

Article

Resilience and Adaptability Analysis of Port-Centric Transport Networks for Meteorological Disasters: A Case of Shanghai Port

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Abstract

Climate change has intensified the frequency and severity of meteorological disasters, posing significant challenges to the resilience and adaptability of port-centric transport networks (PCTNs) and global trade stability. Unlike previous studies that adopt generalised resilience frameworks or treat disaster types uniformly, this study develops a disaster-specific, integrated assessment framework whose novelty lies in coupling three complementary methods, each playing a distinct role: (i) integer programming optimises post-disaster recovery decisions under budgetary constraints by selecting cost-effective measures that maximise re-stored container-handling capacity; (ii) Monte Carlo simulation (10,000 iterations) captures the stochastic nature of meteorological disruptions and quantifies probabilistic resilience under typhoons, storm surges, and heavy fog; and (iii) an Analytic Hierarchy Process–Evidence Reasoning (AHP–ER) hybrid integrates subjective expert judgement with objective field data to evaluate adaptability across a four-level indicator system, thereby reducing the subjectivity of conventional multi-criteria approaches. Applied to Shanghai Port, the framework yields normalised resilience scores on a [0, 1] scale, where 1.0 denotes full operational continuity (network throughput equals demand) and values below 0.80 indicate substantial disruption requiring urgent intervention. Heavy fog produces the lowest score (0.73, ‘moderate-to-severe disruption’), followed by typhoons (0.81, ‘mild disruption’) and storm surges (0.89, ‘near-normal operation’), revealing that low-visibility events—not high-energy storms—pose the dominant operational threat at Shanghai Port. Translating these findings into practice, the study recommends the following: (1) deploying real-time visibility-monitoring (LiDAR) and AI-driven traffic-scheduling systems to mitigate fog-related disruptions; (2) reinforcing gantry-crane anchoring and prepositioning emergency power supplies in typhoon-prone berths; (3) prioritising hinterland-port handling redundancy in Jiangsu and Anhui sub-networks (adaptability scores 0.639 and 0.642); and (4) piloting an integrated Shanghai–Zhejiang cross-regional emergency-response corridor with shared berthing rights and standardised joint drills. These targeted, quantitatively



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grounded recommendations offer port authorities and policymakers an evidence base for prioritising infrastructure investment and organisational reform to safeguard global supply chains against escalating climatic threats.

Keywords: port-centric transport networks; meteorological disasters; evidence reasoning; maritime transport resilience

1. Introduction

The global shipping industry is the backbone of international trade, enabling the seamless movement of goods across continents. Port-centric transport networks (PCTNs) are particularly crucial, enabling the efficient, cost-effective movement of products between manufacturers and consumers worldwide. Ports, which play a significant role in the shipping network as both starting and ending points for shipments, are particularly susceptible to the impacts of climate change, including rising sea levels and extreme weather events. Ports serve as vital nodes in this network, linking maritime and inland transport modes and supporting the complex logistics of the global supply chain [1,2]. However, the stability of these networks is increasingly vulnerable to the rising frequency and intensity of meteorological disasters, including typhoons, hurricanes, storm surges, heavy rainfall, and extreme temperatures [3,4].

In recent decades, climate change has been a significant driver of the increase in meteorological extremes. Scientific studies have shown that rising global temperatures contribute to more frequent and severe weather events, which, in turn, disrupt port operations and logistics chains [5]. These disruptions can have far-reaching consequences, not only causing immediate economic losses from delays and damaged goods but also undermining long-term trust in the reliability of global supply chains. The need to understand and mitigate the impact of these disasters on port operations is now more urgent than ever.

Given the critical role of ports in global trade, enhancing the resilience and adaptability of PCTNs is vital. Resilience, in this context, refers to the capacity of these networks to absorb shocks, maintain functionality during a crisis, and recover swiftly from disruptions [6]. Adaptability, on the other hand, refers to these networks' capacity to evolve in response to changing environmental conditions, including integrating new technologies, reconfiguring infrastructure, and adopting innovative management strategies. Both resilience and adaptability are essential to ensuring the smooth operation of ports amid increasingly unpredictable and severe weather patterns [7,8].

This study aims to provide a comprehensive analysis of the resilience and adaptability of port container transportation networks in the face of various meteorological disasters. By examining case studies from various global ports and applying advanced quantitative models, this research aims to identify the key factors contributing to the robustness of these networks. Additionally, the study explores the effectiveness of strategic interventions, such as early warning systems, infrastructure upgrades, and policy reforms, in strengthening the resilience and adaptability of port operations.

The findings of this research are expected to provide valuable insights for port authorities, policymakers, logistics companies, and other stakeholders involved in global shipping. By highlighting the vulnerabilities of current port infrastructure and offering practical solutions, this study contributes to the broader discourse on climate resilience within critical infrastructure systems. Ultimately, it underscores the importance of proactive measures to safeguard global trade routes against the growing threat of meteorological disasters, thereby ensuring the continued flow of goods and services.

Shanghai Port was selected because it represents one of the world's largest and most technologically advanced container ports, with high exposure to multiple meteorological hazards and complex hinterland connectivity [9]. These characteristics make it an appropriate benchmark for evaluating resilience and adaptability frameworks applicable to other major international hub ports.

This study addresses these challenges by focusing on three representative meteorological disasters—typhoons, storm surges, and heavy fog—and their specific impacts on the Shanghai PCTN. To investigate how these distinct hazards differentially affect network resilience and adaptability, and to provide actionable insights for port management, this study poses the following research questions:

- RQ1: How can the resilience of a PCTN be quantitatively differentiated across distinct meteorological disaster types under stochastic disruption scenarios?
- RQ2: Which immediate recovery measures most effectively restore container-handling capacity within budgetary constraints during typhoon, storm-surge, and heavy-fog events?
- RQ3: How can the long-term adaptability of hinterland sub-networks be evaluated using an integrated framework that combines expert judgement with objective field data?
- RQ4: What disaster-specific, sub-network-targeted interventions best enhance PCTN resilience and adaptability?

To clarify the contributions and added value of this study, the main contributions can be summarised as follows. First, the study develops a disaster-specific resilience assessment framework that differentiates among typhoon, storm-surge, and heavy-fog scenarios rather than treating meteorological events generically. Second, the study integrates integer programming, Monte Carlo simulation, and an Analytic Hierarchy Process–Evidence Reasoning (AHP–ER) hybrid into a unified framework that jointly evaluates short-term resilience and long-term adaptability, thereby reducing subjectivity and enhancing reproducibility. Third, the research derives scenario-specific recovery strategies that maximise container-handling capacity within budget constraints and provide empirically grounded recommendations for infrastructure investment and organisational reform. Finally, the paper demonstrates the framework's applicability through a comprehensive case study of Shanghai Port and its four hinterland subnetworks, illustrating how the methodology can be adapted to other ports by recalibrating disaster parameters, recovery measures, and indicator weights.

This paper is organised as follows. Section 1 introduces the background on the resilience and adaptability of PCTNs in the context of meteorological disasters and poses the research questions. Section 2 reviews the literature on the resilience and adaptability of maritime transport to climate change. Section 3 outlines the methodology, including the resilience metrics and the integer programming model. Section 4 presents a case study of Shanghai PCTN, applying the models to assess resilience and adaptability. Section 5 concludes this study and suggests directions for future research.

2. Literature Review

This section presents the methodological framework for assessing the performance of PCTNs under climate-related disruptions. Section 2.1 focuses on evaluating resilience, examining the system's ability to maintain operations and recover under various meteorological disaster scenarios. Section 2.2 then addresses adaptability, assessing the capacity of maritime transport systems to implement long-term structural and managerial adjustments in response to climate change.

2.1. Resilience of Maritime to Climate Change

The resilience of PCTNs to climate change has emerged as a critical area of research, yet existing studies exhibit significant gaps in addressing the specific challenges posed by meteorological disasters. While prior work has established foundational frameworks for assessing resilience in maritime networks [10,11], these studies often adopt a generalised approach, overlooking the nuanced impacts of distinct disaster types such as typhoons, storm surges, and heavy fog. For instance, Justice et al. [10] introduced a risk-based resilience framework for Liner Shipping Networks (LSNs), but their focus on recovery strategies lacks granularity in differentiating between disaster scenarios. Similarly, Bathke et al. [11] analysed container shipping networks using geospatial connectivity, yet their methodology fails to account for the dynamic operational disruptions caused by specific meteorological events.

A recurring limitation in the literature is reliance on static models that fail to capture the temporal and spatial variability of climate impacts. Wu et al. [12] explored resilience through port coalitions, emphasising collaboration but neglecting the role of real-time adaptive measures during disasters. More recently, Verschuur et al. [13] quantified the cascading economic impacts of port disruptions on global supply chains, further underscoring the need for dynamic, scenario-based resilience assessments that capture network-wide effects. Yuan et al. [14] highlighted vulnerabilities in global container networks but did not integrate stochastic optimisation techniques to simulate disaster scenarios. Balakrishnan et al. [15] proposed a methodology for evaluating the economic risks of hurricane-related disruptions to port operations, yet their framework does not incorporate stochastic optimisation to capture the full range of meteorological uncertainty. This oversight is critical, as resilience metrics must reflect the probabilistic nature of meteorological disruptions. The present study addresses this limitation by proposing a dynamic, scenario-based resilience assessment framework that quantifies operational continuity under typhoon, storm-surge, and heavy-fog conditions, leveraging Monte Carlo simulations to model stochastic impacts.

