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Dynamic resilience assessment of global shipping networks against cascading effects: An AIS data-driven complex network analysis

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ABSTRACT

Assessing the resilience of global shipping networks is essential for understanding and mitigating systemic disruptions in maritime transport and their cascading impacts on global trade. Existing studies, however, have largely emphasized static network structures while overlooking the dynamic processes that govern cascading failures. To bridge this gap, this study proposes an Automatic Identification System (AIS) data-driven framework integrating network modeling, cascading failure simulation, and resilience quantification. A deadweight tonnage (DWT)-weighted global shipping network is constructed by combining 2022 AIS data with vessel capacity information. Unlike conventional analyses at the terminal level, this study advances resilience assessment to the port level, enabling evaluation of large-scale disruptions that affect entire ports or strategic maritime corridors (e.g., the Suez Canal blockage and Red Sea crisis). Port communities are identified through DBSCAN-based clustering, while ship trajectories are simplified using the Douglas-Peucker algorithm to preserve key navigational nodes. Four attack scenarios, random, degree-based, betweenness-based, and TOPSIS-based hybrid attacks, are simulated to examine how static robustness metrics evolve during cascading failure propagation. Results show that targeted attacks on high-betweenness nodes can triple cascading failure severity compared with random disruptions. Regional analyses further indicate that European networks suppress failure propagation 22 % more effectively than Asia-Pacific systems, where single-node capacity losses above 20 % can trigger systemic collapse. These findings reveal significant regional disparities in resilience and highlight the importance of safeguarding hub ports and optimizing port capacity. The proposed framework provides new empirical insights into the dynamic resilience of global shipping networks and offers valuable implications for maritime policymakers and port authorities to strengthen global supply chain stability.

1. Introduction

Maritime transportation accounts for approximately 80 % of global trade, making it a critical backbone of the international economy. However, the increasing vulnerabilities of shipping networks to localized disruptions poses mounting challenges to the stability and resilience of global supply chains. Recent high-impact events, such as the Suez Canal blockage and the COVID-19 pandemic, triggered severe port congestion, network overloads, and widespread disruptions that reverberated across international trade markets (Chu et al., 2024). Given this, these events underscore the urgent need for a systematic resilience framework that reflects the structural and operational characteristics of shipping systems, thereby enhancing their capacity to accommodate variable and unforeseen disruptions (Bai et al. 2023). Here, resilience refers to a system's ability to absorb shocks, adapt to changing conditions, and rapidly recover critical functions while preserving the integrity of maritime infrastructure and operations amid disruptions.

The resilience analysis in maritime transportation has advanced through a range of established frameworks that systematically assess cascading risks and recovery pathways (Yang et al. 2017). While current frameworks provide foundational insights into maritime network resilience, they often fall short in capturing the multilayer interdependencies

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inherent to global waterway systems. Existing evaluations largely rely on static topological metrics, which, although useful for identifying pre-disruption vulnerabilities, fail to adequately represent the dynamic redistribution of cargo flows and propagation of cascading failures that occur during disruptions (Wu et al. 2024). This limitation constrains a systematic understanding of risk transmission across interconnected maritime networks, making it difficult for stakeholders to anticipate, absorb, and recover from disruptions—particularly as sea lanes become increasingly congested and subject to tighter environmental and regulatory constraints (Notteboom et al. 2021).

Furthermore, most existing studies focus on a single vessel type, most commonly container ships, thereby overlooking macro-level interdependencies among heterogeneous ship categories. Such an approach neglects the collective operational impact of large-scale accidents on port systems, which function as integrated entities within the global maritime network. Addressing these gaps requires long-term, high-resolution datasets encompassing all vessel types and ports worldwide, posing significant research and data integration challenges.

Shipping network disruptions arise from a range of factors, including port congestion, navigational accidents, and extreme weather events. A notable example is the 2021 grounding of the 20,000 TEU container ship Ever Given in the Suez Canal, which stranded >400 vessels and caused Europe-Asia freight rates to surge by 47% within two weeks. Given the high level of interconnectivity within global maritime systems, such localized disruptions can propagate through chains of dependent failures, commonly referred to as cascading failures (Su et al. 2025). Although cascading-failure models have been proposed to investigate these mechanisms, their application to maritime contexts remains limited due to methodological simplifications and insufficient adaptability to operational realities.

Despite progress in directed and weighted network modeling, three major limitations persist. First, existing directed network models often oversimplify continental-scale trade asymmetries, failing to reflect the uneven nature of global cargo flows, such as the approximately 40% higher westbound volumes between Asia and Europe. Second, current weighted approaches inadequately represent disruption thresholds that depend on the economic interdependence of trade partners, resulting in biased resilience estimates. For instance, the global impact of a port disruption differs substantially depending on whether it serves predominantly intra-Asian or intercontinental trade routes (Zhou and Elmokashfi, 2018). Third, most frameworks conceptualize disruption propagation as purely topology-driven, disregarding trade-priority-based responses in which shipping lines strategically protect high-value routes. These oversights undermine the realism and validity of resilience evaluations, neglecting the adaptive rerouting behaviors and operational prioritization strategies that shape post-disruption recovery in maritime transport systems.

Addressing these methodological and conceptual limitations requires an integrative, data-driven approach capable of linking static structure and dynamic behavior. To this end, this study develops a big-data-driven analytical framework for evaluating global shipping network resilience using worldwide AIS data. The proposed framework integrates deadweight tonnage (DWT)-weighted network construction with dynamic cargo flow analysis, offering a unified perspective that bridges static and dynamic dimensions of maritime resilience. Specifically, a directed and weighted shipping network is constructed by linking ports through the Automatic Identification System (AIS) trajectory data from 2022, where nodes represent ports and edge weights capture the aggregated ship DWT as a proxy for route capacity.

Static resilience is examined using community structure detection to identify regional clustering patterns, alongside scale-free network analysis to assess structural robustness. Dynamic resilience, in turn, is quantified via a cascading-failure model that simulates cargo flow redistribution under targeted disruptions, incorporating realistic vessel rerouting and adaptive port dynamics (Wang et al., 2024a). These components enable a comprehensive assessment of both pre-disruption vulnerabilities and post-disruption recovery dynamics.

Building upon these methodological innovations, the study achieves three major advancements in maritime network resilience analysis. First, it provides a systematic evaluation of port-level resilience through standardized aggregation of all vessel types, supporting evidence-based enhancement of critical hub ports. Second, it incorporates real-time failure propagation dynamics into network-wide disruption management, enhancing the efficiency and timeliness of emergency resource allocation. Third, it introduces adaptive routing protocols to maintain navigational continuity during multi-stage disruptions, thereby promoting a proactive approach to resilience engineering in global maritime transport systems.

The specific contributions of this paper are summarized as follows:

(1) A holistic multi-class maritime network framework

This study proposes a holistic maritime transportation network framework that captures the interdependent nature of global shipping systems. By integrating multiple vessel classes within a unified network structure, the model reveals systemic vulnerabilities that remain obscured when networks are constructed based on a single vessel type. This multi-class integration enables the identification and quantification of cross-sectoral dependencies and infrastructure-related risks, extending the analytical scope from individual ship categories to the resilience of the entire maritime transportation system.

(2) Integration of topological and dynamic resilience modeling

To overcome the limitations of static network assessments, this study develops an integrated framework that combines topological analysis with dynamic cascading-failure modeling for comprehensive resilience evaluation. Beyond traditional graph-theoretic metrics (e.g., node degree, clustering coefficient), a load redistribution algorithm, aligned with realistic vessel rerouting behaviors, is implemented to simulate post-disruption dynamics. This approach allows for a quantitative assessment of network degradation and recovery processes, offering deeper insights into the adaptive capacity of shipping systems under stress.

(3) Capacity-weighted network construction and empirical validation

A capacity-weighted shipping network is established using transport capacity estimations derived from vessel dimensional parameters, enabling a more functionally meaningful representation of maritime connectivity. Utilizing 2022 AIS trajectory data for large-scale trajectory reconstruction, the proposed network architecture demonstrates improved precision and operational relevance compared with conventional traffic-based models. The framework provides a practical foundation for global cargo flow simulation and infrastructure resilience assessment, bridging the gap between theoretical network modeling and engineering-oriented maritime applications.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the methodological framework. Section 4 reports the analytical results. Section 5 discusses theoretical and practical implications. Section 6 concludes the study.

2. Literature review

Network resilience research has evolved around two closely interrelated themes. First, the construction and characterization of complex network structures form the foundation of resilience analysis, grounded in graph-theoretic principles and dynamical system modeling (Benson et al., 2016). Second, quantitative frameworks have been developed to evaluate topological robustness under both sequential cascading failures and random disruptions (Artime et al., 2024). Although these approaches have substantially advanced theoretical understanding, critical limitations remain in capturing multi-scale interdependencies and adaptive recovery mechanisms that characterize real-world transport systems.

To provide a structured overview of the state-of-the-art, Section 2.1 reviews methodological developments in network modeling techniques, while Section 2.2 synthesizes recent progress in resilience assessment frameworks. The research gaps and corresponding contributions of this study are summarized in Section 2.3.

2.1. Theoretical foundations of complex networks

The systematic characterization of complex networks has been shaped by decades of interdisciplinary exploration across mathematics, physics, and engineering sciences (D'Souza et al., 2023). Fundamental principles rooted in graph-theoretic formalisms and nonlinear dynamics have been established to decode topological patterns and emergent behaviors in interconnected systems (Shu et al., 2023). These theoretical advancements collectively serve as the cornerstone for analyzing network resilience, necessitating a rigorous synthesis of static topology, dynamic interactions, and failure propagation mechanisms (Yin et al., 2023). Subsequent discussions will methodically unpack these conceptual pillars to contextualize modern resilience analytics.

As a systematic review, Yang et al. (2023) summarized the research progress of complex systems modeling and analysis from the perspective of network science. This study included related techniques and methods like network modeling, vital node analysis, network invulnerability analysis, network disintegration analysis, resilience analysis, complex network link prediction, and the attacker-defender game in complex networks. Dai et al. (2021) proposed a structured compressive sensing method that reconstructed the topology of complex network globally. This analysis exposed critical methodological limitations in modern network studies. Current research on directed and weighted networks has established a relatively comprehensive theoretical and methodological framework (Cheung et al., 2020), yet overlooks the embedded cargo flow hierarchies and trade interdependencies within shipping networks.

