Transportation Research Part A 208 (2026) 104987

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Resilience assessment of multimodal container ports under operational disruptions: a global sensitivity analysis

Jinglin Zhang [a], Xuri Xin [a,b,*], Rameshwar Dubey [c,d], Trung Thanh Nguyen [a], Xiaoning Shi [e], Na Li [f], Zaili Yang [a,*]

[a] Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK
[b] School of Navigation, Wuhan University of Technology, Wuhan, Hubei, China
[c] MBS School of Business, 2300 Avenue des Moulins, 34080 Montpellier, France
[d] Liverpool Business School, Faculty of Society and Culture, Liverpool John Moores University, Liverpool, Merseyside L3 5UG, UK
[e] Institute of Transport Research, German Aerospace Center (DLR), Berlin 12489, Germany
[f] College of Transportation Engineering, Dalian Maritime University, Dalian 116026, China

ARTICLE INFO

Keywords:
Container supply chain
Port disruption
Ripple effect
Resilience
Global sensitivity analysis

ABSTRACT

Assessments of port operational resilience are often fragmented in the existing literature and practices, primarily concentrating on local-level risks related to individual components and/or subsystems. These evaluations treat each component and subsystem in a port independently, neglecting the interconnected ripple effects throughout the port from a multimodal perspective. Consequently, improvements targeting individual components may not yield an optimal outcome for the entire port system. Key components, including liner shipping, feeder shipping, railroads, and trucking, constitute the fundamental operational structure of a multimodal container port. As ports evolve to incorporate new technologies, the complexity of their operations increases, emphasising the need for accurate management of port operational resilience. In response, this paper introduces a novel methodology to assess multimodal port resilience by quantifying the impact of various disruptions and identifying the interactions among them that could lead to a ripple effect. In this framework, port operations are first simulated through System Dynamics (SD) modelling. The resulting performance is then transformed into resilience indicators, which are synthesised across subsystems using the Evidential Reasoning (ER) method. Finally, the Sobol Global Sensitivity Analysis (GSA) is employed to assess the influence of individual and joint disruptions. To assess the consistency of the results, the Intraclass Consistency Coefficient (ICC) is calculated for three different GSAs. Using historical failure data and field evidence, multiple disruption scenarios are explored. The outcomes indicate that failures of yard and quay cranes have the greatest impact on port resilience. It is further observed that many disruptions arise from interdependent failures rather than individual malfunctions, leading to amplified ripple effects. The results provide a data-driven foundation for policymakers and port managers to shift from experience-based to evidence-based allocation of emergency resources, with evidence generated through large-scale simulations of plausible but previously unobserved disruption scenarios. They also support cross-agency coordination for integrated resilience management against compound disruptions arising from ripple effects. In summary, this framework, for the first time, offers

* Corresponding authors at: Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK.

E-mail addresses: xrxin@whut.edu.cn (X. Xin), Z.Yang@ljmu.ac.uk (Z. Yang).

https://doi.org/10.1016/j.tra.2026.104987
Received 29 July 2025; Received in revised form 31 January 2026; Accepted 18 March 2026
Available online 28 March 2026

crucial insights for bolstering long-term resilience in multimodal container port operations from a systematic overall perspective.

1. Introduction

Container ports, as pivotal hubs within the global container logistics network, play a crucial role in linking multiple transportation modes and facilitating the seamless transhipment of containers (Guo et al., 2023b). However, inherent vulnerabilities such as geographical locations, political and economic significance, and the surrounding infrastructure development, coupled with external challenges such as complex transportation networks, severe weather events (Wang et al., 2024; Wen et al., 2024; Jiang et al., 2021), geopolitical tensions, labour market fluctuations, terrorism, and broader economic disparities render the ports highly susceptible to disruptions. Global disruptions, including the COVID-19 pandemic (Gu et al., 2025), nationwide port strikes in the US (Zhao et al., 2024) and the Red Sea crisis (Wu and Liu, 2025) have underscored the pressing need for enhancing port resilience.

Beyond these external vulnerabilities, the ports' core transhipment function further increases their internal instability. By linking multiple transport modes, including liner and feeder shipping, rail, and trucking, ports operate as tightly coupled systems in which disturbances in one mode can propagate to others (Zhang et al., 2025b). This high level of interconnectivity allows disruptions in a single subsystem to cascade throughout the entire network, amplifying operational instability and generating ripple effects across multiple transport modes, as evidenced by the previous studies in which the indirect damages caused by the ripple effects of such disruptions frequently exceed the direct losses (Bai et al., 2022). Due to the high connectivity of port systems, the rapid propagation of risks, and the extensive consequences they entail, incorporating the ripple effect into port resilience research is a crucial yet under-explored area in existing literature (Dolgui and Ivanov, 2021; Jiang et al., 2024). Therefore, in this study, disruption refers to an event that compromises the port component's functionality, potentially affecting other interconnected components and overall operations. Besides, the selection of these disruptions is based on real-world accident reports. In contrast to other metrics employed to assess systems' responses to disruptions, the concept of resilience provides a holistic representation of the system's ability to remain reliable, robust, and recoverable (Gonçalves and Ribeiro, 2020). Consequently, resilience has become widely recognised, particularly in the maritime field, where it is often measured by performance over time (i.e., the resilience triangle) (Wan et al., 2019). Previous studies defined resilience through three fundamental criteria: (i) a gradual degradation process (i.e., a low rate of performance degradation), (ii) a swift restoration process (i.e., a high rate of performance restoration), and (iii) satisfactory performance throughout the observation timeframe (Cheng et al., 2022).