2.2. Adaptability of Maritime Transport to Climate Change

This study adopts the definitions by the United Nations Office for Disaster Risk Reduction (UNDRR): resilience refers to the ability of a system to absorb disturbances and maintain functions, quantified by the recovery rate of actual throughput; adaptability refers to the capacity of a system to proactively respond to long-term climate change through structural adjustments (such as infrastructure upgrades or management strategy iterations), evaluated via a multi-level indicator system [16]. The distinction between them lies in resilience, focusing on short-term recovery, while adaptability emphasises long-term evolution.

Research on the adaptability of maritime transport networks has primarily focused on long-term climate adaptation strategies, such as infrastructure upgrades and policy reforms [17,18]. However, these studies often conflate adaptability with resilience, failing to distinguish between reactive recovery and proactive evolution. For example, Notteboom [17] examined port adaptations to mega-vessels but did not evaluate how organisational and infrastructural flexibility mitigates immediate disaster effects. Panahi et al. [18] identified economic implications of climate inaction but offered limited insights into decision-making frameworks for real-time adaptability.

Earlier work by Zhang and Lam [19] quantified the economic losses from port disruptions caused by extreme wind events, providing a foundational empirical basis for scenario-based loss estimation in port resilience research. Tian et al. [20] further extended this line of inquiry by assessing the regional economic losses along China's coastline due to

typhoon-induced port disruptions, reinforcing the need for differentiated, hazard-specific impact analysis. A notable gap lies in the lack of integrated methodologies that combine expert judgement with empirical data to assess adaptability. While Chhetri et al. [21] emphasised workforce adaptive capacity, their qualitative approach lacks quantitative rigour. Mou et al. [22] assessed the reliability impacts of typhoon-induced port disruptions across Chinese coastal ports, highlighting the importance of network-level adaptability metrics. Similarly, Yang and Ge [23] evaluated port infrastructure adaptations but did not incorporate multi-criteria decision-making tools, such as the Analytic Hierarchy Process (AHP), to prioritise actions. Our study bridges these gaps by introducing an AHP-Evidence Reasoning (ER) hybrid model, which synthesises expert scoring with objective data to reduce subjectivity and enhance decision accuracy. This approach not only evaluates current adaptability but also identifies targeted improvements for specific disaster scenarios, such as optimising road systems for heavy fog or enhancing organisational protocols for typhoons.

Taken together, the above review reveals three key gaps in the existing literature. First, existing studies rarely differentiate the impacts of distinct meteorological disaster types—typhoons, storm surges, and heavy fog—on port-centric transport networks within a single analytical framework. Most prior work either aggregates all disasters into a generic ‘disruption’ category or focuses on a single hazard type, obscuring the potentially divergent resilience and adaptability profiles that different disasters demand. Second, few studies have integrated stochastic optimisation with multi-criteria decision analysis to jointly assess short-term resilience and long-term adaptability. Existing approaches tend to address these two dimensions in isolation, leaving a methodological gap in capturing their interaction. Third, limited research provides sub-network-level adaptability diagnostics that can guide targeted policy interventions; most studies report aggregate port-level or network-level results, offering insufficient granularity for regional planning and resource allocation. The present study addresses these gaps by integrating integer programming, Monte Carlo simulation, and AHP-Evidence Reasoning into a unified framework, as detailed in Section 3.

3. Methodology

To evaluate PCTN performance under meteorological disasters without overextending the analytical structure, the methodology assigns a distinct role to each method. Integer programming is used to identify cost-constrained recovery actions that maximise restored handling capacity; Monte Carlo simulation is then used to propagate disaster uncertainty and estimate short-term resilience; and AHP-ER is used separately to assess longer-term adaptability on the basis of infrastructure and organisational indicators. This sequencing keeps optimisation, uncertainty analysis, and multi-criteria evaluation analytically distinct while allowing their outputs to inform a unified set of policy recommendations [6,24].

The proposed framework is structured into three interrelated phases. The first phase, resilience assessment (Section 3.1), quantifies short-term operational continuity under different disaster scenarios using integer programming and Monte Carlo simulation. The second phase, adaptability evaluation (Section 3.2), examines long-term structural and organisational flexibility using a multi-level indicator system integrated with AHP-ER. The third phase focuses on policy recommendations (Section 4) that translate the quantitative findings into targeted managerial strategies for port authorities and policymakers. This structure strengthens the logical coherence between modelling, analysis, and decision-making while improving the overall readability of the framework.

While previous studies have advanced the understanding of resilience and adaptability in container ship networks within the broader context of climate change, limited

attention has been paid to the specific effects of distinct meteorological disasters on PCTNs. To address this gap, this paper proposes a methodological approach to analyse the resilience and adaptability of PCTNs across various meteorological disaster scenarios. This approach provides a more detailed, context-specific examination of network performance in response to these challenges, as shown in Figure 1. The integer programming model generates post-disaster recovery capacity and operational recovery time parameters, which are subsequently used as stochastic input variables in the Monte Carlo simulation to estimate resilience distributions under different disaster scenarios. The resilience outputs, together with infrastructure and organisational indicators, inform the AHP-ER adaptability assessment and the formulation of targeted policy interventions.

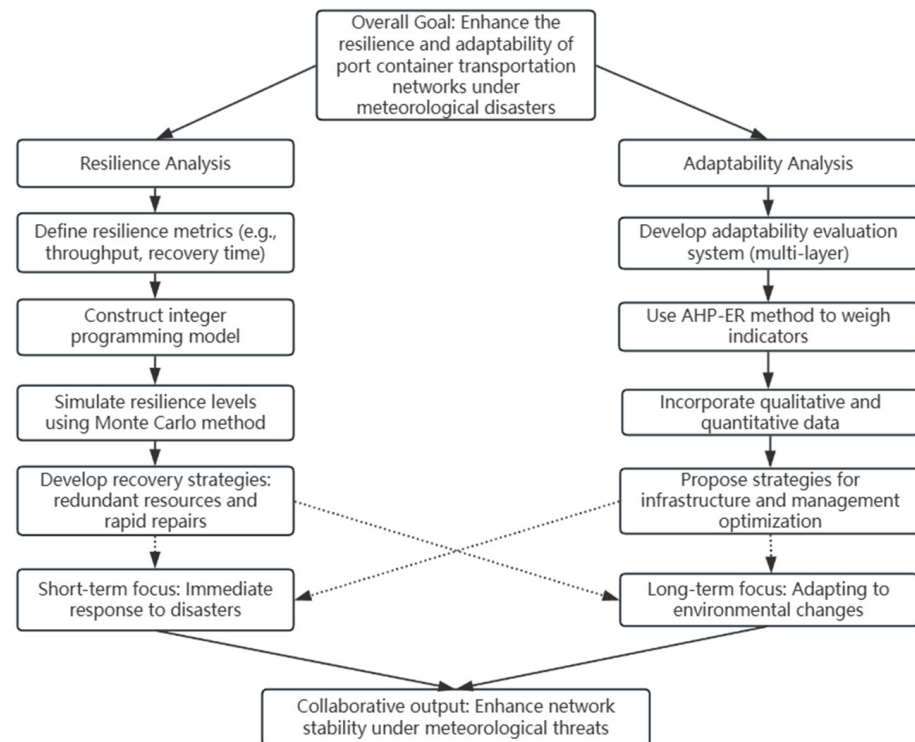


Figure 1. Methodological framework for assessing the resilience and adaptability of PCTNs under meteorological disasters.

3.1. Resilience Analysis of PCTNs

The quantitative value E of the resilience level of the transport network after meteorological disasters can be expressed as the operational capacity that the container transport system maintains. Mathematically, it is represented as the ratio of the actual container handling capacity Z of the port after climate disasters to the total demand D^0 of the network container under normal conditions. This ratio reflects the network's ability to maintain operational continuity and efficiency in the face of disasters. For a comprehensive network resilience evaluation, the mean value $\mu(\xi)$ of all possible cases is used as the final network resilience evaluation metric [25].

$$E(\mu) = \text{Mean}\left(\sum Z(\mu(\xi)) / D^0(\mu(\xi))\right) \quad (1)$$

Conceptually, this resilience metric reflects the port-centric transport network's ability to continue handling cargo flows and maintain logistics connectivity under disruptive weather conditions. A higher resilience score indicates that the network can preserve a larger proportion of its normal operational capacity during and after meteorological disturbances, thereby reducing delays, cargo congestion, and economic losses across

the supply chain. From an operational perspective, the model captures how quickly ports can restore handling capacity through emergency recovery measures and resource allocation strategies.

The data sources for these variables are explained in Table 1. Port container handling capacity (C) and annual throughput are obtained from the China Port Yearbook (2023 Edition) and published port statistics [24]. The average cargo value per container (p) is calculated by dividing the total annual import and export value of containerised goods at Shanghai Port by the corresponding annual container throughput. Disaster probability weights for δ are derived from a risk assessment specific to Shanghai Port, with normalised values of 0.327 for typhoon, 0.070 for storm surge, and 0.602 for heavy fog. Recovery measure parameters (b_j , t_j , ΔC_j , Q_j^R) are based on a combination of port operational records and informed estimates, as detailed in Section 4.1.1.

Table 1. Definition of variables.

