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The resilience evolution and dynamic process identification of the global shipping network

Yafeng Qin[a], Jianke Guo[b,c,1,*], Shasha Wu[b,c]

[a] School of Economics and Management, Dalian University of Technology, Dalian, 116024, Liaoning, China
[b] Key Research Base of Humanities and Social Sciences of the Ministry of Education: Center for Studies of Marine Economy and Sustainable Development, Liaoning Normal University, Dalian, 116029, Liaoning, China
[c] University Collaborative Innovation Center of Marine Economy High-Quality Development of Liaoning Province, Dalian, 116029, Liaoning, China

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ABSTRACT

The port and shipping industry has experienced unprecedented market fluctuations, resulting in a volatile environment characterized by congestion, soaring freight rates, loading delays, and disruptions in maritime supply chains. Therefore, ensuring the stability and resilience of shipping networks is crucial for ensuring industrial and supply chain security. This study adopts an interdisciplinary approach, integrating geography transportation engineering perspectives, to develop a theoretical framework and identification model combining static indicators and dynamic scenarios to assess shipping network resilience. Using global shipping data from 2018 to 2022, the model's feasibility was verified, revealing patterns in the evolution and dynamic processes of global shipping network resilience. The resilience index—0.620, 0.612, 0.587, 0.576, and 0.597—showed an initial decline followed by recovery. Port resilience exhibited spatial imbalance and regional clustering, with high-resilience ports such as Singapore, Port Kelang, Shanghai, and Hong Kong. Compared to previous studies, the proposed framework better captures the complexity and dynamic nature of resilience. Notably, resilience under specific strategies (node degree and risk probability) was generally lower than that in random node strategies. In 2020, the rate of decline was relatively high, while the recovery rate remained low. These findings offer insights and theoretical guidance for maritime supply chain security and sustainable development.

1. Introduction

Maritime shipping connects global production clusters and consumer markets, serving as the primary carrier of international economic and trade flows, and accounts for approximately 90 % of global trade transportation (Guo et al., 2021; Liu et al., 2019). The rise of container transport in the 1970s and 1980s led to significant technological and organizational advances in shipping, enhancing efficiency and reducing costs. This transformation reconfigured the spatial distribution of global production factors, deepening the international division of labor and accelerating global integration (Douet and Cappuccilli, 2011). The global shipping network has gradually evolved into a multi-level, multi-center system, with port nodes efficiently linked by dense shipping routes. This facilitates the large-scale flow and aggregation of resources, promoting regional collaboration and supporting the global economic system.

However, the network has also become increasingly sensitive and vulnerable to external disturbances. As open spatial hubs embedded in the global supply chain, ports face multiple risks—including natural disasters, public health crises, geopolitical conflicts, and supply chain disruptions (Hu et al., 2023; Pratson, 2023). In a highly interconnected system, risks can spread rapidly through network pathways, triggering chain reactions and following a "point-line-plane" diffusion pattern. For example, the 2015 Tianjin Port Explosion disrupted the Bohai Rim region's port system, and the 2011 Tohoku earthquake halted several ports, causing container backlogs and shipping delays (Attar et al., 2024). Furthermore, the 2021 COVID-19-related closure of Yantian Port in Shenzhen resulted in severe congestion in the Pearl River Delta (PRD). These incidents highlight the hidden vulnerabilities and systemic risks within efficient shipping networks (Chen and Yang, 2018; Wu et al., 2024).

In this context, resilience has emerged as a key concept for

* Corresponding author.
E-mail address: gjianke98@126.com (J. Guo).
[1] Mainly engaged in transportation geography and port and shipping network, marine economic geography, and urban geography.

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understanding and managing complex shipping systems. Resilience encompasses system stability and functionality in the face of sudden shocks, as well as the capacity for responsiveness, adaptability, and recovery. Existing studies assess either network topology—focusing on connectivity and redundancy—or port-level functionality, but few integrate these "local-whole" perspectives. As the shipping network comprises multiple port nodes connected by routes, its resilience must address interdependent and co-evolving aspects of "port node resilience" and "overall network resilience.". Port node resilience enables the system to sense and absorb local shocks, while overall network resilience reflects structural reconfiguration, path reorganization, and system-level adaptive capacity.

This study proposes a multidimensional resilience evaluation model that integrates static indicators with dynamic scenarios to reveal the evolution and dynamics of global shipping network resilience under major disruptions. First, unlike most existing research that overlooks the role of node variability in system risk evolution, this study adopts an interdisciplinary approach that combines geography and transportation engineering. It systematically divides shipping network resilience into two hierarchical dimensions—port node resilience and overall network resilience. The study develops a comprehensive evaluation index system and measurement model encompassing structural, functional, and locational attributes. The framework identifies vulnerable ports at the micro level and assesses network stability at the macro level, broadening the theoretical and practical scope of shipping resilience research.

Second, while shipping network research often focuses on frequent, observable disruptions, this study also addresses unpredictable risks—"degree disturbance," "probabilistic risk disturbance," and "random disturbance"—to simulate the dynamic response of the shipping network to various disruptions. By emphasizing adaptability, recovery mechanisms, and behavioral uncertainty, this study enriches the understanding of complex networks' risk responses and offers strategies to enhance the networks' adaptive capacities.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature, Section 3 develops a resilience model, and Section 4 applies the model using disruption simulations. Sections 5 and 6 provide the discussion and conclusions, respectively.

2. Literature review

Holling (1973) introduced the concept of resilience in ecology as a system's capacity to recover from shocks. Over time, the concept expanded beyond natural sciences to engineering, sociology, economics, geography, and other disciplines, forming a broad and complex theoretical system.

With the rapid advancement in global shipping networks, the connections between ports have strengthened and the network structure has become increasingly intricate. Damage to critical nodes can trigger a "single point of failure—system diffusion" chain reaction, affecting the network's functional stability and service efficiency (Deng et al., 2025; Gao et al., 2025). As a result, various recovery measures are required to restore the system. However, studies on pure resilience shipping network resilience are scarce; most focus on robustness, vulnerability, and destruction resistance (Guo and Lyu, 2024; Xin et al., 2025). Robustness examines the effects of randomly deleting nodes or edges on network connectivity (Lu and White, 2014; Xu et al., 2024a). Vulnerability emphasizes the extent to which the failure of ports or shipping routes within the network affects its transportation functionality (Guo et al., 2024). Destruction resistance measures the network's capacity to maintain operations after a failure (Dui et al., 2021). Conversely, resilience highlights the ability to prevent, absorb, respond to, and recover from extreme disruptions (Chacon-Hurtado et al., 2020), ensuring adaptability and long-term mitigation. Higher resilience correlates with lower vulnerability, greater shock resistance, and absorptive capacity.

Research on the resilience of shipping networks began with (Notteboom and Winkelmans, 2001), who analyzed the shipping market's macro risks and proposed countermeasures. Since then, several studies in this field have been conducted (Su and Lu, 2025; Wang et al., 2025; Yang et al., 2025), particularly in response to increasing risks from global pandemics. Current research focuses on two areas.

The first is the resilience of elements related to the shipping industry. Regarding port node resilience, the focus is on assessing the economic impact of port operational disruptions (Hamano and Vermeulen, 2020; Shilpi et al., 2024). These studies use unprecedented events such as natural disasters, terrorist attacks, major accidents, and global pandemics as triggering events. They apply input-output models, system simulation, and risk analysis to evaluate the direct losses and indirect spillover effects of port closures (Ronza et al., 2009). For example, Ducruet et al. (2023) analyzed port traffic dynamics, network topology, and geographic variations using graph theory and complex network methods to examine the effects of the global financial crisis on maritime networks. Lucio et al. (2024) combined a port-specific risk framework, high-resolution nearshore climate modeling, and facility reliability analysis to evaluate functional degradation and economic losses in port infrastructure under extreme and routine conditions. Conversely, port resilience is assessed by establishing relevant evaluation frameworks (Qin et al., 2023). Related studies use static indicators, such as throughput and facility capacity, and apply the resilience loss triangle model to evaluate port performance during post-disaster recovery. These studies have gradually developed several quantitative resilience assessment frameworks (Vanlaer et al., 2022; Wan et al., 2022). Asadabadi and Miller-Hooks (2020) proposed a game-theoretic, two-layer optimization model to enhance port resilience within global multimodal transportation systems.

Regarding maritime infrastructure resilience, research frameworks are based on the fundamental elements of resilience. These frameworks cover port infrastructure system resilience, maritime transport network infrastructure resilience, and coastal civilian infrastructure resilience (Mou et al., 2020; Panahi et al., 2022). Nocera et al. (2024) proposed a mathematical model to quantify the cascading impacts of natural disasters on transnational multimodal transport infrastructure and supply chains, assessing economic consequences through retailer losses. The model was validated in simplified and real-world national supply chain cases. Conversely, Shi et al. (2021) quantitatively assessed port structural damage through maritime accident simulations and established a port resilience evaluation process that considers recovery procedures, restoration timelines, and costs. Huang et al. (2024) built upon developments in maritime route network (MRN) research by identifying route nodes, extracting pathways, and developing comparative methodologies that represent the overall maritime transport network structure, thus forecasting promising future research directions in this field.

The second is shipping network resilience. One approach measures resilience using complex network theory indicators such as degree distribution, independent paths, clustering coefficient, network efficiency, and connectivity (Bai et al., 2023; Xu et al., 2024a). For example, degree distribution shows the dominance of key nodes (e.g., hub ports); independent paths indicate alternative routes, clustering coefficient reflects synergy among local nodes, and network efficiency and connectivity measure the smoothness and redundancy of cargo flows globally (Deng et al., 2025). Highly centralized networks are vulnerable to failures at key hubs (Yang et al., 2025), whereas decentralized, redundant networks with multiple paths exhibit stronger resilience (Wang et al., 2023). A second approach involves simulating disruptions to analyze changes in network resilience (Bedoya-Maya et al., 2025). Rogerson et al. (2022) used system dynamics and found that disruptions cause regional and global capacity imbalances that ripple through the supply chain, intensifying risks. Verschuur et al. (2020) empirically demonstrated that while cargo can divert to alternative routes after disruptions, this capacity is limited, and overdependence on single channels heightens vulnerability. Wan et al. (2024) developed a port typhoon resilience assessment model based on the 4R framework (reliability, redundancy, robustness, and recoverability) to quantitatively evaluate ports' resilience against typhoon disasters. Zhang et al. (2015) simulated blockages in the Suez Canal, Panama Canal, and Strait of Malacca to systematically assess the effects on global shipping network accessibility, connectivity, and stability (Xu et al., 2024b).

