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## Does the Chinese coastal ports disruption affect the reliability of the maritime network? Evidence from port importance and typhoon risk

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### ABSTRACT

Traditional studies typically employed random and deliberate attack methods to explore port failure, overlooking real-world factors. In this research, we focus on exploring the reliability of the Maritime Silk Road (MSR) container shipping networks after the failure of Chinese coastal ports due to the impact of typhoons. This article analyzes AIS trajectory data and typhoon occurrence data through entropy weight method and grey correlation analysis, to construct an evaluation model for the failure of Chinese critical ports. Then, we will look at the effects of deliberately removing Chinese critical ports from the MSR container shipping system. The main conclusions drawn are as follows: (1) Except for some of the largest ports (i.e., Ningbo-Zhoushan, Shanghai, and Kaohsiung), the importance of Chinese coastal ports varies slightly in the MSR container maritime network, while it varies widely in their exposure and resistance to typhoons. (2) Ports of Ningbo Zhoushan, Shanghai, Hong Kong, Shekou, Kaohsiung, and Yantian rank high in the comprehensive evaluation results. They have a higher probability of failure when affected by typhoon risks. (3) After the failure of Chinese crucial ports, the reliability of the MSR container maritime network successively declined, recovered, and stabilized. This study can offer a valuable reference for relevant actors involved in safeguarding crucial ports, finding alternative ports, optimizing shipping routes, and improving the reliability of maritime networks under typhoons and other major natural disasters.

### 1. Introduction

About 90 % of global trade volumes rely on maritime transport.<sup>1</sup> The proposal of the “the Belt and Road” initiative has an important impact on the evolution pattern of the global maritime transport. The maritime shipping network between China and countries along the route is an important support for the prosperity and development of the Maritime Silk Road (MSR). As key nodes, ports play a vital role in maritime networks, serving as essential hubs for facilitating global trade. Their functionality not only depends on comprehensive infrastructure and ample financial support but also on the ability to overcome various exogenous shocks (Asadabadi and Miller-Hooks, 2020). In recent years, frequent natural disasters have had a huge impact on ports and maritime

transportation. Typhoons are natural disasters among the greatest threats; their impact is the most difficult to evaluate. The disaster chain caused by extreme weather events such as typhoons not only seriously affects the operation safety of ports, but also has a profound effect on the circulation of maritime cargo and network reliability.

Reliability is a concept based on fault cognition, which reveals the mechanism and laws of faults. Numerous scholars studied various real-world networks from a reliability perspective, such as computer networks (Forghani-elahabad and Kagan, 2019), power networks (Chang, 2022), logistics networks (Niu et al., 2017), and transportation networks (Feng et al., 2019). Within the realm of transportation, reliability refers to the transportation network’s capacity to achieve an acceptable service level after multiple, unexpected events occur (Soltani-Sobh et al.,

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<sup>1</sup> <https://www.icontainers.com/international-shipping-cost-guide/>.

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2016). It emphasizes the ability of the network to respond to – or achieve a satisfactory level from – unexpected interruptions. Existing research focused on public transport networks (Serdar et al., 2022), railways (Yeh et al., 2021), roads (Zhou and Wang, 2018), waterways (Liu et al., 2020), airlines (Hassan et al., 2021), and multimodal networks (Stamos et al., 2015), leaving maritime networks somewhat behind.

Regarding research methods, as the reliability of transportation networks gauges the transportation performance pre and post disruption of infrastructure components, identifying the most vulnerable or robust nodes and/or links is a key step.

When the important transportation network is disturbed by various events, it is easy to cause node failure, link degradation, network interruption, and even cascading failures (Bešinović et al., 2022). Currently, scholars have proposed comprehensive methods to assess the importance of ports in maritime transportation, such as the shift-share and interlocking network model (Wang et al., 2022), the principal eigenvector method (Wang and Cullinane, 2008), network hub port assessment (Low et al., 2009), and the hubs and authorities centrality (Tocchi et al., 2022). Traditionally, scholars look at port importance, through measures such as degree centrality, closeness centrality, and betweenness centrality (Wan et al., 2021; Zhou and Wang, 2018). For example, Mou et al. (2021) and Peng et al. (2018) combined the port's regional competitiveness, network status, and other indicators, and established a comprehensive evaluation model of port development potential to reveal the port location advantage. However, these centrality measures are insufficient in expressing ports' overall importance and the network's percolation ability. An improved eigenvector centrality proposed by Cheung et al. (2020) and Piraveenan et al. (2013) with the first to propose percolation centrality can address the shortcomings mentioned above. Other approaches mainly simulated random or targeted attacks based on degree and betweenness centrality to observe structural changes as well as their statistical and geographical distribution (Ducruet, 2016; Peng et al., 2017). Few scholars, yet, have incorporated real-world factors, such as typhoons, into the assessment of infrastructure operations from a reliability perspective. Some scholars' work remained limited to connection reliability, time reliability, and capacity reliability (Ilalokhoin et al., 2023). The impact of climate change has been considered (Stamos et al., 2015), but there are still shortcomings, such as the lack of detailed quantitative studies about ports, maritime networks, and specific natural disasters.

The evaluation of important ports under typhoon disasters integrates multiple factors and variables. These indicators usually do not belong to the same system and are prone to problems such as difficulty in determining indicator weights and strong subjectivity. Entropy, AHP, and Fuzzy, as well as different combination methods, are the most commonly used methods in existing evaluation models. Mou et al. (2020) explored the diverse combination methods mentioned above in their research on the development potential of ports, all of which had difficulties in determining indicator relevance. In contrast, the grey correlation analysis method (Liu et al., 2022) disregards the significance and correlation of each evaluation indicator, yielding the correlation coefficient and ranking between the evaluation object and each indicator. Therefore, combining grey correlation analysis with the entropy weight method to construct a comprehensive evaluation model for ports has certain advantages compared to other combined methods.

This article thus proposes a quantitative analysis of how Chinese coastal port failures due to typhoons impact the reliability of container shipping networks. Attention will be drawn to how Chinese ports respond to typhoon attacks? How does the reliability of the maritime network change after the failure of Chinese ports? We employed the entropy weight method and grey correlation analysis, combined with additional methods of graph theory (e.g., percolation centrality) and typhoon-related impacts, to evaluate the order of Chinese ports failure under the influence of typhoons. In addition, the current research further advances the concept of reliability and explores the qualitative and quantitative changes of the reliability of MSR maritime network

under port disruptions. This study thus contributes to further understanding the evolution of port operations in maritime networks under extreme circumstances, while it adds to the existing literature on networks and reliability in more general terms.

## 2. Data and methods

### 2.1. Study area and data

#### 2.1.1. Study area

The 21st Century MSR is an inclusive and open maritime cooperation network. There are mainly two key directions: one is to extend from the Chinese coastal ports to the South China Sea, the Indian Ocean, and Europe; another path extends from Chinese coastal ports through the South China Sea and Oceania to the South Pacific. As key nodes for maritime cooperation and trade along the MSR, the safety and stability of Chinese ports are crucial for the economic activities of countries along the route and the global supply chain (Xu et al., 2023). This article, considering the data availability, representativeness and container network evolution, selected 731 container ports from 71 countries along the MSR as the research objects, including 52 coastal container ports in China (which includes Hong Kong, Taiwan, and Macau). Fig. 1 illustrates the distribution of the study areas and ports.

#### 2.1.2. Data

##### (1) AIS data

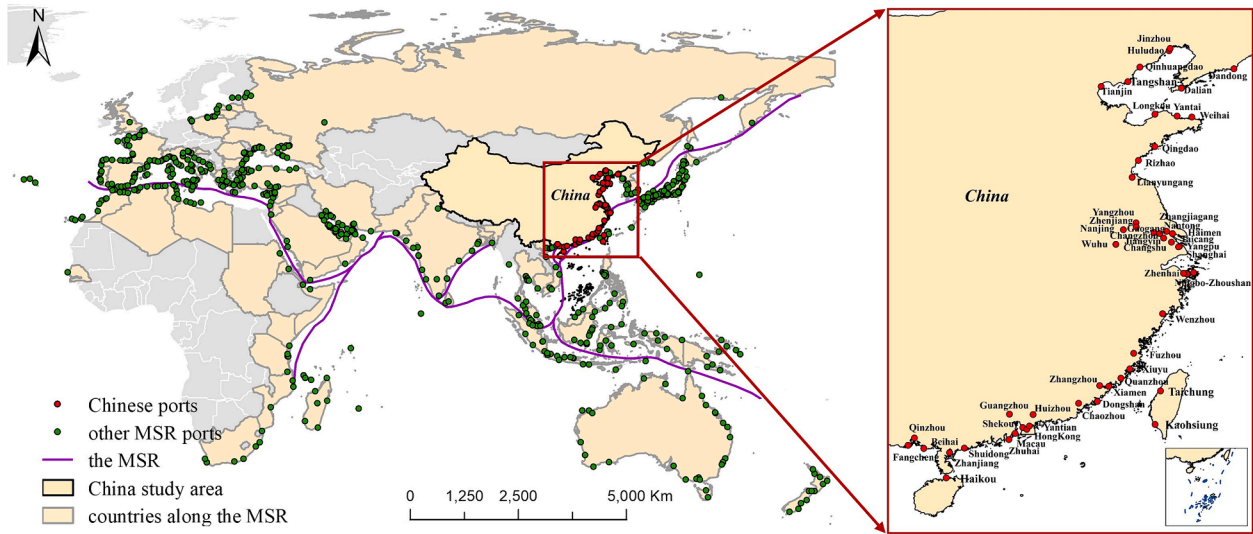
Given that the purpose of this article is to analyze the reliability changes of the container shipping network after the failure of Chinese coastal ports due to typhoon risk, rather than investigating network trends and evolution, data for only one-time point were selected. After a detailed analysis of the availability and effectiveness of the data, we extracted 191,114 container AIS data along the MSR spanning January 1 to December 31, 2014, by using methods of ship type identification, spatial position matching, and data cleaning.

