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Assessing the impact of the Covid-19 epidemic on the resilience of Chinese coastal ports

Lang Xu [a], Yajing Shen [b], Jihong Chen [c,*], Guangnian Xiao [d,*], Liying Liu [e,*]

[a] College of Civil & Environmental Engineering, Nanyang Technological University, Singapore
[b] College of Transport & Communications, Shanghai Maritime University, PR China
[c] College of Management, Shenzhen University, China
[d] School of Economics & Management, Shanghai Maritime University, PR China
[e] Naval Medical Center, Naval Medical University, PR China

A R T I C L E I N F O

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A B S T R A C T

The COVID-19 pandemic severely disrupted global maritime transport, while Chinese coastal ports demonstrated remarkable resilience, continuing to play a pivotal role in the shipping industry. This study categorizes resilience into five key properties (redundancy, flexibility, stability, recoverability, and scalability) using tier-1 and tier-2 indicators to evaluate the resilience performance of 16 ports from 2013 to 2022. To standardize the data, we apply the min-max normalization, followed by entropy weighting to evaluate the performance of various resilience indicators, then construct a DBN model to reflect the state transitions of resilience indicators. The findings reveal strong financial health is crucial for maintaining port resilience. Enhancing financial management and improving profitability provide a robust economic foundation for the sustainable development of ports. Additionally, cargo throughput and import-export trade are highly sensitive to port resilience.

1. Introduction

Maritime transport is the cornerstone of global trade, with ports serving as the crucial hubs that connect and propel global market, much like a constantly turning engine (Chen et al., 2022; Xu et al., 2024a). However, the COVID-19 pandemic has significantly disrupted the maritime industry in recent years, leading to widespread port congestions worldwide, such as the Port of Long Beach in Southern California (Xu et al., 2022; Xiao et al., 2024; Shi et al., 2024). This issue stems not only from limited port operational capacity but also from challenges related to shipping companies, land transport connections, and labor systems, as illustrated in Fig. 1.

Specifically, due to varies of lockdowns and restrictions implemented worldwide, e-commerce has become the main shopping method for consumers. In response to concerns about supply chain stability and market volatility, traders have proactively increased their purchases and stockpiled goods as precaution (Xu et al., 2024b; Xu et al., 2024c). Meanwhile, as some governments eased restrictions and introduced stimulus packages, maritime trade flows increased. The surge in demand for goods fueled a boom in manufacturing, leading to the severe congestions on global shipping routes, particularly those from Asia to North America and Europe, and causing significant port congestion.

In contrast, China's ports demonstrated remarkable resilience during the pandemic, maintaining efficient operations and playing a crucial role in the integration of the global economy and trade (Yuan et al., 2023; Liu et al., 2023; Chen et al., 2024). Based on the China Marine Economy Statistical Bulletin (*www.stats.gov.cn/sj/zxfb*), ports in China handled 9.97 billion tons of cargo and 250 million TEUs in container throughput. Additionally, China's total imports and exports through coastal ports increased by 22.4 % in 2021.

Therefore, evaluating port resilience is crucial for port development, and this research offers valuable insights for port management in the face of unexpected events, such as the COVID-19 pandemic. In this research, the min-max normalization approach is utilized to eliminate differences among various indicators via linear transformations. Then, entropy weighting is employed to assess resilience performance. Further, the transfer probability is calculated based on the elasticity and inelasticity of indicator weights to determine port resilience over time.

The analysis provides the following managerial insights: First, strong financial health is a critical factor in the resilience and stability of ports. Enhancing profitability not only provides a solid economic foundation for the sustainable development of ports but also facilitates the rapid

* Corresponding authors.
E-mail addresses: xulang@shmtu.edu.cn (L. Xu), cxjh2004@163.com (J. Chen), gnxiao@shmtu.edu.cn (G. Xiao), llyhys@163.com (L. Liu).

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mobilization of resources during emergencies. Additionally, the long-term impact of sustainability on port resilience should not be overlooked. Achieving high resilience and stability over the long term requires sustainable infrastructure investment, technological innovation, and improved service levels. Moreover, cargo throughput and import-export trade are highly sensitive to port resilience. Investing in infrastructure and improving cargo handling capacity ensure that port operations can quickly resume in the face of emergencies, maintaining stable revenues and profitability.

The rest of this paper is organized as follows: Section 2 reviews the relevant research, outstanding the research gap, then further proposing our aims. Data source is introduced in Section 3 and the methodology for evaluating port resilience is in Section 4. The empirical discussion is discussed from the insights of single port and port group in Section 5. Finally, Section 6 concludes the findings and managerial insights.

2. Literature review

Port resilience is essential for ensuring that maritime infrastructure can withstand and recover from disruptions. As global trade and climate challenges intensify, understanding how to evaluate and improve port resilience via data-driven method becomes increasingly critical. Various factors, consisting of natural disasters, cyber threats, and low efficiencies, influence port resilience (Gao et al., 2023; Liu et al., 2024; Xu et al., 2024). Scholars have identified that climatic events such as hurricanes and rising sea levels pose significant risks to port operations, with hurricanes in particular causing long-term damage and disrupting operations (Smith et al., 2021). In addition, cyber threats have emerged as a critical concern, given ports' increasing reliance on intelligent infrastructure, which is vulnerable to attacks (Jones and Murray, 2020). Operational challenges, such as the outdated infrastructure and insufficient investment in technologies, further weaken port resilience (Brown and Green, 2019). Furthermore, Henderson and Lopez (2020) revealed that climate change exacerbates the frequency and intensity of extreme weather events, thereby challenging port resilience even more. Martin et al. (2018) highlighted that the interconnectivities of global supply chains means that disruptions in one part of the world can have cascading effects on port operations elsewhere.