In general, despite advances in theory and methodology, gaps persist. First, although vulnerability, accessibility, reliability, and risk assessments exist, most studies focus on immediate responses rather than on gradual recovery and adaptation, omitting resilience's full cycle.

Second, there is insufficient adoption of a systems perspective. Most research emphasizes individual ports or regions, neglecting system-wide evolution and recovery processes. Furthermore, resilience strategies rely heavily on topology indicators (e.g., node degree) while overlooking non-structural factors such as operational efficiency, functional linkages, and resource allocation capabilities, thus limiting practical policy application.

Third, shipping networks are inherently spatial systems constrained by geopolitical, infrastructural, and market factors. However, existing studies primarily focus on topological properties, neglecting key functional, spatial-temporal, complementary, and competitive dynamics.

Given today's uncertain and unstable external environment, future research should address static and dynamic aspects of resilience, including the evolution of node failures. Although awareness of the importance of resilience is growing, a systematic, dynamic understanding of port network resilience remains an academic challenge. Therefore, this study proposes an integrated framework and measurement model that combines static and dynamic perspectives of shipping network resilience. Using global ports as a case study, the study quantifies and reveals their resilience characteristics and evolution process. It aims to provide a methodological reference for measuring shipping network resilience and a theoretical foundation for optimizing the organization and layout of shipping spaces in the new era.

3. Method

3.1. Analytical framework

As a vital carrier of economic trade links between countries, a stable and resilient shipping network ensures safe operation of industrial and supply chains during unexpected events (Dirzka and Acciaro, 2022). Given the complexity of assessing shipping network resilience, this study focuses on its most relevant features to simplify evaluation. The shipping network evolves through interaction among shipping activities, considering ports as nodes and routes as links. Central to this interaction is the relationship between the power of key ports or routes and their influence on others. The shipping network is a complex system with multiple attributes, including routes, ports, capacity, and regional cohesion (Zhang et al., 2022). Routes and ports directly shape the network's spatial organization. Shipping capacity primarily relates to the network's functional resilience. Regional cohesion reflects the interconnections among ports.

Thus, the resilience system should capture the physical characteristics, logistical links, and roles of nodes, lines, and surfaces within the network. Spatial differences and processes shaped by geographic location and geospatial interactions determine the strength, magnitude, and duration of resilience. These factors form the basis for a comprehensive understanding of shipping network resilience.

The ideal resilience framework integrates these features, synthesizing multidimensional aspects to identify resilience (Fig. 1). This clarifies the conceptual and influencing factors and guides the model and technical approach. This study evaluates resilience from static and dynamic perspectives. The static assessment establishes multidimensional resilience indices based on port nodes and the overall network. The dynamic approach applies disruption simulation to model network resilience after node failure under different scenarios, revealing its resistance, adaptation, and evolutionary process facing internal or external disturbances.

3.2. Modeling

This study adopts established measurement models of shipping and city network resilience to construct indices for node hierarchicality, agglomeration, and substitutability as port resilience assessment indicators, incorporating network weights and geographic areas (Table 1). Network matching, transportability, and agglomeration are used as indicators of overall network resilience. All indicators are derived from the weighted shipping network and calculated using the NetworkX module in *Python*, *UCINET*, and *Gephi*.

3.2.1. Static resilience evaluation indicators of the network

3.2.1.1. Port node resilience.

a. Port Node Hierarchy

Measured by node strength (degree) in the shipping network, this indicator reflects the power and influence of a port node within the

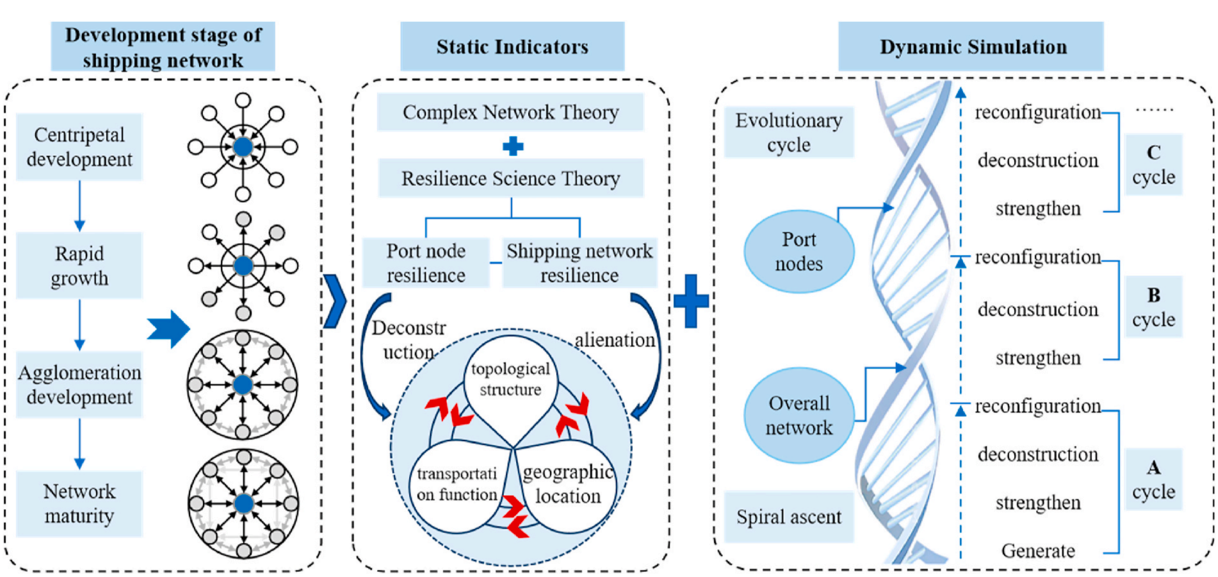


Fig. 1. Model and steps for identifying shipping network resilience.

Table 1
Evaluation index system.

Assessment Dimension	Resilience Characteristic	Measurement Indicator	Indicator Meaning
Topological Structure	Node Hierarchy	Node Strength	Hierarchy of nodes
	Network Matching	Network Association	Connection tendency of the network
Shipping Capacity	Node Centrality and Dispersion	Eigenvector Centrality	Functional characteristics of nodal transportation
	Network Transportability	Network Efficiency	Transfer function and efficiency of the network
Geographical Location	Node Substitutability	Homophily Value	Location advantage of nodes
	Network Clustering	Clustering Coefficient	Agglomeration degree and clustering capacity of the network

network (Qin et al., 2023). A higher value indicates that a port holds a core position with strong influence and control, contributing to a greater structural resilience. Disruptions of such nodes significantly impact the network during dysfunction and external attacks.

$$Si = \sum_{j \in Ni} wij \tag{1}$$

where S_i is node strength, N is the set of port nodes, and W_{ij} represents the weight of the link between nodes i and j.

b. Node Centrality and Dispersion

Eigenvector centrality characterizes the centrality and dispersion functions of nodes, reflecting their transportability. A node's importance depends on the number of neighboring nodes (degree) and importance of those neighbors.

$$EC_i = x_i = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} \times x_j \tag{2}$$

where x_i is the eigenvector centrality value of node i, λ is a constant, and A_{ij} is the adjacency matrix ($A_{ij} = 1$ if i and j are connected; otherwise, $A_{ij} = 0$). A higher eigenvector centrality indicates a node with stronger centralization, typically occupying a key position in resource and information flow and possessing greater adaptability and resilience. Conversely, nodes with low values are less capable of withstanding and absorbing shocks.

c. Node Substitutability

This indicator assesses node homophily. In the network, if nodes i and j share a common neighbor node k, node k is considered part of the intersection of their neighboring sets. Let f_i and f_j represent the sets of neighboring ports for nodes i and j, respectively. Their intersection, fi and fj, represents the largest set of identical neighboring ports—i and j share similar roles and positions in the network. If a node has a larger intersection with other nodes, it is more functionally diverse and structurally complex, enhancing its ability to substitute for others. Conversely, a smaller homomorphism value implies weaker substitutability—the node's function in the network is more easily replaced by other, more substitutable ports. Therefore, its capacity to support the network independently is lower.

$$F_i = \sum_{j=1}^{n} \left| f_i \cap f_j \right| = \sum_{j=1}^{n} \left| \left\{ k_{ij} | k \in f_i \wedge k \in f_j \right\} \right| \tag{3}$$

where F_i is the homophily value of the node i, $|f_i \cap f_j|$ is the size of the intersection between the neighbor sets, and k_{ij} denotes the degree of structural similarity between nodes i and j. Substitutability reflects a port's locational advantage—greater homophily indicates more common neighbors within the network.