Current studies have demonstrated its inherent strengths, primarily reflected in methodological objectivity and theoretical precision. As exemplified in Hu et al. (2022), six network topological attributes were systematically investigated: degree centrality, clustering coefficient, closeness centrality, betweenness centrality, nodal strength, and average shortest path length. Building upon this six-dimensional topological framework, another study engineered an enhanced spatiotemporal network architecture that synthesized multi-attribute topological features (Zhang et al., 2015). Empirical validation through comparative analysis against baseline models containing conventional Graph Convolutional Networks confirmed the proposed architecture's superior performance in traffic flow prediction accuracy and system robustness (Li et al., 2024a). Complex networks exhibit distinct architectural signatures defined through three cardinal topological properties. Small-world networks, for example, demonstrate efficient global connectivity through localized connections, balancing two critical features: a compact path structure and the presence of short intermediary pathways connecting most node pairs (Gan et al., 2025b). Nodes form tightly knit local groups while maintaining sparse long-range connections (Xiao et al., 2017). This dual architecture enables both specialized local interactions and rapid global information transfer.

Hierarchical organization arises from intra-module density, characterized by modules containing densely interconnected nodes with shared functional specializations (Su et al., 2021). Inter-module sparsity complements hierarchical organization by maintaining limited bridging connections between distinct functional units. This principle interacts with intra-module density to achieve a balance between specialized clusters (via dense internal connectivity) and system wide coordination (Zarei and Meybodi, 2020). Heterogeneous connectivity patterns are characterized by uneven link distributions, where global connectivity is anchored by a minority of highly connected hubs (Li et al., 2021). This architecture creates inherent robustness against random disruptions but heightened vulnerability to targeted hub attacks, evident in shipping network.

Building on prior insights, this study establishes two foundational methodological imperatives. First, capacity-weighted networks are constructed by deliberately avoiding unweighted paradigms. Vessel capacity metrics are systematically incorporated into edge weighting protocols. Second, the complex nature of the shipping network is verified through the tripartite validation criteria, meeting established thresholds for small-world properties, modular organization, and adherence to power law distribution patterns (Derrible and Kennedy, 2010). To advance conventional methodologies, a dual analytical perspective is adopted. Static topological evaluation is conducted via established metrics, including centrality, clustering coefficient, path length, to assess network structure. Meanwhile, dynamic temporal analysis is performed through failure propagation modeling under time-evolving operational scenarios. Together, these methodological innovations collectively enable a holistic understanding of network resilience mechanisms, with detailed presented in Section 3.

2.2. Resilience analysis in shipping network systems

To date, the resilience analysis of the shipping network has primarily focused on evaluating static structural properties such as topology, modularity, connectivity, robustness, and vulnerability (Cao et al., 2025). These concepts have evolved under varying terminologies across different stages of network development, as illustrated in Fig. 1. Although these terms share semantic proximity in describing adaptive capacity, they represent distinct conceptual dimensions that require rigorous analytical differentiation. Resilience in shipping networks is quantified through several interrelated attributes. Topology describes the spatial configuration of nodes (ports) and edges (shipping routes), which determines how structural disruptions propagate (Tsiotas and Ducruet, 2021). Modularity characterizes the network's subdivision into clusters, allowing localized failures can be absorbed within modules without cascading globally (Liu et al., 2024a). Connectivity measures the redundancy and density of pathways between nodes, indicating the ability to reroute cargo flows under disturbances (Yue et al., 2024a). Robustness reflects the system's capacity to maintain functionality under stochastic or low intensity stressors (e.g., weather delays), emphasizing resistance to gradual degradation (Wang et al., 2016). Vulnerability identifies critical nodes or edges whose removal disproportionately disrupts operations, reflecting sensitivity to targeted attacks (Guo et al., 2024). While these concepts collectively address adaptive capacities, their operational definitions diverge. Topology and modularity focus on structural configurations, describing the arrangement and clustering of ports and routes. Connectivity and robustness highlight functional persistence, measuring the ability to sustain essential operations during disturbances. Vulnerability centers on systemic fragility, pinpointing weak points whose failure could trigger widespread operational breakdowns (Gu and Liu, 2025). Recognizing these distinctions is essential to ensure conceptual clarity and methodological consistency when linking analytical frameworks to specific resilience objectives.

Resilience assessment indicators for shipping network can be categorized into three classes, comprising network topology indicators, resilience characteristics-based indicators, and performance metrics-based indicators (Zhou et al., 2019). Among these, network-topology indicators play a central role in assessing structural features of resilience. For instance, Xu et al. (2024a) evaluated network resilience under random node or edge removals, using topological metrics such as average node degree and redundancy coefficient to quantify alternative routing paths. Duan et al. (2024) employed node centrality to assess shipping network resilience. This method strategically identified topological hubs to expose systemic vulnerabilities and global impacts from critical node removal. Wang et al. (2024b) measured shipping network resilience using network efficiency. This research emphasizes the significant impact of typhoons on multiple ports, where the stable operation of ports is ensured and resilience in typhoon prevention is improved under the changing climate. Yue et al. (2024a) quantified shipping

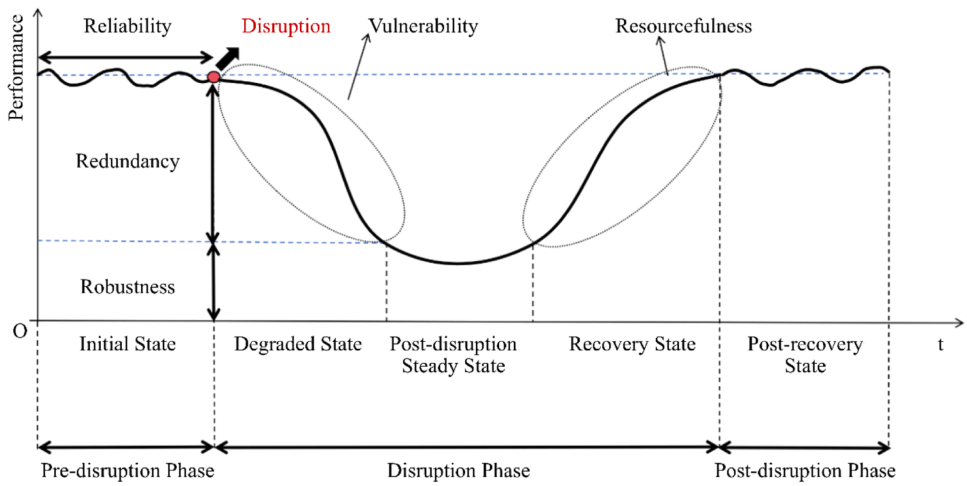

Fig. 1. Phases of the shipping network responding to disruptive events (Poulin and Kane, 2021).

network resilience via largest connected component analysis to monitor structural disintegration thresholds. Simultaneously, detour connectivity efficiency in hub-and-spoke systems is evaluated using average shortest path length metrics reflecting optimal routing adaptability (Guo et al., 2023a). Table 1 summarizes key network topology indicators and their functions, systematically categorizing how degree distribution, path hierarchy, and modularity dissect distinct dimensions of resilience mechanisms. These metrics enable systematic classification of resilience definitions.

However, network topology indicators analyze resilience from a static perspective. As previously mentioned, conclusions derived from static analyses are limited, as they neglect spatiotemporal factors such as time-varying demands and spatial heterogeneity. Consequently, these indicators offer limited practical relevance and cannot fully reflect real-world scenarios. To address this limitation, this study introduces a more comprehensive approach to evaluating shipping network resilience. It combines static topological analysis with dynamic resilience assessment. These metrics are further integrated with region-specific operational parameters, such as port capacity and network efficiency, to better reflect actual cargo flow patterns across different areas.

System-level cascading-failure modeling has been applied to quantify risk-propagation pathways triggered by disruptions such as port closures and channel obstructions. These risks propagate through mechanisms including load redistribution, congestion spillovers, and scheduling cascades. Recent studies have integrated complex network theory and flow dynamics to quantify resilience thresholds. For example, Chen et al. (2021) modeled cargo flow rerouting-triggered cascades in hub-and-spoke networks, revealing vulnerability hotspots in transshipment hubs like Singapore and Rotterdam. Lu et al. (2024) incorporates vessel scheduling interdependencies, demonstrating that time-delay cascades from typhoon-induced port disruptions can amplify initial capacity losses by 40–60% in liner shipping networks. Empirical analyses of historical events, such as the 2021 Suez Canal blockage, validate cascading impacts through metrics like global schedule reliability decay and fuel cost escalation from prolonged detours.

Methodological advancements include adaptive network flow models that prioritize dynamic resource reallocation (Wu et al., 2024), coupling hydrodynamic risks (e.g., siltation in tidal channels) with cargo backlog propagation. Researchers have also emphasized resilience-oriented redundancy strategies, such as strategic buffer vessel deployment or hybrid hub diversification, to interrupt failure cascades. Emerging research explores AI-driven simulation frameworks to predict cascading paths under climate-change scenarios, underscoring dynamic resilience research as a key point for mitigating systemic fragility in global shipping systems (Cao et al., 2025).

Table 1
Network static topology.

Indicator	Category	Definition	Function	Reference
Average Node Degree	Node Criticality	Average value of degrees across all nodes in the network	Reflects node importance	(Kanrak et al., 2023; Wang et al., 2024b)
Betweenness Centrality	Node Criticality	Frequency of a node occurring in all shortest paths of the network	Reflects node importance	(Kanrak and Nguyen, 2022; Zhang et al., 2022)
Largest Connected Component (LCC)	Network Connectivity	Subnetwork with the most nodes retained after network disruption	Reflects network connectivity	(Liu et al., 2024a; Yue et al., 2024a)
Average Shortest Path	Network Connectivity	Average distance between all node pairs in the network	Reflects network connectivity	(Koza et al., 2020; Wang et al., 2024b)
Clustering Coefficient	Network Redundancy	Degree of interconnection	Reflects network redundancy	(He et al., 2022; Liu et al., 2014)
Redundancy	Network Redundancy	Availability of alternative paths between nodes	Reflects network redundancy	(Jiang et al., 2024; Xu et al., 2024a)

2.3. Research gaps

Existing literature has made substantial progress in the construction of complex maritime networks and the evaluation of resilience. However, in response to the evolving demands for shipping network development, three persistent research gaps are identified and targeted mitigation strategies are proposed.