##### (2) Typhoon data

Our aim is not to conduct empirical research on the immediate impact of a specific typhoon on the port, but to study the potential risk exerted by typhoons on ports. Therefore, we obtained typhoon track data from 2001 to 2022 instead of 2014. Firstly, using long-term typhoon data can better capture the cumulative impact of typhoons on the ports over the years and help evaluate the overall risk faced by the port. Secondly, in 2014, there were only 6 typhoons passing through Chinese coastal ports, mainly affecting coastal ports near and south of the Yangtze River such as Ningbo Zhoushan, Nanjing, Wenzhou, Fuzhou, Quanzhou, Chaozhou, etc. Comparing the typhoon risk levels of various ports, it is difficult to achieve the research objectives using only typhoon data from 2014. After location extraction, information filtering, and elimination, a total of 18,239 typhoon trajectory points and 580 trajectory lines in China were selected. The data includes information such as typhoon ID, name, time, wind speed, direction, intensity, impact radius, longitude, and latitude. Through spatial analysis of port and typhoon data, the typhoon number and average intensity of 52 coastal container ports in China are obtained. Table 1 summarizes all data sources.

### 2.2. Methodology

This article proposes a research framework on the impact of Chinese port failures on the reliability of maritime networks under typhoon disasters. The main idea is to a) use multi-source data to construct an evaluation index system from the perspectives of port importance and typhoon risk; and to b) use the entropy weight method and grey



**Fig. 1.** Distribution of study areas and ports Note: This article identified ports with the ability to handle container cargo as container ports, including multifunctional ports, not limited to container single function ports. Referring to the research of He et al. (2022) and Mou et al. (2022).

**Table 1**  
Data sources.

Data	Source
Port hinterland cities; Vector data of the MSR	The hinterland Gross Domestic Product (GDP) data of Chinese ports comes from the National Basic Geographic Information Center ( <a href="https://www.ngcc.cn/">https://www.ngcc.cn/</a> ); the MSR data is provided by the Belt and Road website ( <a href="https://www.yidaiyilu.gov.cn/">https://www.yidaiyilu.gov.cn/</a> )
Port data	The basic port details are from the World Port Index (WPI) provided by the National geospatial intelligence Administration ( <a href="https://www.nga.mil/">https://www.nga.mil/</a> ); The port cargo throughput comes from the Ministry of Transport of the People’s Republic of China ( <a href="http://www.mot.gov.cn/">http://www.mot.gov.cn/</a> )
AIS data	Automatic Ship Identification (AIS) data sourced from HiFleet Ltd ( <a href="https://www.hifleet.com/">https://www.hifleet.com/</a> )
Typhoon data	Typhoon data are sourced from the Central Meteorological Observatory Typhoon Website ( <a href="https://typhoon.nmc.cn/web.html">https://typhoon.nmc.cn/web.html</a> )

correlation analysis to calculate the comprehensive relative correlation of 52 Chinese coastal ports, and rank them. Finally, the evaluation ranking of ports was deliberately removed in order, and reliability research was conducted to analyze the impact of the failure of Chinese coastal ports on the structure of the MSR container shipping network. Fig. 2 shows the technical framework.

2.2.1. Construction of evaluation model

This article constructs an evaluation model from two perspectives: port importance and typhoon risk. The importance of Chinese ports in the network is evaluated using weighted degree centrality, eigenvector centrality, and percolation centrality. Concurrently, we comprehensively evaluate the typhoon risk from two perspectives: disaster-affected factors (refer to various factors that affect ports caused by typhoon disasters, such as typhoon intensity, wind speed, radius of influence, etc.) and disaster-bearing factors (refer to various factors that ports resist to typhoon disasters, such as geography, socioeconomic factors, technology, etc).

(1) Evaluation indicators for port importance

Centrality is an important tool for network analysis and has been extensively applied in recent years to assess and ascertain the importance of ports (Sui et al., 2022). Weighted degree centrality indicates the

traffic volume or importance of a port. It considers the weights of port connections (that is calculated in TEU), not just the number of connections (Cai et al., 2021). Eigenvector centrality is used to assess the transmission between ports. The basic principle is that connections from important nodes are more valuable than connections from unimportant nodes, and ports connected to highly centralized ports have better development prospects (Cheung et al., 2020). Percolation centrality shows the centrality by computing the connectivity and percolation status of nodes. It can be represented as the proportion of a “percolation path” for a specific node within a given time, as shown in the formula (1):

$$PC^t(v) = \frac{1}{N-2} \sum_{s \neq v \neq r} \frac{\sigma_{s,r}(v)}{\sigma_{s,r}} \frac{x_s^t}{[\sum x_i^t] - x_v^t} \tag{1}$$

Where  $\sigma_{s,r}$  represents the sum of the shortest paths from node  $s$  to node  $r$ ,  $\sigma_{s,r}(v)$  is the frequency of these paths through the node  $v$ .  $x_i^t$  is the percolation state of node  $i$  at a time  $t$ .  $x_i^t = 0$  and  $x_i^t = 1$  respectively represent the non-percolating state and complete percolating state. Values between 0 and 1 indicate partial percolation.

(2) Evaluation indicators for typhoon risk in ports

Risk assessment involves analyzing and evaluating the hazards of disaster-causing factors such as the environment, humans, and property that may cause harm, as well as the bearing ability of the disaster body, to determine the nature and scope of the risk (Liu et al., 2016). The article takes the typhoon number and average intensity as key indicators to assess the impact on ports, determining the likelihood of disaster-causing factors in the studied ports over time. Two economic indicators, namely port cargo throughput and hinterland GDP, are used to measure the disaster-bearing capacity of ports.

Typhoon Number: it refers to the frequency of typhoons hitting ports. The more frequently typhoons affect ports, the greater the risk of port paralysis.

$$TN(i) = \sum_{i=1}^M \left( \bigcap_{j=1}^K (G_i \cap \{p \in R^2 : distance(p, P_j) \leq r_j\}) \neq \emptyset \right) \tag{2}$$

Where  $TN(i)$  represents the number of typhoons for the  $i$ th port;  $M$  and  $K$  are the total number of ports and typhoons respectively;  $G_i$  and  $P_j$  represent the positions of the  $i$ th port and the  $j$ th typhoon respectively;  $r_j$  is the influence radius of the  $j$ th typhoon;  $Distance(p, P_j) \leq r_j$  defines the