Variables	Meanings
U	Set of climate change types, $\mu \in U$
Ξ	A set of scenarios for some kind of climate disaster, $\xi \in \Xi$
J	Immediate recovery measures taken by the port operator, $j \in J$
D_w	Hinterland W container demand
p	Average cargo value of a container
$\gamma_j(\mu(\xi))$	0–1 variable indicating whether the port operator takes recovery measures j ; 1 if adopted, 0 if not adopted
τ	Actual port operation time
δ	0–1 parameter indicating whether the port has suffered a climate disaster; 1 = Yes, 0 = No
t_j	Port operation time after taking restoration measures j
Q_j^R	Implementation time of restoration measures j taken by the port
b_j	Cost of implementation of port restoration measures j
B	Cost constraints of port recovery measures
C	Port container capacity after disaster
ΔC_j	Increased capacity of the port after the restoration measures of the port j

3.1.1. Formulation

For readability, only the objective function and key constraints are summarised here. The complete mathematical formulation, including decision variables and parameter definitions, is provided in Appendix A.

In this study, the maximum number of containers a port can handle in a working day is measured in TEU. Given that the network spans several hinterland subnetworks labelled W , this paper assumes that the container demand D_w for each hinterland is fixed and does not change during the period affected by meteorological disasters.

For further analysis, the total container demand of the network is defined as D^0 , and the sum of all hinterland subnetwork demands D_w . Based on this assumption, D^0 is also a constant, meaning that the total demand for containers from each network component remains unchanged in the face of meteorological disasters. By doing so, the study ensures that the quantitative analysis of container transport networks and their capacity is based on consistent and accurate metrics.

In the wake of meteorological disasters, port operators face critical decisions about container handling. This study assumes that port operators must select the most appropriate recovery measures from available options to restart port operations after disasters. Since the implementation time, cost and recovery effectiveness of each measure vary, it is critical to select the best measure to maximise the port's operational efficiency within the

budget. In this way, the port can minimise the economic impact of disasters while maintaining operational efficiency and quickly restoring container-handling capacity, thereby reducing financial pressure on customers and partners. It not only helps the port maintain business continuity but also enables it to return to normal operations after a disaster quickly. Accordingly, under the scenario ξ caused by climate hazard type μ , the decision-making process of the port operator can be described by the following integer programming model:

$$\begin{aligned} \text{Min}_{\gamma_j(\mu(\xi))} T(\mu(\xi)) &= \tau(\mu(\xi)) + \delta(\mu(\xi)) \times \sum_{j=1}^J [\{t_j(\mu(\xi)) - \tau(\mu(\xi))\} * \\ &\quad \gamma_j(\mu(\xi))] + \delta(\mu(\xi)) \times \sum_{j=1}^J (Q_j^R(\mu(\xi)) * \gamma_j(\mu(\xi))) \end{aligned} \quad (2)$$

subject to

$$\sum_{j=1}^J b_j(\mu(\xi)) \times \gamma_j(\mu(\xi)) \ll B(\mu(\xi)) \quad (3)$$

$$B(\mu(\xi)) = p \times \max\{0, [(\sum_{w=1}^W D_w) - C(\mu(\xi))]\} \quad (4)$$

$$\sum_{j=1}^J \gamma_j(\mu(\xi))''1 \quad (5)$$

$$\gamma_j(\mu(\xi)) \in \{0, 1\}, \forall j \in J \quad (6)$$

In the above formulas, $\gamma_j(\mu(\xi))$ as the decision variable, represents the immediate recovery measures chosen by the port decision maker. $T(\mu(\xi))$ denotes the time required for the port to process the normal container volume under the scenario ξ following the occurrence of a meteorological disaster type μ . Assuming the port container operation rate remains constant, the port's operation time is inversely proportional to its capacity.

Constraints (3) and (4) represent the cost constraints for the port operator in implementing restoration measures. After port operations are disrupted, the operator faces financial claims from customers and collaborators for losses. Therefore, the port's cost constraint is related to the cargo's value in the container after operations are interrupted. Constraint (5) ensures that only one immediate recovery measure can be taken after a climatic disaster. Constraint (6) specifies that the decision variable is an integer-valued 0–1 variable.

After the port operator determines a response to a climate disaster, the actual handling capacity $Z(\mu(\xi))$ of the port container can then be expressed as

$$Z(\mu(\xi)) = C(\mu(\xi)) + \delta(\mu(\xi)) \times \sum_{j=1}^J [\Delta C_j(\mu(\xi)) \times \gamma_j(\mu(\xi))] \quad (7)$$

3.1.2. Methodology Flow

As shown in Figure 2, the Monte Carlo method [26] is employed to calculate the resilience level of the network under the climatic disaster type μ . The algorithm consists of the following three steps.

While meteorological disasters exhibit non-stationary and skewed distributions, the Monte Carlo method enables probabilistic sampling of extreme scenarios (e.g., 100-year storm surges) by integrating historical disaster frequency and severity data [27]. This approach aligns with resilience studies in critical infrastructure, where stochastic optimisation captures uncertainty in disaster recovery [3]. In the simulation process, the occurrence probabilities of typhoon, storm surge, and heavy fog scenarios were represented using scenario-based stochastic sampling derived from the normalised disaster risk weights presented in Section 4.1.1. For each iteration, disruption severity, operational capacity reduction, and recovery duration were sampled proportionally according to the predefined disaster-specific parameter ranges. The simulation assumes that the probability distributions of operational disruptions exhibit bounded stochastic variation around calibrated baseline values, enabling the representation of uncertainty in disaster impacts and recovery

performance. A total of 10,000 Monte Carlo iterations were conducted for each disaster scenario to ensure numerical convergence and stability of the resilience evaluation results [25]. Specifically, operational capacity reduction for each disaster scenario is modelled using a uniform distribution within the calibrated minimum and maximum bounds for that hazard, while recovery duration follows a triangular distribution defined by minimum, most likely and maximum repair times. These distributional assumptions, derived from historical records and expert estimates, capture bounded uncertainty without imposing unrealistic tails and enhance the reproducibility of Monte Carlo sampling.

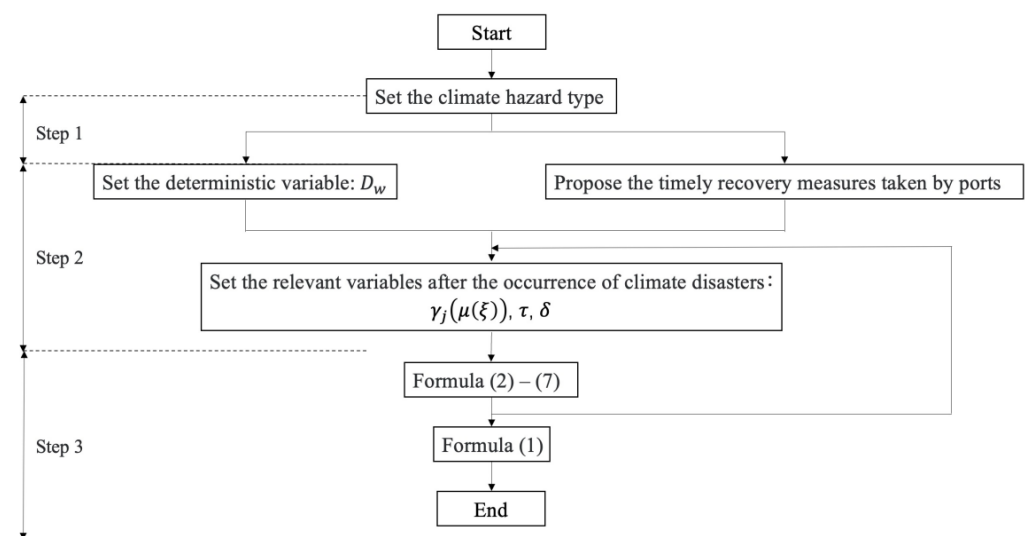


Figure 2. Procedure for solving the horizontal model of network toughness.

3.2. Adaptability Analysis of PCTNs

3.2.1. Adaptability Evaluation System

The proposed adaptability evaluation index system consists of three hierarchical levels, which are consulted by the expert team. The first layer, called the target layer, is specifically aimed at assessing the adaptability of the container railway transport network. The second layer is the primary index layer, which expands the network's adaptability into four levels, each directly related to a component of the container railway transport network. The third layer is the secondary index layer. In selecting secondary indicators, the principles of high differentiation, strong operability and precise directivity are followed. These secondary indicators further refine the evaluation of each primary index. The meanings and justifications for selecting these secondary indicators are detailed in Tables 2 and 3.

Table 2. Network adaptability evaluation system.

Target Layer	Primary Index	Secondary Index
Adaptability assessment	Natural conditions	Geographical distance from Shanghai Port
	Social and economic conditions	Road container transport cost advantage
	Infrastructure	1. Highway density 2. Highway traffic congestion degree 3. Redundancy of container handling capacity of hinterland ports
	Organisational management	Ownership form and management mode of the port

Table 3. The definitions of the secondary indexes of the evaluation system.