Qualitative approaches often assess the organizational and structural aspects of ports, utilizing case studies, expert interviews, and stakeholder analyses to identify resilience factors. For instance, Hollnagel et al. (2011) emphasized the importance of organizational resilience, which includes the ability to adapt and respond to unexpected disruptions. Boin and van Eeten (2013) discussed resilience in terms of governance and decision-making processes, stressing the need for adaptive practices that enable port to respond to dynamic challenges. Bruneau et al. (2003) introduced the resilience triangle, a model that quantifies resilience by measuring the chances it takes for a port to recover to its pre-disruption state, thereby identifying the factors affecting port resilience. Pant et al. (2014) utilized a combination of infrastructure and financial metrics to assess port resilience, highlighting the importance of robust infrastructure and financial stability in maintaining port operations during crises.

Data-driven technologies, on the other hand, allow for the real-time monitoring and analysis of port operations, providing insights that were previously unattainable. Xu et al. (2018) investigated the use of big data analytics to identify patterns and anomalies in port operations that could indicate the vulnerabilities. Similarly, He et al. (2019) explored the application of AI in predictive maintenance and risk assessment, enhancing the ability to foresee and mitigate potential disruptions.

Improving port resilience involves a combination of operational, technological, and policy measures. Investment in intelligent infrastructure, regular risk assessments, and the development of comprehensive contingency plans are key strategies. Miller and Davis (2020) found that upgrading port infrastructure with the latest techniques, including automation and digital twins, could significantly enhance resilience. Garcia and Perez (2017) found that integrating sustainability practice, such as green port initiative, improves both operational efficiency and environmental resilience and operational efficiency. Additionally, Parker et al. (2019) found that ports with adaptive management practices are better equipped to respond to unexpected challenges and adjust their strategies accordingly.

In summary, assessing port resilience requires a multifaceted approach that includes qualitative assessments, quantitative models, and data-driven techniques. As the maritime industries to evolve, integrating the emerging techniques and developing the standardized resilience metrics will be crucial for enhancing our ability to evaluate and improve port resilience.

3. Data source

In order to investigate the impacts of the Covid-2019 epidemic on port resilience, the time span of the research is from 2013 to 2022. Considering the availability of data, 16 coastal above-scale ports in China are selected as the study object for port resilience, namely Dalian Port, Yingkou Port, Qinhuangdao Port, Tianjin Port, Yantai Port, Qingdao Port, Rizhao Port, Lianyungang Port, Shanghai Port, Ningbo-Zhoushan Port, Xiamen Port, Guangzhou Port, Shenzhen Port, Zhuhai Port, Zhanjiang Port, and Haikou Port as shown in Fig. 2. Notice that those ports are divided as five groups based on the geographic location to investigate the difference of individual and total resilience performance.

According to the previous literature (Sun et al., 2024; Gu et al., 2024), five main tier-1 indicators (*infrastructure*, *scale capacity*, *managerial ability*, *hinterland economy*, and *sustainable capacity*) are shown in Table 1. For the infrastructure, there're four tier-2 indicators (*Length of production terminals, Number of production berths, Number of over* 10^3 *ton production berths, Annual container throughput capacity*) to reflect the equipment loading and unloading cargo, where the data is from China Port Yearbook (*data.stats.gov.cn*). For scale capacity, the tier-2 indicators include *Cargo throughput*, *Container Throughput*, *Liner Shipping Connectivity Index*, and *Seaward Expansion*, where the data is collected from China National Bureau of Statistics (*www.stats.gov.cn/sj/zxfb*) to represent the level of port throughput capacity. For managerial ability, there are mainly *Operating income, Operating Cost, Operating Profit and Total Profit* to measure the profitability, where the data is collected from Sina Finance (*finance.sina.com.cn*) and China Finance & Economy (*www.fecn.net*). In order to consider the impacts of port hinterland's economy, *GDP*

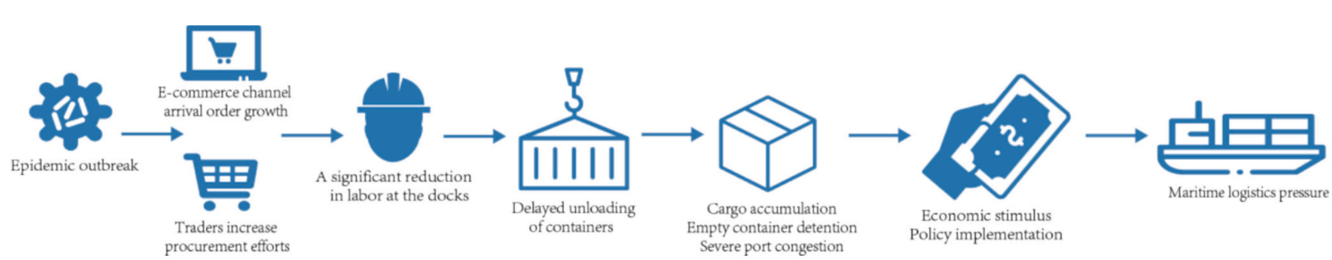

Fig. 1. Resilience pressure transmission in the global maritime industry.