Recognising the unpredictable nature of port disruptions establishes a context where decisions to enhance resilience are inherently linked to uncertainty. Within this broad framework, it becomes necessary to evaluate how different uncertainties affect port disruptions and identify key determinants. Consequently, this necessitates adopting methodologies to accurately quantify uncertainty and explain how changes in output (i.e., resilience) can be attributed to inputs (i.e., variability in disruptions).

Within the context of Uncertainty Quantification (UQ), Sensitivity Analysis (SA) methods are one of the most effective in screening out highly influential input parameters, which are categorised into Local Sensitivity Analysis (LSA) and Global Sensitivity Analysis (GSA) (Schmitz et al., 2023). The LSA method, also referred to as "one at a time" (OAT), involves changing a single variable while holding the others constant to observe changes in the output. It is generally unsuitable for complex, high-dimensional models because it allows only single-parameter variations. In contrast, the GSA method evaluates the effects of input parameters across the entire feasible range of the input space, allowing the analysis of interactions among input parameters (Cheng et al., 2023; Saltelli et al., 2010).

Although GSA is highly effective for identifying highly influential disruptions, applying it to the context of port resilience introduces additional complexities. The first issue is the lack of real cases in current datasets, resulting in a predominance of unknown disruptive scenarios over known ones. Moreover, due to the complex dynamics and highly nonlinear interactions among all influential factors, compounded by the ripple effect, these interactions remain poorly understood. Furthermore, since different SA methods originate from fundamentally different philosophies, they may yield varied and inconsistent outcomes when addressing the same issue (Razavi et al., 2021). Therefore, the challenge of addressing these inconsistencies in SA and accurately measuring the actual impact of disruptions on port resilience remains unresolved. Accordingly, this study seeks to address the following research questions: (1) How can the potential impacts of unprecedented disruptions on port resilience be effectively evaluated using simulation-generated evidence when directly comparable historical data are unavailable? (2) Which disruptions and their interactions most strongly influence overall port resilience? (3) How to ensure the consistency of the SA outcomes?

To address these questions, it is crucial to project potential disruptive scenarios through simulation, consider the ripple effect among these factors, and minimise model discrepancies. The Sobol quasi-random technique is used to sample disruptive variables extensively, exploring the full range of possible combinations to ensure that all disruptions that could affect port resilience are adequately examined. System Dynamics (SD) (Liu et al., 2023c), chosen for its strength in modelling dynamic interactions, is employed to simulate port disruptions and calculate resilience values for five transportation subsystems (i.e., liner shipping, feeder shipping, railway, truck, and yard) based on their operational performance under these disruptions. Evidential Reasoning (ER) (Liang et al., 2025), well-suited for integrating multiple indicators under uncertainty, is employed to synthesise these values, forming an overall port resilience. Additionally, a GSA called Sobol's method (Sobol', 2001), chosen for its ability to examine both first- and second-order sensitivity influences, is employed to determine the comparative significance of disruptive factors affecting port resilience. To validate the reliability, the outcomes obtained from Sobol's method are compared with those from two other common GSA methods, namely the Fourier Amplitude Sensitivity Test with Random Balance Design (FAST-RBD) (Cukier et al., 1973) and Probabilistic Analysis for

Non-linear propagation of WAveforms under Non-parametric approach (PAWN) (Coppola et al., 2023), using the Intraclass Correlation Coefficient (ICC) (Shrout and Fleiss, 1979) consistency checks. ICC is selected because it is effective for comparing differences between evaluation methods. The primary objective of this study is to scientifically identify disruptive variables that contribute most to the uncertainty in port resilience and support evidence-based risk management by translating sensitivity-based evidence into actionable implications. In addition, practically speaking, effective assessment requires appropriate SA to guide managerial efforts (Taghizadeh et al., 2021). Therefore, the main contributions of this study are:

1. This study develops an enhanced SD-based resilience assessment framework by integrating GSA to quantitatively evaluate both the individual and joint influences of disruptive variables on port operation resilience, transforming the model from descriptive simulation into quantitative sensitivity-based resilience analysis.
2. The model defines empirical probability distributions of disruption factors and employs Sobol quasi-random sampling to efficiently explore the parameter space, ensuring comprehensive and realistic coverage of uncertainty conditions.
3. To strengthen methodological credibility, the study conducts cross-verification among three complementary GSA methods (Sobol, FAST-RBD, PAWN) and applies ICC testing to verify the stability and reproducibility of sensitivity results.
4. The proposed framework translates analytical outcomes into evidence-based decision-support tools for port authorities and operators, guiding maintenance scheduling, emergency coordination, disruption prioritisation, and investment planning to enhance real-world port resilience.