Name of Index	Explanation
Geographical distance from Shanghai Port	Under the natural condition layer. Proximity to the seaport increases the feasibility of switching to road transport during an outage, making the network more adaptable.
Road container transport cost advantage	This index belongs to the social and economic conditions layer. The network's adaptability depends on its ability to switch to all-road transport during disruptions. If the cost advantages of road container transport are more pronounced, then the network's ability to cope is stronger.
Highway density	Part of the infrastructure layer. As a key factor for adaptive capacity, higher highway density strengthens network resilience by enabling a switch to road transport when rail transport is disrupted.
Highway traffic congestion degree	Under the infrastructure layer. Congestion reduces the feasibility of switching to all-road transport during an outage and, in turn, undermines the advantages and network resilience of the hinterland road system.
Redundancy of container handling capacity at hinterland ports	This index is part of the infrastructure layer, which enhances the network's adaptability. By emphasising the redundancy of port container operations, it can effectively mitigate the adverse impact of reduced container throughput when the network is disrupted.
Ownership Structure and management model of the port	This indicator falls under the organisation's management and reflects the port enterprise's emergency capacity in the event of a disruption. Generally, public and private ports have strong emergency response capacity in the event of a disruption, while instrument and landlord ports are relatively weak.

3.2.2. AHP-ER Method

AHP [28,29] is a structured decision-making method for addressing complex problems by breaking them down into smaller, more manageable components. These components are organised into a hierarchical structure, typically consisting of a goal, criteria, sub-criteria, and alternatives. AHP is a widely used research method, especially where relative measurements and prioritisation are required. The key advantage of AHP lies in its ability to determine the relative importance of candidates or indicators, especially when these indicators are difficult to quantify directly due to inherent ambiguity or uncertainty, thereby providing an intuitive and scientific basis for judgement.

The application of AHP typically follows three main steps. Firstly, researchers structure the research problem hierarchically, decomposing it from the top down. The top layer represents the decision goal, the middle layer represents various indicators or criteria influencing the decision, and the bottom layer is the candidate scheme or choice. This hierarchy helps to clarify and organise the key elements of the decision-making process, ensuring that the decision focus at each level is clearly defined. Secondly, researchers compare the elements in the hierarchy, especially the indicators or criteria within the same level. This step helps to reveal the relative importance of different indicators, thus determining a local weight for each indicator. Finally, the research process enters the weight synthesis stage.

Considering the intense subjectivity inherent in the traditional AHP and the close dependence of decision results on experts' professional backgrounds, this study adopts an improved method that combines expert judgement with field data. In particular, we introduce the Evidence Reasoning (ER) approach to handle the complex indicators in this evaluation system. A significant advantage of ER is its ability to handle multiple indica-

tors simultaneously, whether qualitative or quantitative, and whether the information is complete. The ER integrated algorithm is used to score and rank the indicators, accommodating both positive and negative relationships, while including both qualitative and quantitative indicators.

By combining the ER method with traditional AHP, the biases stemming from reliance solely on expert judgement or objective field data are significantly reduced, thereby improving the objectivity, accuracy, and rigour of the decision-making process. This comprehensive evaluation approach makes the AHP-ER method more effective and reliable for complex decision problems. Therefore, the scoring and ranking of hinterland ports provide more objective, scientifically sound decision support. Figure 3 indicates the implementation process of the AHP-ER methodology.

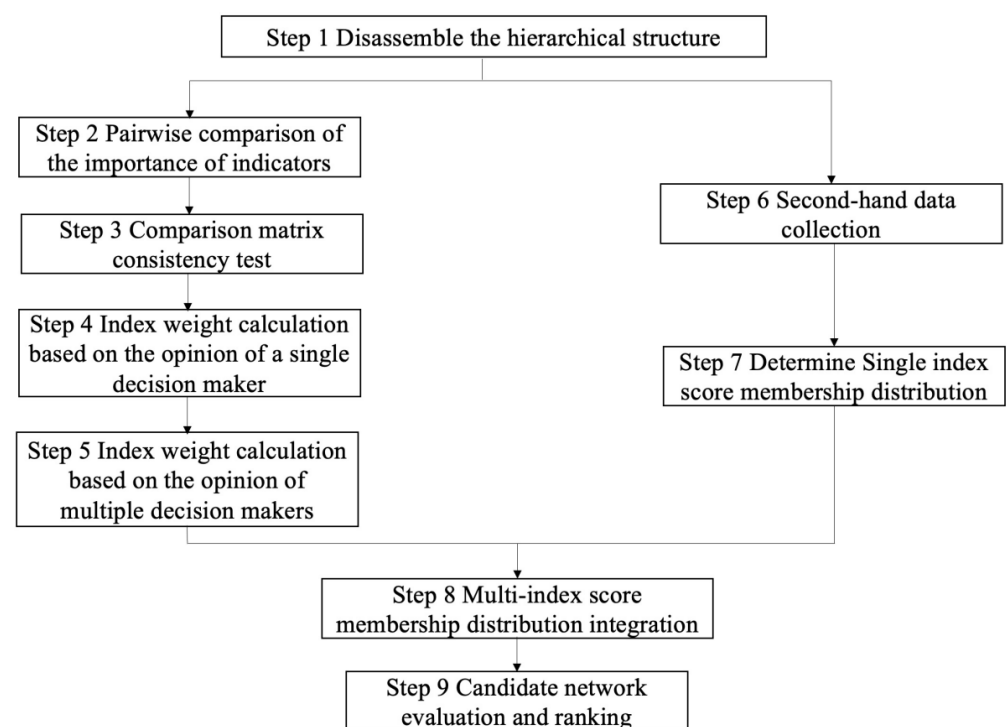


Figure 3. AHP- ER process.

Step 1: The adaptability analysis of the port container railway transport network can be structured into four tiers.

Step 2: An expert group composed of K experts compares the importance of the second- and third-tier indicators in the evaluation system, conducts pairwise comparisons, and provides independent scores. Specifically, for each pair of indicators of the h comparison group h_l in layer l , namely $x_{h_l}^m$ and $x_{h_l}^n$, each expert k gives the relative ratio of their importance to the upper indicator $c_{h_l-mm}^k$. The value of $c_{h_l-mm}^k$ is given by expert k based on the five-component scale of relative importance, as shown in Table A1 in Appendix A. For each group of comparison indicators, each expert's score results will form a comparison matrix $C_{h_l}^k$. Each panel member must have a senior academic or industry background relevant to the research, as shown in Table 4.

Step 3: A consistency test is performed on each comparison matrix $C_{h_l}^k$ provided by each expert. The Consistency Index (CI) and Consistency Ratio (CR) are used to test the consistency of the comparison matrix. When the CR of the comparison matrix is ≤ 0.1 , it can be considered to have passed the consistency test. To ensure the reliability of the experimental results, all unqualified comparison matrices are discarded and cannot be used for subsequent calculations.

Table 4. AHP- ER method parameters and definitions.

Parameters	Definitions
A	Candidate network set
L	Evaluation system level set, $L = \{1, 2, 3, 4\}$
X_l	The index set of the l -layer of the evaluation system
H_l	Comparison index group set at the l -level of the evaluation system, $h_l \in H_l$
N_{h_l}	Compare the set of indicators in indicator group h_l
K	A collection of experts who score the importance of indicators by pairwise comparison, $k \in K$
$c_{h_l-mn}^k$	The h_l given by expert k compares the importance ratio of indicator m to that of indicator n in the indicator group
$C_{h_l}^k$	The pairwise comparison matrix of importance of h_l comparison index group given by expert k is a positive and inverse matrix of N_{h_l} , and the element in the m row n column is $c_{h_l-mn}^k$
$w_{h_l}^k$	Based on the importance of indicators given by experts k , h_l is the local weight vector of indicators in the indicator group
w_{h_l}	By using the weighted arithmetic average method and integrating the opinions of all K experts in $w_{h_l}^k$, the local weight vector of indicators in indicator group h_l is obtained
w_l	The global weight vector for the index weights of layer l
G	A collection of scores for adaptive evaluation, $G = \{G_1, G_2, G_3, G_4, G_5\}$
S	The candidate network adaptability evaluation score set is calculated from the expected utility of the candidate network's comprehensive membership distribution on the evaluation score set G

Step 4: Based on the comparison results given by expert k , the eigenvector method is used to obtain the local weight vector of each index in the L th-layer comparison index group h_l from the comparison matrix $C_{h_l}^k$.

Step 5: The weighted arithmetic average method is employed to synthesise the local weight $w_{h_l}^k$ provided by all k experts to obtain the index local weight w_{h_l} based on the expert opinions. In this step, it is necessary to consider the influence of the expert k in the decision-making process. However, since more than 30 opinions were collected, assigning influence weight to individual experts is cumbersome. Therefore, for simplicity, it is assumed that all experts have equal influence in decision-making (as highlighted in the Bayesian prioritization procedure proposed by [30]). For instance, in scenarios where expert consistency levels are either unknown or difficult to quantify, equal weighting serves as a parsimonious default that maintains computational feasibility.

Step 6: The original secondary data can be either qualitative or quantitative. This depends on the type of secondary indicators in the third layer of the evaluation system, as shown in Table A2 in Appendix A. It is necessary to convert qualitative data into quantitative data using a five-component scale before proceeding to the next step.

Step 7: The input raw data to the unified evaluation score set G to establish the membership distribution of the candidates' evaluation scores for each secondary index. For the sake of simplification, the study adopts a uniform qualitative evaluation score set G is adopted, where $G = \{\text{very poor, poor, medium, good, excellent}\}$. In addition, when mapping the original input data, it uses a rule-based information conversion method, as shown in Table A3 in Appendix A, to uniformly map qualitative or quantitative data with

different units to the evaluation score set G . Based on the data types (region-related or port-related; qualitative or quantitative; positive or negative), the six three-level indicators in the evaluation system are divided into five types (see Table A3 in Appendix A) and converted according to the rules in Table A4 in Appendix A.

Step 8: The ER integration algorithm is employed to integrate the candidate network's evaluation score membership distribution across all indicators.