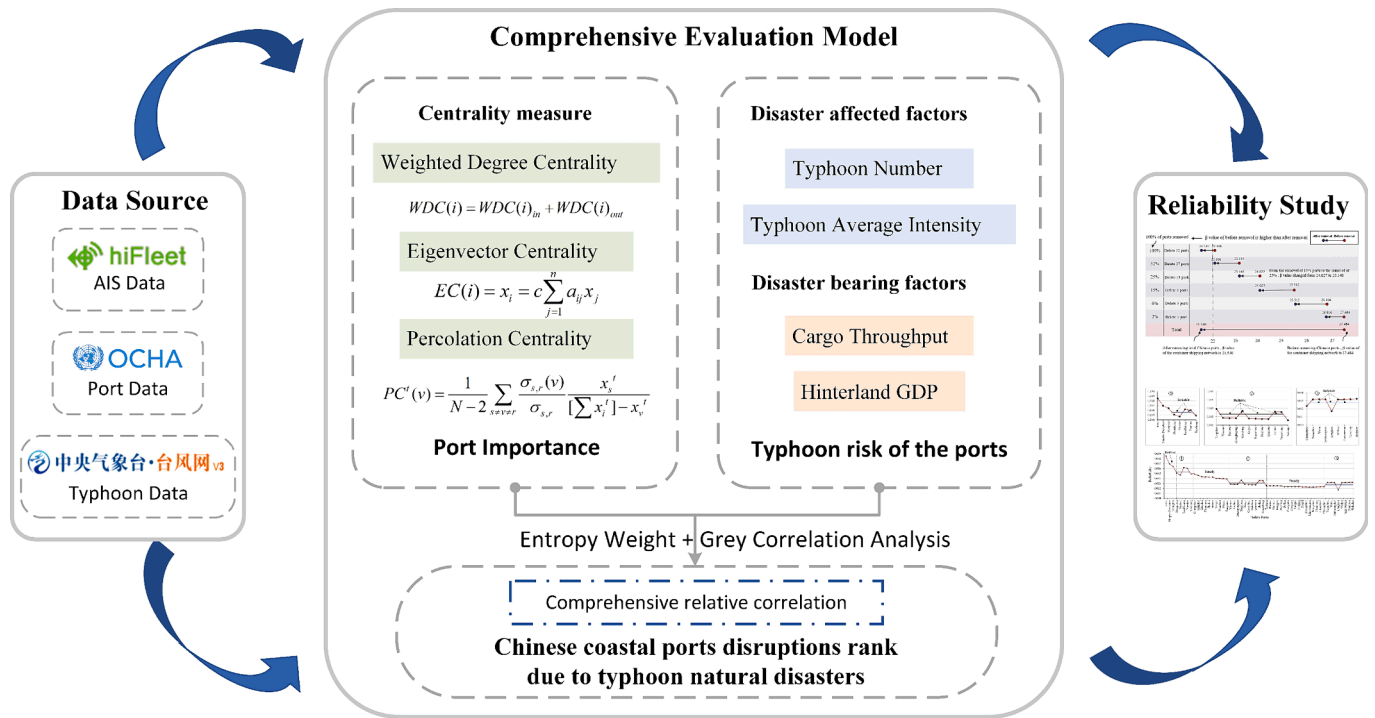


Fig. 2. Technical Framework.

buffer zone  $B_j$  of the  $j$ th typhoon, which is the set of points  $p$  that is not more than their influence radius  $r_j$  from the center of the typhoon  $P_j$ ;  $V$  represents a logical OR operation, used to indicate the existence of at least one  $j$  that intersects  $G_i$  and  $B_j$ .

Typhoon Average Intensity: it reveals the intensity of typhoons attacking ports, obtained by dividing the total intensity of typhoons passing through the port by the typhoon number. Generally speaking, the higher the average intensity of a typhoon, the stronger the destructive power it causes, and the more likely the port is to be interrupted.

$$TI(i) = \frac{\sum_{m=1}^n I_{i(m)}}{n_{(i)}} \quad (3)$$

Where  $TI(i)$  represents the average intensity of typhoons passing

through the  $i$ th port,  $I_{i(m)}$  is the typhoon intensity of the  $m$ th typhoon passing through the  $i$ th port.

Cargo Throughput: it refers to the total volume of goods processed through a port or transportation node within a specific time. It is often utilized to gauge the operational efficiency and scale of ports, logistics centers, or transportation networks.

Hinterland GDP: it represents the overall scale and vitality of the economy within a port city. More GDP also means more infrastructures, people, and industries, so a bigger impact in the case of a big typhoon, in absolute terms. It reflects the port's ability to withstand typhoon disasters.

### 2.2.2. Calculation of evaluation index weights and comprehensive relative correlation

Employing the entropy weight method and grey correlation analysis,

Table 2  
Introduction and calculation steps of the grey correlation analysis.

Methods	Introduction	Calculation steps
The grey correlation analysis	It pertains to a method used to quantitatively depict and compare the evolution of a system. It combined with the entropy weight method, to calculate comprehensive relative correlation for each port. A higher value indicates a stronger correlation between the port and the indicators, showing greater influence.	<p>Step 1: Standardize indicator data, as in step Eq. (A.1).</p> <p>Step 2: Calculate the spacing.</p> $\Delta y_{ij} =  \max(y_j) - y_{ij}  \quad (4)$ <p>Where <math>\Delta y_{ij}</math> is the spacing between the value of the <math>i</math>th port at the <math>j</math>th indicator and the maximum value of the <math>j</math>th indicator, <math>\max(y_j)</math>; <math>y_{ij}</math> is the data for the <math>i</math>th port after dimensionless processing of the <math>j</math>th indicator.</p> <p>Step 3: Calculate the correlation coefficient of each port.</p> $\xi_{ij} = \frac{\min(\Delta y_{ij}) + \rho \cdot \max(\Delta y_{ij})}{\Delta y_{ij} + \rho \cdot \max(\Delta y_{ij})} \quad (5)$ <p>Where <math>\xi_{ij}</math> is the correlation coefficient between the <math>i</math>th port and the <math>j</math>th indicator. <math>\rho</math> is the resolution coefficient and <math>\rho = 0.5</math>.</p> <p>Step 4: Calculate the comprehensive relative correlation, importance correlation, and typhoon risk correlation of each port.</p> $IC_{(i)} = \omega(WDC) \cdot \xi_{(i,WDC)} + \omega(EC) \cdot \xi_{(i,EC)} + \omega(PC) \cdot \xi_{(i,PC)} \quad (6)$ $TRC_{(i)} = \omega(TN) \cdot \xi_{(i,TN)} + \omega(TI) \cdot \xi_{(i,TI)} + \omega(T) \cdot \xi_{(i,T)} + \omega(GDP) \cdot \xi_{(i,GDP)} \quad (7)$ $CRC_{(i)} = IC_{(i)} + TRC_{(i)} \quad (8)$ <p>Where <math>IC_{(i)}</math> represents the importance correlation of port <math>i</math>, with a higher value indicating greater port significance; <math>TRC_{(i)}</math> is the typhoon risk correlation of port <math>i</math>, with a higher value indicating increased typhoon risk for the port; <math>CRC_{(i)}</math> represents the comprehensive relative correlation of the <math>i</math>th port.</p>

we calculate the weights of each indicator and the comprehensive relative correlation of 52 Chinese ports. The entropy weight method assigns weights based on index variability, with lower entropy indicating less variation, higher weight, and more significant in the comprehensive model. The calculation process is detailed in Table A1. Table 2 summarizes the introduction and steps of the grey correlation analysis.

### 2.2.3. Measurement of network reliability

In this study, network reliability refers to a port's or network's capacity to maintain satisfactory connectivity and closeness due to its ability to recover and resist when affected by a typhoon disaster. Based on the definition of network reliability and concerning relevant literature (Calatayud et al., 2017), this article combines average path length ( $L$ ), network diameter ( $D$ ),  $\beta$  Index ( $\beta$ ), and  $\gamma$  Index ( $\gamma$ ), using qualitative and quantitative methods to analyze the change in the reliability of container maritime networks. Table 3 describes the indicators. The formula for calculating network reliability is:

$$R = \frac{\beta \cdot \gamma}{L \cdot D} \tag{9}$$

## 3. Results and explanations

### 3.1. Evaluation of important ports affected by typhoon disasters

#### (1) Calculation of port importance

This article uses three measurement indicators: weighted degree centrality, eigenvector centrality, and percolation centrality to calculate centrality of each port along the MSR. The results of the calculations are presented in Table 4.

1) From the perspective of weighted degree centrality, China's container ports have a strong transport capacity, taking up most of

**Table 3**  
Evaluation indicators for network reliability.

Indicators	Meanings	Formulas
Average Path Length	It is the average value of the shortest path length among all ports in the network. When a network is deliberately attacked but not yet broken, the average path length reflects the average separation between ports.	$L = \frac{1}{2N(N-1)} \sum_{i \in N} \sum_{j \neq i} S_{dij} \tag{10}$ <p>Where <math>N</math> denotes all study ports, <math>S_{dij}</math> is the number of edges through the shortest path between any two ports. The higher the <math>L</math> value, the more dispersed the network is and the poorer its reliability. Therefore, this indicator is inversely proportional to reliability.</p>
Network Diameter	It is the maximum of the distance between any two nodes in the network.	$D = \max_{ij} d_{ij} \tag{11}$ <p>Where <math>D</math> is the diameter of the largest connected subgraph in the network after simulation removal; <math>d_{ij}</math> is the distance between any two ports. The diameter is inversely proportional to network reliability.</p>
$\beta$ Index	It is the average number of connections in a network and serves as a metric for network connectivity.	$\beta = l/N \tag{12}$ <p>Where <math>\beta</math> denotes the connectivity of the largest connected subgraph in the network after simulation removal, <math>l</math> denotes the count of edges in the largest connected subgraph. The larger <math>\beta</math> values indicate better connectivity of the network.</p>
$\gamma$ Index	In a network, it is the ratio of the actual number of connections to the maximum. It is used to reflect the connectivity in a regional network.	$\gamma = 2l/[N(N-1)] \tag{13}$ <p>Where a larger value of <math>\gamma</math> indicates better connectivity of the network.</p>

the capacity along the MSR, and are more evenly distributed along the Chinese coast. Specifically, there are 16 ports with a weighted degree of 600–2000 million TEUs, with Chinese ports accounting for as much as 10/16. Apart from the ports of Keppel and Pulau Bukom in Singapore and Klang in Malaysia, the ports of Ningbo Zhoushan, Hong Kong, Shekou, Shanghai, and Taiwan's Kaohsiung in China with over 1,000 million TEUs are far ahead of other ports.