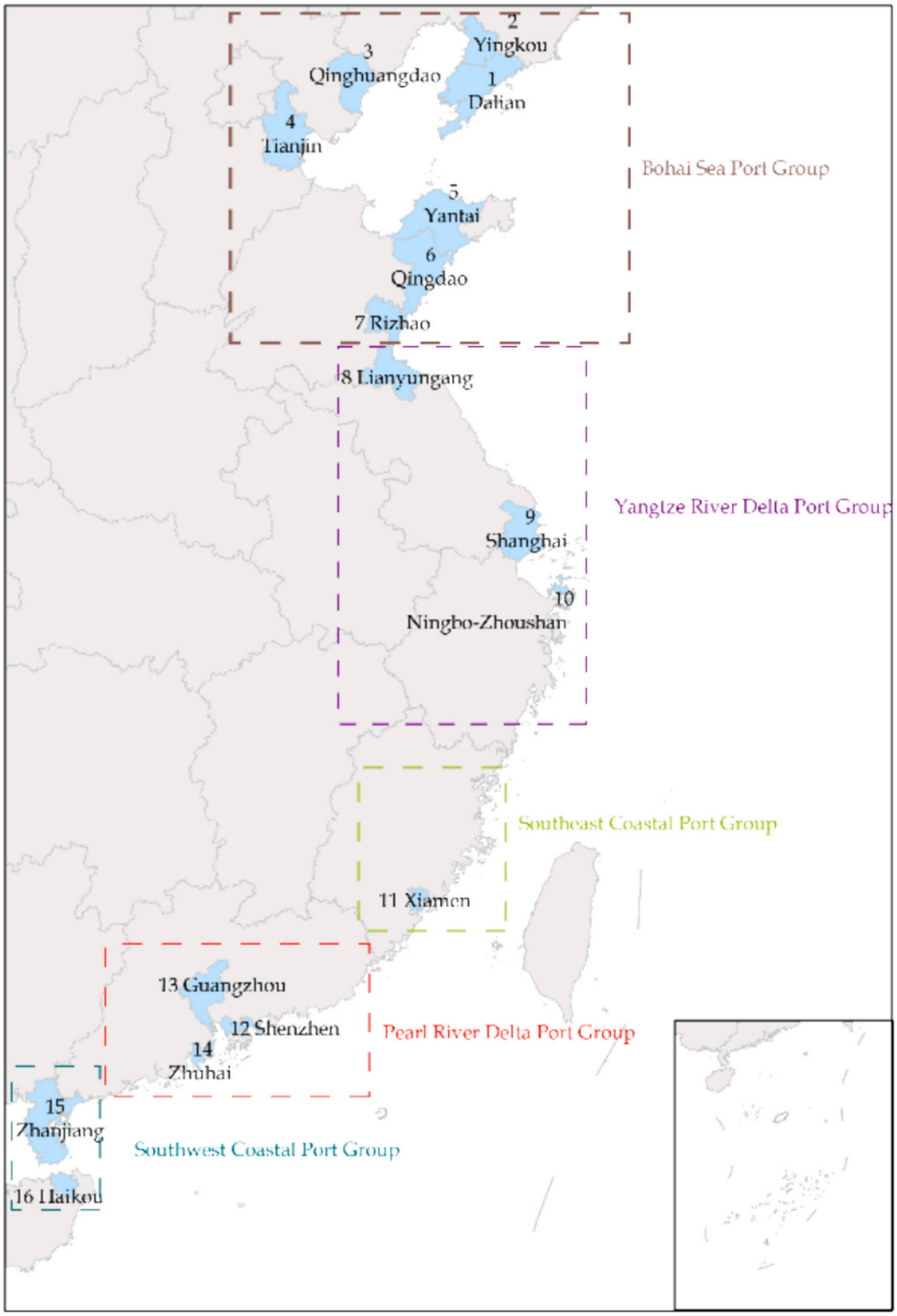

Fig. 2. The research object.

of hinterland, Import & export value of hinterland and Tertiary industry value of hinterland are introduced to the tier-1 indicator of Hinterland economy, which is from China National Bureau of Statistics (www.stats.gov.cn/sj/zxfb). For sustainable capacity, here it mainly includes three tier-2 indicators (*Hinterland GDP growth rate, Growth rate of cargo throughput, and Container throughput growth rate*), where the data is from United Nations Conference on Trade and Development (digitallibrary.un.org).

4. Methodology

In order to enable comparisons among the different indicators, a linear transformation is first utilized the min-max normalization method to eliminate the difference between the data. Next, the weights of the resilience performance, tier-1 and -2 indicator, as well as the weights of each port under different indicators are decided by entropy weighting method. Subsequently, the resilience and non-resilience states of tier-2 indicators between the study period are decided based on port weights, then the initial transfer probability is assumed according to the outcomes in the final state, and the state transfer probabilities of resilience and non-resilience in the state combinations are determined by the assumed initial transfer probabilities and indicator weights, and finally the outcomes of port resilience at different times are obtained, where the process flow is shown in Fig. 3.

Transforming linearly the collected data adjusts the results in the range of [0,1] to meet the uniform criterion that the pre-processed data can be restricted to a certain range, which facilitates the comparison of data. Additionally, the positive and negative attributes of the indicators are considered, with positive attributes meaning a positive effect of the indicator on the port's resilience; conversely, negative attributes

Table 1
Descriptive statistics of data used in this research.

Tier-1 indicator	Tier-2 indicator	Unit	Min	Max	Mean	S·D
Infrastructure (A)	*Length of production terminals* (A1)	Meter	457,223	572,708	521,648.52	40,301.59
	Number of production berths (A2)	Each	3111	3325	3248.91	68.96
	Number of over 10^3 *ton production berths* (A3)	Each	1069	1448	1275.62	130.85
	Annual container throughput capacity (A4)	$\times 10^4$ TEU	10,80	13,793	12,545.44	1044.01
Scale capacity (B)	*Cargo throughput* (B1)	$\times 10^8$ ton	55.95	68.514	63.09	4.30
	Container Throughput (B2)	$\times 10^4$ TEU	15,415.44	22,503	18,896.55	2347.23
	Liner Shipping Connectivity Index (B3)	/	22,330.51	27,904	25,039.34	1977.30
	Seaward Expansion (B4)	km^2	425.32	554.5	522.32	39.40
Managerial ability (C)	*Operating income* (C1)	$\times 10^2$million yuan	1062.16	1913	1433.79	265.47
	Operating Cost (C2)	$\times 10^2$million yuan	745.45	1420	1057.98	201.22
	Operating Profit (C3)	$\times 10^2$million yuan	219.63	465	306.11	87.50
	Total Profit (C4)	$\times 10^2$million yuan	189.83	387	256.37	66.14
Hinterland economy (D)	*GDP of hinterland* (D1)	Billion yuan	10,790.49	19,811	15,044.27	3020.29
	Import & export value of hinterland (D2)	Billion dollars	14,775.12	21,906	17,645.98	2351.29
	Tertiary industry value of hinterland (D3)	Billion yuan	5730.51	12,430	9052.05	2298.41
Sustainable capacity (E)	*Hinterland GDP growth rate* (E1)	%	38.21	160	106.21	37.01
	Growth rate of cargo throughput (E2)	%	−22.87	136	55.20	52.47
	Container throughput growth rate (E3)	%	−19.02	166	92.10	58.14