The paper proceeds as follows: Section 2 summarises previous research on port resilience and SA. Section 3 outlines the proposed methodology, which includes identifying influential factors using SD simulation, quantifying resilience, ER, and Sobol SA. Section 4 presents an empirical application to a multimodal container terminal to verify its applicability. Section 5 details the managerial insights and implications. Section 6 concludes with key contributions and suggestions for future research.

2. Literature review

The review of existing studies on port resilience is divided into 2 key areas: The first part focuses on concepts and methodologies related to port operational resilience, including the representation of the ripple effect in port operations management, the application of SD for operational simulations, methods for quantifying resilience, and the integration of multiple indicators in evaluating port resilience. The second part introduces the SA methods and explains the rationale for their selection.

2.1. Port operation resilience analysis

2.1.1. Ripple effect in port operations

Despite considerable interest in port resilience research from both qualitative (including conceptual) and quantitative perspectives, most studies continue to treat the port as a whole system (Gu and Liu, 2023; Xiao and Bai, 2022; Verschuur et al., 2022). This approach overlooks the complex interplay among various transportation modes within the port, a critical hub for cargo handling that inherently embodies a multimodal structure, as reflected in its loading, transhipment, and storage functions. Consequently, it fails to account for the ripple effects of disruptions as they propagate through these modes. This oversight limits the precise and scientific analysis of operational patterns and risk management in response to port disruptions.

The concept of the ripple effect, also known as “risk propagation”, “risk diffusion”, “cascading effect”, “snowball effect”, and “domino effect”, was first formalised in 2018 (Dolgui et al., 2018). It reflects the way disruptions cascade from one part of the network to another, amplifying their overall impact (Ghadge et al., 2022). Recently, this concept was applied across various dimensions within maritime transportation, including port equipment scheduling (Cai et al., 2024), port skip strategies (Xiao and Bai, 2022), port infrastructure (Hossain et al., 2020), and terminal congestions (Guo et al., 2023a; Bell et al., 2023), as well as in container load redistribution (Lu et al., 2024). However, most existing studies addressing the ripple effect are limited to the propagation of disruptions within a single mode of transportation, thereby overlooking broader ripple effects across multiple transportation modes linked to maritime supply chain operations, such as port activities.

2.1.2. Development of SD in port modelling

Regarding methodological approaches, SD offers distinctive advantages over techniques such as Agent-Based Modelling (ABM), Discrete Event Simulation (DES), and Monte Carlo Simulation (Ivanov, 2017), primarily because it is particularly suited to examining ripple effects within large-scale systems that feature complex, multi-variable interactions (Liu et al., 2023c; Bell et al., 2023). By identifying causal relationships among operational variables, disruptive factors, and their impacts, SD not only establishes a robust feedback mechanism but also effectively captures cumulative effects over time (Lai et al., 2023), thus paving the way for subsequent resilience measurement. Additionally, SD aids in the development of scenario-based SA (Valaei Sharif et al., 2023), which further facilitates quantifying the impact of various disruptive factors. Consequently, this paper employs an SD-based simulation to model the operations of various transportation modes at ports during disruptions.

2.1.3. Resilience quantification in port operations

Before its adoption in the maritime transportation sector (Wan et al., 2018), t he quantification of resilience has already been extensively explored in other fields, leading to the development of diverse measurement methods. These methods are generally divided into three primary groups (Wang and Yuen, 2022): (1) topological attribute-based, which leverages graph theory or network metrics; (2) attribute-based, which is grounded in abstract concepts such as resistance, absorption, maintenance, and endurance (Gu et al., 2024) and (3) performance-based, which tracks the fluctuations of specific indicators over a specified period. Both attribute-based and performance-based approaches effectively capture the dynamics of a system. However, the performance-based method, which assesses resilience across multiple indicators and different dimensions, provides a more thorough and standardised approach (Wang and Yuen, 2022). Thus, this study employs the performance-based method to measure port resilience.

The "resilience triangle" provides an effective performance-based method where resilience is quantified by the integral of performance over the disruption and recovery period (Bruneau et al., 2003). In recent years, numerous scholars have enhanced and expanded the "resilience triangle" (Gu and Liu, 2023; Zohoori et al., 2023). The most authoritative definition stated that a resilient system must exhibit strong capabilities in three key areas: a gradual decline during the disruptive phase, rapid recovery in the recovery phase, and stable overall performance (Cheng et al., 2022). However, the existing methods for measuring resilience are inadequate, as they might equate a system that deteriorates slowly and recovers slowly with one that deteriorates rapidly but rebounds swiftly (Sun et al., 2024). This overlooks the critical third criterion of resilience. Besides, such an approach fails to align with the operational priorities of port managers, who favour overall system stability. To address this, the present study introduces and validates a refined computational method that builds on prior research and enhances the original resilience triangle concept. This revised methodology assesses three distinct aspects previously introduced (Ayyub, 2014).