3.2.1.2. Network resilience.

d. Network Matching

This indicator mainly describes the correlation between nodes. Each node has a set of directly connected neighbors. Based on this, the average degree $\overline{K_h}$ of all neighbors of node h is calculated.

$$\overline{K_h} = \sum_{i \in v} \frac{K_i}{K_h} \tag{4}$$

A linear estimation is then performed between K_h and $\overline{K_h}$.

$$\overline{K_h} = D + bK_h \tag{5}$$

Here, K_i is the degree of each neighbor of node h, v is the set of node h's neighbors, D is a constant, and b is the degree association coefficient. A positive b ($b > 0$) indicates homophily—nodes of similar degree are more likely to connect. A negative b ($b < 0$) indicates heterophily—nodes of differing hierarchical levels, cultural backgrounds, and economic statuses tend to connect.

e. Network Transportability

This is measured using the network efficiency index, which quantifies the effectiveness of transport functions within the network. Network efficiency is determined by the shortest paths between node links that reflect the quality of resource flows.

$$E(G) = \frac{\sum_{i \neq j \in G} \frac{1}{d_{ij}}}{N(N-1)} \tag{6}$$

where $E(G)$ is network efficiency (ranging from 0 to 1), d_{ij} is the shortest path between nodes i and j, and N is the total number of nodes.

f. Network Clustering

Network agglomeration, influenced partly by geography, is measured using the average clustering coefficient. This coefficient reflects the extent to which nodes cluster together. A higher average clustering coefficient suggests a closer interconnection among nodes and a stronger capacity for interaction and transmission. A lower coefficient suggests weaker connectivity and transmission capacity. The average clustering coefficient is the ratio of the actual number of connection variables between node i and its connected node j to the total number of edges when it is fully connected to the total number of nodes.

$$AC_i = \frac{\frac{t_i}{q_i(q_i - 1)}}{N} \tag{7}$$

Here, AC_i is the average clustering coefficient of node i, t_i is the actual number of edges among node i's neighbors, and q_i is the number of neighbors of node i. Network clustering is significantly influenced by spatial elements, including port proximity, regional layout, and hinterland economic ties. Ports located near each other or within the same economic circle are more likely to be connected, forming a highly clustered local structure. For instance, the U.S. West Coast port cluster—Los Angeles, Long Beach, and Oakland—has dense shipping routes and high agglomeration due to their proximity and strong interconnectivity. Although clustering is a structural metric, it indirectly reveals how geography shapes the network's resilience and organization.

3.2.1.3. Composite resilience index. Combining the above indicators, three node-level indicators—hierarchy, centrality-diffusivity, and substitutability—and three network-level indicators—matching, transporting, and clustering—are selected to construct a resilience assessment model for port nodes and shipping networks. The process involves standardizing indicators and determining their weights using the linear weighted combination method:

$$w = \alpha a_i + (1-\alpha) b_i, (0 \le \alpha \le 1) \tag{8}$$

where w is the combination weight of the i-th index, and a_i and b_i are its objective and subjective weights, respectively. Subjective weights are derived via the analytical hierarchy process (AHP), involving five experts in shipping, logistics, and GIS who evaluated indicator importance. Judgment matrices were built and passed a consistency test (CR < 0.1). Objective weights were calculated using the entropy weight method by normalizing data, computing each index's proportion p_{ij} across samples and determining information entropy.

$$e_i = -k \sum_{j=1}^{n} p_{ij} \ln p_{ij}, k = \frac{1}{\ln n} \tag{9}$$

Difference coefficients and objective weights were derived from the entropy value. The combined weight sets subjective and objective components equally (i.e., $\alpha = 0.5$). Sensitivity analysis with $\alpha = 0.3$, 0.5, 0.7 confirmed model stability. The comprehensive resilience score remained stable across different α values, confirming the robustness of the combined score.

Resilience scores for each port node or shipping network dimension are calculated using a weighted sum model that combines the weights of the indicators.

$$R_p = \sum_{i=1}^{n} X_i w_i \tag{10}$$

where X_i and w_i are the value and weight of the i-th indicator, respectively, and p represents resilience for topology (x), shipping capacity (y), and geographic location (z) dimensions ($0 < R_p < 1$). The overall resilience index combines these three dimensions:

$$R = \sqrt{\left(W_x R_x{}^2 + W_y R_y{}^2 + W_z R_z{}^2\right)} \tag{11}$$

where W_x, W_y, and W_z are the weights of the three dimensions of resilience, respectively. In this paper, the entropy weight method is used to determine the weights of the three dimensions, which is consistent with the aforementioned method. First, the degree of difference between the three-dimensional indicators in the sample is calculated to determine the information entropy. Then, the weights are determined according to the entropy value to enhance the objectivity of the model. R_x, R_y, and R_z are the resilience scores of the three dimensions, respectively.

3.2.2. Dynamic resilience evaluation indicators of the network

Dynamic network resilience is assessed by modeling the network's capacity to withstand external disturbances and its ability to return to its initial state after such disturbances cease. A dynamic resilience measurement model is thus developed. The process is analyzed through disruption simulations, which involve running a program that periodically perturbs the network according to predefined rules. After each perturbation, the program restores the failed nodes and edges based on specific criteria (Li et al., 2023). External disturbances include natural disasters, accidents, trade frictions, geopolitical conflicts, and other disruptions affecting the stable operation of the shipping network. Based on Nan and Sansavini (2017), dynamic resilience is evaluated by dividing resilience into stages and defining resilience capacity for each stage.

Fig. 2 illustrates the stages of generalized system resilience after a disturbance. The vertical axis represents $R(t)$, the network's resilience level over time, normalized within the interval [0,1], where 0 indicates complete network paralysis, and 1 denotes optimal operation. The initial resilience value R_0, before the disturbance, serves as the normalized baseline—commonly set to the resilience level of a chosen reference year (e.g., the year 2018). This baseline represents the system's state before the disturbance, against which the resilience levels of subsequent phases are dynamically assessed.

3.2.2.1. Initial stage ($t_0 < t < t_d$). In this stage, the shipping network operates without external disturbances and provides full transportation services. The resilience index is calculated using Equation (10).

3.2.2.2. Disturbance stage (DS) ($t_d < t < t_r$). During this phase, the shipping network experiences external disturbances, leading to performance degradation. The disturbances begin at time t_d, with performance and resilience declining to a minimum at time t_r. The lowest point of resilience, referred to as the nadir, is quantified as robustness (RB), which measures the network's ability to maintain basic stability and withstand the maximum impact during the disturbance period. The rate of change in dynamic stability (ROC_{DS}) indicates how quickly resilience deteriorates during this phase.

$$RB = \min\{R(t)\}, t_d < t < t_r \tag{12}$$

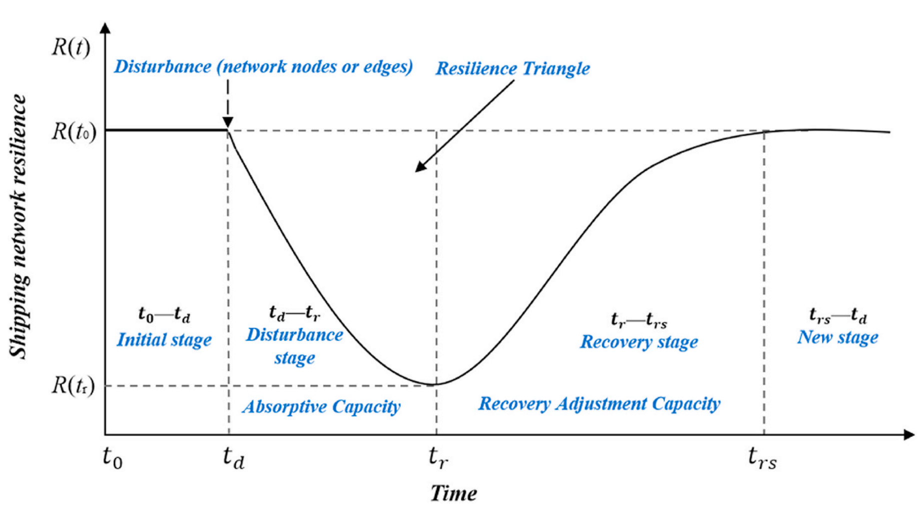


Fig. 2. Network damage and recovery process.

$$ROC_{DS} = \frac{R(t_i) - R(t_i - \Delta t)}{\Delta t} \quad 13$$

where $R(t)$ is the discrete function of network resilience over time.

t_{rs} denotes the moment when network resilience returns to its initial steady state, and Δt represents the change in time. The loss of network resilience during the disturbance stage (LOR_{DS}) measures the network's capacity to absorb destruction. LOR_{DS} is quantified as the area between the discrete function $R(t)$ and the straight-line $x = t_r$, $y = R(t_0)$ over the disturbance period.

$$LOR_{DS} = \int_{t_d}^{t_r} (R(t_0) - R(t))dt \quad (14)$$

where t_0 is the initial stabilization moment, and $R(t_0)$ represents the initial network resilience level. To better capture the dynamics of resilience loss during the disturbance phase, unit time of resilience loss during disturbance stage ($UTLOR_{DS}$) is introduced, reflecting the average resilience loss as an indicator of network stability.

$$UTLOR_{DS} = \frac{LOR_{DS}}{(t_r - t_d)} \quad (15)$$

3.2.2.3. Recover stage ($t_r < t < t_{rs}$). During this phase, network resilience gradually recovers to its initial level. Corresponding to the disturbance stage, the rate of change during recovery stage (ROC_{RS}), loss of network resilience in the recovery phase (LOR_{RS}), and unit time loss in the recovery phase ($UTLOR_{RS}$) are defined to assess the network's recovery capacity.

$$ROC_{RS} = \frac{R(t_i) - R(t_i - \Delta t)}{\Delta t}, t_r < t < t_{rs} \quad (16)$$

$$LOR_{RS} = \int_{t_r}^{t_{rs}} (R(t_0) - R(t))dt \quad (17)$$

$$UTLOR_{RS} = \frac{LOR_{RS}}{(t_{rs} - t_r)} \quad (18)$$

3.2.2.4. New stage ($t \geq t_{rs}$). At this stage, the network has recovered, and its resilience level may be lower than, equal to, or greater than the initial level. This study assumes full recovery ($R = 1$). Comprehensive resilience ability (CRA) integrates the above measures.

$$CRA = RB \times \frac{ROC_{RS}}{ROC_{DS}} \times \frac{1}{UTLOR_{DS} + UTLOR_{RS}} \quad (19)$$

3.3. Data sources

3.3.1. Data sources

For shipping networks, destructive resistance and recovery capacity significantly influence the efficient operation of maritime transportation. These factors enable shipping networks to better withstand disasters and crises, serving as intuitive manifestations of the network "resilience," which is dynamic and relative (Bai et al., 2023). The emergence, disappearance, and rise and fall of ports indicate that the shipping network system undergoes a continuous cyclical development process. In a relatively safe environment, shipping network elements accumulate; otherwise, the system may regress or even collapse (Xin et al., 2025; Xu et al., 2025).