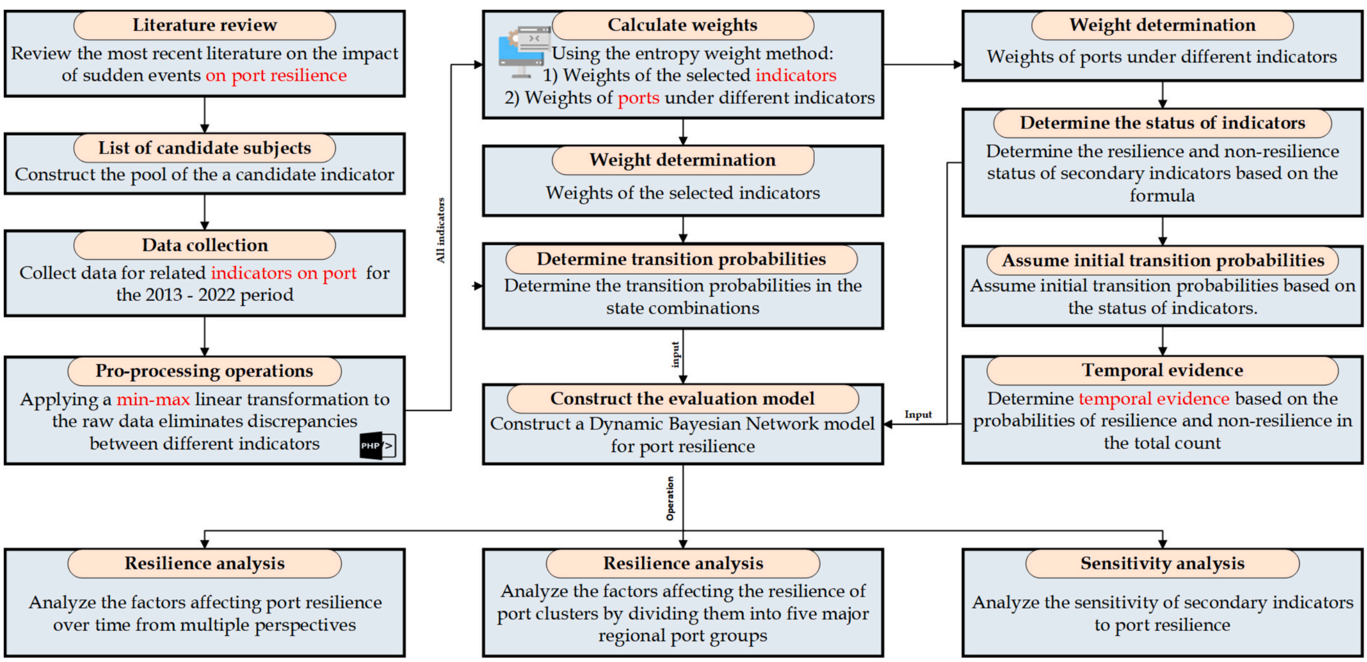

Fig. 3. Data processing flow.

representing a negative effect of the indicator on the port's resilience. Here, the actual values x_{ijp} are standardized to obtain the values of the positive and negative data for indicator port p of indicator j in year i as follows

$$r^+_{ijp} = \frac{x_{ijp} - min(x_{1j1}, \cdots, x_{ijp}, \cdots, x_{mjP})}{max(x_{1j1}, \cdots, x_{ijp}, \cdots, x_{mjP}) - min(x_{1j1}, \cdots, x_{ijp}, \cdots, x_{mjP})}, where\ 0 \le r^+_{ijp} \le 1 \tag{1}$$

$$r^-_{ijp} = \frac{max(x_{1j1}, \cdots, x_{ijp}, \cdots, x_{mjP}) - x_{ijp}}{max(x_{1j1}, \cdots, x_{ijp}, \cdots, x_{mjP}) - min(x_{1j1}, \cdots, x_{ijp}, \cdots, x_{mjP})}, where\ 0 \le r^-_{ijp} \le 1 \tag{2}$$

According to the concepts of information entropy, the entropy weight as an objective assignment is introduced to determine the weights of multiple indicators (Zhan et al., 2024; Yan et al., 2024). Among them, the smaller the entropy value calculated by the weight, the larger the weight of the indicator; otherwise, the smaller the weight of the indicator. In this method, the information entropy H_j of indicator j is a mathematical concept to measure the amount of information as

$$H_j = -\frac{1}{lnm}\sum_{i=1}^{m}\sum_{p=1}^{P}\frac{r_{ijp}}{\sum_{i=1}^{m}\sum_{p=1}^{P} r_{ijp}} \bullet ln\frac{r_{ijp}}{\sum_{i=1}^{m}\sum_{p=1}^{P} r_{ijp}}, \text{where } r_{ijp} = r^+_{ijp} \cup r^-_{ijp} \tag{3}$$

where m indicates the number of evaluated years. From the information entropies of each indicator, the weight of the indicator j can be calculated as follows

$$w_j = \frac{1 - H_j}{\sum_{j=1}^{n}(1 - H_j)} \tag{4}$$

where n means the number of indicators. Further, before calculating elasticity performance weights, the weights assigned to 16 ports under each indicator is also discussed to decide the status of each indicator. Therefore, the information entropy and weight of port p are as follows