2.1.4. Multi-indicator aggregation for port resilience evaluation

Port performance has been assessed using a wide range of well-established indicators proposed and identified from multiple perspectives, including financial performance, customer service, internal operational processes, logistics network, technological capability, and environmental sustainability, among others. These indicators, which have been proposed and applied in previous studies (Praharsi et al., 2025; Ha and Yang, 2017; Ha et al., 2019; Zhang et al., 2024), are summarised in Table 1. As the primary objective of this study is to examine the resilience of port operations, only performance indicators that are associated with port operational efficiency are considered appropriate. Other dimensions, although important, fall outside the scope of this study and are therefore not explicitly analysed. Operational efficiency indicators can generally be classified into two categories: volume-based and time-based. Volume-based indicators, such as throughput and total container handling volume, are relatively insensitive to short-term disruptions and therefore have limited ability to capture variations in operational resilience under disruptions (Mustafa et al., 2021). Consequently, this study adopts time-based port efficiency indicators, which are more responsive to operational disruptions and better reflect the dynamic port resilience.

Given that ports operate across multiple transport modes, resilience must be assessed using multiple efficiency indicators to avoid bias. Integrating diverse information sources is crucial for assessing port resilience (Wen et al., 2024). Traditionally, classic methods for multiple indicator integration include the Analytic Hierarchy Process (AHP) (Ayaz et al., 2022), Data Envelopment Analysis (DEA), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the Decision Making Trial and Evaluation Laboratory (DEMATEL) (Liang et al., 2025). However, with technological advancement, more innovative approaches were applied in the maritime sector, such as fuzzy TODIM (Interactive and Multi-criteria Decision-Making, the acronym in Portuguese) (Liu et al., 2023b), PROMETHEE, super-efficiency slacks-based measure network data envelopment analysis (SBM-NDEA) (Gu et al., 2025).

A leading method for synthesising multiple indicators is ER (Yang and Singh, 1994), influenced by the Dempster-Shafer evidence theory (Dempster, 2008). ER adopts a hierarchical approach to aggregate multiple KPIs, linking high-level resilience outcomes with lower-level indicators via probabilistic relationships. A key advantage of ER over other methods lies in its capacity to accommodate uncertainty through belief functions to assign probabilities to each criterion, thereby capturing all possible combinations of scenarios in the powerset of the defined criteria (Wen et al., 2024). Moreover, ER reveals results not only at the top level but also across different levels and indicators, illustrating the ripple effects among various transportation modes, thus facilitating the precise quantification of influential factors (Yang and Xu, 2013). Furthermore, ER does not rely on subjective data or expert opinions, allowing for a more objective and accurate integration of KPIs. Hence, ER is used to support the operational evaluation of port resilience by combining KPIs across transportation modes.

Table 1
Review of port performance indicators.

Type	Indicators
Finance	Revenue-generating capability, financial robustness and cash-flow stability
Customers service	Reliability of service, customer-perceived service quality
Internal operation efficiency	Time efficiency of operational processes including ship loading and unloading rate, berth occupancy, crane efficiency, number of vessels, idling time at berth, vessel turnaround time, truck turnaround time, dwell time, average pre-berthing waiting time Throughput-oriented productivity including traffic handled, number of vessels handled, throughput
Network and logistics	Network connectivity, gate accessibility, and cost of hinterland distribution
Capability development	Workforce skills and expertise, organisational capital and corporate social performance
Political	Stakeholder influence, regulatory and policy environment affecting port operations
Economy	Capital mobilisation and investment attractiveness, value creation within the regional and national economy
Social	Contribution to social welfare and local development, commitment of management to responsible governance
Technology	Automation, intelligent infrastructure, integrated monitoring and optimisation system
Environment	Efficiency of energy use, greenhouse gas and pollutant emissions, wastewater and discharge management, and adoption of renewable energy sources

2.2. Method selection

2.2.1. Comparison with other uncertainty quantification methods

A significant advancement in managing port disruptions involves refining uncertainty assessments and accurately tracing their origins within the affected components. In other words, this involves understanding how port resilience changes with varying types and degrees of disruption. More broadly, it aims to capture how fluctuations in input parameters influence model results. To achieve this, the selected modelling approach should fulfil three primary objectives: (1) scientific discovery, which explores causal relationships and examines how a system is affected by various parameters, scales, and their combinations and interactions; (2) factor reduction and prioritisation, which identifies redundant uninfluential factors to be removed and influential essential factor to be prioritised; (3) decision support, which assesses the sensitivity of model outcomes to different scenarios, decisions, and uncertainties (Razavi et al., 2021). SA is particularly well-suited to this task, as it enables a detailed breakdown of output uncertainties, attributing them to specific factors and their interactions. This approach is closely aligned with “factor prioritisation”, one of the four primary objectives of SA (Schmitz et al., 2023). A detailed comparison of SA with other highly recognised UQ methods is shown in Table 2.