2) From the perspective of eigenvector centrality, the ports with greater influence in the container maritime network are located in Singapore, Malaysia in Southeast Asia, and the China-Japan region. Generally, Chinese coastal ports exhibit a higher proportion of highly significant ports, due to their role as gateways rather than hubs. The eigenvector values of Ningbo Zhoushan (1), Shanghai (0.942), and Hong Kong (0.933) all exceed 0.900, playing a pivotal role in the MSR container shipping network.

3) From the perspective of percolation centrality, ports with significant scores are more evenly distributed from west to east along the MSR. For example, Ningbo Zhoushan, Shanghai, and Hong Kong rank high in weighted centrality and eigenvector centrality, but their percolation centrality is only 0.804, 0.583, and 0.461. In other words, ports with high percolation centrality, such as Keppel (1.000), Jurong (0.664) in Singapore, Port Klang (0.829) in Malaysia, Jebel Ali (0.758) in Dubai, Perama (0.847) and Valencia (0.601) in Spain, are all located in strategic shipping zones like the Strait of Malacca, the Strait of Hormuz, and the Strait of Gibraltar. Ningbo Zhoushan, which is not located in an important strait area, has a percolation centrality of up to 0.805, which indirectly reflects another kind of strategic position, between North and South China.

#### (2) Analysis of Typhoon Risk in Ports

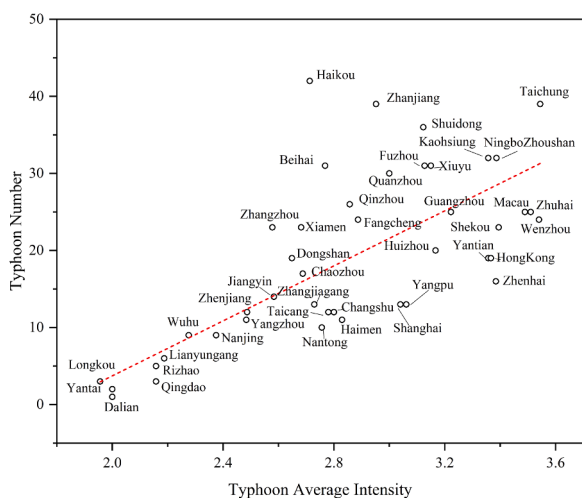
Using formulas (2) and (3), we calculated the number of typhoons and typhoon average intensity in Chinese ports and obtained the metrics of disaster-affected factors. Then, we collected the cargo throughput and hinterland GDP of Chinese ports as the metrics of disaster-bearing factors. The statistical results of typhoon risk metrics for Chinese ports are shown in Fig. 3.

As shown in Fig. 3 (a), A noticeable positive correlation exists between the typhoon average intensity and the typhoon number in the disaster-factors of Chinese coastal ports. As the typhoon average intensity increases, most Chinese ports also undergo more typhoons. Ports around the Bohai Sea, such as Longkou, Dalian, Yantai, Qingdao, and Rizhao, have relatively low typhoon numbers and typhoon average intensity, and their intensity of typhoon attacks is relatively low. The ports with the highest typhoon number and average intensity, such as Haikou, Taichung, Zhanjiang, Ningbo Zhoushan, Kaohsiung, and Fuzhou are mainly located in Hainan Province, Taiwan Province, Guangdong Province, Zhejiang Province, and Fujian Province, which are prone to typhoon disasters. Furthermore, it is noteworthy that ports like Zhuhai, Wenzhou, Shekou, Hong Kong, Zhenhai, Yantian, and Shanghai have been around 15 in 22 years, while the typhoon average intensity has surpassed 3, reaching the level of the severe tropical storm, which is extremely vulnerable to typhoon damage.

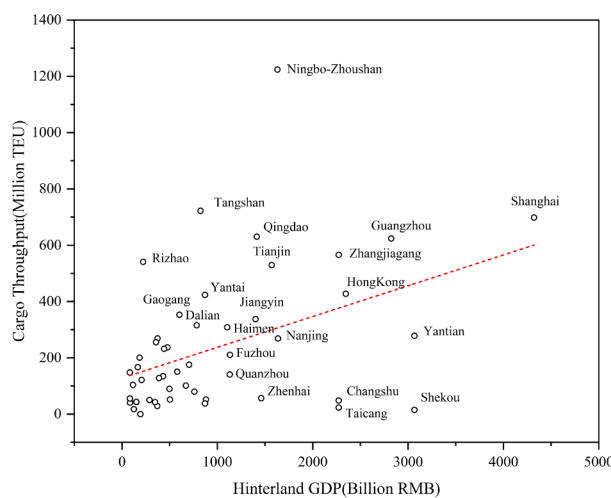
The statistical results in Fig. 3(b) indicate that the ability of Chinese ports to withstand typhoon hazards is characterized by significant imbalances. There is a weak positive correlation between hinterland GDP and cargo throughput. In terms of cargo throughput, Ningbo Zhoushan Port, Tangshan Port, and Shanghai Port have strong potential to withstand typhoons. The reason is that these ports are located in important areas such as the Bohai Bay and the Yangtze River Delta, and have unique geographical locations, coastal protection structures, emergency response plans, and scale, making them less vulnerable to typhoons than some other ports. In terms of hinterland GDP, Taichung Port, Ningbo Zhoushan Port, and Kaohsiung Port, which have suffered more severely from typhoons, have lower hinterland GDP, indicating that the economic support for port construction and maintenance are at a disadvantage, which will increase the typhoon risk of the ports.

**Table 4**  
Ports ranked in the top 16 for each centrality indicator.

Rank	Weighted degree	Port	Country	Eigenvector	Port	Country	Percolation	Port	Country
1	1966	Ningbo-Zhoushan	China	1	Ningbo-Zhoushan	China	1.000	Keppel	Singapore
2	1955	Hong Kong	China	0.956	Keppel	Singapore	0.847	Perama	Greece
3	1791	Shekou	China	0.942	Shanghai	China	0.829	Klang	Malaysia
4	1122	Keppel	Singapore	0.934	Hong Kong	China	0.805	Ningbo-Zhoushan	China
5	1111	Shanghai	China	0.876	Klang	Malaysia	0.758	Jebel Ali	Dubai
6	1006	Kaohsiung	China	0.875	Kaohsiung	China	0.664	Jurong	Singapore
7	991	Klang	Malaysia	0.871	Shekou	China	0.601	Valencia	Spain
8	987	Yantian	China	0.862	Pulau Bukom	Singapore	0.587	Algeciras	Spain
9	945	Pulau Bukom	Singapore	0.836	Jurong	Singapore	0.583	Shanghai	China
10	944	Pusan	Korea	0.786	Busan	Korea	0.563	Pulau Bukom	Singapore
11	852	Qingdao	China	0.770	Qingdao	China	0.539	Busan	Korea
12	736	Jebel Ali	Arab	0.748	Tanjung Pelepas	Malaysia	0.484	Tanjung Pelepas	Malaysia
13	686	Xiamen	China	0.733	Tianjin	China	0.478	Chongjin	Korea
14	685	Tianjin	China	0.720	Xiamen	China	0.466	Marsaxlokk	Malta
15	678	Zhenhai	China	0.681	Zhenhai	China	0.461	Hong Kong	China
16	653	Jurong	Singapore	0.659	Yantian	China	0.448	Shekou	China



(a) Disaster-affected factors in Chinese ports



(b) Disaster-bearing factors in Chinese ports

**Fig. 3.** Statistical results of typhoon risk indicators in Chinese ports.

(3) Calculation of evaluation index weights

This study assumes that the port importance indicator and the port typhoon risk indicator have the same weight, both at 0.5 and that the disaster-affected factors and disaster-bearing factors of the port typhoon risk indicator have the same weight, both at 0.25. We standardized the seven sub-indicators within the port importance indicator group and port typhoon risk indicator group, and then calculated the weight values of each sub-indicator according to Eqs. (A.1)–Eq. (A.4) in Appendix, as shown in Table 5. From the allocation results of indicator weights, the impact ranking of the port importance indicators is PC (0.222) > WDC (0.208) > EC (0.07), the ranking of disaster-affected factors is TN (0.136) > TI (0.114), and the ranking of disaster bearing factors is T (0.141) > GDP (0.109).

**Table 5**  
Calculation results of evaluation index weights.

	Importance indicators (0.5)			Disaster-affected factors (0.25)		Disaster-bearing factors (0.25)	
	WDC	EC	PC	TN	TI	T	GDP
Weight	0.208	0.07	0.222	0.136	0.114	0.141	0.109

**Notes:** WDC: Weighed Degree Centrality; EC: Eigenvector Centrality; PC: Percolation Centrality; TN: Typhoon Number; TI: Typhoon Average Intensity; T: Cargo Throughput; GDP: Hinterland GDP.

