rainfall, and low elevation and slope topography. The high-risk area also has relatively low values of resilience, such as for road density, and most counties at high risk are distributed along the coast.

This study further analyzed the indirect economic impact based on a spatial and temporal cumulative risk analysis. We used the CGE model to simulate the process of disaster influence for the whole economic system through industrial linkage, which ended up affecting the total regional economic output and produces indirect economic losses. In this process, the production and consumption activities of various economic entities and the flow of economic factors changed, and the demand of the economic entities upstream of the industrial chain was also abnormal. The results showed changes in some important macroeconomic indicators. We set the three economic entities of households, enterprises, and government departments in the simulation. Except for residents' consumption and total investment, which increased in the short term due to the stimulation of disasters, other macroeconomic variables decreased in different ranges. The results indicate that typhoon and flood disasters have negative effects on real GDP, residents' income, consumption, and several other macroeconomic indicators. The real GDP changed from $-2.8017\%$ to $-0.0146\%$, total household consumption changed from $-0.7729\%$ to $0.3736\%$, and household income changed from $-2.2097\%$ to $0.2801\%$.

The output of industries showed a decreasing trend, among which the top industries with the largest output reduction were communication equipment, construction, instrument making, general equipment, special equipment, electrical machinery and equipment, scrap and waste, nonmetallic mineral, metal smelting and rolling, and timber and furniture. As disasters have a great impact on enterprise activities, mainly due to typhoon and flood disasters, this leads to the damage and collapse of factory buildings and project interruption, which has a great impact on industrial production. The results show that in general, compared with labor-intensive industries, capital-intensive industries are more affected by disasters in terms of the output. The characteristics of their industrial structure determine the higher demand for personnel allocation, geological structure, and capital factors. When affected by disasters, industries stop production and need to replace or repair the damaged and lost assets. As a result, these sectors are facing greater economic losses. Since government departments need to take various measures to reduce the impact of disasters after the occurrence of disasters, disasters will have negative effects on government revenue, savings, and other activities.

The prices of most products displayed a growth trend, which was mainly affected by the decrease of the industrial output, among which gas production and distribution had the largest price increase, far exceeding that of other industries. Education, real estate, public and social management, and wholesale and retail trades, as well as other products of service industries, exhibited a decrease in price. In terms of employment change, labor in manufacturing industries such as metal smelting...
and rolling, communication equipment, other nonmetal ore mining, construction, and metal ore mining, as well as service industries such as technical services and wholesale and retail trades, showed a decreasing trend after the shock of a typhoon flood disaster. According to Schumpeter’s “destructive hypothesis” theory [42], disasters will destroy the existing social and economic structure to a certain extent, but also generate new opportunities for economic growth. The results of our study also verify Okuyama’s conclusion that when natural disasters destroy capital [43], damage to vulnerable equipment and its replacement have a positive impact on economic development. Although the typhoon disaster caused many economic losses in Guangdong Province, it also promoted the economic growth to a certain extent.

Disaster-risk provision measures of hierarchical responses can be formulated according to the results with different risk levels in this study in order to respond to complex and unpredictable disaster risk in a more flexible way. For example, a scientific scheduling mechanism can be established between the allocation of disaster subsidies and for other purposes of funding, according to the level of risk. In this study, the minimum spatial unit of risk analysis is districts and counties, which can more accurately describe the specific location of pre-disaster warning and formulate effective escape routes for residents and property transfers. Additionally, the absence of risk-oriented land-use planning will potentially increase the flood risk in coastal areas [44]. The results of this study can help to improve regional spatial planning with the consideration of a disaster’s risk from the provincial and city level to county level to enhance infrastructure construction; reduce potential disasters’ impacts on industries; and minimize the impacts on surrounding populations, environments, and properties in the coastal areas with a high incidence of typhoon and flood disasters. What is more, post-disaster reconstruction can not only rely on the input of material capital, but also, from the perspective of human resources development and utilization, continuously improve the quality of personnel, strengthen the training of disaster prevention and mitigation knowledge, avoid risks to a greater extent, and promote long-term economic development. Our estimates provide scientific support for spatial planning and disaster-risk management in this important region. They are also relevant for the development of disaster management strategies in similar climatic regions globally.

To further improve the accuracy of the assessment of the economic impact of typhoon flood disasters, especially based on risk analysis, further work can be conducted in the future. First, the assumption of CGE model optimal behavior of economic agents and the elasticity parameter setting in model equations often lead to extreme changes in the price and outputs, which may underestimate the comprehensive impact of disasters on the economy [45]. Therefore, improvement of the accuracy of estimation would improve the methodology. In addition, a simulation of the effects of disaster policies represents further work that can be done, as the CGE model has advantages in policy analysis. Second, our disaster-risk analysis can be improved to reduce the subjectivity, combining the AHP method with other methods such as the random forests method. Correlations of the indicators should be further calculated. Third, in terms of the uncertainty of disaster occurrence, the frequency and intensity of typhoons were accumulated in the temporal and spatial dimension in our study. The characteristics of typhoon flood disasters can be further studied with the accessibility of various data such as wind field data and water level data [46], or by using a hurricane tracking model [47] or depth-damage functions [44] to estimate the risk. In addition, a more refined division of land use for production and infrastructure is necessary according to the data availability, in order to analyze the regional vulnerability in the future.