2.2.2. Selection of sensitivity analysis methods

SA can typically be classified into LSA and GSA, depending on the scope of input space exploration (Saltelli et al., 2010). The majority of LSA approaches utilise OAT strategies that repeatedly modify parameters within the solution neighbourhood. While LSA is straightforward and effective for analysing easy models, it falls short in handling complex models featuring high-dimensional, nonlinear, and interdependent variables, primarily because it does not fully explore the entire range of input parameters (Cohen et al., 2024).

GSA can be categorised into four types: derivative-based, distribution-based, variogram-based, and regression-based approaches (Razavi et al., 2021). Derivative-based methods evolve from LSA, calculating local sensitivities at various “local points” across the input space and then aggregating these to form a GSA. Within this group, the Morris method is often utilised (Morris, 1991). Distribution-based methods evaluate the distributional properties of outputs to understand how different input combinations influence these characteristics. Variance-based methods, favoured for their clear conceptual framework and simple implementation, break down the overall variation in the output into components reflecting individual effects and their combinations. Among these methods, Sobol (Sobol', 2001) and FAST (Cukier et al., 1973) stand out as particularly prevalent. Notably, the Sobol method surpasses FAST by quantifying interaction effects, which illustrate the degree of interactions between variables (Sobol', 2001). Moreover, some distribution-based approaches go beyond traditional variance analysis to investigate the impact of inputs on the output’s higher-order moments, often referred to as “moment-based” methods. These strategies excel in processing data with pronounced skewness and effectively handling kurtosis. Key techniques in this group are PAWN (Pianosi and Wagener, 2015) and Regional Sensitivity Analysis (RSA) (Spear et al., 1994). The variogram-based approach bridges derivative and distribution-based methods (Razavi et al., 2019), but since it is relatively new, its stability, applicability, and practicality have yet to be fully demonstrated. In the regression-based method, a set of response surface points is modelled using coefficients in a linear regression framework. This approach has been criticised for its substantial dependence on pre-existing assumptions, which can oversimplify the interactions between inputs and outputs, especially in cases involving non-linear and non-monotonic relationships (Song et al., 2015). Therefore, to effectively reveal the relationships between disruptive factors and their impact on port resilience, this paper adopts Sobol as the primary method for SA. Subsequently, it utilises PAWN and the improved FAST-RBD for sensitivity verification and employs ICC to analyse the consistency of the results.

SA is widely applied across multiple domains, including climate change (Collins et al., 2012), hurricanes (Iman et al., 2005), earthquakes (Chen and Zhang, 2021), hydrology (Schmitz et al., 2023), and epidemics (Lu and Borgonovo, 2023). The expansive and growing use of SA highlights its potential to emerge as an independent discipline, providing significant advantages for the broader

Table 2
Comparison of SA and other UQ methods.

Method	Main Function	Whether it meets the three objectives		
		(a)	(b)	(c)
Markov Chain (Sun et al., 2024)	Models risk evolution through state transition probability	√		√
Multi-criteria Decision Making (MCDM) (Liu et al., 2023b)	Evaluates disruptions by weighting and aggregating multiple conflicting criteria			√
Bayesian Network (BN) (Liang et al., 2025)	Establishes causal relationships and conditional probability among disruptive factors through graphs	√		√
Fault Tree Analysis (FTA) (Qazi et al., 2018)	Identifies and quantifies failure logic by decomposing into contributing causes	√		√
Failure Mode and Effects Analysis (FMEA) (Wan et al., 2019)	Evaluates potential failure modes, their causes, and effects to prioritise risk mitigation	√		√
Petri Nets (PN) (Sun et al., 2021)	Models dynamic, concurrent, and event-driven risk evolution processes using states and transitions.	√		√
ANOVA (Fisher, 1970)	Statistical tests whether variations in outputs are significantly affected by input factors.		√	
SA (Schmitz et al., 2023)	Quantifies how input variations influence output to identify key contributing disruptive factors	√	√	√