$$H_p = -\frac{1}{lnm}\sum_{i=1}^{m}\sum_{j=1}^{n} \frac{r_{ijp}}{\sum_{i=1}^{m}\sum_{j=1}^{n} r_{ijp}} \bullet ln\frac{r_{ijp}}{\sum_{i=1}^{m}\sum_{j=1}^{n} r_{ijp}}, \text{where } r_{ijp} = r_{ijp}^{+} \cup r_{ijp}^{-} \quad (5)$$

$$w_p = \frac{1-H_p}{\sum_{p=1}^{P}(1-H_p)} \quad (6)$$

Next, port resilience is divided into five resilience properties (i.e., *redundancy*, *flexibility*, *stability*, *recoverability*, and *scalability*) based on the relationships between the indicators. In order to calculate the weight of resilience performances, the initial weight of each resilience performance is decided to be the sum of the weights of the tier-1 indicators. The cumulative combined weight of the resilience performance is the sum of the initial weights of the five-resilience property. Hence, the resilience weight w_d is calculated from the indicator weight w_j and corresponding initial resilience performance μ_j as follows

$$w_{d-sum} = \sum_{j=1}^{n} w_j \bullet \mu_j, where\ \mu_j = \begin{cases} 0 & , if\ j \notin \aleph \\ 1 & , if\ j \in \aleph \end{cases} \quad (7)$$

$$w_d = \frac{w_{d-sum}}{\sum_{d=1}^{u} w_{d-sum}} \quad (8)$$

where $\aleph = \{A, B, C, D, E\}$ is the set of resilience performance. Due to the above-mentioned, the state probability transfer between indicators is calculated by deciding whether the state of port p's indicators in the tth year is resilience (R) or non-resilience (N) as follows

$$D_i = \begin{cases} R & , if \sum_{p=1}^{P} x_{ijp} \bullet w_p > \frac{\sum_{i=0}^{m}\sum_{p=1}^{P} x_{ijp} \bullet w_p}{m} \\ N & , if \sum_{p=1}^{P} x_{ijp} \bullet w_p < \frac{\sum_{i=0}^{m}\sum_{p=1}^{P} x_{ijp} \bullet w_p}{m} \end{cases} \quad (10)$$

Port resilience refers to the abilities of a port to adapt, recover and continue to operate in the face of various shocks and stresses, such as climate changes, economic fluctuations, man-made accidents and natural disasters. To evaluate port resilience, a range of indicator and method are commonly utilized to quantify and analyze port performance. The transfer probability is the probability that each tier-2 indicator transfers between resilient and non-resilient states. Thus, transfer probability is introduced to investigate the performance and changes of ports in different states. The criteria for defining initial transfer probabilities are primarily based on the historical performance of the indicators. By analyzing the historical data of the indicators within the study period and considering the frequency of resilient and non-resilient states, a reasonable initial probability distribution is determined. Additionally, insights from similar studies are referenced to establish initial transfer probabilities suitable for port resilience analysis. To calculate the transfer probability of tier-2 indicator from 2013 to 2022, the initial transfer probability (*ITP*) of tier-2 indicator in 2013 is first set as P_{Rl} and P_{Nq}, where the initial transfer probability of resilience (*ITP-R*) is considered as the probabilities of resilient states and the initial transfer probability of non-resilience (ITP—N) is considered as the probabilities of non-resilient states during 2013–2022. Based on the built-in state combinations in the GeNIe 4.1, the probability X of resilience can be described as followed

$$\text{Prob}(X=R) = \frac{\sum_{j=1, j\in R}^{l}(w_j \bullet P_{Rl})}{\sum_{j=1, j\in R}^{l}(w_j \bullet P_{Rl}) + \sum_{j=1, j\in N}^{q}(w_j \bullet P_{Nq})}, \text{where Prob}(X=N) = 1 - \text{Prob}(X=R) \quad (12)$$

where l and q indicate the number of state R and N, w_{Rl} and w_{Nq} are the weight of state R and N, respectively.

5. Discussion

In this section, the indicator contributions to the port resilience is first calculated, then a dynamic Bayesian network (DBN) model is first constructed to reflect the results of the indicator states and temporal variations, further port resilience is investigated in terms of the multi-level indicators and port clusters, respectively.

5.1. Resilience performance weight

Based on the entropy weighting approach, the weights of tier-1 and -2 indicators, as well as the weights of the resilience performance are shown in Fig. 4.

From Fig. 4, stability is the highest weighting of five resilience properties, whereas extensibility is the lowest weighting. High stability ensures that ports are able to respond in a timely manner in the changes of shipping market. Meanwhile, if policy changes and natural disasters occur, ports are able to timely respond to the risks and quickly return to normal operations. In contrast, extensibility has a lesser influence on the port resilience, as extensibility usually requires significant investment and is difficult to realize in the short period. Beyond that, among the tier-1 indicators, business capability has a relatively large weighting on the port resilience, mainly because it reflects the port's economic growth and financial situation, which has a direct impact on the stability of its operations. The weight of sustainability in port resilience assessment is relatively small because the port resilience focuses more on the port's ability to respond to and recover from the sudden incidents. In contrast, sustainability primarily reflects the port's long-term development trends under normal operations. Although sustainability is crucial for the port's overall competitiveness and long-term development, when assessing port resilience, the emphasis is more on the port's short-term crisis response capability.