(1) Single ship-type network construction. Most existing studies construct shipping networks based on a single ship type (e.g., container ships or oil tankers), which facilitates focused analysis of specific operational patterns but overlooks the interdependence among heterogeneous shipping activities. In practice, vessels of different types

frequently share critical maritime chokepoints such as canals and straits. Disruptions in these shared corridors, arising from canal blockages, geopolitical tensions, or regional crises, can induce cascading impacts across multiple sectors of maritime transport. The prevailing single-type approaches therefore fail to capture the cross-network dependencies and systemic vulnerabilities inherent in real-world shipping systems.

(2) Static resilience assessment frameworks. Current research predominantly relies on static topological indicators derived from graph theory to assess network resilience, emphasizing pre-disruption vulnerability and structural robustness. While informative, such static assessments are insufficient to characterize the dynamic reconfiguration and recovery behaviors of shipping networks following disruptions. A more systematic resilience framework should integrate temporal dynamics and adaptive responses to capture the evolution of network performance over time.

(3) Underrepresentation of trade-weighted capacity dynamics. Existing shipping network analyses often rely on ship movement frequency or port throughput metrics, underutilizing trade-weighted indicators such as DWT. Directed weighted models therefore tend to emphasize spatial flow quantification rather than reflecting the underlying economic or engineering significance of vessel capacity. Empirical evidence, however, suggests that shipping system robustness is more closely associated with trade-weighted vessel capacity than with traditional traffic-based parameters. Incorporating capacity-weighted dynamics is thus essential for a more realistic and functionally meaningful representation of network resilience.

3. Methodology

The methodological framework is structured through three interconnected components. The global shipping network is modeled in Section 3.2. The cascading failure model is integrated in Section 3.3. In Section 3.4, network resilience is evaluated from both static and dynamic perspectives.

3.1. The proposed framework

This study proposes an AIS-driven analytical framework to dynamically evaluate global shipping network resilience by integrating three interconnected components. First, the framework advances port-level network modeling through DBSCAN-based spatial clustering, which resolves ambiguities in port boundary definitions by aggregating ship trajectories into geographic port communities, The Douglas-Peucker algorithm simplifies AIS trajectories to retain key navigational nodes such as strategic straits and canals. Unlike conventional terminal-level approaches, edge weights in this network are defined by vessel deadweight tonnage (DWT), capturing real-world cargo flow disparities. Building on this foundation, the framework simulates cascading failure dynamics through hybrid attack scenarios that combine structural metrics (e.g., betweenness centrality) with operational criteria using TOPSIS multi-criteria decision-making, where adaptive load redistribution mechanisms model how disrupted cargo flows propagate failures across interconnected ports. Finally, dynamic resilience is quantified through four topological metrics and a decay parameter to jointly capture structural fragmentation, functional survivability, and cascading failure dynamics. These metrics include Average Path Length, Average Clustering Coefficient, Effective Scale, and Network Efficiency. The decay parameter modulates cascading severity by governing how failures propagate. The complete methodological framework is depicted in Fig. 2.

3.2. Complex network theory

3.2.1. Global shipping network

To construct the shipping network, conventional methodologies typically rely on two spatial methods: the L-space method and the P-space method. Specifically, the L-space method is used to model ports as nodes and physical shipping routes as edges, thereby reflecting geographical connectivity. In contrast, the P-space method is employed to emphasize direct cargo exchange relationships between ports. Intermediate stops are disregarded to capture trade organization patterns (Kang and Woo, 2017).

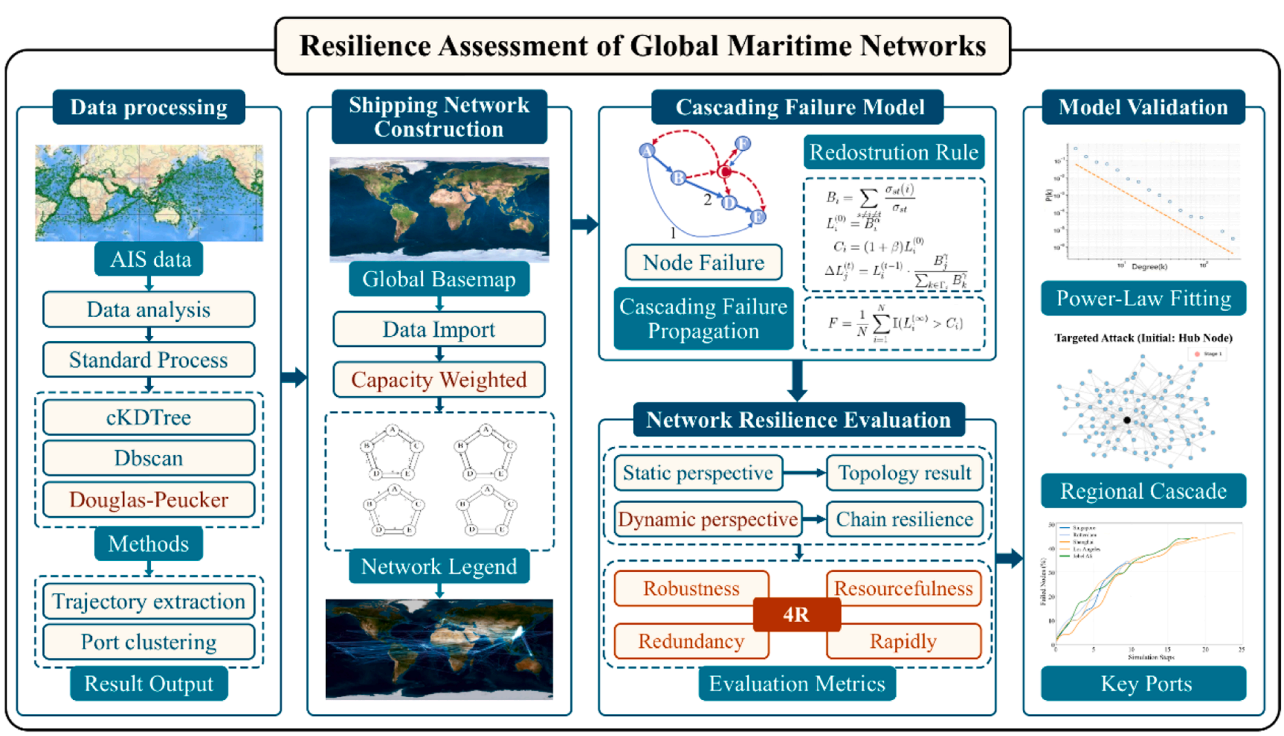

Fig. 2. The methodological framework.

In this study, a systematic framework is established to analyze shipping network resilience through four integrated innovations. Firstly, the cKDTree geospatial clustering algorithm (a spatial indexing structure optimized for large-scale datasets) is employed to automate the identification of core ports by calculating trajectory density distributions between AIS data and port coordinates (Fontes and Goncalves, 2021). This approach overcomes limitations of traditional grid-based clustering in handling irregular maritime activity patterns. Trajectory density can be defined as:

$$\rho\left(p_j\right) = \frac{1}{V_j}\sum_{i=1}^{n}\frac{1}{1+d\left((x_i,y_i),\left(x_j^p,y_j^p\right)\right)^2}\cdot\chi_{T_i\cap T_j\neq\varnothing} \tag{1}$$

where V_j is the volume of the spatial region around port p_j that is partitioned by the KDtree. $d\left((x_i,y_i),\left(x_j^p,y_j^p\right)\right)$ is the Euclidean distance between the AIS data point (x_i,y_i) and the coordinate $\left(x_j^p,y_j^p\right)$ of port p_j. $\chi_{T_i\cap T_j\neq\varnothing}$ is an indicator function. It takes the value 1 when the time interval T_i of the AIS data and the active time interval T_j of port P_j intersect, and 0 otherwise.

Secondly, path weights are dynamically quantified using a novel transportation frequency index. This index synthesizes both ship traffic volume (deadweight tonnage) and voyage frequency, offering a dual-dimensional metric to evaluate port influence. The spatial hierarchy of ports is further visualized through adaptive brightness gradients, enabling intuitive interpretation of regional cargo flow intensity (Xu et al., 2022). Thirdly, trajectory compression is achieved using the Douglas-Peucker (DP) algorithm. This geometric simplification technique is applied to preserve critical navigational features, such as turning angles and berthing durations, while redundant data points are eliminated (Lee and Kim, 2024). To identify and preserve critical navigation nodes, thresholds for turning angles (angles with a change $\geq 15^\circ$) and berthing durations (durations $\geq$ 30 min) are first defined as criteria. For turning angles between three consecutive points P_{i-1}, P_i, P_{i+1}, the angle θ_i is computed as:

$$\theta_i = \arccos\left(\frac{\vec{a}\cdot\vec{b}}{|\vec{a}||\vec{b}|}\right) \tag{2}$$

where $\vec{a}$, $\vec{b}$ are vectors from P_{i-1} to P_i and P_i to P_{i+1}. For berthing durations, $D_i = t_{\text{departure},i} - t_{\text{arrival},i}$ (with $t_{\text{arrival},i}$, $t_{\text{departure},i}$ as arrival and departure times).

During the DP algorithm execution, nodes meeting these criteria are marked as "must-keep". For quantitative metrics, the compression ratio, root mean square error and average angular error ($< 8^\circ$ for turning angles) are used to show that over 90% of critical nodes are retained while reducing data volume by 70%. Processing time is reduced by over 60% in this step while the connections between routes are kept unchanged, which is a critical requirement for modeling large networks. Finally, a hybrid L-P space model is proposed to unify topological and functional network representations. By retaining the physical route connectivity of L-space (node-edge mapping) and integrating P-space attributes through tonnage-weighted edges. This model captures both infrastructure interdependencies and cargo movement dynamics, addressing the historical incompatibility between structural realism and flow-based analysis in maritime research (Xu et al., 2024b). This approach systematically transforms raw vessel movement patterns into a multidimensional network by synergizing spatial clustering with dynamic edge weighting.