Step 9: Based on the distribution of the evaluation score, the expected utility of the evaluation score is used as the final adaptability score for ranking the candidate network. Here, a uniform distribution function is used, where u (very poor) = 0, u (poor) = 0.25, u (medium) = 0.5, u (good) = 0.75, u (excellent) = 1.

4. Case Study

Shanghai Port was selected as the focus of this case study due to its representative characteristics, including large-scale infrastructure, high container throughput, and significant exposure to extreme weather events. These factors make it an ideal subject for evaluating both resilience and adaptability within port transport networks.

4.1. Resilience Analysis of Shanghai PCTNs

The case study considers three main types of meteorological disasters—typhoons, storm surges and heavy fog—each with varying probabilities and impacts on network damage. Seaports do not adjust immediate recovery measures based on the type of disaster. Therefore, in all disaster situations, seaport infrastructure and equipment are likely to be destroyed. We assumed that two key recovery strategies employed by seaports aim to rapidly mitigate the impacts of disasters. First, seaports can utilise prepared redundant resources, such as additional gantry cranes and available storage space, to maintain a certain level of container handling during meteorological disasters. These measures, however, come with additional costs to prevent and mitigate the effects of disasters before they occur. Second, ports focus on urgently repairing damaged infrastructure and equipment to restore container handling capacity as quickly as possible. Although this may take longer than relying on existing redundant resources, it may ultimately lead to a more robust recovery effect. Effectively implementing these two strategies requires the harbour to have high predictability and rapid response to potential meteorological disasters. By efficiently applying these two recovery measures, seaports can quickly restore their operational status after experiencing varying levels of disaster impact, minimise economic losses, and accelerate the return to normal container-handling efficiency.

The variables used in this study are drawn from the most recent and accessible sources available for each parameter. Therefore, the reference years are not identical across all variables. The 2025 railway freight capacity parameter is used because it reflects the updated operating capacity of freight trains in China, while the 2021 Shanghai Port throughput and trade-value data are adopted because they provide complete and comparable port-level information on container volume and cargo value. Although this cross-year data setting may introduce a certain degree of temporal inconsistency, the variables are mainly used for scenario simulation and relative comparison among disaster types rather than for estimating the exact annual operating performance of Shanghai Port. To reduce the influence of scale differences, key disaster-related parameters are normalised before being incorporated into the resilience model.

4.1.1. The Variable Setting

The parameter values used in the simulation are drawn from multiple publicly available sources, including the China Port Yearbook, Shanghai Port annual statistical bulletins,

and prior risk assessment studies [31–34]. Key empirical inputs and their derivations are described below.

In 2025, each freight train operating in China can carry 55 40-foot containers, up from 50, increasing the average container-carrying capacity by about 8% [32]. In 2021, the container handling capacity of Shanghai Port reached 26.27 million TEU [31]. The container's time at the port depends on the container operating rate, defined as the average number of containers handled per hour. According to statistics [31], the Port of Shanghai can handle an average of 3800 containers per hour. Therefore, the standard operating time of Shanghai Port is the port's container demand divided by its container handling rate.

The values of the variables set above are all within normal limits. Disaster prediction relies on integrated technologies, including IoT-enabled tide gauges for storm surges, LiDAR for fog detection, and AI models analysing historical typhoon trajectories [33]. Shanghai Port's 'Smart Port' initiative employs these tools to provide 24–72 h advance warnings, enabling preemptive recovery measures [34]. According to the risk assessment for the three kinds of climate disasters in Shanghai Port, the normalised weights of the risk indicators of typhoon, storm surge and heavy fog, specifically the probability of port damage (related to variables δ), are 0.327, 0.070 and 0.602, respectively. Generally, the reduced capacity of a port due to damage (with variable C correlated) and the increased operating time due to damage (correlated with variables τ) are proportional to the probability of port damage. Since this study focuses on comparing the impact of different disaster types on port resilience, the capacity reduction and the increase in operating time due to damage are set at 32.7%, 7%, and 60.2% of normal port operation for the three disaster scenarios. It should be noted that the probability of port damage and the magnitude of operational impact are conceptually different. The former reflects the likelihood that a meteorological disaster will disrupt port operations, while the latter reflects the severity of capacity loss and delay once the disruption occurs. In the present simulation, these two dimensions are linked via normalised disaster-risk weights, as complete empirical data on disaster-specific capacity losses are not available. This setting is intended to provide a tractable first-stage comparison of different meteorological hazards rather than a fully separated probability–impact risk model.

To avoid over-interpreting the results, the resilience scores should therefore be understood as scenario-based relative indicators. Future research can improve this model by independently estimating the probability of disaster occurrence and the magnitude of its impact. For example, typhoon probability could be derived from historical landfall frequency, while impact magnitude could be estimated from observed port closure duration, berth suspension time, equipment damage records, or AIS-based vessel delay data.

For simplicity, this simulation assumes that all containers have the same average cargo value. This assumption does not mean that the real cargo values of different containers are identical. In actual port operations, cargo value varies significantly by commodity type, trade route, consignee, and time sensitivity. However, detailed container-level commodity-value data are difficult to obtain because of commercial confidentiality and data availability constraints. Therefore, the study uses the average cargo value per TEU as a simplified proxy to estimate the potential economic exposure associated with port disruption.

This simplification allows the resilience model to maintain a unified measurement standard and ensures that different disaster scenarios can be compared on a common economic baseline. In 2021, the total value of imported and exported container goods at Shanghai Port was 72.68 billion USD, and the annual container throughput was 47.03 million TEU. Thus, the average value of imported and exported container goods at Shanghai Port in 2021 was approximately 1545 USD per TEU. Nevertheless, this assumption may underestimate the losses associated with high-value or time-sensitive cargoes and overestimate the losses

of low-value bulk containerised goods. Future studies could introduce heterogeneous cargo-value scenarios by classifying containers according to commodity type, value density, or delivery urgency.

Table 5 presents the values of the variables involved in the immediate recovery measures. Measures 1 and 2 correspond to using the port's redundant capacity to maintain a basic level of container throughput and to urgently repairing damaged equipment and infrastructure, respectively. Some of these variables can be calculated directly from actual data, while others rely on estimates. The data for recovery measure 1 primarily concern additional resources available at the port, whereas Measure 2 concerns an estimate of the extent of damage and repair speed. Accurate acquisition and analysis of these data are essential to ensure the reliability and practicality of the simulation. The effects and implementation of different recovery strategies in real disaster situations can be systematically understood and evaluated through these simulations.

Table 5. Port to take immediate recovery measures variable simulation value.

Restoration Measure	Recovery Capacity of Damaged Facilities	Operation Time After Recovery	Required for Recovery Measures	
			Time	Cost
1	Pre-disaster level x 60%	Pre-disaster level x 160%	50%	310,000 USD
2	Pre-disaster level x 80%	Pre-disaster level x 120%	150%	690,000 USD

4.1.2. Results Analysis

Independent simulations were conducted for three different types of meteorological disaster scenarios, and the specific results are shown in Figure 2. The simulations reveal clear differences regarding the impact of the three types of natural disasters on the railway transportation network of Shanghai Port and its hinterland. When heavy fog disrupts the port, the network resilience is 0.73, the lowest of the three resilience scores. The typhoon ranked second in resilience level (0.81), while the highest level of network resilience is under climatic disasters such as storm surges. The simulation results show that storm surges have the least impact on Shanghai Port operations, whereas low-visibility conditions caused by heavy fog have a more significant impact on the resilience of both Shanghai Port and the entire hinterland network. Specifically, the port container transport network needs to prioritise the prevention of heavy fog-related disruptions. It is necessary to rely on the network's conditions to strengthen adaptability to heavy fog across various aspects, including early investment, preventive measures, post-recovery strategies, and relevant policies.

In addition to the average resilience values reported in this study, the simulation results also exhibited noticeable variability across iterations due to stochastic differences in disruption severity, operational recovery time, and transport capacity reduction. The distribution of resilience outcomes remained relatively stable across iterations, indicating satisfactory convergence of the Monte Carlo simulation. The variability observed under heavy fog scenarios was generally larger than that under storm surge scenarios, reflecting the higher uncertainty and operational instability associated with visibility-related disruptions in multimodal transport systems.

This difference can be explained by the operational characteristics of the three disaster types within the model structure and real-world port operations. Storm surges are generally associated with shorter-duration disruptions and can often be mitigated through advanced warning systems and temporary suspension strategies. In contrast, heavy fog simultaneously affects vessel navigation, berth allocation efficiency, road transportation visibility, and multimodal coordination, thereby generating broader and more persistent disruptions

across the entire PCTN. From a modelling perspective, the higher disruption probability and longer operational recovery time assigned to heavy fog scenarios significantly reduce the network's effective handling capacity, leading to lower resilience scores.

These scenario-dependent resilience scores reflect distinct causal mechanisms. Heavy fog impairs visibility across road, rail and maritime sectors, creating cascading delays and heightened coordination complexity; typhoons primarily damage port superstructure and energy supply but can be mitigated through pre-emptive equipment anchoring and power backup; and storm surges are relatively transient and localised, allowing for suspension-and-resumption strategies. The results, therefore, highlight that investments in real-time meteorological monitoring, flexible traffic scheduling and cross-modal substitution yield greater resilience benefits than structural hardening alone. From a managerial standpoint, port authorities should integrate forecasting with dynamic resource allocation, adjust berth schedules to prioritise recovery-critical cargo, and coordinate with hinterland agencies to ensure redundancy across transport modes.