This study examines the global shipping network from 2018 to 2022 to ensure a comprehensive and rigorous analysis. COVID-19, which emerged in December 2019 and spread rapidly in early 2020, posed unprecedented challenges to the shipping industry. The selected data period covers the initial shock, gradual recovery, and optimization phases of the shipping network's resilience during this global crisis, capturing its adaptive adjustments and dynamic changes at different stages.

The pandemic caused substantial volatility in the shipping industry from 2018 to 2022, including declines in shipping demand, port disruptions, and route interruptions. Using this period allows for a robust validation of the shipping network resilience model's sensitivity, effectiveness, and applicability under multiple disturbances. It also minimizes bias from short-term fluctuations or selective sampling, ensuring the scientific and representativeness of the results.

Shipping schedule data from the Alphaliner database, covering global container liner shipping companies, were used for statistical analysis. Detailed data include shipping companies, origin and destination ports, call ports, ship capacities, and route frequencies (calls per week). The database was systematically cleaned, corrected, and processed before network construction. Owing to incomplete records of port and route suspensions in Alphaliner for 2020, supplementary data from *Drewry*, *Container Trades Statistics (CTS)*, *the "List of Suspended Routes,"* and *the "Schedule Adjustment Announcement"* from the Ministry of Transportation and Communications (MOTC) were used. Routes interrupted for over four consecutive weeks were classified as "temporarily missing" and either removed or replaced in the network model.

Given the characteristics of liner shipping networks, this study integrates two spatial models. The P-space model represents port-connectivity strength and regularity, while the L-space model reflects transit realities and geospatial constraints, collectively constructing the global shipping network.

3.3.2. Study area

Routes were identified from the global shipping database, including regions such as the East Coast of South America, Pacific Islands, Western Hemisphere, Middle East, European Black Sea, Southeast Asia, Canada, West Coast of South America, Chinese ports, Taiwan, East and North Africa, Red Sea, Adriatic Sea, and offshore Japan. From these, over 1200 ports were selected as the study sample (Fig. 3), encompassing key areas such as Northwest Europe, the Mediterranean, East and Southeast Asia, the Middle East, North America, Latin America, and Africa.

4. Results

4.1. Static resilience assessment of the global shipping network

Between 2018 and 2022, the number of ports and routes initially increased before declining. By 2022, there were 49 fewer ports and 208 fewer routes compared to 2018. Factors such as heavy rains in Brazil, hurricanes in Australia, and seasonal downturns in shipping weakened the global shipping market. The onset of the COVID-19 pandemic further exacerbated this decline, severely disrupting port operations and reducing cargo flow efficiency.

Using a GIS platform, the spatial linkages of the global shipping network from 2018 to 2022 were visualized. Each year's network was classified into hierarchical levels using the natural breaks method. The results, illustrated in Fig. 4, include six hierarchical levels; however, the sixth level (the base network) is omitted for clarity due to the large number of routes. As the network's spatial characteristics remained relatively stable, only the 2018 results are shown. The spatial pattern consistently exhibited "multi-polar leadership, multi-point stimulation, and regional clustering." This was characterized by east-west linkages forming two central zones: East Asia and Western Europe-North America.

Based on the shipping network resilience model, this study calculates the resilience value and comprehensive resilience index of each port node worldwide (Fig. 5). Following related studies (Qin et al., 2023), $R < 0.3$ indicates low resilience, $0.3 \leq R \leq 0.6$ indicates medium resilience, and $R > 0.6$ indicates high resilience. These global shipping networks' comprehensive resilience indices for 2018 to 2022 were 0.620, 0.612, 0.587, 0.576, and 0.597, respectively. These indices initially increased,

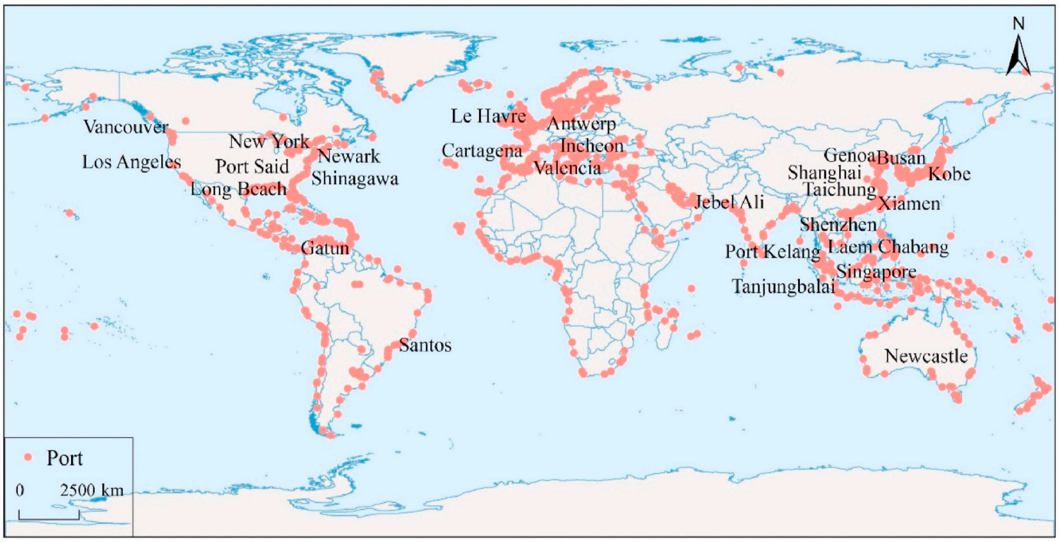


Fig. 3. Study scope based on the global shipping network
Note: Based on the standard map from the Ministry of Natural Resources (Approval No. GS [2016]; base map remains unmodified.

then declined, and slightly recovered, but the overall resilience level decreased by 3.71 %.

The network's lowest combined resilience occurred in 2020, mainly due to cascading disruptions from the global COVID-19 outbreak. In the pandemic's early stages, Chinese ports faced large-scale supply chain interruptions from blockades and quarantine policies. The MOTC[2] reported an 8.5 % year-over-year decrease in throughput at major Chinese coastal ports in the first quarter of 2020. Ports such as Wuhan and Qingdao experienced monthly declines that exceeded 15 %. As the epidemic spread to Europe and North America, congestion severely affected ports such as Singapore, Rotterdam, and Los Angeles, breaking key links in the network and increasing vulnerability. Additional disruptions, such as the grounding of the Chang Ci in early 2020, further exposed the network's heavy reliance on critical nodes. These shocks reduced structural stability and functionality and delayed recovery. Despite the gradual recovery in port operations after 2021 and rebounds in some performance indicators, the system's resilience has not fully returned to pre-pandemic levels.

As seen in Figs. 5 and 45.60 % of port nodes experienced varying degrees of decline in resilience indices, while 54.40 % showed no change or slight improvement. From 2020 to 2022, node resilience gradually recovered at different rates. Some ports saw moderate improvements in resilience in 2021, with most experiencing significant growth by 2022. This suggests that COVID-19's impact on global ports was temporary. As the pandemic subsided, industries and nations resumed normal production, and life stabilized, increasing material consumption demand, which contributed to port resilience.

Further analysis shows distinct spatial imbalances among port types, with clear regional clustering characteristics. High-resilience ports are concentrated in Asia, Europe, and North America, mainly in a few countries or regions, forming point-like or small-block patterns. Representative ports include Hong Kong, Singapore, Shanghai, and Rotterdam. These hubs possess strong infrastructure, efficient logistics systems, comprehensive service networks, and high adaptability to global trade flows, ensuring robust resilience.

Medium-resilience ports are distributed across all continents but show significant regional differences, forming clustered areas. Examples include Fuzhou, Valencia, Las Palmas, and Auckland. These ports have regional importance and adaptability but lower global network influence and recovery capacity compared to high-resilience hubs.

Low-resilience ports, also globally distributed, tend to form belt-like patterns along coastlines. Representative ports include Lumut, Maoming, Charleston, and Picton. These ports are ypically located in more remote regions or less-developed economies, and lack support systems and adaptability to complex changes. Their low resilience reflects port vulnerability and weak roles within the global network.

4.2. *Dynamic process identification of network resilience based on scenario simulation*

The maritime network, a spatial system comprising port nodes, vessels, and route resources, exhibits resilience that reflects the interconnected physical and logistical links between its components. The resilience is influenced by the geographical location and environmental factors of key port nodes, as well as the connections and spatial interactions between major ports. These factors determine how disruptions propagate through the network, influencing their direction, path, and intensity.

This section employs deterministic and randomized disturbance strategies. The former systematically removes port nodes based on their degree and risk probability and restores them according to a queuing approach (first to fail, first to be restored). The randomized strategy randomly removes nodes, stimulating attacks that cause failure, and then randomly recovers nodes. In each period, 1 % of the nodes fail until 50 % of all nodes are affected, after which the disturbance ceases and the network recovers to its initial state. The "first to fail, first to recover" rule facilitates simulation. The recovery phase assumes complete recovery, meaning the resilience index fully returns to its original state—an idealized condition that excludes topology optimization or new steady-state after formation.

According to these rules, perturbation and recovery procedures were coded using the networks package in *Python*. Changes in network performance during perturbation and recovery are shown in Fig. 6. At $t = 0$, perturbation begins, and network resilience declines, reaching its lowest level between $t = 50$ and $t = 55$ in all five years.

Under node random perturbation, the lowest resilience values were as follows: 0.045 at $t = 50$ in 2018; 0.088 at $t = 54$ in 2019; 0.042 at $t = 53$ in 2020; 0.044 at $t = 54$ in 2021; and 0.044 at $t = 54$ in 2022. As shown in Fig. 7, the highest decline occurred in 2020, followed by 2021, 2022, 2019, and 2018. The fastest recovery occurred in 2019, followed by 2018, 2022, 2021, and 2020.