3.2.2. Statistical characterization of complex network

The degree of a node indicates the number of edges connected to that node. A node with a higher degree generally has a greater impact on the entire shipping network and is often referred to as a critical node. Within complex network analysis, node importance exhibits a direct relationship with vertex degree magnitude (Jiang et al., 2021). The degree of a node can be defined using the network's adjacency matrix:

$$A_i = \sum_{j\in N} e_{ij} \tag{3}$$

where N is the total number of nodes in the network, e_{ij} is the number of edges between nodes i and j. Network diameter and average path length indicate the dispersion of nodes in a network. The network diameter is the longest distance in a complex network, which represents the farthest propagation path in the network (Yue et al., 2024b). It is a crucial parameter, and its expression is:

$$D = \max_{i,j\in V}(d_{ij}) \tag{4}$$

where d_{ij} is the distance between node i and node j.

Average path length (APL) L refers to the average value of all pairwise connection paths between nodes, i.e., the mean number of edges (Guo et al., 2017). The average path length quantifies systemic vulnerability, with longer paths indicating multi-stage failure propagation requiring coordinated intervention strategies. Its expression is:

$$L = \frac{1}{\frac{1}{2}N(N-1)}\sum_{i\neq j} d_{ij} \tag{5}$$

The clustering coefficient reflects the clustering state of nodes in a network, indicating whether the network exhibits community structure (He et al., 2022). The clustering coefficient $C(i)$ of node is the ratio of the actual number of edges between its neighbors to the maximum possible number of edges among them. The Equation is:

$$C(i) = \frac{2E(i)}{A_i(A_i-1)} \tag{6}$$

where $E(i)$ is the actual number of edges existing between the neighboring nodes of node i. The global clustering coefficient of the entire network is defined as the average of the clustering coefficients $C(i)$ across all nodes in the network (He et al., 2022). Its mathematical expression is:

$$C = \frac{1}{N}\sum_i^N C(i) \tag{7}$$

The global clustering coefficient of the network takes values within the range of $[0,1]$. When $C = 0$, no edges exist between any nodes, and the network is a fully disconnected network (all nodes are isolated). When $C = 1$, every pair of neighboring nodes is interconnected, and the network becomes a fully connected network.

3.3. Cascading failure modeling

In this study, dynamic failure propagation is analyzed by combining port throughput-based load-capacity thresholds with sequential node removal models simulating real-world accidents (Gan et al., 2023). This framework further incorporates nonlinear flow redistribution algorithms that account for maritime vessel effective operational capacity.

In the Motter-Lai cascade failure model (Lai et al., 2005), data and information propagate along the shortest paths between node pairs. A failed node is assumed to be unrecoverable to its initial operational state and will be removed from the network. Here, betweenness centrality is used to calculation the load redistribution proportion, given the strong coupling between a node's topological role and the evolution of dynamic loads. The betweenness centrality is calculated as follows:

$$B_N(i) = L_0(i) = \sum_{s\neq i\neq t}\frac{\delta_{s,t}(i)}{\delta_{s,t}} \tag{8}$$

where $\delta_{s,t}$ is the total number of shortest paths between nodes s and t.

$\delta_{s,t}(i)$ is the number of paths passing through node i. In fact, $L_0(i)$ is equivalent to $B_N(i)$, and it is an expression used to calculate the betweenness centrality of node i.

In cascade failure models, node capacity defines the maximum sustainable load handling ability under normal operation, characterizing information propagation capability (Qin et al., 2023). Once external disturbances lead to the failure of a node, the failed node needs to transfer its load to adjacent nodes to eliminate the risks. If the load received by these adjacent nodes surpasses their capacity, they will become overloaded or congested, affecting their normal operation efficiency and leading to another round of redistribution. This hierarchical load transfer initiates an iterative rebalancing process until network stabilization. For any node i, its capacity is defined as:

$$Cap(i) = (1+\alpha)L_0(i) \tag{9}$$

where $\alpha(\alpha > 0)$ represents the tolerance coefficient. Larger α values correlate with enhanced load-bearing capability and reduced failure susceptibility. Theoretically, sufficiently large α can prevent cascade-triggered network failures, while practical constraints prevent implementing arbitrarily large α due to economic limitations.

Given the above definitions, the post-failure load redistribution in this study is governed by a triphasic mechanism integrating capacity-driven redistribution, path-based compensation, and emergency buffering. The redistributed load ΔL_{ij} from node i to adjacent node j follows a capacity-weighted rule:

$$\Delta L_{ij} = \frac{C_j^{\text{res}}}{\sum\limits_{k \in \mathcal{N}(i)} C_k^{\text{res}}} \cdot L_i^{\text{fail}} \tag{10}$$

where $C_j^{\text{res}} = C_j - L_j(t)$ denotes the residual capacity of node j. $\sum_{k \in \mathcal{N}(i)} C_k^{\text{res}}$ represents the sum of the remaining capacities of all adjacent nodes. $N(i)$ represents the set of nodes adjacent to failed node i, and L_i^{fail} is the instantaneous overload triggering failure. This protocol ensures preferential load absorption by high-capacity nodes while preventing localized congestion through shortest-path spillover to non-adjacent nodes. The iterative rebalancing process terminates when satisfying:

$$\min_{1 \le i \le N}\left(\frac{Cap_i - L_i(t)}{Cap_i}\right) \ge \theta \quad \text{and} \quad \left\| \frac{dL(t)}{dt} \right\|_2 \le \epsilon \tag{11}$$

where θ defines the minimum nodal safety margin, ϵ is the convergence threshold, and N is the network size. The dual condition ensures both static stability (individual node safety) and dynamic equilibrium (global load balance), rigorously preventing residual cascade propagation.

To dynamically assess the resilience of cooperative clusters during cascading failures, this study introduces the failure pressure index, which quantifies the ratio of accumulated failure impacts to the cluster's residual mitigation capacity (Li et al., 2024b). This metric bridges the gap between localized node failures and global load redistribution:

$$F(t) = \frac{\sum\limits_{i \in f(t)} L_i(0)}{\sum\limits_{j \in H} (C_j - L_j(t))} \tag{12}$$

where $f(t)$ contains the failed nodes at time t. The numerator sums the initial loads $L_i(0)$ of nodes in the collection defined by $f(t)$, and the denominator sums the residual capacities $C_j - L_j(t)$ of nodes in set H. The i and j nodes belong to $f(t)$ and H respectively.

While Eq. (10) evaluates cluster-level pressure, localized imbalances within a cluster can persist even if $F(t)$ is within the normal range. Therefore, the load balance index addresses this by measuring intra-cluster load distribution uniformity (Jiang et al., 2024), ensuring that no single node becomes a secondary failure hotspot due to disproportionate redistribution:

$$B_H = 1 - \frac{\max_{j \in H}\left|L_j(t) - \bar{L}_H(t)\right|}{\bar{L}_H(t)} \tag{13}$$

where $\bar{L}_H(t)$ calculates the average real-time load across cluster H, serving as the equilibrium reference. $|H| \ge 3$ enforces a minimum cluster size to avoid complex calculation. $L_j(t)$ incorporates both the intrinsic load of node j and redistributed loads from Eq. (8), ensuring consistency with prior cascade dynamics.

This research selected metrics including betweenness centrality, node capacity, and load balancing index to quantitatively analyze relationships between static topological bottlenecks, dynamic load propagation, and system stability during network cascading failures. Redundant metrics and variables with low explanatory power (e.g., node degree centrality) were systematically excluded.

3.4. Resilience quantification metrics

Performance-based metrics in transportation resilience are quantified through the tracking of operational performance during and after disruptions. System functionality is directly linked to resilience outcomes. Commonly applied examples include cumulative performance loss, which is also referred to as the resilience triangle, and residual degradation, which is used to evaluate the time-dependent recovery loss ratio (Zobel and Khansa, 2014). Specifically, the resilience triangle was first proposed by Bruneau et al. (2003), defining resilience as a transportation network's capability to respond to disruptive events, which can be characterized by its performance evolution curve. Post-disruption losses in network functionality directly reflect the resilience. Consequently, the "triangular area" bounded by the performance curve and coordinate axes is utilized to quantify resilience loss in Fig. 3. The mathematical expression is as follows:

$$R_1 = \int_{t_0}^{t_1} [100 - Q(t)]dt \tag{14}$$

where $Q(t)$ represents the system's performance level, t_0 denotes the disruption initiation time and t_1 indicates the recovery completion time. This metric quantifies the cumulative performance loss of the network from disruption onset to restoration to a stable state.

The methodological significance of the Resilience Triangle framework has been substantially enhanced through systematic refinements by subsequent researchers. This advancement is exemplified by Bocchini and Frangopol (2012), who established a quantifiable metric through dividing the total cumulative performance by the recovery duration, mathematically expressed as:

$$R_2 = \int_{t_0}^{t_1} \frac{100 - Q(t)}{t} dt \tag{15}$$

Ouyang et al. (2012) introduced a normalized metric by dividing the area under the actual performance curve $Q(t)$ by the area under the target performance curve $T_p(t)$. $Q(t)$ is the curve that describes how the actual performance of the transportation system, such as traffic capacity or flow, changes over time t. $T_p(t)$ is the target curve that represents the desired performance of the transportation system, like traffic capacity or flow, as a reference standard, varying with time t. A unified resilience quantification framework was developed to address the challenges of comparing recovery capabilities across heterogeneous systems. This standardization process allowing direct comparison between infrastructures of varying scales and configurations. The Equation is:

$$R_3 = \frac{\int_{t_0}^{t_1} Q(t)dt}{\int_{t_0}^{t_1} T_p(t)dt} \tag{16}$$

The Time-Dependent Recovery Loss Ratio evaluates residual performance degradation across five system states defined during