This finding is generally consistent with previous studies highlighting the vulnerability of port operations to visibility-related disruptions and operational uncertainty under adverse weather conditions. Compared with studies primarily focusing on large-scale disasters such as typhoons or storm surges, the present study further demonstrates that lower-intensity but high-frequency meteorological events, such as heavy fog, may generate more persistent operational disturbances in highly connected PCTNs. This result extends existing resilience research by providing a disaster-specific comparison framework for evaluating different types of climate-related disruptions (Figure 4).

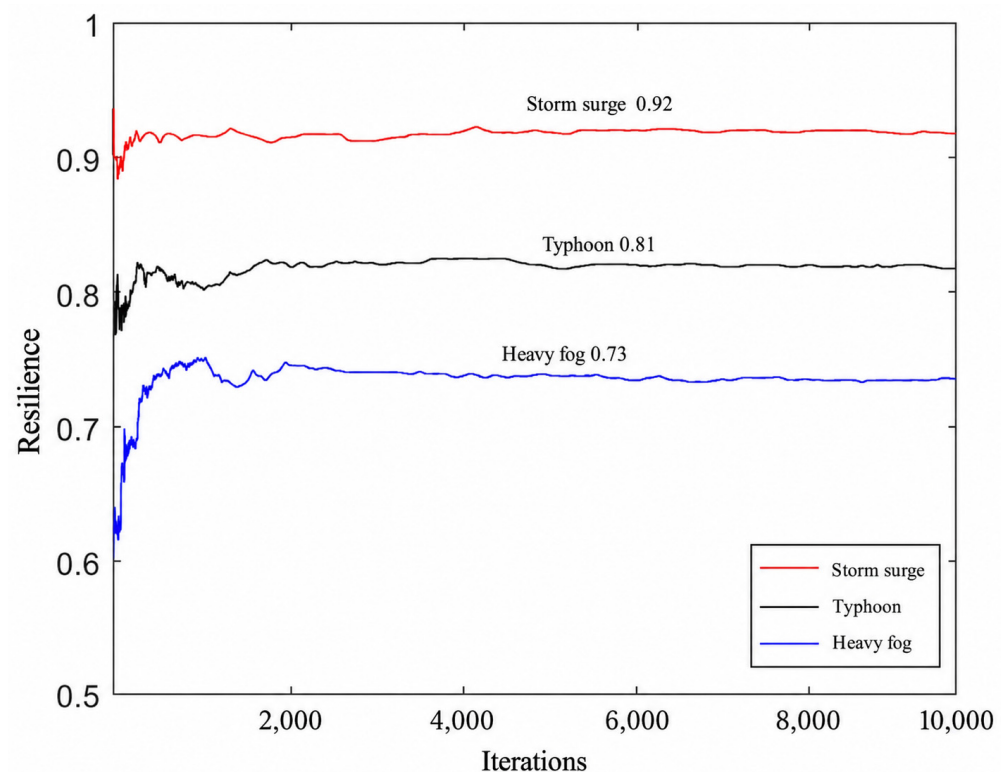


Figure 4. Network resilience under three kinds of meteorological disasters.

4.2. Adaptability Analysis of Shanghai PCTNs

The evaluation system outlined above is applied to the container railway transport network of Shanghai Port in China, using the AHP-ER method to assess network adaptability and enhance resilience against various meteorological disasters.

4.2.1. Data Collection and Processing

In order to ensure the successful execution of the port meteorological disaster adaptability assessment questionnaire, the authors first selected professionals with extensive experience in port management, transportation policy, meteorological disaster management, and other relevant fields. The potential interviewees were identified through industry contacts, academic networks, and professional conferences. Afterwards, the detailed questionnaire was carefully designed and trialled on a small scale to ensure its scientific validity and effectiveness. During the trial phase, participant feedback was collected, and necessary adjustments and improvements were made. Once the trial was completed and modifications were incorporated, the questionnaires were officially distributed to the selected experts via email, online questionnaire platforms or offline mail. Each participant receives an invitation letter with a link to the questionnaire or a physical copy explaining the purpose of the survey, its importance, and instructions for participating.

The questionnaire was designed according to the hierarchical structure of the adaptability evaluation index system. It mainly contained pairwise comparison questions for the AHP procedure and supplementary questions concerning experts' professional background. Before the formal survey, a pilot test was conducted with a small group of respondents familiar with port operations and transport planning. The purpose of the pilot test was to examine whether the indicator descriptions were clear, whether the pairwise comparison logic was understandable, and whether the questionnaire length was acceptable. Based on the feedback, ambiguous wording was revised, and the sequence of questions was adjusted to improve readability and response quality.

To ensure the reliability of expert judgments, the study applied the AHP consistency test to each pairwise comparison matrix. Matrices that did not satisfy the consistency threshold were excluded from the subsequent weight calculation. This procedure helped reduce the influence of logically inconsistent judgments and improved the robustness of the final index weights. Although no additional psychometric reliability test, such as Cronbach's alpha, was conducted because the questionnaire was designed for pairwise comparison rather than latent-variable measurement, the consistency-ratio screening provides a methodological check on the reliability of the expert evaluations.

To develop the index weight system based on the expert group's opinions, 36 questionnaires were distributed, and 30 were completed (the detailed experts' information in Appendix Table A4), resulting in an 84% response rate. The sample size is relatively small, but it is considered acceptable for an expert-based AHP-ER evaluation, as the survey's purpose is not to conduct population-level statistical inference but to obtain structured professional judgments from specialists with relevant knowledge. The 30 valid responses cover port operations, transport policy and planning, railway transport administration, port risk management, and academic research. This diversity helps ensure that the evaluation reflects multiple dimensions of PCTN adaptability rather than the opinion of a single professional group. However, the sample may still be subject to regional and professional bias, as most experts are connected with the Yangtze River Delta port and transport system. Therefore, the results should be interpreted as expert-supported case-study evidence rather than a universal evaluation of all port-centric transport networks. The above steps guarantee a high response rate and robust data quality, providing a solid foundation for subsequent analysis. The appendix includes background information on the experts who participated in the survey. The questionnaire primarily focused on the importance of evaluating indicators from the second to fourth layers of the evaluation system, with scores determined through pairwise comparisons. During this process, to ensure the independence and objectivity of the evaluation, each invited expert independently rated the importance of each indicator,

thereby systematically collecting and organising expert opinions and providing support for the subsequent weight analysis.

Additionally, field data from the Shanghai PCTN were collected as secondary inputs for the ER stage. These data were converted into a unified decision matrix using the rule-based information conversion procedure reported in Appendix Table A3. The resulting matrix was then processed through the ER algorithm to generate comparable indicator scores and final subnetwork rankings.

4.2.2. Weights of Indexes

A total of 180 pairwise comparison matrices were obtained, including 60 for each disaster scenario. Of these, 34 were excluded after the consistency screening described in Section 3.2.2. The remaining 146 matrices were aggregated under equal expert weights to derive the primary- and secondary-level indicator weights reported in Tables 6 and 7.

Table 6. Primary-level adaptability weights across meteorological disaster scenarios.

Primary Indicator	Typhoon	Storm Surge	Heavy Fog
Natural conditions	0.196	0.114	0.219
Social and economic conditions	0.158	0.230	0.179
Infrastructure	0.409	0.307	0.323
Organisational management	0.237	0.349	0.279

Table 7. Global weights of secondary adaptability indicators across disaster scenarios.

Secondary Indicator	Typhoon	Storm Surge	Heavy Fog
Geographical distance from Shanghai Port	0.196	0.114	0.219
Road container transport cost advantage	0.158	0.230	0.179
Highway density	0.151	0.101	0.123
Highway traffic congestion degree	0.141	0.096	0.114
Redundancy of container handling capacity of hinterland ports	0.117	0.110	0.086
Ownership form and management mode of the port	0.237	0.349	0.279

In the case of typhoon disasters, compared to external factors (e.g., natural environment and socio-economic conditions), the internal capacity of the network (e.g., infrastructure and organisational management) is more important, accounting for more than 60% of the weight. This suggests that strengthening internal capacity-building is more critical to disaster response than focusing on external conditions. This means that infrastructure is the first priority for improving network adaptability during typhoon disasters, while also enhancing organisational management, which is crucial. The most effective way to mitigate the risks posed by typhoon disasters is to improve infrastructure to minimise losses when disasters occur.

For storm surge disasters, the weight of organisation and management is 0.349, indicating that organisation strategies play a leading role in handling storm surge impacts. Ports can improve their ability to manage storm surges through effective management strategies. Port authorities can ensure orderly evacuations, protect ships and cargo, and reduce property damage during emergencies by developing and testing emergency response plans for storm surges. Organising the necessary training enables all staff to become familiar with storm-surge procedures and responsibilities. These training activities include drills and educational sessions to improve employees' disaster awareness and response capacity and

establish a disaster recovery plan to quickly restore the port's operational capacity and reduce economic losses. On the other hand, effective organisational measures can enhance ports' resilience during storm surge disasters, reduce potential economic losses, and ensure the safety of personnel and ships [35].

In the case of heavy fog, although the weight of infrastructure remains the highest, the impact of natural conditions is significantly greater than in typhoons and storm surges. Heavy fog is a critical meteorological hazard that reduces visibility and poses risks to shipping and port operations. The natural conditions of the port play a fundamental role in preventing and responding to the disaster. For instance, the latitude and distance from the ocean where the port is located could affect its current movement and humidity level, determining the frequency and intensity of heavy fog disasters.