[2] https://www.mot.gov.cn/shuju/.

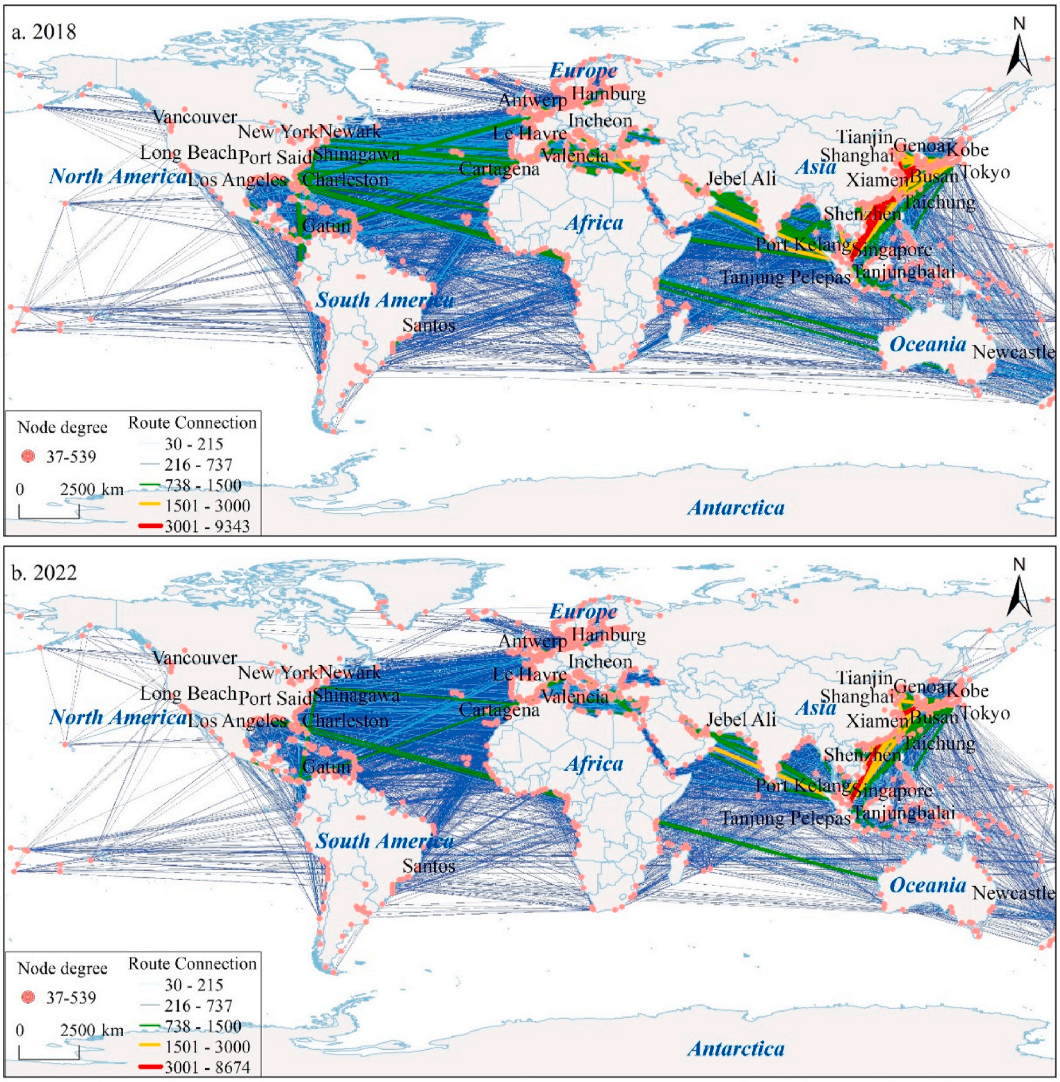


Fig. 4. Global shipping network linkage map for 2018 and 2022
Note: Based on the standard map produced by the Ministry of Natural Resources' standard map service website (review number GS [2016] 1665). No modifications were made to the base map boundary. The map includes six levels; the sixth (base network) is omitted due to excessive detail. Only 2018 and 2022 features are shown due to space constraints; however, all data from 2018 to 2022 were analyzed.

Under node risk perturbation, the lowest resilience values were as follows: 0.040 at $t = 53$ in 2018; 0.038 at $t = 54$ in 2019; 0.038 at $t = 53$ in 2020; 0.041 at $t = 52$ in 2021; and 0.034 at $t = 54$ in 2022. The rate of decline was highest in 2020, followed by 2021, 2018, 2022, and 2019. Recovery was fastest in 2018, followed by 2019, 2022, 2021, and 2020.

Under node degree perturbation, the lowest resilience values were as follows: 0.045 at $t = 53$ in 2018; 0.045 at $t = 54$ in 2019; 0.038 at $t = 53$ in 2020; 0.041 at $t = 52$ in 2021; and 0.043 at $t = 54$ in 2022. Decline rates were highest in 2020, followed by 2018, 2021, and then 2019 and 2022 (equal). Recovery was fastest in 2019, followed by 2018, 2022, 2021, and 2020. The recovery process showed two phases: $t = 55$–80 and after $t = 81$—the network's recovery corresponds to disturbance severity.

Under the node random perturbation-recovery, $UTLOR_{RS}$ values are as follows:

Perturbation: 0.013 (2018), 0.016 (2019), 0.019 (2020), 0.012 (2021), 0.015 (2022). Recovery: 0.017 (2018), 0.017 (2019), 0.015 (2020), 0.011 (2021), 0.016 (2022). Here, 2018, 2019, and 2022 showed strong absorption but weak adaptive adjustment, while 2020 and 2021 displayed weak absorption but strong adaptive adjustment. For the node risk perturbation-recovery approach, $UTLOR_{RS}$ values are as follows:

Perturbation: 0.016 (2018), 0.018 (2019), 0.020 (2020), 0.019 (2021), 0.018 (2022). Recovery: 0.014 (2018), 0.017 (2019), 0.018 (2020), 0.013 (2021), 0.019 (2022). In this case, 2018–2021 had weak absorption but strong adaptive adjustment, while 2022 exhibited the reverse.

For the node degree perturbation-recovery approach, $UTLOR_{RS}$ values are as follows:

Perturbation: 0.015 (2018), 0.016 (2019), 0.018 (2020), 0.019 (2021), 0.017 (2022). Recovery: 0.017 (2018), 0.016 (2019), 0.011 (2020), 0.015 (2021), 0.018 (2022). Here, 2018; 2022 showed strong absorption but weak adaptation, 2020 and 2021 demonstrated the opposite, and 2019 balanced both capacities. Overall, the shipping network's absorptive and adaptive capacities evolved alongside the industry's development.

Comparing overall resilience, the CRAs were as follows:

Random perturbation-recovery: 0.334, 0.347, 0.301, 0.328, and 0.335. Risk perturbation-recovery: 0.330, 0.341, 0.287, 0.315, and 0.322. Degree perturbation-recovery: 0.329, 0.313, 0.299, 0.281, and 0.301. In each year, deterministic strategies resulted in consistently lower resilience than stochastic strategies, although the degree varied.

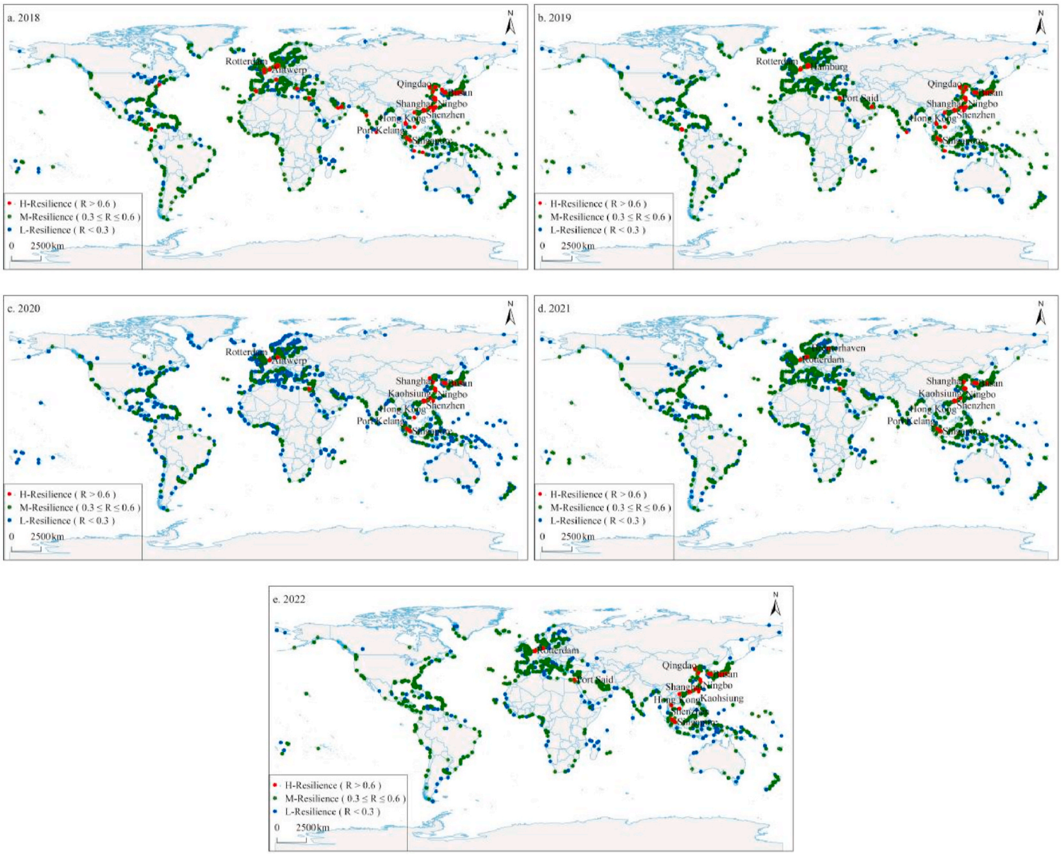


Fig. 5. Port node resilience value from 2018 to 2022.