Further, among the tier-2 indicators, operating profit carries a relatively large weight in port resilience assessment, whereas the weight of seaward expansion area is relatively small. Operating profit reflects the port's financial condition and profitability; thus, ports with strong profitability have sufficient funds to carry out repair and improvement in the face of unexpected events, thereby enhancing resilience. Also, high operating profit means that the port has more financial resources to handle potential risks, allowing it to maintain normal operations and recover quickly. Meanwhile, ports with high operating profits can attract more firms to continuously invest in infrastructure and technological innovations. On the other hand, seaward expansion area reflects the port's physical strategic capability. Although it is crucial for the port's long-term development and capacity expansion, its smaller weight because it has a limited effect on the port's ability to respond to and recover from sudden incidents. In addition, seaward expansion is a long-term construction project, with limited short-term effectiveness. Therefore, in resilience assessment, the focus is more on short-term response capabilities rather than long-term expansion capability.

5.2. DBN model

The DBN model uses annual data from 2013 to 2022 as the base data and therefore has ten-time steps in the time board, each referring to a year. During the modelling process, all nodes (indicators, sub-dimensions, dimensions, resilience performance and port resilience) are placed in the network. Since this study analyzes the dynamic changes of port resilience, it is necessary to introduce temporal variations, connecting those with a time-oriented arc. Further, DBN determines the relationship between the metrics by calculating the resulting transfer probabilities to construct dynamic assessment model. The results of the indicator states and corresponding temporal variations

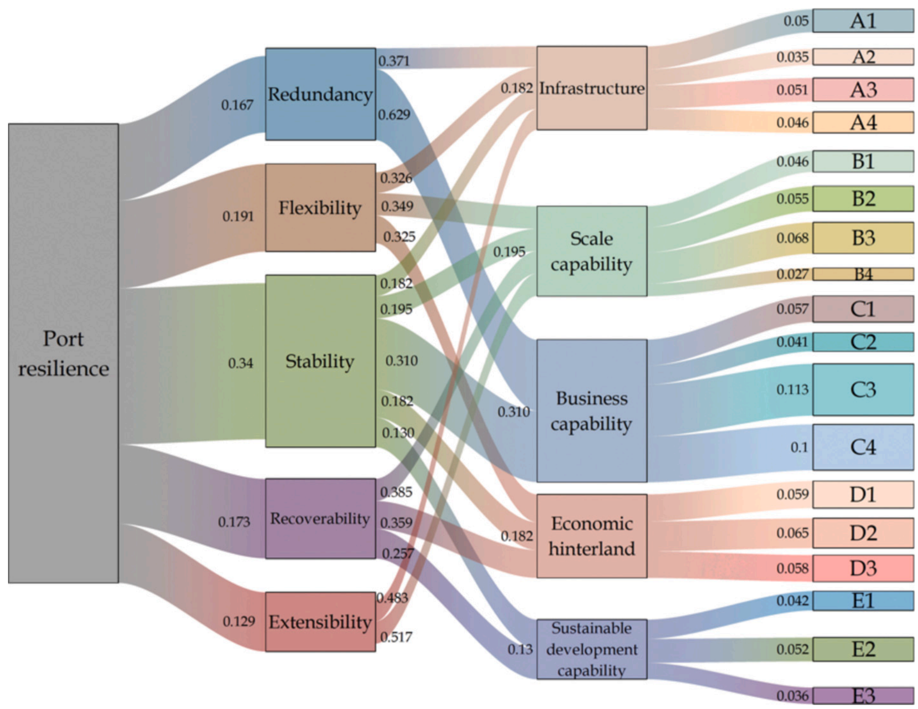

Fig. 4. Contributions of tier-1 and -2 indicators to port resilience.

are shown in Table 2.

From 2013 to 2016, ports are in a non-resilient state (*N*). However, starting from 2017, the ratio of resilient states (*R*) gradually increased. After 2018, the resilient state changes significantly and peak in 2021. Further, the proportion of non-resilient states significantly declines in 2018 and reaches its lowest point in 2021. This trend indicates that since 2017, ports' abilities to cope with unexpected events improve. Before this period, most indicators are in a non-resilient state, reflecting significant improvements in infrastructure, capacity, operational capability, hinterland economic level, and sustainability. From 2013 to 2016, infrastructure indicators are in a non-resilient state, indicating that port infrastructure does not undergo significant changes or enhancements during this phase. However, from 2017 onwards, these indicators gradually shift to resilient, showing a marked improvement in port infrastructure, likely due to expansion and modernization efforts during this period. These improvements enable ports to more effectively handle operational pressures and external challenges. Similar to infrastructure, the indicators of capacity are also in a non-resilient state before 2017, then transition to resilient. These indicates significant progress in the ports' ability to handle cargo and container throughput, maintain connectivity with global shipping network, and expand port area. These improvements not only enhanced port operational efficiency, but also strengthened their competitiveness in international trade.

In terms of operational capability, the indicators exhibit different trends. Operating income and total profit show the resilience state since 2018, whereas operating costs turn the non-resilient state after 2018. This may indicate that despite the increase in port income, operating cost control still presents a key challenge. In addition, operating profit turns the resilient state since 2018, aligning with the growth trend in operating revenue. Regarding hinterland economic level, the economic effect of the port on the host city and surrounding areas gradually become apparent. In particular, GDP and the value of the tertiary

Table 2
Results of temporal variation in the status of indicators.