After steps 6 and 7, we obtain the vertical coordinate, which is the global weight value, and the horizontal coordinate is the top-down arrangement of the secondary indexes in Table 6. The weights of the secondary indexes of the evaluation system are shown in Figure 5. The more effective measures are often aimed at secondary indicators with higher importance rankings to improve network adaptability. In other words, by prioritising each secondary index's ranking, adopting corresponding measures can more effectively enhance the network's adaptability. For typhoons and storm surges, the top two indicators are "geographical distance from Shanghai port" and "port ownership form and management mode", while for heavy fog, the top two indicators are "road container transportation cost advantage" and "port ownership form and management mode". The network's overall adaptability is affected by various factors, including whether the port has sufficient awareness of natural disaster risk, whether its organisational management model is appropriate, and whether the natural conditions are favourable. Together, these factors determine the network's adaptive level. After Steps 6 and 7, the indicator weights are obtained and reported in a more readable form. Table 6 summarises the primary-level weights for the four adaptability dimensions, while Table 7 lists the global weights of the six secondary indicators used to construct Figure 5. The figure therefore visualises the differences in the secondary-level weights without requiring readers to extract them from a highly condensed table.

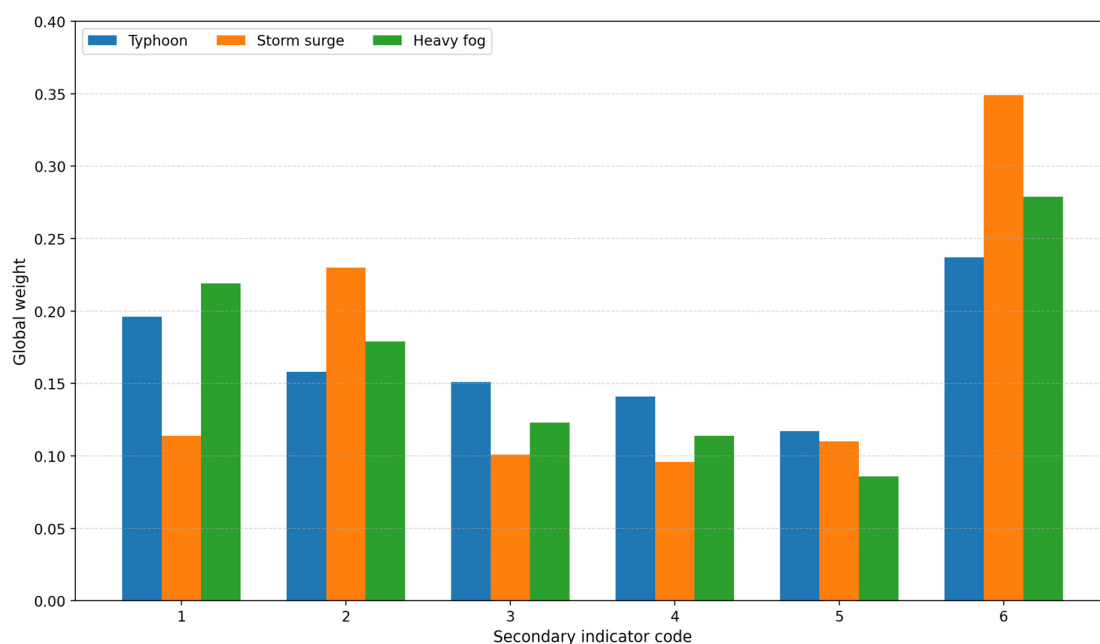


Figure 5. Relative weights of secondary indicators under three disaster scenarios.

In Figure 5, the horizontal axis (1–6) denotes six secondary indicators: (1) geographical distance from Shanghai Port, (2) road container transport cost advantage, (3) highway density, (4) highway traffic congestion degree, (5) redundancy of container handling capacity at hinterland ports, and (6) ownership form and management mode of the port. The vertical axis reports the corresponding global weight, allowing direct comparison across the three meteorological disaster scenarios.

Figure 5 also reveals that the importance of adaptability factors is scenario-dependent rather than fixed. Infrastructure-related indicators remain prominent across the three scenarios, but organisational management becomes relatively more salient under storm-surge conditions, while natural-condition sensitivity becomes more evident under dense fog. The figure, therefore, supports a differentiated reading of adaptability: a single generic improvement package would overlook the distinct priorities implied by each meteorological hazard.

4.2.3. Result Analysis

The composite adaptability scores and rankings of the four candidate subnetworks under typhoon, storm-surge, and heavy-fog scenarios are summarised in Table 8, while Figure 6 visualises the cross-scenario score differences. The full five-grade membership distributions are retained in Appendix Table A3.

The ranking results are generally consistent with previous studies that emphasise the importance of infrastructure redundancy, organisational coordination, and adaptive management for port resilience. Existing research has shown that port networks are affected not only by the physical exposure of port facilities but also by the ability of operators and public authorities to coordinate resources, adjust transport routes, and maintain service continuity during disruptions. In this study, Shanghai ranks first across all three disaster scenarios, reflecting its stronger economic foundation, denser infrastructure network, and more mature port management capacity. However, differences among Zhejiang, Anhui, and Jiangsu indicate that adaptability is not determined solely by geographical proximity. Instead, it depends on the combined effect of road transport substitution capacity, hinterland port redundancy, congestion conditions, and management structure.

The results also show that different meteorological disasters require different adaptation priorities. For typhoons, infrastructure-related indicators are particularly important because strong wind and rainfall can directly affect cranes, storage yards, access roads, and intermodal transfer facilities. For storm surges, organisational management receives a higher weight, suggesting that emergency planning, evacuation coordination, cargo protection, and post-disaster recovery arrangements are central to reducing losses. In heavy fog, the cost advantage of road container transport and traffic conditions become more influential, as low visibility can repeatedly interrupt port access and inland distribution, increasing the need for flexible road–rail substitution and real-time traffic scheduling.

Based on the adaptability rankings, different improvement strategies should be adopted for the four sub-networks. For the Shanghai sub-network, the main task is to reduce congestion around the port area and improve emergency traffic organisation. Practical measures include strengthening real-time traffic guidance near terminal gates and improving coordination between terminal operators, road authorities, and railway dispatching departments, especially during heavy fog or other short-term disruptions.

For the Zhejiang sub-network, greater attention should be paid to risk warning and emergency response coordination with Shanghai Port. Zhejiang ports could improve information sharing on meteorological warnings, berth availability, and temporary cargo diversion plans, so that part of the cargo flow can be adjusted in advance when Shanghai Port faces disruption.

For the Jiangsu sub-network, the priority is to improve backup handling capacity and temporary storage capacity at hinterland ports. This can be achieved by reserving flexible yard space, preparing mobile handling equipment, and strengthening coordination with nearby ports during peak disruption periods.

For the Anhui sub-network, improvement should focus on inland transport connectivity and emergency management capacity. Local authorities and transport operators should strengthen coordination between road and rail, improve emergency communication mechanisms, and gradually reduce bottlenecks in major container transport corridors.

These adaptability patterns complement the resilience findings. The relatively strong performance of Shanghai reflects the combined advantages of spatial proximity, transport substitution potential, and managerial capacity, whereas the lower-ranked subnetworks face greater constraints when disruption requires rapid modal or operational adjustment. This interpretation is consistent with the earlier literature, which emphasises the importance of infrastructure robustness, organisational preparedness, and long-term adaptive capacity in port systems.

From a practical perspective, the results support three targeted priorities: strengthening visibility monitoring, berth scheduling coordination, and truck/rail dispatch under dense fog; improving equipment protection, emergency maintenance readiness, and staged restart procedures under typhoons; and reinforcing cross-agency warning transmission and emergency coordination under storm-surge conditions. These recommendations are directly tied to the scenario-specific patterns identified in the case analysis.

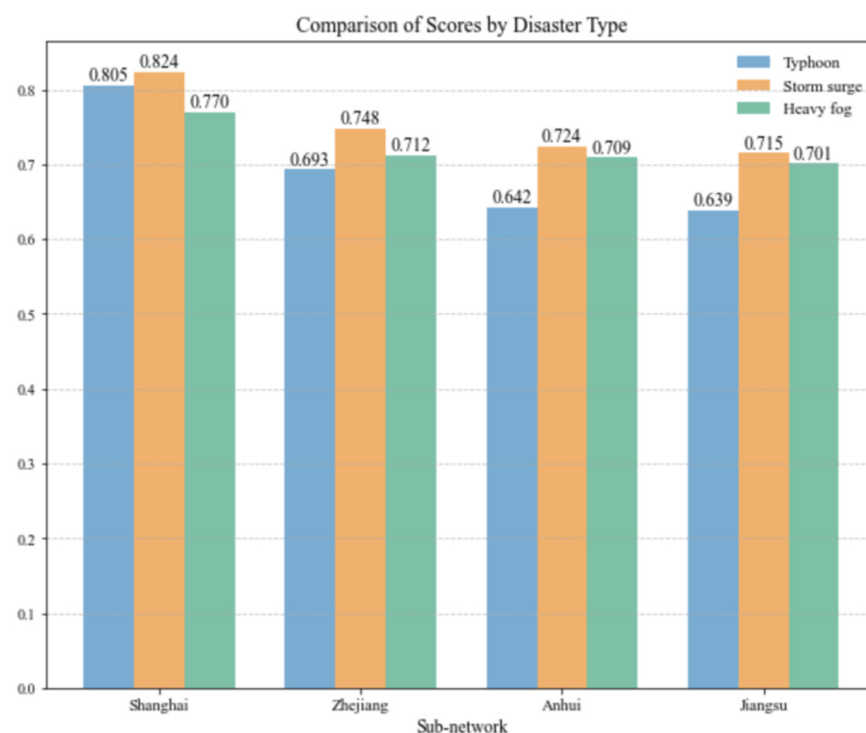


Figure 6. Adaptability scores of Shanghai PCTNs.