When comparing the robustness (RB) of the shipping network under different strategy perturbations, RB values are consistently lower under deterministic strategies—deterministic perturbations have a greater impact on network robustness than random perturbations. The overall trend of network resilience under deterministic perturbations shows a linear decline. Notably, network robustness decreases sharply when approximately the first 8 % of ports are disrupted. After this, the rate of decline slows until the network effectively fails when disruptions reach 50 %. This indicates that certain nodes in the network significantly contribute to or inhibit the enhancement of network resilience; such nodes are more resilient and have relatively higher centrality values.

The conclusion corresponds to real-world conditions, reflecting that the impact of natural, economic, and social contingencies on shipping network resilience in large ports or regions is greater than that of random factors. Therefore, this study further designed sensitivity and scenario simulation analyses to construct three spatial layout scenarios: increased node agglomeration, failure of key nodes, and network decentralization. Network efficiency and CRA were measured under each scenario to compare their response performance under different structural adjustments.

Under the increased node-clustering scenario, network efficiency and CRA increase by 11.4 % and 9.7 %, respectively, compared to the original network. This indicates that functional concentration among ports contributes to path configuration optimization, improving transportation efficiency and enhancing local structural resilience. Conversely, under the critical node failure scenario, network efficiency decreases by 28.5 % and CRA decreases by 35.6 %. This reflects the system's heavy dependence on a few high median ports. When these nodes are disrupted, network efficiency drops rapidly, and effective alternative paths are limited, exposing the vulnerability of a "single point of failure." Conversely, under the decentralized layout, network efficiency decreases slightly by 6.8 %, while the CRA remains stable, increasing by 2.3 %, demonstrating stronger system performance. This high path redundancy and node substitutability in this structure effectively buffer the impact of local disruptions on overall network performance.

These simulation results show that different spatial layouts significantly affect shipping network resilience. Moderate node clustering and redundancy improve the network's shock resistance and resilience without significantly reducing efficiency. However, overreliance on central nodes exposes the system to systemic risk from a "single point of failure" during localized disruptions. Conversely, a decentralized structure enhances overall robustness by balancing the layout, although with slightly reduced efficiency.

5. Discussion

Amid a century-defining transformation and the global pandemic, the strategic significance of the shipping industry has been unequivocally affirmed. Within the global shipping network, resilience—defined as the system's capacity to absorb and respond to external shocks—is shaped by the interplay of multiple factors. This study investigates the mechanisms through which pandemic-induced disruptions, port spatial configurations, and nodal hierarchies influence network resilience, aiming to advance understanding of the global shipping system's complex adaptive dynamics and inform port and maritime governance.

First, the systemic impact of the 2020 epidemic on global shipping networks manifested in various ways. At the overall network level, approximately 12 % of scheduled routes were suspended or skipped between March and May of that year, significantly reducing port connectivity and average efficiency of shipping routes. At the local node level, port congestion and declining node efficiency amplified functional vulnerability. For instance, Singapore's port experienced an increase of over 35 % in average berthing wait time in April 2020, while the ports of

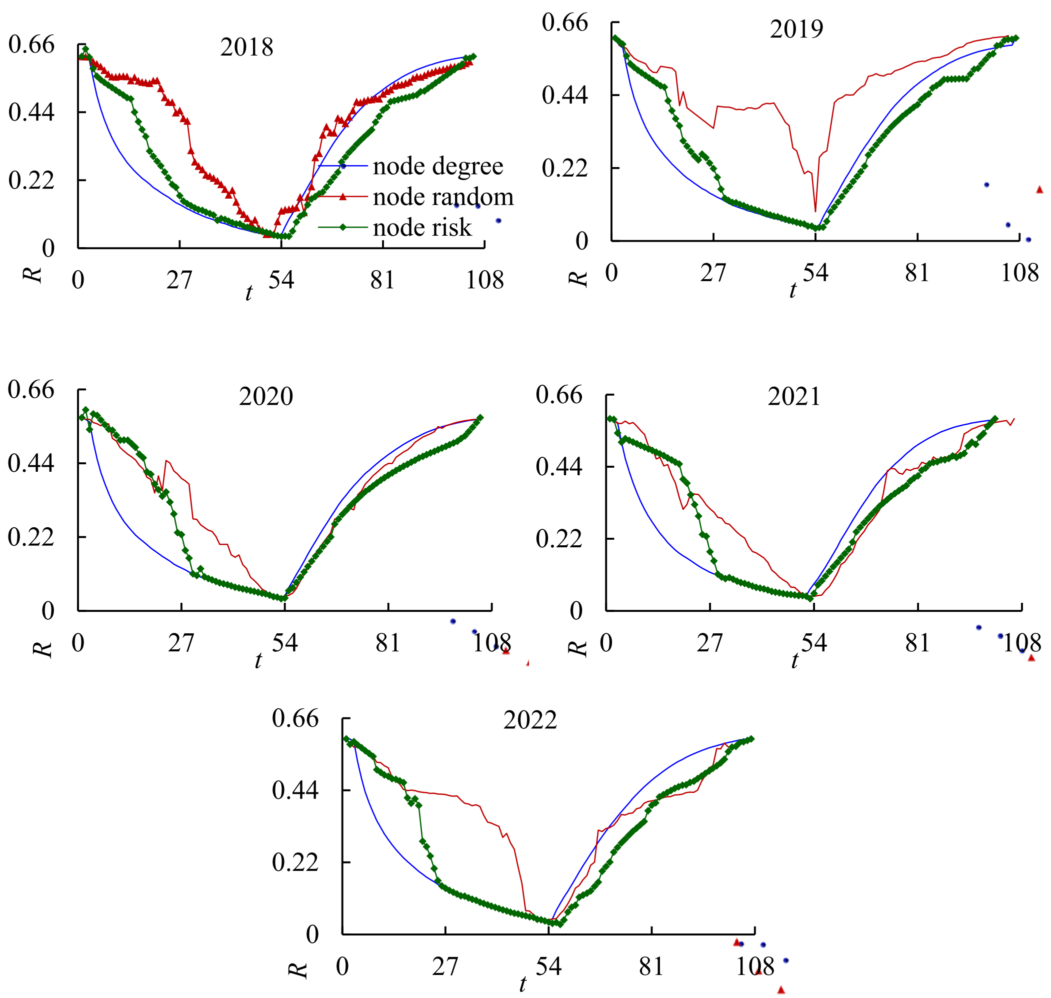
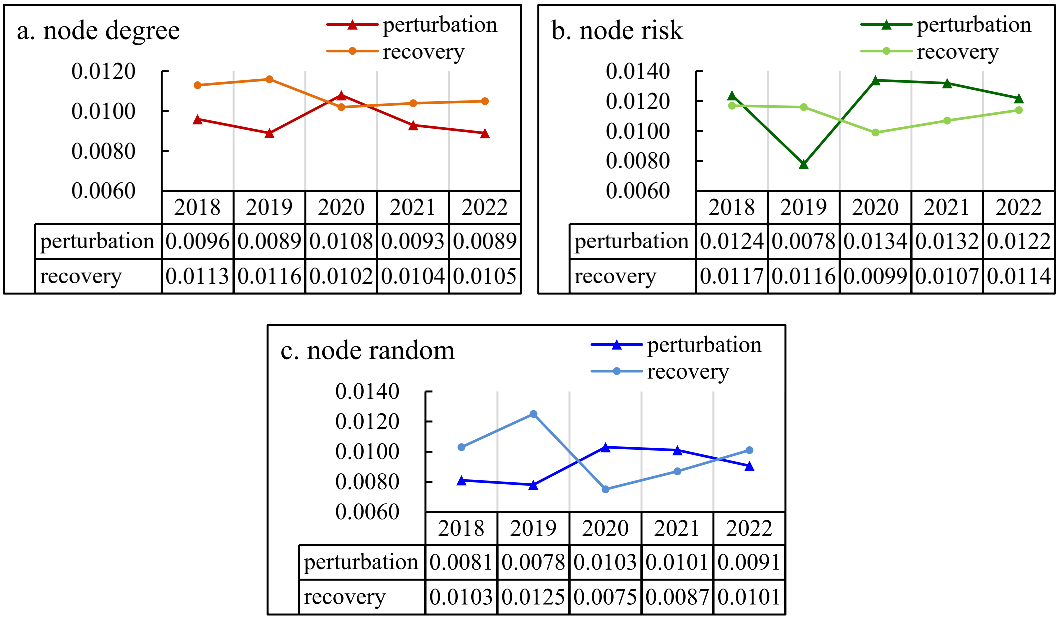


Fig. 6. Changes in shipping network resilience under different disturbances and recovery strategies
Note: Panels a–e show resilience changes caused by different disturbance and recovery strategies between 2018 and 2022. The x-axis (*t*) represents the number of disturbance–recovery steps during the simulation process (0–108), while the y-axis denotes network resilience (*R*). Blue, red, and green lines correspond to node degree, random disturbance, and node risk strategies, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Los Angeles and Rotterdam recorded efficiency declines exceeding 30 %. These disruptions caused "path breaks" and "node downgrading" at the structural level, substantially weakening the timeliness and connectivity of global cargo flows at the functional level. Thus, the decline in the global shipping network's overall resilience in 2020 resulted from the interplay of abnormal factors, including reduced port efficiency on the supply side and network coordination barriers arising from transportation corridor constraints and fragmented multinational policies. This finding highlights the imperative for port authorities and shipping enterprises to reinforce emergency response mechanisms and improve scheduling flexibility at high-risk nodes, thereby mitigating the impact of unforeseen disruptions and safeguarding network performance.