scientific community (Razavi et al., 2021). However, there remains a notable limitation in the application of GSA models to enhance resilience in transportation operations research sectors (Taghizadeh et al., 2021). A few examples are identified as follows: In autonomous driving, PAWN density-based SA was used to pinpoint operational areas and conditions that are prone to dangerous human behaviours, thus enhancing safety measures in autonomous vehicles (Coppola et al., 2023). Likewise, employing variance-based SA helped calibrate microscopic traffic flow models through “factor fixing” (Punzo et al., 2015), highlighting the importance of SA in transportation management. In the field of operations management, an innovative GSA is proposed to pinpoint suppliers at risk in multi-product supply chain networks, incorporating a risk aggregation model to mitigate variability (Mizgier, 2017). Additionally, variance-based SA was applied in deep-tier supply chains to equip decision-makers with strategic insights on improving network resilience by identifying and prioritising critical suppliers who significantly influence performance variability (Taghizadeh et al., 2021). Regarding resilience-related concepts, a refined social fabric index was developed to assess community vulnerability to natural hazards. To validate the model’s robustness, internal uncertainty and GSA were employed (He et al., 2023). Building on this framework, the authors used OAT SA as the core method in subsequent research. This methodology, integrated with Dempster-Shafer (DS) theory and clustering, was specifically designed to evaluate regional resilience against the preliminary impacts of earthquakes (He and Guan, 2024).

Overall, the application of SA can be broadly categorised into three main functions: (1) In model validation, it is applied to ensure model robustness and reliability by varying parameter values (Liu et al., 2023a). (2) In policy-oriented research, this approach is used to assess how changes in parameters influence policy outcomes, offering insights into the potential effectiveness and implications of various policy options (Liu et al., 2020). These two practices are especially prevalent in current engineering and operations management research, mostly through LSA. (3) It is also aimed at reducing uncertainties in model configurations and identifying key parameters. For instance, GSA is widely used to screen and prioritise inputs in hydrology and water quality research (Cohen et al., 2024; Schmitz et al., 2023; Cheng et al., 2023).

In summary, although SA is highly transferable across contexts and applicable in numerous fields, an extensive literature review has identified three primary shortcomings in its application to port resilience: (1) Most studies employ LSA for model validation, which fails to provide accurate, measurable SI for critical disruptive factors. (2) There is a significant disconnection between sophisticated theoretical SA methodologies and their practical implementations, as evidenced by one class featuring proposals for advanced and refined SA methods with a simple demonstrative case developed by SA experts. The other comprises application papers in which weak SA is performed by researchers outside the SA field (Razavi et al., 2021). (3) Fundamentally different philosophical approaches to uncertainty tracing are adopted in different SA methods, leading to inconsistencies in outcomes. Addressing this issue, a few studies utilise multiple SA techniques for cross-validation and perform consistency checks on the results of sensitivity indices (SI), including variance-based Sobol and moment-independent Delta methods (Taghizadeh et al., 2021); Polynomial Chaos Expansion (PCE), Stochastic Collocation (SC), and Arbitrary Polynomial Chaos (APC) (Zhao et al., 2019); Sobol, PAWN, and Patient Rule Induction (PRI) (Jaxa-Rozen et al., 2021). This study aims to address these issues by refining the application of SA to enhance the practicality and reliability of port resilience assessments.

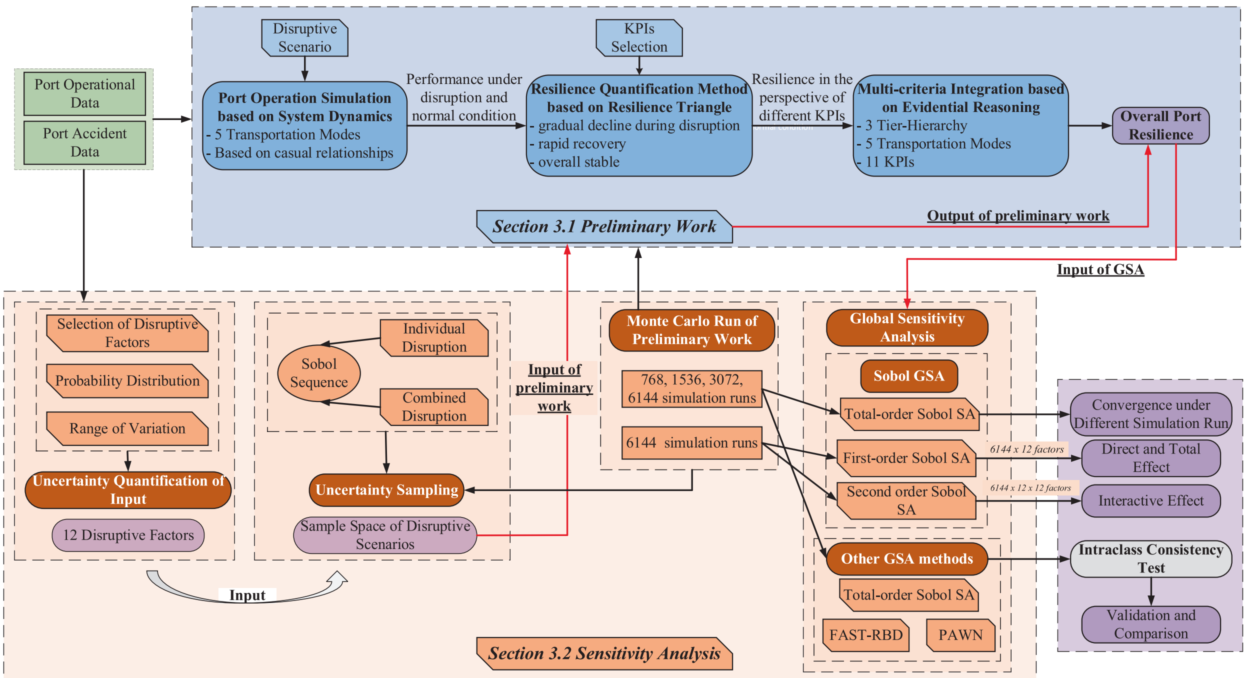


Fig. 1. Flowchart of the framework.