(4) The correlation between evaluation indicators and ports

The importance indicators and typhoon risk indicators of the 52 container ports on the Chinese coast were dimensionless and spaced using formulas (4) and (5), and the correlation coefficients between Chinese container ports and each indicator were calculated (Fig. 4). The purpose is to quantify the correlation between each indicator and each port.

Except for the distribution centers and transit ports such as Ningbo Zhoushan, Shanghai, Hong Kong, and Shekou, the distribution of centrality among other Chinese coastal ports is distributed more evenly. The correlation coefficients of weighted degree centrality and eigenvector centrality show that the position of these container ports in the entire network is comparable and their influence on the network is relatively balanced. This also indicates that the construction of ports along the Chinese coast shows a trend of comprehensive and balanced development. However, the correlation coefficient of percolation centrality shows that except for Ningbo Zhoushan Port, the percolation effect of other Chinese ports is relatively low. In addition, because the ports of Hong Kong, Ningbo Zhoushan, Shekou, and Shanghai are the main import and export ports in China, their centrality is also relatively high in the MSR container maritime network.

The typhoon average intensity affects Chinese ports much more than the typhoon number. Although China's coastal areas are hit by multiple typhoons every year, usually only a few typhoons reach tropical storm

### Correlation coefficient

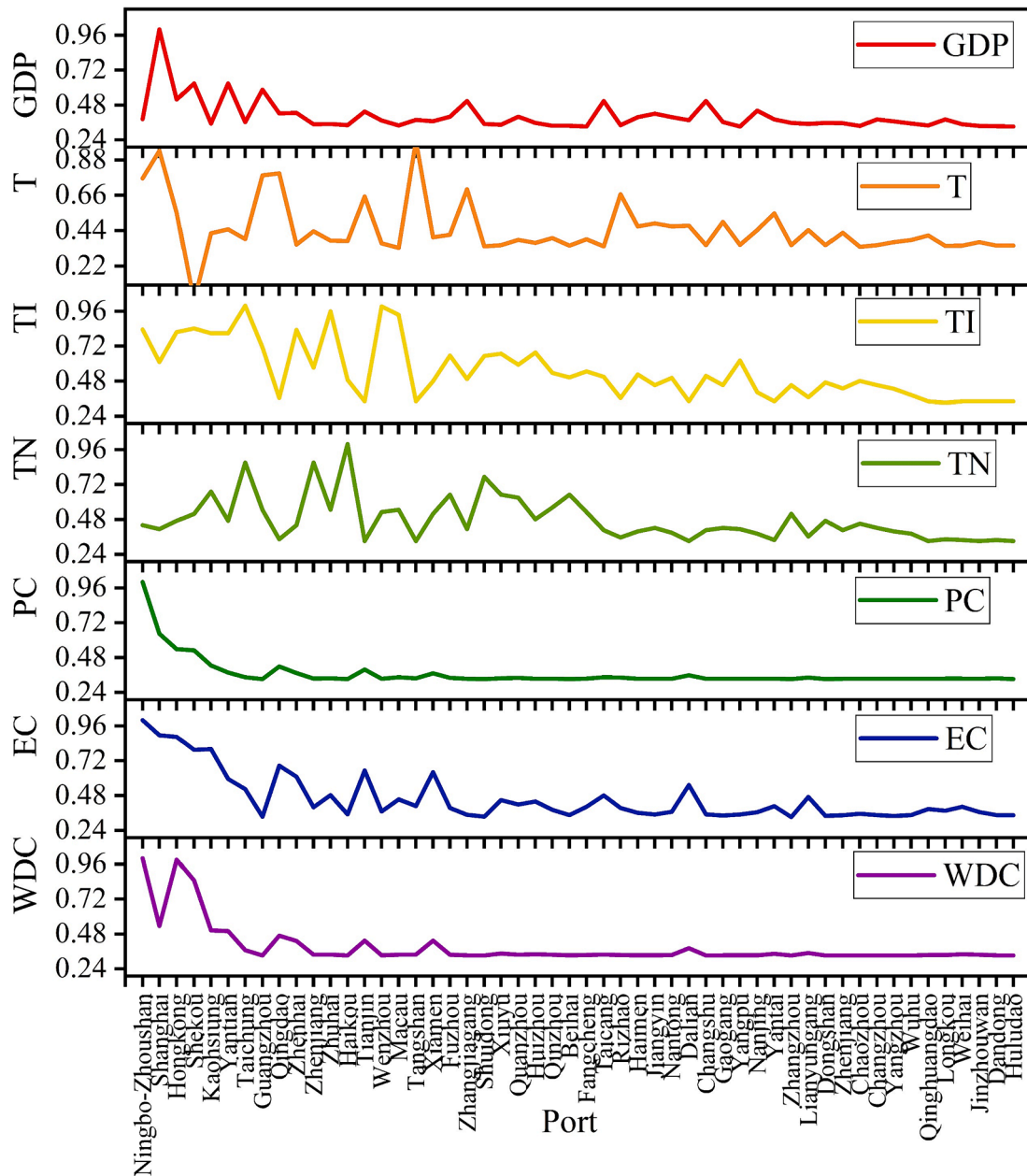


Fig. 4. Correlation between Chinese container ports and each indicator.

levels or above, and these strong typhoons may have serious impacts on port facilities and shipping safety, and vice-versa. For example, the ports of Guangzhou, Zhuhai, and Wenzhou have suffered fewer typhoons over the years, but their average typhoon intensity is at the leading level. The cargo throughput expresses the ability of ports to withstand typhoon risk much more than the hinterland GDP. Although the hinterland cities of ports have strong comprehensive economic capabilities, once the port size is limited and unable to accommodate more container vessels, it will also weaken the port's ability to withstand typhoon disasters. For example, the ability of Shanghai and Tangshan to resist typhoon risk is closely related to cargo throughput, reaching 0.937 and 1 respectively. This indicates that ports of Shanghai (including Yangshan Port) and Tangshan have high cargo throughput and high-quality natural endowments, which have attracted container vessels from other countries to berth. There exists a notable difference in both the risk of exposure to typhoons and the ability to withstand typhoons among Chinese coastal

ports.

#### (5) Evaluation results of comprehensive relative correlation

Using the entropy weight method and grey correlation analysis method, combined with formulas (6)–(8), the importance correlation, typhoon risk correlation, and comprehensive relative correlation of Chinese coastal 52 container ports were calculated. We employ the natural discontinuity method to divide the results into five levels (Fig. 5).

Fig. 5(a) shows the importance correlation of Chinese coastal ports in the MSR container shipping network. The results show that large ports such as Ningbo Zhoushan (0.500), Hong Kong (0.387), Shekou (0.350), Shanghai (0.317), and Kaohsiung (0.256) have a high importance correlation. This indicates that these ports are crucial for economic activities in the southeastern coastal areas of China. The operation of these



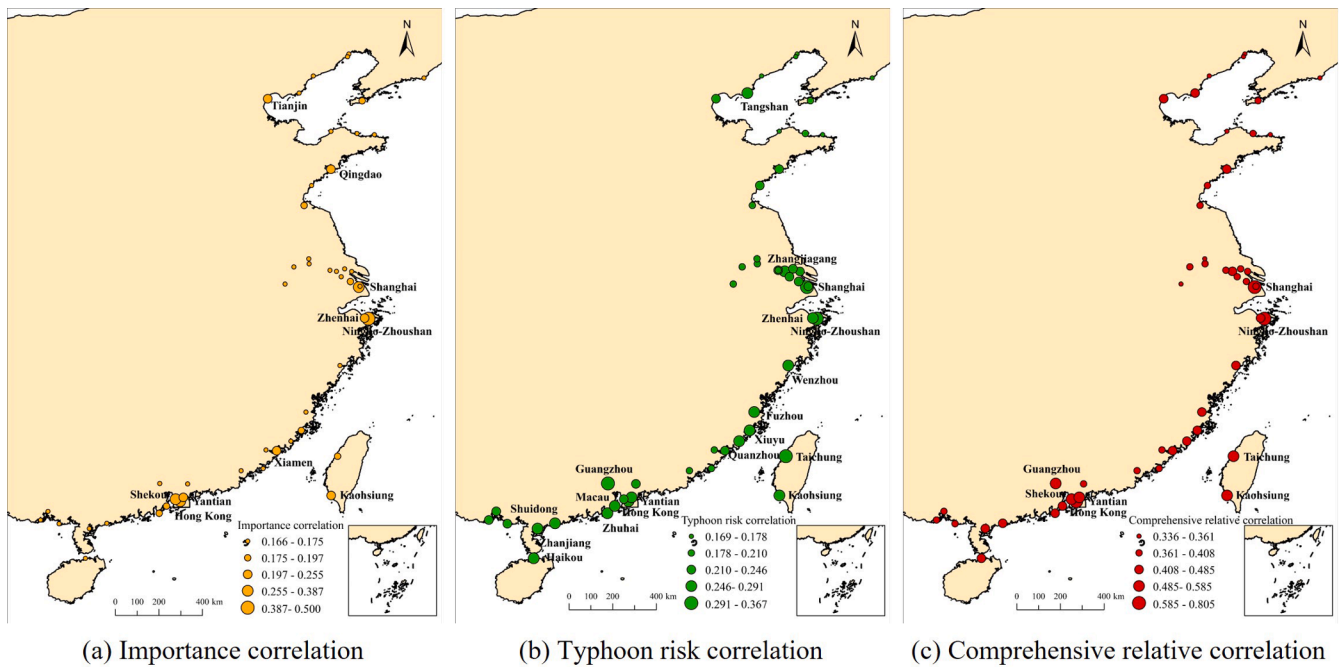
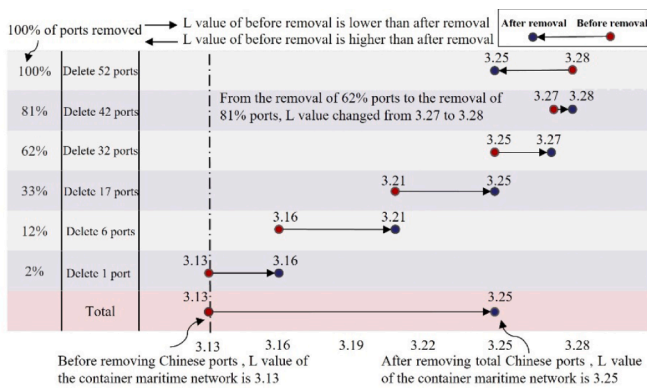