Tier-2 indicator		2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
A1		N	N	N	N	R	R	R	R	R	R
A2		N	N	N	N	R	R	R	R	R	R
A3		N	N	N	N	R	R	R	R	R	R
A4		N	N	N	N	N	R	R	R	R	R
B1		N	N	N	N	R	R	R	R	R	R
B2		N	N	N	N	N	R	R	R	R	R
B3		N	N	N	N	N	R	R	R	R	R
B4		N	N	N	N	R	R	R	R	R	R
C1		N	N	N	N	N	N	R	R	R	R
C2		R	R	R	R	N	N	N	N	N	N
C3		N	N	N	N	N	R	R	R	R	R
C4		N	N	N	N	N	R	R	R	R	R
D1		N	N	N	N	N	R	R	R	R	R
D2		N	N	N	N	N	N	N	N	R	R
D3		N	N	N	N	N	R	R	R	R	R
E1		R	R	R	R	R	N	N	N	R	N
E2		R	R	N	N	R	R	N	N	R	N
E3		R	R	N	N	R	R	N	N	N	N
Temporal variation	R	0.222	0.222	0.111	0.111	0.444	0.778	0.722	0.722	0.889	0.778
	N	0.778	0.778	0.889	0.889	0.556	0.222	0.278	0.278	0.111	0.222

industry shows resilience after 2018, indicating that port development significantly contributes to regional economic growth. However, the hinterland import and export trade volume don't show the resilience state until 2021, reflecting that this indicator is highly influenced by the global trade environment, with resilience improvement lagging behind. However, growth rate indicators exhibit some volatility. Although the resilience is observed in certain years, overall, these indicators' resilience is less stable compared to other aspects. GDP growth rate of port hinterland cities and the cargo throughput growth rate show resilience in 2017 and 2018 but then revert to a non-resilient state. This suggests that the port's growth rate is significantly influenced by the macroeconomic environment, especially during periods of global economic fluctuations.

5.3. Analysis of temporal changes in port resilience

After constructing the DBN model for port resilience and determining the transition probabilities for the input of port indicator states, the time-varying evidence is input into the DBN model, as shown in Fig. 5.

As shown in Fig. 5, port resilience is at its lowest level in 2015 and reaches its peak in 2021, with resilience performance exhibiting a similar trend to overall port resilience. In 2015, port resilience is affected by environmental policies in the global economic and trade situation. For environmental policies, Chinese government intensifies the implementation of sulfur emission control areas, with the environmental laws requiring ports to undergo infrastructure modifications and operational adjustments. This increased operational cost leads to a decline in resilience related to operational capability. In terms of changes in the global economic and trade environment, the slowdown in domestic economic growth and the decline in hinterland import and export trade negatively impact cargo flow, resulting in a decrease in port throughput and affecting overall port resilience.

From 2018 to 2020, port resilience declined. During this period, the trade war broke out in 2018 and escalated continuously, with both sides imposing tariffs on each other. This leads to a significant decrease in China's export trade to the U.S., directly influencing port cargo throughput and causing a decline in port resilience starting in 2018. In addition, the outbreak of the COVID-19 pandemic in early 2020 had a tremendous impact on the global trade, disrupting shipping and reducing port operational efficiency. The global economy slowed down between 2018 and 2020, and during the pandemic, it entered a recession. The combined effects of the trade war, the COVID-19 pandemic, and other factors contribute to the decline in port resilience during this period. Due to significant success in controlling the COVID-19 epidemic, it exists a gradual return to normalcy in domestic production. As the

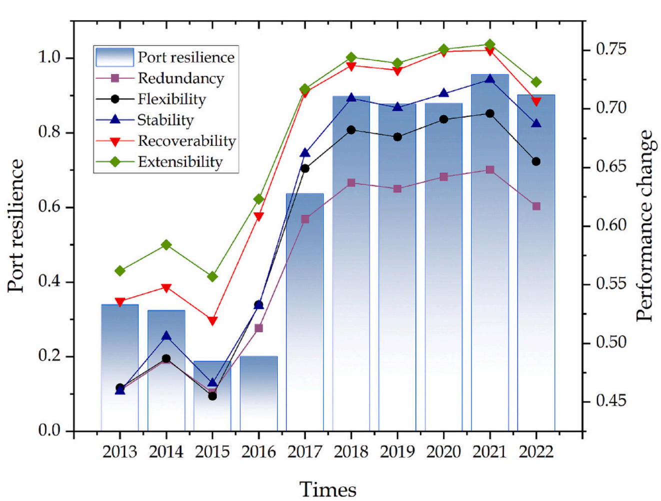

Fig. 5. Temporal variations of port resilience and resilience properties.

international economic situation recovered, port operations return to normal, cargo throughput increased, and port resilience improved. Further, China continues to advance the intelligent construction of ports, with the application of smart technologies enhancing operational efficiency and overall port resilience. However, the Russia-Ukraine conflict that broke out in early 2022 has a significant impact on global supply chains and trade. Geopolitical tensions lead to a rise in energy price, with international oil price and logistics cost increasing, which directly influence port cargo throughput and operational efficiency, raised operating costs, and further reduced port resilience.

5.4. Sensitivity analysis

Based on the above results, to decide whether there is a low accuracy of port toughness at different times, the sensitivity analysis is used calculated using the traditional method, namely the sensitive degree is equal to the ratio of test probability and priori probability. In order to improve the accuracy of the sensitivity obtained by this method, it is validated by the sensitivity algorithm constructed into the GeNIe 4.1 software to determine the level of sensitivity of the tier-2 indicators, so that it could be determined which tier-2 indicators can be improved to effectively improve the resilience toughness. The sensitivity results of the secondary indicators under both methods are shown in Fig. 6.

As shown in Fig. 6, it exists the significant differences in the sensitivity of various indicators. In particular, the sensitivity under the two methods is relatively close, but the GeNIe 4.1 method generally shows higher sensitivity. From the trend, A1, A3, B2, C2, C4, D2, and E3 exhibit significant sensitivity within their respective tier-1 indicators. In terms of infrastructure, the tier-2 indicator with a higher potential to improve port resilience is the production quay length. The length of production quays and the number of operational berths is key infrastructure indicators for measuring port resilience. In particular, a longer quay length serves more ships, thereby increasing the port's and handling efficiency. In the event of unexpected disruptions, a longer quay length enables more ships scheduling, reducing congestion and delays, thus enhancing the port's resilience.