Second, the degree of optimization in the port spatial layout is a critical structural factor affecting the stability of the shipping network. It directly influences the system's shock resistance and resource dispatching efficiency (Ducruet and Beauguitte, 2014; Notteboom and Rodrigue, 2005). High-resilience port nodes are concentrated in specific regions, such as East Asia and Northwestern Europe, slightly enhancing intra-regional connectivity and functional redundancy. However, the global port layout remains uneven, particularly along Africa's east and South America's west coast. The weak functional substitutability and poor connectivity of these ports create "fragile chains" and potential "weak links" in the network, increasing susceptibility to systemic failures during external shocks. Variations in port spatial layouts underscore the need for administrators to reinforce regional coordination and inter-port linkage mechanisms. For ports located in low-redundancy regions, strategic focus should be directed toward enhancing connectivity and cultivating collaborative capacity to reduce dependence on core nodes.

Finally, shipping networks exhibit a hierarchical structure. High-ranking port nodes serve as core hubs for cargo flow, focusing on transshipment, distribution, and ocean transportation. Nevertheless, this concentration also introduces the risk of a "single point of failure." For example, operational disruptions at mega-hub ports such as Rotterdam, Shanghai, and Singapore often trigger cascading impacts that disturb the entire route network within a short time. Conversely, while low- and medium-level ports play a limited role in daily operations, they provide critical "functional redundancy" during disruptions by serving as backup nodes when primary routes are compromised. Enhancing the service capacity and connectivity efficiency of these ports can reduce overreliance on core nodes and improve the network's overall resilience and redundancy. Furthermore, this study identifies several "potential pivotal ports"—including Qingdao, Barcelona, and Busan—that demonstrate high betweenness centrality and strong economic linkages within the network. Their multifaceted roles confer a stabilizing effect under systemic shocks such as the pandemic. These suggest that future



a. node degree	2018	2019	2020	2021	2022
perturbation	0.0096	0.0089	0.0108	0.0093	0.0089
recovery	0.0113	0.0116	0.0102	0.0104	0.0105

b. node risk	2018	2019	2020	2021	2022
perturbation	0.0124	0.0078	0.0134	0.0132	0.0122
recovery	0.0117	0.0116	0.0099	0.0107	0.0114

c. node random	2018	2019	2020	2021	2022
perturbation	0.0081	0.0078	0.0103	0.0101	0.0091
recovery	0.0103	0.0125	0.0075	0.0087	0.0101

Fig. 7. Rate values of the shipping network under different perturbations and recovery strategies
Note: Figures a–c illustrate the trends and numerical values of the decline and recovery rates in the shipping network under three scenarios: node degree, node randomness, and node risk.

efforts to enhance shipping network resilience should prioritize the functional integration of mid- and low-tier ports and emergent hubs. Through optimized scheduling and coordinated deployment, the network's adaptive capacity and resilience reserves can be substantively reinforced.

In summary, the resilience of the global shipping network is governed by a constellation of mechanisms—including emergency pressure, structural layout heterogeneity, and variations in node functional levels—rather than any singular determinant. For port and shipping management, this underscores the need to extend resilience-building efforts beyond the optimization of core node efficiency, incorporating the synergistic roles and redundancy value of lower-tier and emergent ports. By identifying critical nodes, latent hubs, and vulnerable linkages, stakeholders can implement targeted resource allocation, capacity reconfiguration, and risk mitigation strategies, thereby strengthening the network's adaptive and recovery capabilities under emergency conditions.

6. Conclusion and implications

6.1. Conclusion

Efficient connectivity of transportation infrastructure is crucial for global facility integration and smooth trade, with maritime route connectivity being vital in promoting interconnectivity among maritime nations and ensuring efficient, convenient shipping. Amid the complexities of global transformations and the COVID-19 pandemic, this study systematically reviewed and summarized existing theoretical and empirical research. An analytical framework and identification model for shipping network resilience, integrating static and dynamic perspectives, were developed. In academic and technical writing, "validate" is used when discussing model or framework testing; "verify" often suggests checking for correctness (typically in programming or process control), whereas "validate" emphasizes proving applicability and accuracy, fitting this context better. A global port case study was conducted to validate the framework's effectiveness and applicability in measuring the evolution and dynamic process of shipping network resilience. The main conclusions are as follows.

(1) This study reexamined factors such as shipping network characteristics, port node attributes, and influencing variables to construct a resilience measurement model that integrates static and dynamic perspectives with quantitative analysis methods. The model fully considers the systemic and complex inter-node relationships, addressing prior shortcomings in assessing network resilience and vulnerability. This enables a more detailed and precise analysis of shipping network resilience, revealing interactions and impacts between the system and the unit levels.

(2) The comprehensive resilience index of the global shipping network for 2018–2022 was 0.620, 0.612, 0.587, 0.576, and 0.597, respectively, transitioning from high to medium resilience. The index initially increased, followed by a decline and slight recovery, with an overall resilience decrease of 3.71 %. Notably, 2020 recorded the lowest resilience value, primarily due to the severe impact of the COVID-19 pandemic.

(3) In terms of node resilience characteristics, the resilience of global ports fluctuated between 2018 and 2022. Approximately 45.60 % of port nodes experienced a decline in resilience, while 54.40 % maintained or slightly improved their indices. Different spatial imbalances and regional clustering were observed across port types: high-resilience ports showed point-like or small cluster distributions, medium-resilience ports formed multiple spatial clusters, and low-resilience ports appeared in band-like patterns along coastal regions.

(4) Disruption simulation analysis revealed that network resilience declined at time $t = 0$ when disturbances occurred, reaching its lowest point between $t = 50$ and $t = 55$. Comparing network robustness (RB) under different disruption strategies showed that resilience under determined strategies (node degree and node risk probability) was generally lower than under the random strategy (node randomness). Further analysis reveals that in 2020, shipping networks exhibited high decline and low recovery rates under all three disturbance scenarios. This suggests that during significant external disruptions, the shipping network's reliance on critical nodes and its vulnerability increased, while its ability to self-repair remained inadequate. These findings

underscore the system's uneven resilience and fragility during this period.

6.2. Implications

Port node and shipping network resilience vary annually by node, influenced by complex and multifaceted factors. Resilience is not absolutely resilient but can be enhanced. Strengthening network resilience requires network organization and dynamic adaptability rather than reliance on a single key node. The findings of this study offer the following implications for developing shipping networks from a systematic security perspective.

Optimize the spatial layout of ports and enhance the fault tolerance and resilience of the network structure. Results indicate that highly resilient ports are concentrated in a limited number of regions—such as Northwest Europe and East Asia—whereas ports in other areas, including the East African coast and the West Coast of South America, display sparse distribution and low functional substitutability. In light of this, efforts should be accelerated to improve infrastructure and service capacity at ports with medium-to-low resilience. Rational planning of functional zoning between hub and secondary ports is essential to establish a hierarchical port network with built-in redundancy. Simultaneously, network analysis should be employed to identify potential nodes and vulnerable links, enabling targeted optimization of shipping capacity allocation and alternative routing. This approach reduces reliance on a small number of core ports and enhances the global network's capacity to withstand disruptions.

Enhance the core role of highly resilient port nodes. These nodes exhibit strong risk-resistance capabilities and resource aggregation effects within the network, enabling them to fulfill critical recovery functions during disruptions. Accordingly, a hierarchical network system centered on major hub ports should be established to reinforce the protection and functional optimization of key nodes. At the same time, efforts should be made to promote rational division of labor and coordinated operations among ports, thereby strengthening the synergistic roles of secondary and potential ports. Reserving backup transport capacity and transshipment channels is essential to mitigate systemic risks arising from the failure of a single node. This approach also provides strategic support for decision-making related to route diversification and regional logistics optimization.

Fully leverage potential hubs and functional redundancy. Medium-to-low-tier ports and potential ports—such as Qingdao, Barcelona, and Busan—can serve as backup nodes under exceptional circumstances, thereby enhancing overall network resilience. Administrators should integrate these ports into dynamic scheduling frameworks and emergency response systems to alleviate pressure on critical cargo flows. In addition, contingency plans should be developed for scenarios such as natural disasters and public health emergencies, further strengthening the network's adaptability and recovery capacity.

Strengthen the early warning mechanism for shipping network disruptions and enhance resilience-building capabilities. Disruption simulation analyses reveal substantial variation in recovery rates following network disturbances. A dynamic monitoring and response system should be established, leveraging big data and artificial intelligence technologies to track network operational status in real time, with particular focus on critical nodes and high-risk areas. Developing node-priority recovery plans and optimizing resource allocation strategies will effectively reduce recovery time. This approach not only shortens disruption response periods but also provides a scientific basis for infrastructure investment and operational decision-making, thereby enhancing network robustness across diverse disturbance scenarios.

Promote coordinated regional development, enhance port agglomeration effects, and strengthen overall network resilience. Leverage the advantages of port clusters by facilitating the sharing of internal information and logistics platforms across ports to eliminate administrative barriers. This enables differentiated resource development and joint planning and investment, thereby improving collaborative efficiency and minimizing redundant construction. Strengthening cooperation among port clusters further supports cross-regional route optimization, improves regional logistics accessibility, and maximizes economic returns—providing strategic support for national, port-level, and shipping enterprise planning.

This study provides a theoretical foundation for regional policy development to promote high-quality coastal growth and fills gaps in shipping network resilience research. The proposed measurement framework helps identify vulnerabilities under diverse disturbances and guides the repair of network mechanisms. It offers transportation management agencies practical tools for infrastructure planning, node-link optimization, and resilience to shocks. Additionally, this study analyzes the global shipping network and constructs an evolutionary framework for resilience analysis. It lays a methodological foundation for future comparative studies across regions and development stages. Future work will expand the time frame and include more variable dimensions to conduct systematic quantitative regressions and compare cross-regional, multi-scale networks. By identifying regional differences in resilience levels, transmission pathways, and adaptability, this study provides more accurate theoretical support and practical guidance for optimizing the structure and strategy of the global shipping network.

CRediT authorship contribution statement

Yafeng Qin: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jianke Guo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Shasha Wu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Data curation.