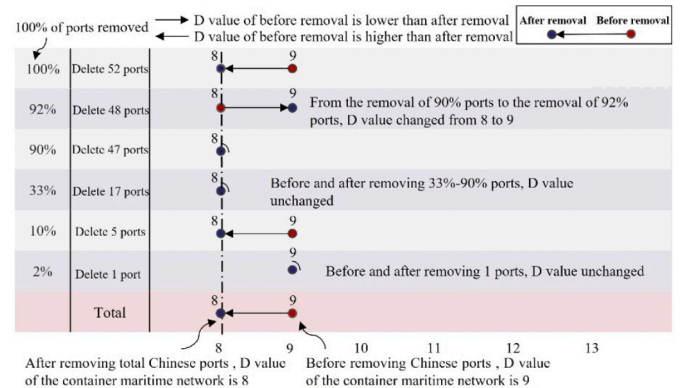
Fig. 5. Correlation and comparison of Chinese ports.

ports has a significant economic impact on the surrounding areas, and any interference with these ports may have a profound impact on the entire region. Fig. 5(b) shows the typhoon risk correlation of Chinese ports. It can be observed that the typhoon risk correlation of ports such

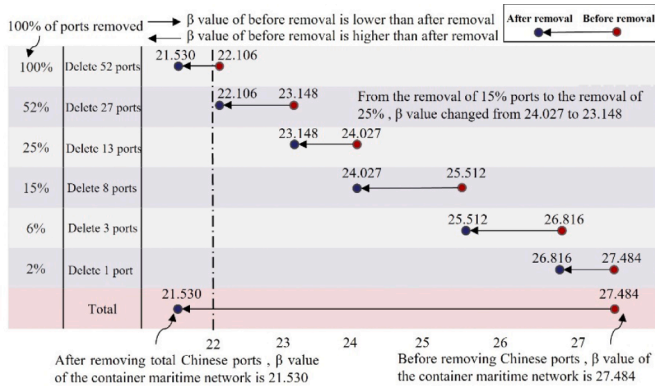
as Shanghai (0.367), Guangzhou (0.330), Taichung (0.327), Ningbo Zhoushan (0.305), and Hong Kong (0.291) is relatively high, while the typhoon risk in the Bohai Rim region is relatively low. This is the result of the comprehensive typhoon disaster-affected factors and disaster-



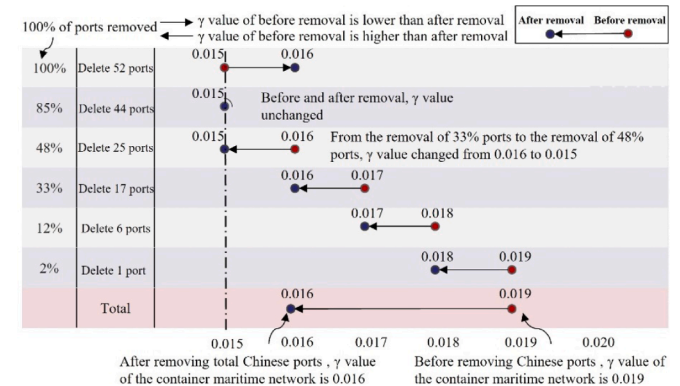
(a)



(b)



(c)



(d)

Fig. 6. Network reliability metrics.

bearing factors of the ports. The comprehensive assessment results of the failure of Chinese important ports affected by typhoon risks are shown in Fig. 5(c). The comprehensive relative correlation of Ningbo Zhoushan (0.805), Shanghai (0.684), Hong Kong (0.679), Shekou (0.585), Kaohsiung (0.538), Yantian (0.518), and Taichung (0.516) ranks in the top ten of the 52 Chinese container ports, all of which are greater than 0.5. On the one hand, these ports held an important position in the MSR container maritime network, thanks to the economic growth of port hinterland cities and the competition and synergy of nearby ports. On the other hand, ports such as Ningbo Zhoushan, Shanghai, and Kaohsiung are located in the coastal areas of China. Although they have an advanced level of economic development, complete infrastructure, and strong resistance to typhoon risk, their inherent geographical location is prone to typhoon attacks, resulting in a higher level of typhoon risk at these ports.

### 3.2. Reliability analysis of container maritime network

According to the evaluation results in Fig. 5, China's coastal ports were deliberately removed in descending order of comprehensive relative correlation, as shown in Table A2 of the Appendix. Fig. 6 (a–d) show the changes in these four metrics respectively, qualitatively reflecting the dynamic changes in network reliability from the perspectives of network connectivity and closeness.

In Fig. 6 (a), the average path length of the container shipping network changes from 3.13 to 3.16 when Ningbo Zhoushan is removed. Deleting all 52 Chinese ports sequentially increases the average path length from 3.13 to 3.25, an increase of 0.12, indicating that the path length of one port in the network to reach the other ports increased by 0.12, showing a weakening of network closeness. From Fig. 6 (b), the network diameter fluctuates around 8 and 9 by removing different numbers of Chinese ports, indicating a slight increase in network closeness. Fig. 6 (c) shows the  $\beta$  value of the network gradually decreases

when the Chinese ports are removed, from 27.484 to 21.53. This trend implies that the average number of links from one port to other ports decreases by almost 6 when Chinese coastal ports are sequentially disabled, and the connectivity of the network decreases significantly. Fig. 6 (d) reflects the  $\gamma$  value of the network decreases from 0.019 to 0.016 and the connectivity of the network decreases.

In summary, the closeness and connectivity of the container network showed varying degrees of decline when the Chinese ports failed in turn. However, due to the inherent resilience of the maritime network and the growth potential of the ports, the container maritime network in general achieves an acceptable service level after uncertain events and shows a certain level of reliability. So how has reliability changed? We quantitatively calculated the reliability of the container shipping network after removing Chinese ports using formula (9), as shown in Fig. 7. According to the definition of maritime network reliability, when the number of ports with reduced reliability is less than or equal to the number of ports with increased reliability, the state of the network reaches an acceptable service level, and the container maritime network is considered reliable. A nearly unchanged reliability value is considered steady.

The reliability of the entire container maritime network before and after the removal of China's coastal ports has gone through a reduce – reliable – steady – reliable process. Overall, after the gradual failures of Chinese ports, due to the substitutability of potential ports, the container maritime network still has a strong ability to recover and eventually reach a steady and reliable state, with high reliability. When removing Ningbo Zhoushan Port, Shanghai Port, Hong Kong Port, and Shekou Port, the reliability of the network continues to decline, from 0.018 to 0.014. The reason for this is that these ports are the major container ports and take up most of the cargo capacity along the MSR. When these ports fail due to natural disasters or other unexpected events, they are difficult to be fully replaced by neighboring ports due to the lack of sufficient reserve support. This will put a huge strain on the connectivity of the network and lead to a decrease in network reliability.