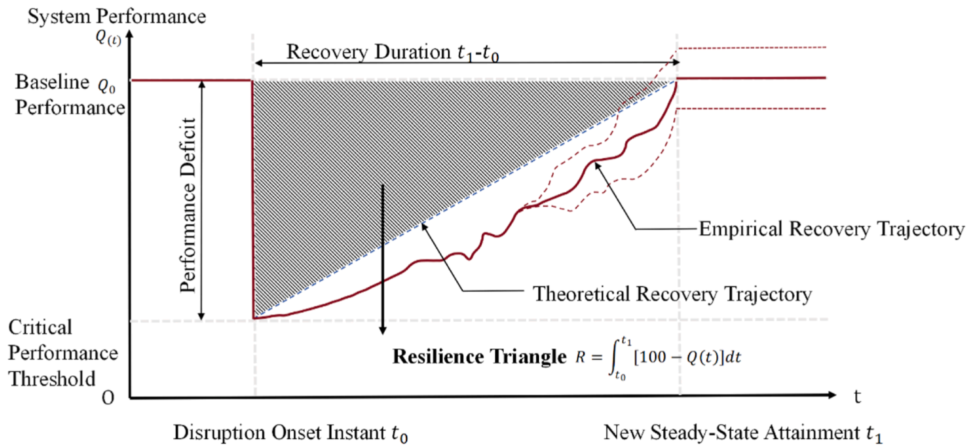

Fig. 3. Dynamic resilience triangle analysis of cascading failures.

disruptions: initial stable state, system disruption, interrupted state, system recovery, and post-recovery stable state, relative to pre-disruption baselines. The Time-Dependent Recovery Loss Ratio quantifies resilience as the ratio of recovered performance to performance loss at time t:

$$\varphi(t_r|e_j) = \frac{\varphi(t_r|e_j) - \varphi(t_d|e_j)}{\varphi(t_0) - \varphi(t_d|e_j)} \tag{17}$$

where $\varphi(t_r|e_j)$ is the system functionality under disruption event e_j at time t. $\varphi(t_d|e_j)$ is the minimum acceptable functionality. $\varphi(t_0)$ is the pre-disruption baseline functionality.

Performance-based resilience metrics incorporate two core measures. The Resilience Triangle quantifies functional deficits in waterway networks following disruptions, while the Temporal Recovery Loss Index assesses restoration efficacy across temporal phases. Unlike conventional network topology indicators (e.g., node degree, clustering coefficient) that statically assess structural properties, these performance metrics adopt a dynamic systems perspective, focusing not only on observing post-disruption behaviors but also on diagnosing actionable recovery pathways (Shu et al., 2025). Real time performance evolution is quantified relative to pre-disruption baselines. This approach captures the core tenets of resilience, where adaptive capacity and functional restoration are prioritized, resulting in stronger alignment with operational demands. However, their practical application necessitates rigorous calibration of performance thresholds and high-resolution temporal data integration to avoid discrepancies between theoretical models and empirical outcomes.

This study evaluates network robustness under four intentional attack strategies, Random, Degree-based, Betweenness-based, and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS)-based hybrid attacks, to uncover structural vulnerabilities. Random attacks serve as a baseline by removing nodes stochastically, independent of topology. Degree-based attacks target highly connected hubs to disrupt global connectivity, while Betweenness-based attacks cripple critical intermediaries on shortest paths. The combined weighted attack which is call the TOPSIS method is implemented as a multi-criteria decision-making framework. The nodal characteristics such as degree centrality and betweenness centrality are systematically integrated. Degree centrality emphasizes a node's direct connectivity impact, while betweenness centrality highlights its role in mediating shortest paths, and the weights balance these two facets of nodal importance. Degree centrality and betweenness centrality are assigned equal weights (0.5 each) to avoid bias toward either nodal characteristic. Through vector normalization and weighted Euclidean distance calculations, attack sequences are optimized by simultaneously minimizing the distance to the positive ideal solution (maximum local disruption) and maximizing the distance from the negative ideal solution (minimum global network functionality).

4. Results

4.1. The global shipping network

The implementation of L-space modeling framework for shipping networks involves systematic acquisition of vessel position temporal dynamics (Su et al., 2025). This shipping network model constructs hybrid nodes representing ports and critical decision point through systematic processing of AIS trajectory data (source: ELANE Company's 2022 global dataset). Vessel-type differentiation is omitted to prioritize the establishment of a macro scale waterway system, with cross-type traffic dynamics and systemic congestion being structurally analyzed.

The constructed topology graphically elucidates regional public maritime connectivity patterns while revealing structural characteristics critical for subsequent resilience assessment (Faure and Ducruet, 2025). The global shipping network construction begins with analyzing AIS ship-port data via cKDTree geospatial clustering, where port identification is achieved by filtering continental coastal clusters with vessel speed thresholds below 1 knot (0.514 m/s) (Gu and Liu, 2025). This is a kinematic criterion calibrated from 12,000 historical berthing events. Port weights are then calculated using a shipping frequency index that combines vessel capacity and edge weights (route traffic density), with visual brightness scaled logarithmically to reflect weight intensity ($\gamma = 0.87 \pm 0.05$). This aligns with the core characteristic of weighted networks, unlike unweighted networks that only focus on the presence or absence of connections, key metrics here rely on weight values for calculation. For example, node degree needs to be calculated as a "weighted degree" (the sum of the weights of adjacent edges) rather than just counting the number of edges. MMSI-tracked trajectories undergo compression using the DP algorithm before network assembly, preserving topological fidelity while reducing data volume by 92.4% (Liu et al., 2024b). The final structure is a directed weighted multigraph, as shown in Fig. 4.

4.2. Network topology

A static analytical perspective is adopted to examine the topological structure of the shipping network. Key topological features such as node degree distribution, clustering coefficient, and average path length are quantified to assess connectivity patterns, structural robustness, and potential bottlenecks. By isolating temporal variability, this static approach captures the network's baseline configuration at a specific time slice and provides a foundational reference for subsequent dynamic analyses. The results contribute to the identification of important nodes,

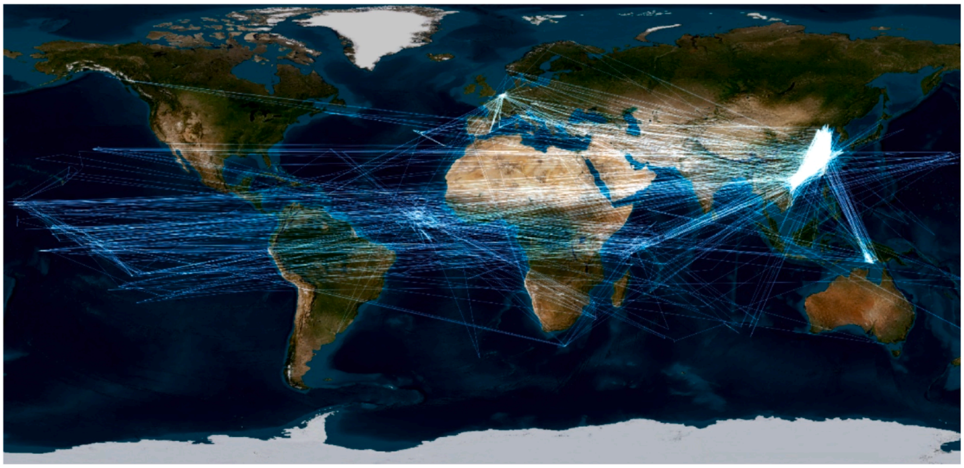

Fig. 4. The global shipping network reconstructed from AIS trajectory data.

the detection of regional community structures, and the development of resource allocation strategies.

4.2.1. *Collapse threshold of shipping network*

To validate the choice of attack patterns, the proposed strategies are compared with established attack methods in terms of network robustness metrics like giant component size, average shortest path length, and global efficiency. Random attacks, serving as a baseline, show gradual performance decay, with the giant component size dropping by 10% after 30% node removal, matching the trend of typical random node removal. Degree-based attacks target highly connected hubs and cause rapid collapse of the giant component, with it decreasing by 48% at 15% node removal, aligning with how targeting degree hubs leads to sharp declines. Betweenness-based attacks disrupt the average shortest path length and global efficiency faster than random attacks; here, global efficiency decreases by 60% at 20% node removal compared to 30% for random attacks, consistent with prior findings.

When compared to single-criterion attacks, TOPSIS-hybrid attacks achieve a 25% greater reduction in the giant component size at the same node removal ratio than degree-only attacks and a 30% greater reduction than betweenness-only attacks. This improvement shows the hybrid strategy's enhanced ability to expose vulnerabilities by balancing connectivity and intermediary roles, thus confirming the attack strategy selection is grounded in existing knowledge while the TOPSIS-hybrid approach offers superior vulnerability detection.

To quantify attack impacts, four key metrics are analyzed. Firstly, APL reflects the network's information transfer efficiency, where increased APL signals fragmentation. Secondly, Average Clustering Coefficient (ACC) measures localized community cohesion, with declining ACC indicating erosion of small-world properties. Thirdly, effective

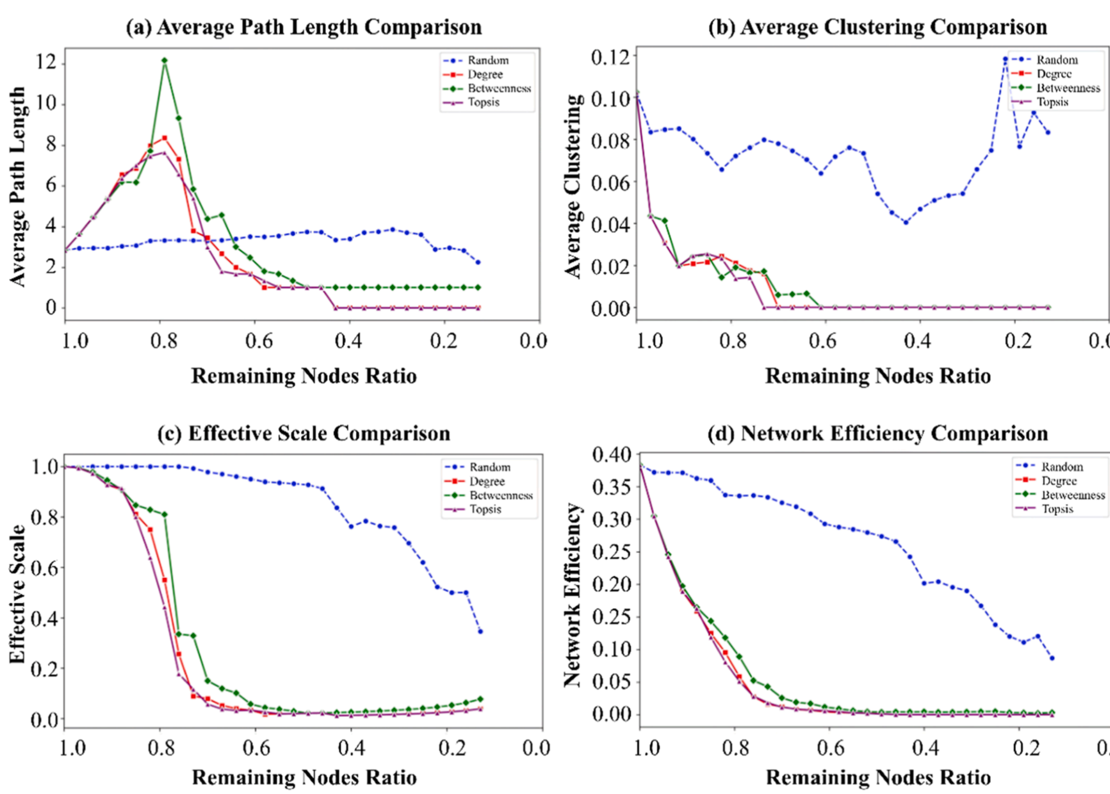

Fig. 5. Comparative analysis of network robustness under random, degree, betweenness and TOPSIS attacks.