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Appendix A. The Judgment Matrix and Consistency Ratio (CR) of the Analytic Hierarchy Process (AHP) Analysis

Table A1. Average consistency random index (RI).

| Order of Matrix | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 | 13 | 14 | 15 |
|-----------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| RI              | 0  | 0  | 0.52 | 0.89 | 1.12 | 1.26 | 1.36 | 1.41 | 1.46 | 1.49 | 1.52 | 1.54 | 1.56 | 1.58 | 1.59 |

The judgment matrix and consistency ratio (CR) and the largest eigenvalue of the judgment matrix of different aspect layers are shown in the tables below.

Table A2. Typhoon flood risk. Note: CR = 0 < 0.1 and λmax = 3.

| Typhoon Flood Risk | Disaster Hazard | Vulnerability | Resilience | W^C |
|--------------------|-----------------|---------------|------------|-----|
| Disaster           | 1               | 9             | 9          | 0.8182 |
| Vulnerability      | 0.1111          | 1             | 1          | 0.0909 |
| Resilience         | 0.1111          | 1             | 1          | 0.0909 |

Table A3. Disaster hazard. Note: CR = 0 < 0.1 and λmax = 3.

| Disaster Hazard       | Typhoon Frequency | Water Density | Mean Annual Rainfall | PE |
|-----------------------|-------------------|---------------|----------------------|----|
| Typhoon frequency     | 1                 | 9             | 9                    | 0.8182 |
| Water density         | 0.1111            | 1             | 1                    | 0.0909 |
| Mean annual rainfall  | 0.1111            | 1             | 1                    | 0.0909 |

Table A4. Vulnerability. Note: CR = 0.0739 < 0.1 and λmax = 4.1972.

| Vulnerability       | Elevation | Slope | Population Density | Land for Production | PE |
|---------------------|-----------|-------|--------------------|---------------------|----|
| Elevation           | 1         | 5     | 0.3333             | 0.25                | 0.1545 |
| Slope               | 0.2       | 1     | 0.2                | 0.1667              | 0.0541 |
| Population density  | 3         | 5     | 1                  | 0.5                 | 0.3055 |
| Land for production | 4         | 6     | 2                  | 1                   | 0.4859 |

Table A5. Resilience. Note: CR = 0.0176 < 0.1 and λmax = 3.0183.

| Resilience        | Road Density | Other Infrastructure Density | GDP per Capita | PE |
|-------------------|--------------|------------------------------|----------------|----|
| Road density      | 1            | 3                            | 0.5            | 0.3196 |
| Other infrastructure density | 0.3333 | 1                            | 0.25           | 0.1220 |
| GDP per capita    | 2            | 4                            | 1              | 0.5584 |
### Appendix B. List of Industries and Commodities in the CGE Model

**Table A6. List of industries and commodities.**

| Industry Number | Commodity Number | Name                          | Industry Number | Commodity Number | Name                          |
|-----------------|------------------|-------------------------------|-----------------|------------------|-------------------------------|
| 1               | 43               | Agriculture                   | 22              | 64               | Other manufacturing products |
| 2               | 44               | Coal                          | 23              | 65               | Scrap and waste               |
| 3               | 45               | Petroleum and gas extraction  | 24              | 66               | Metal products and equipment |
| 4               | 46               | Metal ore mining              | 25              | 67               | Electric and heat power       |
| 5               | 47               | Other nonmetal ore mining     | 26              | 68               | Gas production and distribution |
| 6               | 48               | Foods and tobacco             | 27              | 69               | Water production and distribution |
| 7               | 49               | Textile                       | 28              | 70               | Construction                  |
| 8               | 50               | Apparel                       | 29              | 71               | Wholesale and retail trades   |
| 9               | 51               | Timber and furniture          | 30              | 72               | Traffic transport and storage |
| 10              | 52               | Papernaking                    | 31              | 73               | Hotels and catering services  |
| 11              | 53               | Petroleum coking and nuclear fuel | 32          | 74               | Information transmission      |
| 12              | 54               | Chemical                      | 33              | 75               | Computer services and software |
| 13              | 55               | Nonmetallic mineral           | 34              | 76               | Financial intermediation      |
| 14              | 56               | Metal smelting and rolling    | 35              | 77               | Leasing and business services |
| 15              | 57               | Metal products                | 36              | 78               | Research, technical services |
| 16              | 58               | General equipment             | 37              | 79               | Water conservancy             |
| 17              | 59               | Special equipment             | 38              | 80               | Environment and public facilities management |
| 18              | 60               | Transportation equipment      | 39              | 81               | Education                     |
| 19              | 61               | Electrical machinery and equipment | 40            | 82               | Health, social security, and social welfare |
| 20              | 62               | Communication equipment       | 41              | 83               | Culture, sports, and entertainment |
| 21              | 63               | Instrument making             | 42              | 84               | Public and social management |
Appendix C. Elasticities of the CGE Model

Table A7. Elasticities and reference.

| Elasticity                              | Reference   |
|-----------------------------------------|-------------|
| Constant elasticity of substitution (CES) between the composite of the production factor and composite commodity (intermediate input) | [48]        |
| Substitution elasticity of the Armington function | [49]        |
| Constant elasticity of transformation (CET) function | [50]        |

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