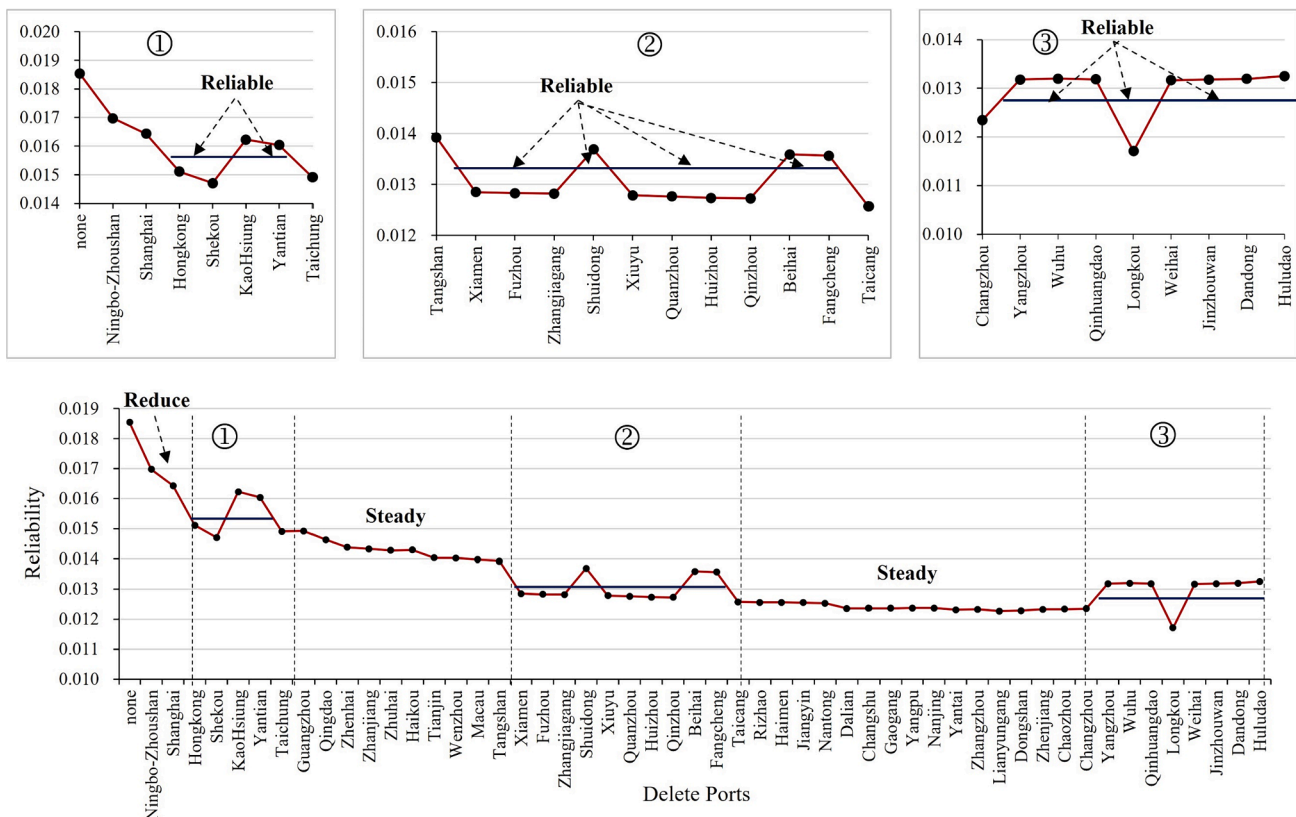


Fig. 7. Reliability changes of MSR container maritime network due to Chinese ports' failure.

With the failure of Kaohsiung Port and Yantian Port, the reliability of the network has been restored, ultimately leading to the network maintaining a reliable and stable state. Because Kaohsiung Port and Yantian Port are important nodes in China's coastal ports, their failure may lead to instability in the container maritime network. However, over time, relevant departments may take measures to optimize the network and solve problems, such as increasing the capacity of other ports or optimizing ship routes. These measures may rebalance the network and maintain a reliable and stable state.

According to the changes in the reliability of the container maritime network, we divide Chinese ports into three hierarchical structures (Fig. 8): key ports (with reduced reliability), alternative ports (with almost unchanged reliability), and potential ports (with increased reliability).

In Fig. 8, the reliability of the container maritime network has decreased after the failure of nine key ports, including Ningbo Zhoushan, Shanghai, and Hong Kong. After the failure of six ports, including Kaohsiung Port, Yantian Port, and Shuidong Port, the reliability of the network has increased, with great development potential. Therefore, in future maritime network planning, it is necessary to focus on protecting these key ports, while also considering ports with development potential as key development targets to further improve the reliability and efficiency of container maritime networks. In addition, when assessing port alternative, it's essential to consider factors beyond geographical proximity and spatial convenience. Port size, hinterland economic conditions, inter-port spatial connections, and the comparability of their support capacities are all crucial. These factors collectively shape the alternative of port functions. By comprehensively evaluating these factors and considering the distance between ports, alternative ports can be categorized into distant alternative ports and nearby

alternative ports (Fig. 9). Due to the geographical distance between container ports such as Taicang, Guangzhou, Qingdao, and Tianjin, the competition between ports has been weakened to some extent and instead has a strong synergetic effect. Therefore, when similar ports fail, they can quickly find corresponding ports as replacements to maintain the normal flow of goods and the stable operation of the maritime network. Furthermore, after the failure of neighboring ports such as Xiamen, Fuzhou, Zhangjiagang, Xiuyu, Quanzhou, Huizhou, and Qinzhou, the reliability of the network can be stabilized at 0.013, making such ports more suitable for use as replacement parts. Firstly, these ports are geographically adjacent and more convenient in space; Secondly, the similar size and hinterland GDP of these ports and their similar support capacity make it easier for port functions to be dominated and coordinated. Finally, the dense spatial clustering of deep-water terminals results in route overlaps, intensifying the spatial spill-over impact of port activities and ultimately enhancing the interchangeability among ports.

#### 4. Discussions

Container transportation on the MSR is susceptible to natural disasters such as rainstorms, tsunamis, typhoons, and earthquakes. Each year, one-third of the world's typhoons pass through the western Pacific Ocean, and China, located in this region, is one of the countries most severely impacted by typhoons in the world. Although many works have focused on modeling port interruptions, such as random attacks, and intentional attacks based on degree or intermediary centrality, various modeling assumptions are detached from real-world factors. When constructing a port interruption model, this article not only evaluates the importance of ports from multiple perspectives, but also considers the impact of typhoons as a practical factor. From the results of the port importance assessment, ports such as Ningbo Zhoushan, Shekou, Shanghai, and Kaohsiung along the Chinese coast have an absolute advantage in the MSR container maritime network, both in terms of connectivity and transit functions. This confirms the conclusion drawn by Zhao et al. (2021) that Chinese ports occupy a significantly larger share of the network compared to other regions. From the results of typhoon risk assessment at ports, ports such as Shanghai, Guangzhou, Taichung, Ningbo Zhoushan, Hong Kong, and Yantian are at high risk of typhoons. Typhoon intensity is the main reason for increasing the risk of Chinese ports. The ability of a port to resist typhoons not only requires a unique geographical location, and complete infrastructure but also financial support from the government and many other factors. The importance and typhoon risk of ports such as Ningbo Zhoushan, Shanghai, Shekou, Hong Kong, and Yantian are among the top, and they were the first to be interrupted in the comprehensive evaluation model results. In addition, what is consistent with our hypothesis is: ports with an important position in the network can be less exposed to typhoon risk, and vice-versa. Therefore, while paying attention to the network status of ports, relevant departments in China should optimize resource allocation, improve economic efficiency, strengthen policy coordination, and be prepared for all emergencies based on the port's situation.

When most scholars study the structural properties of maritime networks, they tend to emphasize the vulnerability, resilience, and other structural properties of the network when ports or routes are disturbed. This study found an interesting regularity: when Chinese ports fail sequentially due to the impact of typhoons, the entire container maritime network exhibits extremely significant reliability. In fact, in the process of actual maritime transport, when a certain port fails, carriers often detour to other ports for docking, so that the volume from the failed port will flow to other ports, thus ensuring the normal operation of maritime trade (see Wang et al., 2016). However, it cannot be ignored that the alternative ports have different natural endowments and infrastructure conditions such as water depth and the number of berths from the failed ports, thus leading to congestion in the alternative ports due to the limitation of water depth conditions and the insufficient number of berths. Therefore, before typhoon disasters occur, the

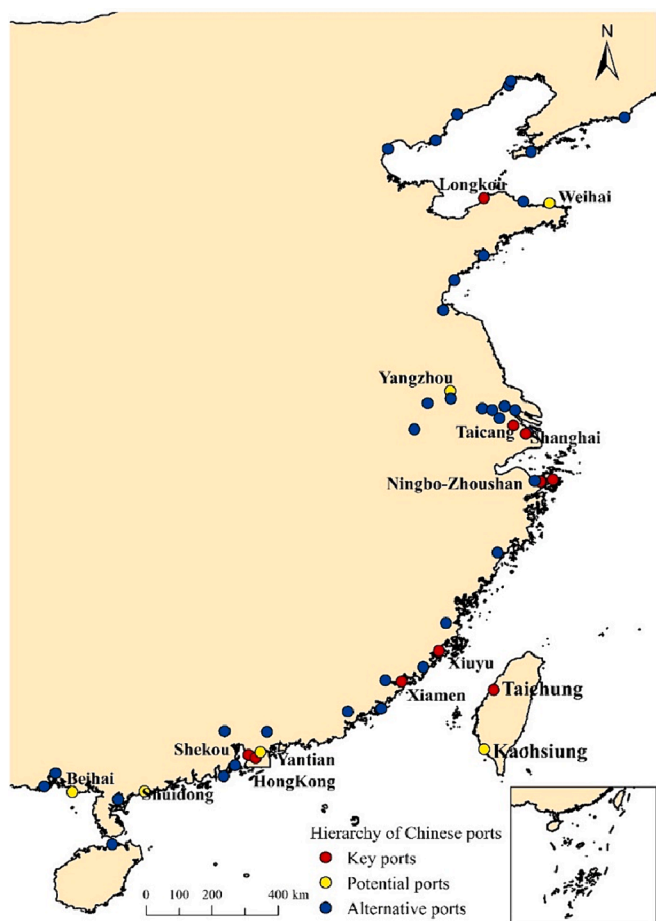


Fig. 8. Hierarchy of Chinese coastal ports.