scale denotes the largest connected component's size, which captures functional survivability. Fourthly, network efficiency accounts for both fragmentation and path elongation to measure the path robustness. These metrics collectively reveal how targeted attacks degrade distinct structural features. By integrating multi-faceted metrics, as demonstrated in Fig. 5, a holistic view of network resilience is provided by the analysis.

As evidenced by Fig. 5a, the average path length is observed to increase most significantly under betweenness-based attacks, as critical bridge nodes are progressively removed, leading to network fragmentation. Degree-based attacks exhibit a slower APL growth rate due to the elimination of hubs that originally shorten global paths. In contrast, random attacks cause minimal APL variation, while TOPSIS-optimized attacks demonstrate non-linear escalation, reflecting their multi-criteria targeting strategy that balances connectivity and structural roles.

Average clustering properties are found to degrade most severely in degree-based attacks, with ACC reductions exceeding 80% when high-degree nodes (often located in clustered communities) are disabled. Betweenness attacks preserve partial clustering by sparing tightly-knit subgroups. TOPSIS methods strategically target and disrupt both critical hubs and bridging nodes through coordinated node removal, achieving similar ACC suppression. Random node removals show stochastic ACC fluctuations, correlating with localized cluster destruction probabilities, visualized in Fig. 5b. As evidenced by Fig. 5c, network effective scale, quantified as the logarithmic ratio of nodes to connections, is maximally compressed by TOPSIS attacks, indicating superior efficiency in breaking scale-free characteristics. Degree attacks reduce effective scale by 72–80% through hub elimination, whereas betweenness attacks achieve similar reduction. Random strategies display limited impact, failing to disrupt the core scale-free topology.

It can be seen that betweenness attacks cause the most severe efficiency loss (93–97%) by systematically removing critical bridge nodes that disrupt shortest paths. Degree attacks reduce efficiency by 90–95% through cascading failures of hub nodes, while TOPSIS-optimized attacks combine both strategies, achieving 85–88% efficiency decline. Random removals show the weakest impact, as efficiency degradation depends solely on the number of nodes removed, not their strategic importance, visualized in Fig. 5d.

4.2.2. *Verification of scale-free network properties*

In scale-free networks, the cumulative degree distribution of nodes follows a power-law pattern. A defining characteristic is that the majority of nodes exhibit low degrees, while a small fraction of nodes has significantly high degrees. This high-degree nodes govern the network's efficiency and play a critical role in maintaining connectivity, particularly within transportation networks. A power-law fitting method is employed to analyze this property, with analysis results visualized in Fig. 6.

This dual-panel visualization characterizes the degree distribution properties of a scale-free network generated via the Barabási-Albert (BA) model. The left subplot displays the degree distribution P(k) on log-log axes, revealing a power-law pattern with fitted slope $\gamma = 2.58$ ($R^2 = 0.954$). While slightly deviating from the theoretical expectation ($\gamma \approx 3$), this result confirms the existence of hub nodes with disproportionately high connectivity. The right subplot validates the heavy-tailed distribution through the complementary cumulative distribution function (CCDF), exhibiting a matching slope $\gamma = 2.56$ that reinforces the scale-free hypothesis. Together, the statistical and graphical evidence systematically demonstrates the network's scale-free architecture.

4.3. *Resilience analysis using cascading failures*

The impact of key nodes on global maritime navigation efficiency is analyzed through the cascade failure model, built upon verified scale-free network properties. Fig. 7 illustrates clustered land-based ports, color-coded by vessel traffic density (darker red indicating higher ship volumes). These hubs are identified through topological analysis of shipping network connectivity and berthing capacity thresholds. The spatial distribution highlights strategic nodes with concentrated shipping activity, providing a visual framework to assess cascade risks in supply chains. This methodology bridges port operational data with geospatial mapping to prioritize infrastructure resilience planning.

Upon constructing the heatmap, the network's cascade failure validation can be systematically executed from local to global scales by utilizing heatmap intensity values as proxies for node degree centrality. Regional simulation analysis uncovers topology-constrained failure propagation mechanisms. As statistically demonstrated in Fig. 8 comparing targeted attacks (strategic hub removal) with multiple random attacks, the network's structural vulnerability is rigorously validated through this multi-scenario computational experimentation framework.

As evidenced by Fig. 9, the validation framework incorporated five critical ports spanning major global trade corridors: Singapore (Asia), Rotterdam (Europe), Shanghai (East Asia), Los Angeles (North America), and Jebel Ali (Middle East). These ports are strategically designated as regional benchmarks based on their proven dominance in transcontinental cargo flows and strategic locations within major economic zones. This selection further reflects their representation of differentiated maritime operational frameworks across shipping hubs in Asia,

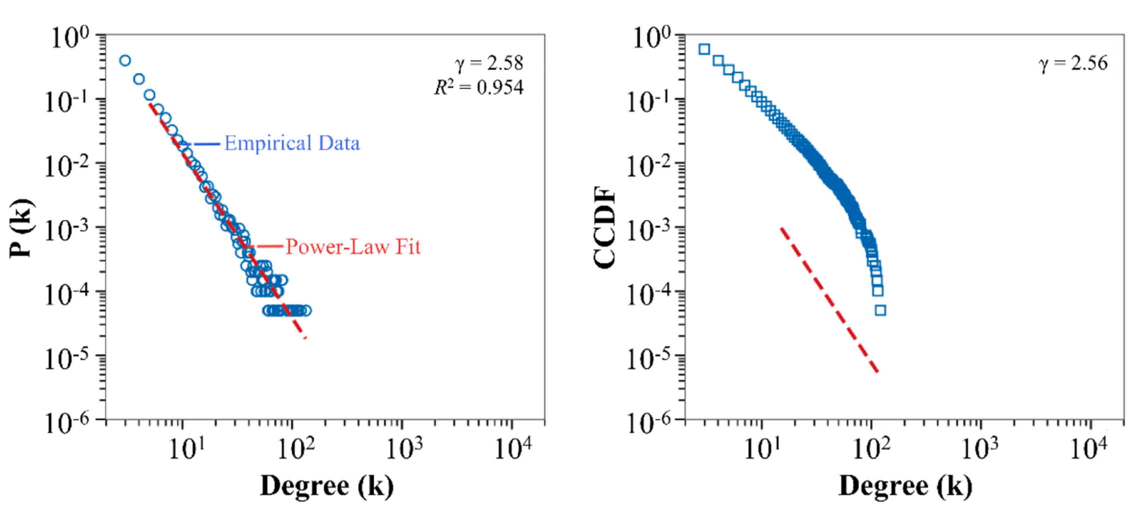

Fig. 6. Power-law fitting of degree distribution.

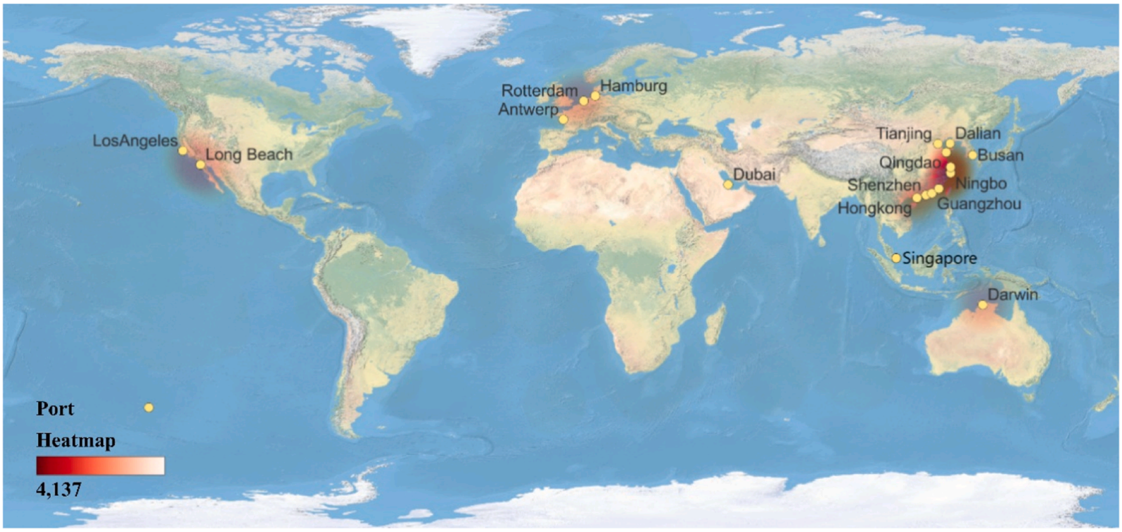

Fig. 7. Heatmap of ports derived from AIS data clustering.