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Declaration of competing interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

References

Asadabadi, A., Miller-Hooks, E., 2020. Maritime port network resiliency and reliability through co-opetition. Transport. Res. E Logist. Transport. Rev. 137, 101916.

Attar, A., Irawan, C.A., Akbari, A.A., Zhong, S., Luis, M., 2024. Multi-disruption resilient hub location–allocation network design for less-than-truckload logistics. Transport. Res. Pol. Pract. 190, 104260.

Bai, X., Ma, Z., Zhou, Y., 2023. Data-driven static and dynamic resilience assessment of the global liner shipping network. Transport. Res. E Logist. Transport. Rev. 170, 103016.

Bedoya-Maya, F., Beckers, J., Cant, J., Martínez-Moya, J., van Hassel, E., Vanelslander, T., 2025. Container port competitiveness amid disruptions: insights from the European maritime network during the Red Sea crisis. J. Transport Geogr. 128, 104304.

Chacon-Hurtado, D., Kumar, I., Gkritza, K., Fricker, J.D., Beaulieu, L.J., 2020. The role of transportation accessibility in regional economic resilience. J. Transport Geogr. 84, 102695.

Chen, D., Yang, Z., 2018. Systematic optimization of port clusters along the Maritime Silk Road in the context of industry transfer and production capacity constraints. Transport. Res. E Logist. Transport. Rev. 109, 174–189.

Deng, Y., Zhang, Y., Wang, K., He, Y., 2025. Navigating through and beyond the COVID-19 crisis: evaluating the resilience of Chinese international air freighter networks. Transp. Policy 163, 285–297.
Dirzka, C., Acciaro, M., 2022. Global shipping network dynamics during the COVID-19 pandemic's initial phases. J. Transport Geogr. 99, 103265.
Douet, M., Cappuccilli, J.F., 2011. A review of Short Sea Shipping policy in the European Union. J. Transport Geogr. 19, 968–976.
Ducruet, C., Beauguitte, L., 2014. Spatial science and network science: review and outcomes of a complex relationship. Network. Spatial Econ. 14, 297–316.
Ducruet, C., Cocuzza, E., Ignaccolo, M., 2023. Analysis of the maritime networks: criticalities and resilience. Transp. Res. Procedia 69, 878–885.
Dui, H., Chen, S., Wang, J., 2021. Failure-oriented maintenance analysis of nodes and edges in network systems. Reliab. Eng. Syst. Saf. 215, 107894.
Gao, L., Liu, Y., Yang, F.X., Liu, H., Wang, Y., 2025. Perspectives of resilience in mega-event studies in the context of urban development: a systematic literature review. Cities 163, 106058.
Guo, J., Feng, T., Wang, S., Qin, Y., Yu, X., 2024. Shipping network vulnerability assessment integrated with geographical locations. Transport. Res. Transport Environ. 130, 104166.
Guo, J., Huang, Q., Cui, L., 2021. The impact of the Sino-US trade conflict on global shipping carbon emissions. J. Clean. Prod. 316, 128381.
Guo, S., Lyu, J., 2024. Evolution and stability of liner shipping networks in Northeast Asia from 2018 to 2022. Transp. Policy 158, 159–174.
Hamano, M., Vermeulen, W.N., 2020. Natural disasters and trade: the mitigating impact of port substitution. J. Econ. Geogr. 20, 809–856.
Holling, C.S., 1973. Resilience and Stability of Ecological Systems. International Institute for Applied Systems Analysis Laxenburg.
Hu, W., Shan, Y., Deng, Y., Fu, N., Duan, J., Jiang, H., Zhang, J., 2023. Geopolitical risk evolution and obstacle factors of countries along the belt and road and its types classification. Int. J. Environ. Res. Publ. Health 20, 1618.
Huang, L., Wan, C., Wen, Y., Song, R., van Gelder, P., 2024. Generation and application of maritime route networks: overview and future research directions. IEEE Trans. Intell. Transport. Syst.
Li, S., Tang, L., Liu, J., Zhao, T., Xiong, X., 2023. Vessel schedule recovery strategy in liner shipping considering expected disruption. Ocean Coast Manag. 237, 106514.
Liu, H., Meng, Z.-H., Lv, Z.-F., Wang, X.-T., Deng, F.-Y., Liu, Y., Zhang, Y.-N., Shi, M.-S., Zhang, Q., He, K.-B., 2019. Emissions and health impacts from global shipping embodied in US–China bilateral trade. Nat. Sustain. 2, 1027–1033.
Lu, X., White, H., 2014. Robustness checks and robustness tests in applied economics. J. Econom. 178, 194–206.
Lucio, D., Lara, J.L., Tomás, A., Losada, I.J., 2024. Probabilistic assessment of climate-related impacts and risks in ports. Reliab. Eng. Syst. Saf. 251, 110333.
Mou, N., Sun, S., Yang, T., Wang, Z., Zheng, Y., Chen, J., Zhang, L., 2020. Assessment of the resilience of a complex network for crude oil transportation on the Maritime Silk Road. IEEE Access 8, 181311–181325.
Nan, C., Sansavini, G., 2017. A quantitative method for assessing resilience of interdependent infrastructures. Reliab. Eng. Syst. Saf. 157, 35–53.
Nocera, F., Contento, A., Gardoni, P., 2024. Risk analysis of supply chains: the role of supporting structures and infrastructure. Reliab. Eng. Syst. Saf. 241, 109623.
Notteboom, T.E., Winkelmans, W., 2001. Structural changes in logistics: how will port authorities face the challenge? Marit. Pol. Manag. 28, 71–89.
Notteboom, T.E., Rodrigue, J.-P., 2005. Port regionalization: towards a new phase in port development. Marit. Pol. Manag. 32, 297–313.
Panahi, R., Sadeghi Gargari, N., Lau, Y.-y., Ng, A.K.Y., 2022. Developing a resilience assessment model for critical infrastructures: the case of port in tackling the impacts posed by the Covid-19 pandemic. Ocean Coast Manag. 226, 106240.
Pratson, L.F., 2023. Assessing impacts to maritime shipping from marine chokepoint closures. Commun. Transport. Res. 3, 100083.
Qin, Y., Guo, J., Liang, M., Feng, T., 2023. Resilience characteristics of port nodes from the perspective of shipping network: empirical evidence from China. Ocean Coast Manag. 237, 106531.
Rogerson, S., Svanberg, M., Santén, V., 2022. Supply chain disruptions: flexibility measures when encountering capacity problems in a port conflict. Int. J. Logist. Manag. 33, 567–589.
Ronza, A., Lázaro-Touza, L., Carol, S., Casal, J., 2009. Economic valuation of damages originated by major accidents in port areas. J. Loss Prev. Process. Ind. 22, 639–648.
Shi, X., Zhuang, H., Xu, D., 2021. Structured survey of human factor-related maritime accident research. Ocean Eng. 237, 109561.
Shilpi, F., Emran, M.S., Blankespoor, B., Coulombe, H., 2024. Temporary trade shocks and regional development: evidence from the closure of Abidjan port. J. Econ. Geogr. 24, 333–352.
Su, W., Lu, J., 2025. Short-term resilience assessment of the global liner shipping network: a case study of COVID-19. Ocean Coast Manag. 262, 107560.
Vanlaer, N., Albers, S., Guiette, A., van den Oord, S., Marynissen, H., 2022. 100% operational! an organizational resilience perspective on ports as critical infrastructures. Case Stud. Transp. Pol. 10, 57–65.
Verschuur, J., Koks, E.E., Hall, J.W., 2020. Port disruptions due to natural disasters: insights into port and logistics resilience. Transport. Res. Transport Environ. 85, 102393.
Wan, C., Tao, J., Yang, Z., Zhang, D., 2022. Evaluating recovery strategies for the disruptions in liner shipping networks: a resilience approach. Int. J. Logist. Manag. 33, 389–409.
Wan, C., Yuan, J., Cao, D., Wang, T., Ng, A.K.Y., 2024. A fuzzy evidential reasoning-based model for evaluating resilience of ports to typhoons. Transport. Res. Transport Environ. 133, 104228.
Wang, J., Liao, F., Wu, J., Sun, H., Wang, W., Gao, Z., 2023. Measurement of functional resilience of transport network: the case of the Beijing subway network. Transp. Policy 140, 54–67.
Wang, N., Yuen, K.F., Gao, X., Nie, Y., 2025. Resilience assessment of global container shipping network via port communities. Transport. Res. Transport Environ. 141, 104649.
Wu, D., Yu, C., Zhao, Y., Guo, J., 2024. Changes in vulnerability of global container shipping networks before and after the COVID-19 pandemic. J. Transport Geogr. 114, 103783.
Xin, X., Cao, Y., Jarumaneeroj, P., Yang, Z., 2025. Vulnerability assessment of International Container Shipping Networks under national-level restriction policies. Transp. Policy 167, 191–209.
Xu, K., Cui, Y., Liu, J., 2024a. Modeling the resilience of liner shipping network under cascading effects: considering distance constraints and transportation time. Comput. Ind. Eng. 197, 110559.
Xu, K., Liu, J., Li, Z., 2025. Vulnerability assessments of global liner shipping network based on extended coupled map lattices. Reliab. Eng. Syst. Saf. 264, 111306.
Xu, M., Zhu, Y., Liu, K., Ng A, K.Y., 2024b. Assessing resilience of global liner shipping network to tropical cyclones. Transport. Res. Transport Environ. 131, 104189.
Yang, L., Zheng, J., Wang, J., 2025. Hub port location and routing for a single-hub feeder network: effect of liner shipping network connectivity. Transp. Policy 160, 212–227.
Zhang, Q., Pu, S., Luo, L., Liu, Z., Xu, J., 2022. Revisiting important ports in container shipping networks: a structural hole-based approach. Transp. Policy 126, 239–248.
Zhang, X., Miller-Hooks, E., Denny, K., 2015. Assessing the role of network topology in transportation network resilience. J. Transport Geogr. 46, 35–45.