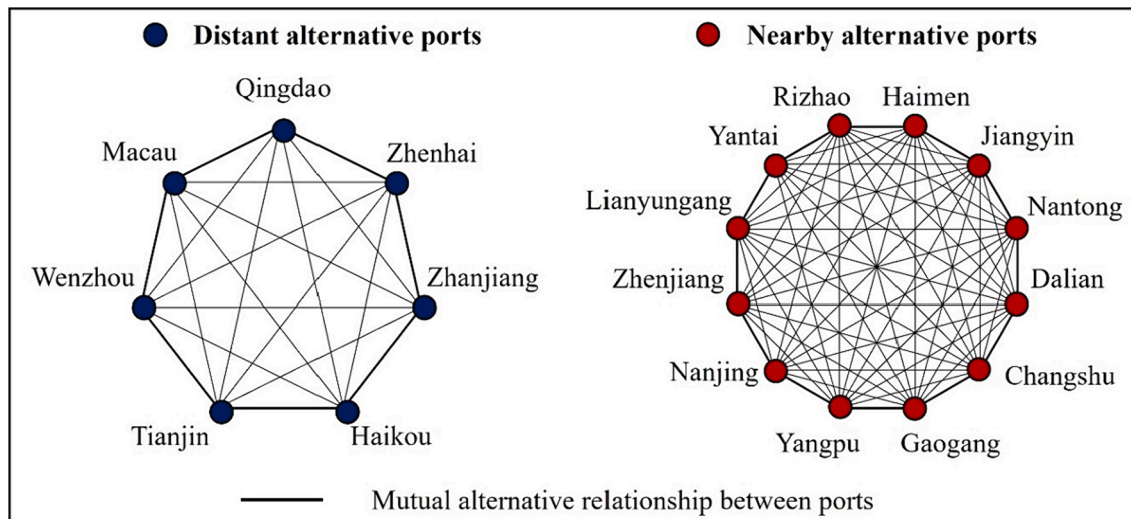


Fig. 9. Bidirectional alternative relationship between ports.

central/local governments and port authorities should pay close attention to typhoons, establish port typhoon warnings, and pre-select potentially important ports with similar functions and comparable scale to the failed ports as replacements. Additionally, increasing the berthing capacity of these selected ports is essential to prevent congestion, ultimately enhancing the reliability and sustainable development of the network.

### 5. Conclusions

This paper constructs a comprehensive evaluation model for port failures from the perspectives of network and natural disasters. And, the proposed model was applied to simulate the interruption of Chinese ports under typhoon risk, further exploring the reliability changes of the MSR container shipping network under the failure of Chinese ports. The following conclusions were drawn:

- (1) Chinese container ports not only have an advantage in quantity, but also have a significant strategic position and influence in the MSR container shipping network. Except for major container ports such as Ningbo Zhoushan Port and Shanghai Port, there is little difference in the importance of other Chinese coastal ports in the MSR container maritime network. However, there is a significant difference in the ability of Chinese coastal ports to face typhoon risk and withstand typhoons.
- (2) The top-ranked ports in comprehensive evaluation are Ningbo Zhoushan, Shanghai, Hong Kong, Shekou, Kaohsiung, and Yantian. Firstly, these ports have an important position in the network; secondly, although the cargo throughput of ports is relatively large, they are located in typhoon areas and are highly susceptible to typhoon attacks due to their high intensity, resulting in a high risk of typhoons.
- (3) Intentionally removing Chinese ports in the order of evaluation, the reliability of the entire container maritime network first experiences a brief decline. Due to the substitutability of ports and the recovery characteristics of the network itself, the reliability shows an upward and downward trend, ultimately reaching a steady and reliable state. This reflects the high adaptability and overall resilience of China’s container shipping network.

This study has strong theoretical and guiding implications for maritime transport and disaster studies. The comprehensive model has high transferability and is not only suitable for various unexpected events (such as natural disasters, political turmoil, and other events), but

also for evaluating global port disruptions. The data in this article has certain limitations. Due to the difficulty in obtaining AIS data, we are unable to use the latest data to simulate the impact of Chinese port failures on the reliability of container shipping networks. However, this has not weakened our research motivation. In addition, in the data processing process, in order to avoid errors caused by port merging, we directly used the ports provided by AIS data for research, which may lead to the inconsistency of port selection rules. In future research, we will further standardize port selection criteria, consider the impact of multi-factor indicators on ports from multiple perspectives, and validate the generalizability of the model by evaluating the interruption of all ports along the MSR. In addition, we will combine different “learning systems” such as machine learning, deep learning, neural networks, etc. to enhance the performance of the predicting/ forecasting system for reliability estimation.

### CRediT authorship contribution statement

**Naixia Mou:** Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Huanqing Xu:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Yong Liu:** Validation, Supervision, Resources, Funding acquisition, Data curation. **Guoqing Li:** Validation, Supervision, Investigation, Data curation. **Lingxian Zhang:** Visualization, Validation, Formal analysis. **César Ducruet:** Writing – review & editing, Formal analysis. **Xianghao Zhang:** Visualization, Validation, Software. **Yanci Wang:** Writing – review & editing. **Tengfei Yang:** Writing – review & editing, Validation.

### Declaration of competing 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.

### Data availability

The authors do not have permission to share data.

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Appendix

Table A1

Calculation steps of Entropy weight method

Method	Calculation steps
Entropy weight method	<p>Step 1: Standardize indicator data processing. For m ports and n indicators, the standardized processing method is as follows:  <math>X = (x_{ij})_{m \times n}; Y = (y_{ij})_{m \times n}, i = 1, 2, 3, \dots, m; j = 1, 2, 3, \dots, n</math></p> $y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \text{ Eq. (A.1)}$ <p>Where X and Y respectively represent the initial matrix and the standardized matrix.</p> <p>Step 2: Calculate the proportion of the <i>i</i>th port under the <i>j</i>th indicator, as well as the entropy value of the <i>j</i>th indicator.</p> $p_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}} \text{ Eq. (A.2)}$ $E_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij} \text{ Eq. (A.3)}$ <p>Step 3: Calculate the weight of each indicator.</p> $\omega_j = \frac{d_j}{\sum_{j=1}^n d_j} \text{ Eq. (A.4)}$ <p>Where <math>d_j = 1 - E_j</math>, represents the redundancy of information entropy.</p>

Table A2

Calculation results of comprehensive relative correlation (CRC).

Order	Removed Ports	CRC	Order	Removed Ports	CRC	Order	Removed Ports	CRC
0	None	0	18	Xiamen	0.439	36	Yangpu	0.381
1	Ningbo-Zhoushan	0.805	19	Fuzhou	0.439	37	Nanjing	0.378
2	Shanghai	0.684	20	Zhangjiagang	0.434	38	Yantai	0.378
3	Hong Kong	0.679	21	Shuidong	0.433	39	Zhangzhou	0.377
4	Shekou	0.585	22	Xiuyu	0.430	40	Lianyungang	0.374
5	Kaohsiung	0.538	23	Quanzhou	0.426	41	Dongshan	0.373
6	Yantian	0.518	24	Huizhou	0.409	42	Zhenjiang	0.371
7	Taichung	0.516	25	Qinzhou	0.401	43	Chaozhou	0.369
8	Guangzhou	0.497	26	Beihai	0.399	44	Changzhou	0.368
9	Qingdao	0.485	27	Fangcheng	0.398	45	Yangzhou	0.362
10	Zhenhai	0.467	28	Taicang	0.398	46	Wuhu	0.356
11	Zhanjiang	0.456	29	Rizhao	0.394	47	Qinhuangdao	0.349
12	Zhuhai	0.454	30	Haimen	0.392	48	Longkou	0.345
13	Haikou	0.450	31	Jiangyin	0.391	49	Weihai	0.345
14	Tianjin	0.448	32	Nantong	0.389	50	Jinzhouwan	0.343
15	Wenzhou	0.447	33	Dalian	0.389	51	Dandong	0.339
16	Macau	0.443	34	Changshu	0.387	52	Huludao	0.337
17	Tangshan	0.440	35	Gaogang	0.386			

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