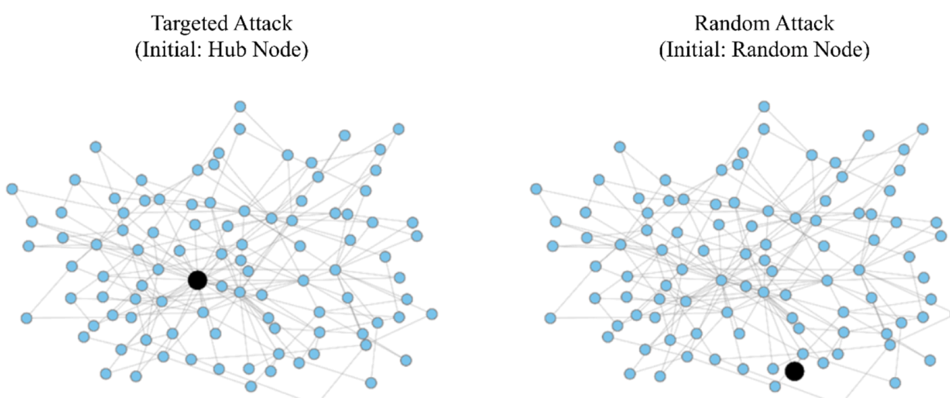

Fig. 8. The comparative analysis of targeted versus random attack.

Europe, North America, and the Middle East. The decay parameter b (0.1, 0.5, 1.0) demonstrated how to modulate the influence range of the five strategic ports. Lower b values result in slower decay and broader influence ranges, whereas higher values lead to faster decay and more localized impacts, enabling a systematic evaluation of their criticality. The spatial analysis reveals these ports' disproportionate impacts on regional connectivity, with complete disruptions potentially causing efficiency reductions in global containerized trade flows (Wu et al. 2024). From the national level, the color gradient quantifies countries' vulnerability levels, while circular markers denote disrupted port. Results emphasize that vulnerability propagation follows both geographical proximity and trade partnership patterns, with landlocked nations showing higher sensitivity to specific port failures than coastal states. These findings underscore the necessity for differentiated regional contingency planning in global supply chain management.

To further investigate the cascading impacts on continental critical ports, targeted node attacks are simulated to observe the emergence of regional failure patterns. Smoothing functions (e.g., Gaussian kernel density estimation) are applied to enhance the visualization of node vulnerability distributions, as illustrated in Fig. 10. The analysis of the smoothed curves reveals that Singapore and Rotterdam experience abrupt mid-simulation disruptions, indicating higher systemic fragility and limited resilience to cascading disruptions. Notably, European ports exhibit a 22% slower failure propagation rate compared to their Asia-Pacific counterparts, which can be attributed to their geographically distributed infrastructure configurations that mitigate concentrated risks. Despite regional operational disparities (e.g., automation levels, hinterland connectivity), the coherence in failure trends across all ports underscores the universal criticality of these hubs in maintaining cargo flow integrity (Xu et al. 2025). Disproportionate network-wide throughput declines result from even partial dysfunction, which is triggered by capacity loss at a single node (Pan et al. 2022). Furthermore, the nonlinear interdependencies inherent in maritime supply chains are directly evidenced by regional variations in failure propagation rates, with Europe at 34% and the Asia-Pacific region reaching 42%.

Maritime-dependent economies exhibit higher vulnerability than diversified trading countries, particularly commodity exporters reliant on strategic gateways for bulk shipments. A critical threshold emerges where simultaneous failures at three or more hub ports trigger nonlinear collapse of global network efficiency, disproportionately impacting countries positioned at mid-level nodes of value chains. Coastal countries demonstrate residual capacity through regional port alternatives, maintaining 12–18% operational efficiency during single-port disruptions, whereas landlocked countries suffer amplified losses from gateway closures due to constrained rerouting options. The analysis confirms no country remains insulated from port-driven trade shocks, with cascading impacts in shipping networks as illustrated in Fig. 11. The analysis also reveals that disruptions to critical ports collectively degrade trade efficiency across approximately 89% of countries, with severity dictated by their integration into global supply chains rather than geographical proximity.

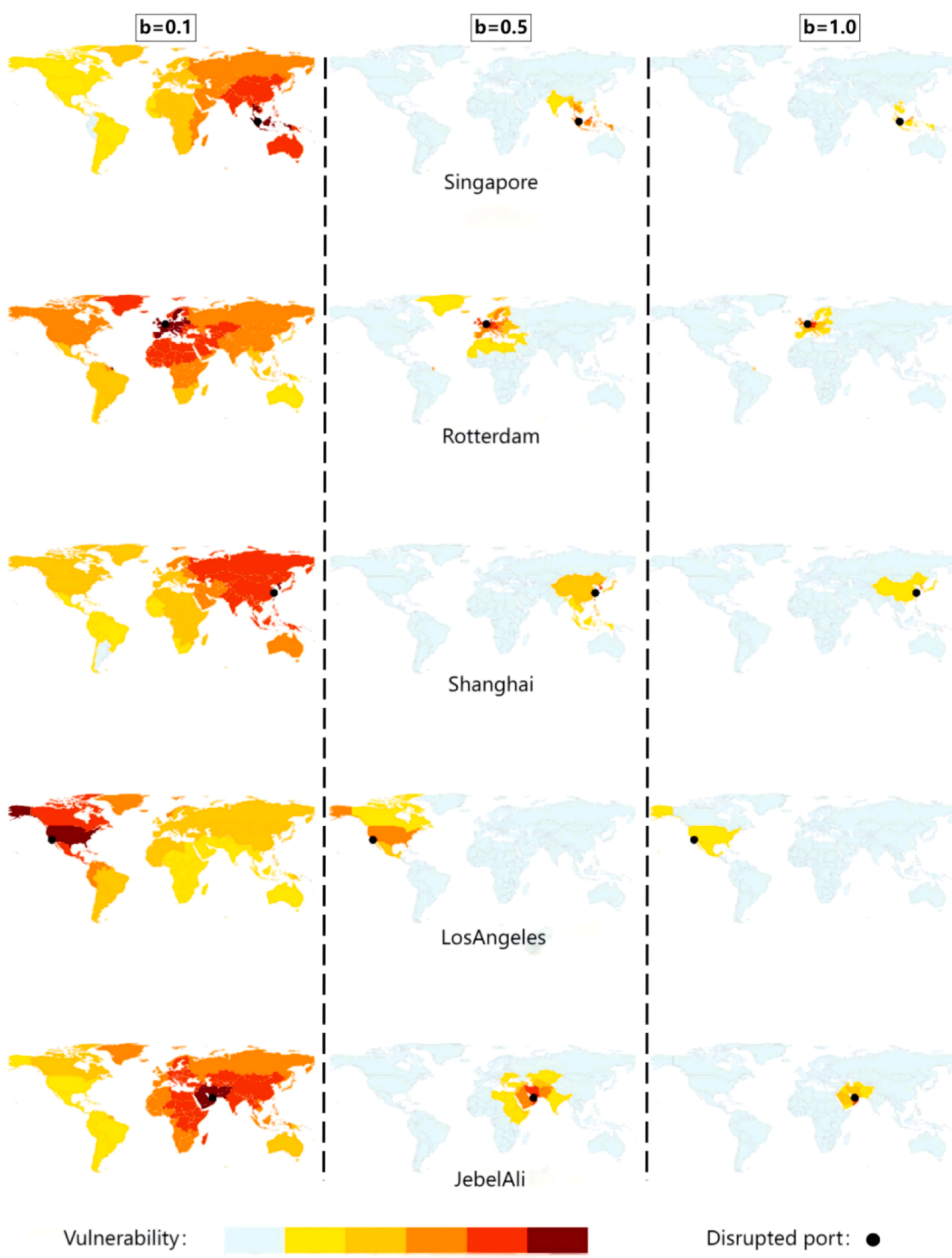

Fig. 9. Vulnerability of individual countries under disruptions of five critical ports.

5. Discussion and implications

5.1. Discussion

Escalating risks from surging vessel traffic (50% growth since 2010), climate disruptions, and geopolitical conflicts expose systemic vulnerabilities in existing maritime transport frameworks (Dui et al., 2021). Traditional port-centric approaches fail to address network-wide cascading failures, as evidenced by the 2021 Suez Canal blockage (Wan et al., 2023). This study advances a dual-perspective resilience framework (static topology + dynamic failure propagation) and, crucially, shifts the core analytical node from terminals to integrated ports (treating ports as real entities), aligning with actual operations where stakeholders interact with "ports" rather than individual terminals. By analyzing 2022 AIS data, this study identified 128 critical hub ports through trajectory density, revealing that 18% handle 55% of global container throughput. This asymmetry challenges the "all-hubs-matter" assumption, supporting geospatial prioritization in infrastructure hardening (Li et al., 2024c). Empirical validation across five mega ports (Singapore, Rotterdam, etc.) demonstrates how static

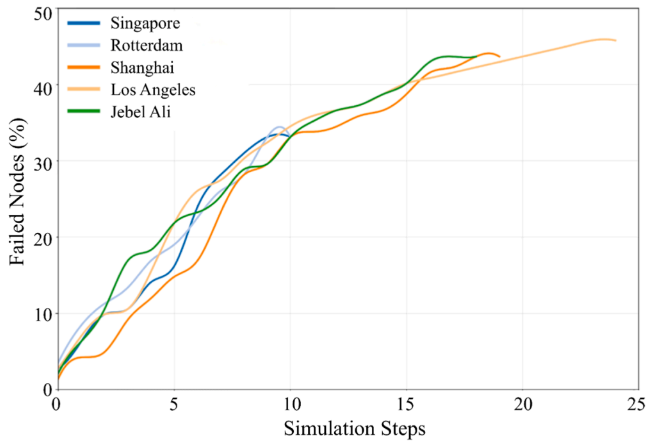

Fig. 10. Cascading failure analysis of key ports.

connectivity imbalances interact with dynamic cascading thresholds.