3. Methodology

The proposed methodology is illustrated in Fig. 1, which provides a flowchart of the integrated SA process for evaluating port resilience under disruption scenarios. Initially, the preliminary work is set by SD, resilience quantification, and ER to incorporate operational and disruption data from the port, thereby calculating the overall port resilience value under various disruptions. Following this, GSA is employed to determine the significance of each type of disruptive variable. The experimental procedure of the framework includes: (1) establishing the range and probability distributions for disruptive variables; (2) sampling of these variables using Sobol sequences to represent each disruption scenario, (3) inputting these samples into the preliminary work to derive overall port resilience values under different disruption scenarios; (4) employing the characteristics of the sampled variables, sampling result and resilience values to compute different SI through GSA.

3.1. Preliminary work

This section explains the development of a resilience assessment model for port disruption, with a focus on the numerical model to which SA is applied. The model is structured into three interrelated components: (a) an SD simulation model; (b) a resilience quantification model; and (c) a KPIs aggregation model based on ER. In this framework, the SD model simulates port operations under a range of disruptive scenarios, evaluating port efficiency by monitoring changes in KPIs across various transportation modes. Subsequently, the resilience triangle method is applied to convert these time-varying KPIs into quantifiable resilience values. Ultimately, these resilience values for different port KPIs are aggregated into a global-level port resilience index, which is utilised as the output metric for the SA process described in Section 3.2. This model is rigorously validated through various methods, including dimensional consistency checks, tests under extreme conditions, and empirical comparisons. The method has demonstrated a reliable capability in reflecting how port resilience dynamically responds to various types of disruptions. Several recently published studies support the selection of variables, model structure, and validation approach (Zhang et al., 2025b; Zhang et al., 2025a), which established generalisable relationships among port subsystems based on standard operational processes. The model structure, parameter ranges, and variable definitions remain consistent with the empirically validated and justified previous work, which utilises evidence from over ten