In terms of scale capacity, container throughput is a highly sensitive tier-2 indicator. Container throughput is a key measure of port performance, directly related to the port's revenue and profitability. Changes in container throughput directly reflect and influence various economic activities and industries. Compared to cargo throughput, fluctuations in container throughput have a broader and more significant impact on different sectors of the economy. Additionally, container throughput responds more quickly and sensitively to changes in market demand, better reflecting the supply and demand conditions of the market in real-time. For operational capacity, operating costs and total profit are the most sensitive factors to port resilience. In the event of disruptions or market fluctuations, ports need to control costs to maintain stability. If operating costs are high, a port's operations may be compromised during a crisis, thus affecting its resilience. Therefore, reasonable control of operating costs can improve a port's competitiveness in the shipping market and help it maintain stable operations and recover quickly during unforeseen events.

With regard to the level of the hinterland economy, the sensitivity of the volume of import and export trade in the hinterland to the resilience of ports is most prominent. The economic level of a port's hinterland city can indirectly determine the level of technology, efficiency and facilities in the port. The higher the economic level of the hinterland city, the more money the port can get to expand its area or improve infrastructure such as yards. High import and export trade volumes mean that the port handles a high volume of cargo and is better able to withstand unexpected shocks. Meanwhile, in terms of sustainability, the growth rate of cargo throughput is the least sensitive. Among the tier-2 indicators, they are generally less sensitive because growth rates are susceptible to factors such as external economic environment, international policies, changes in market demand and industrial restructuring, reducing the

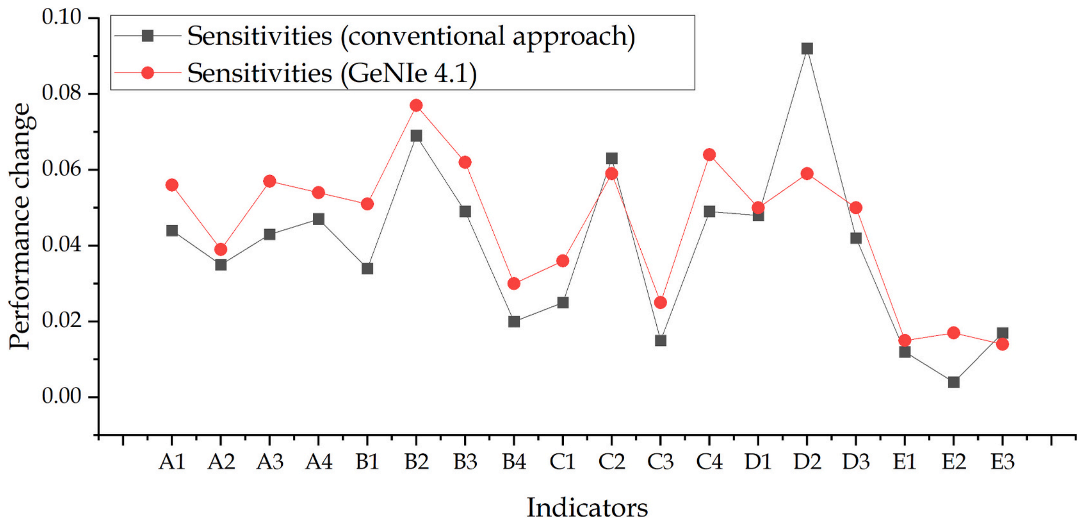

Fig. 6. Sensitivities for tier-2 indicators between conventional approach and GeNIe 4.1.

sensitivity of the overall sustainability to the resilience of ports. Cargo throughput growth rates are more affected by market cycles, seasonal changes and short-term economic fluctuations.

6. Conclusions

Resilience assessment is crucial for the future development of coastal ports. This study first divides the resilience into five resilience properties with tier-1 and tier-2 indicators to assess the resilience of 16 ports from 2013 to 2022. Further, the min-max normalization is applied to standardize the data, followed by entropy weighting to determine the resilience performance of various indicators to construct DBN model reflecting the state transitions of port resilience indicators. On this basis, the port resilience is dynamically evaluated from multiple dimensions and feasible directions for improving port weaknesses are provided.

From the results, the main insights can be summarized. First, stability has the highest weight among the five resilience attributes of ports, showing that stability plays a key role in ensuring that ports can quickly recover from market fluctuations, policy changes, and natural disasters. Flexibility and redundancy also significantly contribute to port resilience by effectively enhancing the port's ability to respond to sudden disruptions and improving its recovery capacity. Further, the overall resilience of domestic coastal ports has shown an upward trend from 2013 to 2022, with major inflection points in 2015, 2018, and 2021. The resilience trends in port groups and overall trend are similar, affected by policies, natural disasters, international economic, and trade environment. Additionally, cargo throughput and import-export trade are highly sensitive to port resilience. In the face of unexpected situations, appropriately improving these indicators can significantly accelerate the port's recovery process.

This study integrates dynamic Bayesian networks with the entropy weight method to assess changes in port dynamic resilience and provide targeted recommendations for ports and shipping companies. However, this study still has limitations. Due to the constraint of port data availability, it is not possible to obtain more comprehensive data for evaluation. Additionally, the study focuses on the overall resilience of sixteen coastal ports in China, which cannot represent the resilience development of all domestic ports. Due to the study's focus on Chinese ports, the findings may have limited applicability on a global scale, as they are influenced by factors such as economic conditions, policies, and management practices specific to China.

In the future, port resilience indicators are refined to study the resilience characteristics of ports of various sizes both domestically and internationally, enabling a more in-depth analysis of port resilience assessments.

CRediT authorship contribution statement

Lang Xu: Funding acquisition, Formal analysis, Data curation. **Yajing Shen:** Writing – original draft, Software, Methodology, Investigation. **Jihong Chen:** Validation, Supervision, Software, Investigation, Funding acquisition. **Guangnian Xiao:** Writing – review & editing, Visualization, Validation. **Liying Liu:** Funding acquisition, Formal analysis.

Declaration of competing interest

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Data availability

The data that has been used is confidential.

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