Compared to previous studies, this study advances maritime resilience research through three methodological breakthroughs. Firstly, previous research was primarily focused on single types of ships. In contrast, this study aims to model the maritime transportation system as a whole, analyzing interactions across all vessel types using global AIS data. Secondly, a dual-perspective resilience framework is proposed. It integrates static topology analysis of port connectivity patterns with dynamic cascading failure simulations, achieving higher precision than single-method approaches. Static analysis identifies critical hubs through traffic flow centrality, while dynamic modeling quantifies how disruptions propagate through weighted cargo networks (Guo et al., 2023b). Moreover, previous studies rely on proxy metrics like vessel counts or TEUs, which distort cargo flow representation. This study innovates by directly weighting network edges using vessel-specific deadweight tonnage derived from AIS trajectories and technical specifications. This enables two critical advancements: Reveals disproportionate reliance on bulk commodity corridors. Propose dynamic buffer capacities for high-risk ports to absorb cascading shocks (Shu et al., 2024).

5.2. Implications

The resilience assessment framework proposed in this research provides an innovative methodology for the full-cycle engineering management of maritime transportation systems, bridging the gap between static vulnerability assessment and dynamic risk governance. It contributes to the growing need for data-driven, adaptive decision-support tools that can strengthen the reliability, sustainability, and security of global supply chains (Verschuur et al., 2020). The broader implications extend across theoretical development, operational management, infrastructure planning, and policy coordination.

(1) Integration of topological and functional resilience

The synergistic mechanism between “topological resilience” and “functional resilience” is revealed through the integration of static topological analysis (e.g., node centrality, path redundancy) and dynamic cascading failure simulations (e.g., typhoon-induced disruptions) (Hosseini and Barker, 2016). Static metrics identify critical hubs, including the 5 global core ports (Singapore, Rotterdam, Shanghai, Los Angeles, Jebel Ali), dominating transcontinental cargo flows. Among them, Singapore and Rotterdam exhibit abrupt mid-simulation disruptions, confirming higher systemic fragility. For these two hubs, prioritize bypass channel construction, as their complete disruption would cause larger efficiency losses in global containerized trade than Shanghai, Los Angeles, or Jebel Ali. Dynamic simulation results further show that failure propagation in European ports is 22% slower than in the Asia-Pacific, reflecting structural and governance heterogeneity. These findings support the design of region-specific contingency frameworks, where resource allocation and response timing are tailored to local propagation dynamics and trade hierarchies (Gan et al., 2025a). Integrating these findings into port investment strategies can transform resilience assessment from a diagnostic tool into a proactive planning instrument that guides capital expenditure and policy prioritization.

(2) Optimization of resilience-efficiency trade-offs in ship scheduling

A dynamic load-redistribution algorithm introduced in this study enables real-time adjustment of routing and scheduling to maintain cargo flow continuity during disruptions. The approach helps reconcile the long-standing resilience-efficiency trade-off, ensuring that protective redundancy does not come at the expense of operational productivity. Results indicate that the Asia-Pacific region faces a 42% throughput-decline risk, compared with 34% in Europe, under concurrent congestion and weather events. Adaptive routing allows the rerouting of vessels toward underutilized regional hubs, reducing total delay times and operational costs.

For instance, during labor strikes or weather-related port closures, the cargo is dynamically redirected to secondary Southeast Asian hubs, mitigating regional supply-chain collapse. These insights highlight the

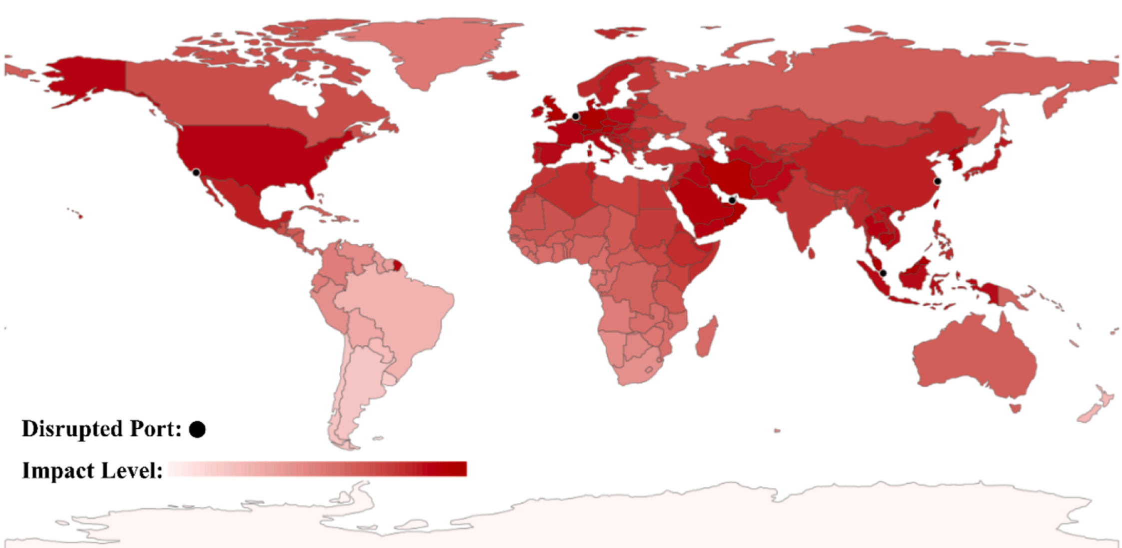

Fig. 11. Global Impacts from Full-Scale Critical Port Disruptions.

potential of intelligent routing algorithms and predictive scheduling systems to enhance the flexibility in global shipping networks. The framework provides a scientific basis for integrating real-time digital twins, AI-driven logistics platforms, and port community systems to improve decision-making under uncertainty, paving the way for next-generation resilient maritime logistics ecosystems (Sun et al., 2018).

(3) Quantification of intercontinental trade dependencies

By leveraging vessel-capacity and DWT-weighted networks, the framework enables the quantitative assessment of intercontinental trade dependencies, offering new perspectives on systemic risk transmission. For example, the Suez Canal's pivotal role in global energy and container transport becomes evident in simulated cascading effects, where congestion at upstream hubs leads to downstream bottlenecks in African feeder ports.

These findings have direct implications for infrastructure investment, insurance, and emergency logistics planning. Policymakers and industry regulators can use such metrics to establish differentiated infrastructure standards, for instance, designing redundant berths or fuel reserves for ports with high global betweenness centrality. Moreover, pre-positioning of emergency resources (e.g., tug vessels, repair equipment, and buffer capacity) at these strategic locations can substantially reduce recovery time after disruptions (Chen et al., 2024). Beyond engineering implications, the results offer a quantitative foundation for resilience-based pricing and insurance modeling, allowing insurers and port authorities to evaluate financial exposure based on systemic criticality rather than asset size alone.

(4) Maritime security and geopolitical risk mitigation

Given that approximately 89% of countries experience measurable efficiency losses following major disruptions, strengthening maritime security coordination is essential. The proposed analytical framework can be embedded within real-time maritime surveillance and monitoring systems to identify abnormal congestion patterns, potential cyber-physical risks, or emergent chokepoints. Defensive resources, such as naval escorts, emergency fleets, and digital security mechanisms, should be strategically prioritized for high-value hubs identified through network centrality and cascading-risk analysis (Fahimnia and Jabbarzadeh, 2016).

At the policy level, the study supports the establishment of internationally coordinated governance mechanisms that institutionalize data sharing and crisis response. Joint customs protocols, integrated logistics information platforms, and standardized sanctions-compliance procedures can reduce inspection redundancies and harmonize maritime operations across regions. Furthermore, incorporating resilience metrics into global trade agreements, for example, within IMO or UNCTAD frameworks, would foster collective accountability for supply-chain continuity. Such mechanisms can help safeguard energy security, humanitarian logistics, and food-supply stability during geopolitical shocks and extreme climate events (Xin et al., 2025).

(5) Strategic, managerial, and research outlook

Beyond its immediate operational relevance, the proposed framework offers a strategic roadmap for future research and policymaking. The integration of big-data analytics and network-theoretic modeling demonstrates the feasibility of quantifying systemic resilience at global scale, providing a replicable template for other transport sectors (e.g., aviation, rail, or multimodal logistics).

For port authorities and shipping alliances, adopting such analytical tools can facilitate resilience-informed investment portfolios, where capital is allocated not solely based on throughput potential but also on systemic importance and recovery capability. The approach also provides empirical evidence for developing maritime resilience indices that can be used by insurers, investors, and international regulators.

6. Conclusion

This research presents an integrated framework for assessing global shipping network resilience by combining community-based static analysis with dynamic cascading failure simulations. A directed and weighted network is constructed using AIS trajectory data in 2022, with edge weights based on deadweight tonnage to represent actual route-level transport capacity. This approach captures not only the structural layout of shipping corridors but also the intensity of cargo flows, providing a more realistic basis for resilience assessment. Static resilience is evaluated through community structure detection, which effectively reveals continent-scale clustering patterns and inter-regional dependencies across port systems. These insights offer a macroscopic understanding of how critical hubs function within global supply chains. Dynamic failure simulations demonstrate that targeted node disruptions produce 40 to 65 percent higher throughput losses compared to random failures, highlighting the fragility of centralized and high-dependency port configurations. Empirical validation conducted across five representative global hub ports indicate that failure propagation in European systems is approximately 22 percent slower than in the Asia-Pacific region. This finding is attributed to the distributed infrastructure layout observed in the European shipping network, which offers greater redundancy and fault isolation capacity. The research contributes a scalable and data-driven method that can be adapted for real-time monitoring, cross-regional comparisons, and policy decision support.

Future research should incorporate more granular operational data, such as cargo load status during voyages and specific port-handling patterns, to better capture the effects of asymmetric trade flows. Expanding datasets to include coastal and inland waterway traffic would also enhance the model's applicability. While this study provides a systematic assessment of shipping network resilience, considering additional structural and operational factors could further improve its explanatory power. Moreover, MMSI-based vessel data may under-represent smaller regional shipping activities, highlighting the need for broader and higher-resolution data sources in future studies.

CRediT authorship contribution statement

Huijun Yang: Writing – original draft, Visualization, Conceptualization. **Chengyong Liu:** Supervision, Project administration. **Yuhao Cao:** Validation, Methodology. **Yaqing Shu:** Data curation, Conceptualization. **Langxiong Gan:** Resources, Formal analysis. **Zhenyuan Liu:** Software, Investigation. **Zaili Yang:** Writing – review & editing, Project administration.

Declaration of competing interest

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

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