Table 8. Adaptability evaluation of Shanghai PCTNs.

Disaster Type	Rank	Sub-Network	Very Poor	Poor	Medium	Good	Excellent
Typhoon	1	Shanghai	0.032	0.045	0.112	0.174	0.607
	2	Zhejiang	0.031	0.089	0.332	0.239	0.325
	3	Anhui	0.069	0.204	0.251	0.110	0.383
	4	Jiangsu	0.049	0.098	0.301	0.318	0.225

Table 8. Cont.

Disaster Type	Rank	Sub-Network	Very Poor	Poor	Medium	Good	Excellent
Storm surge	1	Shanghai	0.092	0.063	0.127	0.136	0.643
	2	Zhejiang	0.036	0.094	0.251	0.264	0.401
	3	Anhui	0.084	0.076	0.237	0.213	0.427
	4	Jiangsu	0.093	0.070	0.249	0.241	0.392
Heavy fog	1	Shanghai	0.071	0.163	0.239	0.264	0.412
	2	Zhejiang	0.136	0.134	0.347	0.159	0.386
	3	Anhui	0.114	0.259	0.302	0.162	0.372
	4	Jiangsu	0.095	0.349	0.249	0.144	0.381

5. Conclusions

This study develops an integrated but functionally separated framework for evaluating how PCTNs respond to meteorological disasters. Applied to Shanghai Port, the results show that heavy fog produces the lowest resilience score (0.73), followed by typhoons (0.81) and storm surges (0.89), indicating that frequent low-visibility disruptions can impose more persistent operational losses than higher-energy but more localised hazards. The analysis therefore shifts managerial attention from structural hardening alone to visibility monitoring, dynamic scheduling, and cross-modal coordination.

The adaptability assessment further shows that Shanghai consistently outperforms the three hinterland subnetworks, while Jiangsu and Anhui remain the most constrained in terms of handling redundancy, inland connectivity, and organisational preparedness. These differences imply that resilience policy should be spatially differentiated: Shanghai requires congestion-management and recovery-coordination refinement; Zhejiang benefits most from tighter warning and diversion coordination with Shanghai Port; Jiangsu requires additional backup handling and storage capacity; and Anhui needs stronger road–rail emergency coordination and corridor upgrades. Scientifically, the study connects hazard-specific resilience modelling with subnetwork-level adaptability diagnostics; practically, it provides a basis for prioritising investments and emergency measures by disaster type and regional function.

Despite the valuable findings obtained in this study, several limitations should be acknowledged. First, the resilience assessment framework relies on a set of simplifying assumptions in the integer programming and Monte Carlo simulation processes, including fixed container demand, uniform cargo value, and predefined recovery strategies, which may not fully capture the operational complexity of real-world port systems. Second, the adaptability evaluation based on the AHP-ER method still depends partly on expert judgement and the availability of regional statistical data, which may introduce subjectivity and affect the robustness of indicator weighting. Third, this study focuses exclusively on Shanghai Port and its surrounding subnetworks; therefore, the findings may not be fully generalisable to ports with different governance structures, climatic conditions, or infrastructure characteristics. In addition, only three representative meteorological disasters—typhoon, storm surge, and heavy fog—are considered in this study, while other climate-related disruptions, such as flooding, heatwaves, and tsunamis, are not included. These limitations provide important directions for future research and highlight the need for broader datasets, dynamic modelling approaches, and cross-regional comparative studies.

In the current framework, each disaster scenario is associated with a single dominant recovery measure to simplify the optimisation and recovery simulation process. However, actual post-disaster port operations often involve multiple parallel recovery actions, including infrastructure repair, emergency rerouting, equipment replacement, and

labour coordination. The single-measure assumption may therefore limit the model's ability to fully capture the complexity and interaction effects of real-world recovery strategies. Although the proposed framework is theoretically transferable to other ports, its applicability may vary depending on differences in governance structures, technological maturity, hinterland connectivity, and operational scale. Future studies should validate the framework using comparative multi-port case studies across different geographical and institutional contexts.

Beyond the Shanghai case, the proposed framework is designed to be transferable to other port systems. To apply it elsewhere, practitioners can recalibrate the integer-programming model with local capacity constraints and disaster-specific recovery options, adjust the Monte Carlo distribution parameters based on regional hazard data, and revise the AHP-ER indicator weights to reflect local infrastructure and organisational contexts. By customising these inputs, the framework can support comparative analyses across different ports and guide tailored resilience and adaptability strategies in diverse geographical and institutional settings.

This paper explores the impacts of three meteorological disasters on PCTNs, taking the Shanghai PCTNs as a representative example. Targeted adaptation measures and management recommendations are provided to further enhance the resilience and adaptability of ports and their sub-networks in response to climate change and extreme meteorological events. Future research could be conducted on the following aspects:

1. **Broader Data Application and Model Integration:** Future studies could incorporate a more comprehensive range of data, including real-time environmental monitoring and socio-economic data, and consider different disaster impacts, such as floods or cold waves. This study specifically focuses on typhoons, storm surges, and dense fog, as the Shanghai Port faces relatively low tsunami threats. Future research could extend to circum-Pacific ports with higher tsunami risks, such as Tokyo Port. At the same time, advanced technologies, such as machine learning, could be introduced to improve the existing impact assessment model by integrating it with highly accurate, practical predictions.
2. **Dynamic Adaptability and Resilience Analysis:** Currently, most research focuses on static toughness assessment. Future research could explore dynamic adaptive models to track and predict network response and recovery processes in real time, both before and after disasters. Furthermore, research could analyse the temporal dynamics of decision-making and explore how to optimise decision-making time to minimise the negative impacts of disasters.
3. **Cross-Regional Collaboration and Resource Allocation Optimisation:** With the development of globalisation, exchanges and cooperation between different regions are increasingly enhanced. Future studies need to explore how to achieve optimal resource allocation and enhance the overall network's resilience through cross-regional coordination and cooperation. This could include, but is not limited to, developing cross-regional emergency response mechanisms and sharing of critical information and resources. A prioritised approach would be to pilot integrated emergency response mechanisms in the Shanghai-Zhejiang corridor, where shared berthing rights allocation and standardised joint drills could be implemented specifically for storm surge scenarios (achieving the highest resilience score of 0.89 in our study).
4. **Multi-Measure Synergy and Operational Coordination:** While the current model employs single-measure simplification to clarify decision hierarchies and compare core strategies, practical scenarios require the concurrent execution of multiple recovery actions. Future research should develop dynamic optimisation frameworks that account for resource conflicts and temporal coupling between measures. This could

be achieved through advanced operational research methods such as stochastic dynamic programming and multi-agent modelling, which enable quantitative analysis of multi-measure synergy effects. Particular emphasis should be placed on temporal coordination among infrastructure hardening, emergency resource mobilisation, and operational rerouting strategies across varying disaster phases.

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Appendix A

Table A1. Five-point scale of relative importance.

Relative Importance	Explanation
1	Indicator <i>i</i> is very important compared to indicator <i>j</i>
2	Indicator <i>i</i> is more important compared to indicator <i>j</i>
3	Indicator <i>i</i> is just as important compared to indicator <i>j</i>
4	Indicator <i>i</i> is less important compared to indicator <i>j</i>
5	Indicator <i>i</i> is not important compared to indicator <i>j</i>

Table A2. Type of secondary index in evaluation system.

Original Data Type	Specific Index
Regional correlation, quantitative and negative influence on adaptability level	1. Geographical distance from Shanghai Port 2. Highway traffic congestion degree
Regional correlation, qualitative and positive influence on adaptability level	Road container transport cost advantage
Regional correlation, quantitative and positive influence adaptability level	Highway density
Port correlation, quantitative and positive influence adaptability level	Redundancy of container handling capacity of hinterland ports
Port correlation, qualitative and positive influence adaptability level	Ownership form and management mode of port

Table A3. Rule-based information conversion method.

Original Data Type		Conversion Method				
		Very Poor	Poor	Medium	Good	Excellent
Qualitative	Positive influence	1	2	3	4	5
Qualitative	Negative influence	5	4	3	2	1
Quantitative	Positive influence	Minimum	Lower quartile	Medium	Upper quartile	Maximum
Quantitative	Positive influence	Maximum	Upper quartile	Medium	Lower quartile	Minimum

Table A4. Expert background.

Number of Experts	Organisation	Position	Professional Field	Working Experience (Years)
12	Shanghai International Port Group	Port operations manager	Port management and operation	5–10
2	Transport research Institute	Researcher	Transport policy and plannin	7
8	Shanghai Railway Bureau	Operation dispatching department	Railway transport administration	3–15
5	Nanjing Port Authority	Risk management manager	Port management and operation	5–14
1	Wuhan University of Technology	Professor	Port risk management	8
1	Changsha University of Science and Technolog	Professor	Rail transit planning	11
1	Hohai University	Associate professor	Transportation Planning and Management	6

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