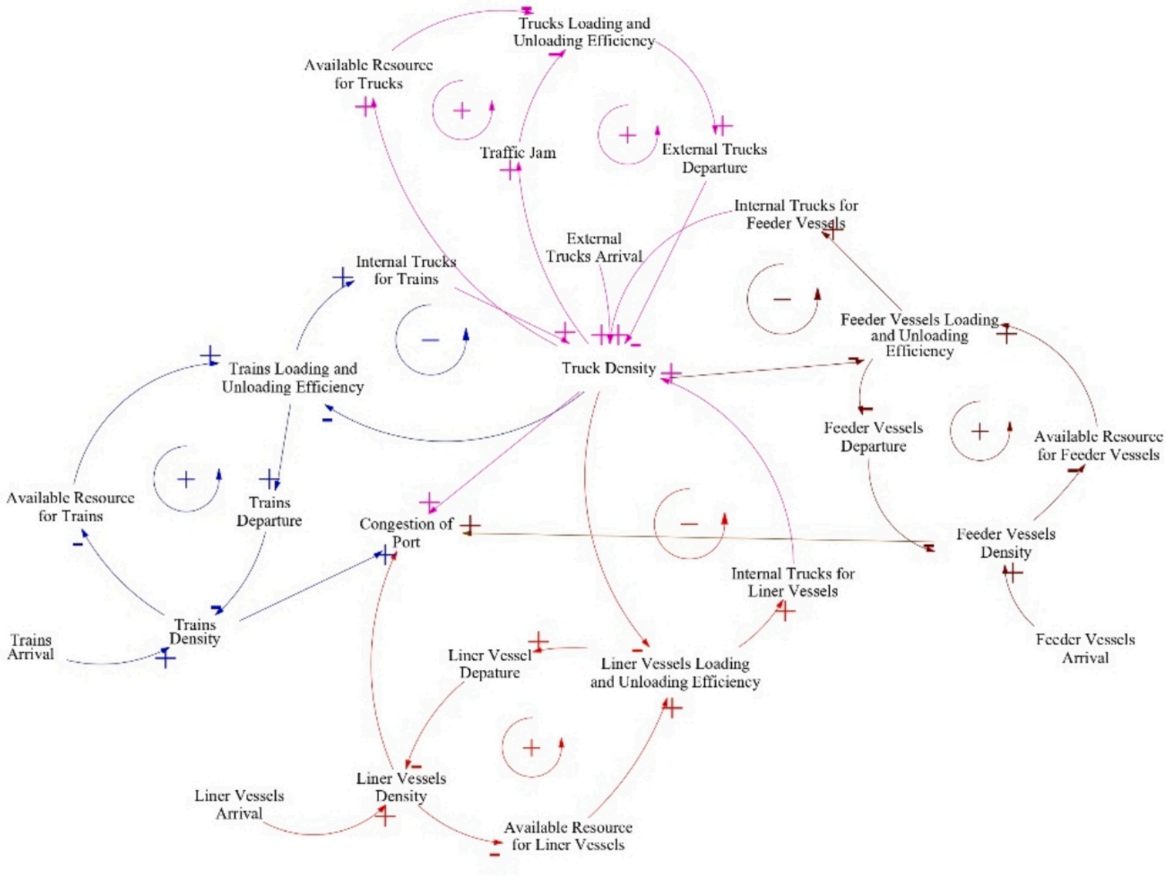


Fig. 2. Causal loop diagram of the SD model. (Adapted from Zhang et al., 2025b)

widely cited academic papers, three industrial organisations, and multiple domain experts.

3.1.1. Simulation modelling based on SD

SD is adopted as the simulation method owing to its robust ability to accurately represent causal relationships and feedback mechanisms among variables. Moreover, it effectively demonstrates the dynamic performance of port systems before, during, and after disruptions, supporting subsequent resilience evaluation. Additionally, SD enables the prediction of discrete outcomes for each potential unplanned disruption, thereby facilitating subsequent GSA. The simulation model involves three phases: (i) assumption establishment, (ii) feedback mechanism definition, and (iii) stock and flow diagram development.

Initial hypotheses are formulated based on empirical research and earlier studies (Liu et al., 2023c; Li et al., 2022; Jin et al., 2021):

Four transportation methods, namely, liner shipping, feeder shipping, railway, and road, along with the container yard, compose the multimodal transport system at the port. Having different responsibilities in container flow, liner, and feeder services are modelled separately to reflect their unique operational dynamics;
Liner containerships import inbound containers, which are subsequently redistributed by feeder ships, rail, and road transport. In return, outbound containers are transported through these modes and stored at container yards before being exported via liner containerships;
Internal trucks facilitate the movement of containers between seaside and landside operations, receiving prioritisation over external trucks in container yards to ensure efficiency;
Port efficiency also depends on the availability of critical resources such as berths and cranes, as well as the operational efficiency of all involved stakeholders;
Internal trucks initiate a cascading effect across the port by disrupting synchronised operations between seaside and landside across multiple subsystems.

As a fundamental part of SD, the causal loop diagram captures the operational processes and logic of multimodal container ports. Based on a field investigation of a highly influential and representative port with a well-developed multimodal system, along with past literature, the system is modularly structured around five interconnected transportation subsystems: liner shipping, feeder shipping, railway, trucking, and container yards, as shown in Fig. 2. Subsequently, the concepts in the causal loop diagram are quantified as specific variables, leading to the development of five detailed stock-and-flow diagrams, each corresponding to a different transportation mode, as detailed in Appendix A. Moreover, the standardisation of layout and operational procedures in multimodal container ports ensures the broad applicability of the proposed simulation model.

3.1.2. Resilience quantification model

The SD-based simulation model generates continuous-time series data that captures fluctuations in port operations. However, this data only reflects the state of the port system at specific moments and does not inherently demonstrate the port's ability to respond to disturbances. Therefore, it is crucial to transform the performance-time curve derived from the simulation model into a measure of system resilience while ensuring calculation accuracy.

To address the previously highlighted issue of unbalanced resilience calculations, this paper proposes a novel computational approach that evaluates resilience across three dimensions: reliability, robustness, and recovery, as shown in Table 3, Eq. (1), and Fig. 3. The scientific validity of this methodology has been substantiated in earlier works (Cheng et al., 2022; Sun et al., 2024). However, its application within the maritime industry remains relatively limited.

$$R_e = \frac{T_i + F\Delta T_f + R\Delta T_r}{T_i + \Delta T_f + \Delta T_r} \tag{1}$$

$$F = \frac{\int_{\mathrm{T_i}}^{T_f} f(\mathrm{t})\mathrm{d}t}{\int_{T_i}^{T_f} P_0(t)\mathrm{d}t}$$

Table 3
Notation for resilience quantification.

Notation	Description
T_0	The moment when disruption occurs
T_i	The moment when disruption impacts onsets
T_f	The moment when performance declines to the lowest level, initiating recovery
T_r	The moment when system fully recovers
ΔT_f	Duration from T_i to the moment of the lowest performance T_f
ΔT_r	Duration from T_f to the moment of total recovery T_r
$P_0(t)$	Normal performance level at time t
$P(t)$	Performance under disruption at time t
$f(t)$	Performance during the failure period at time t
$r(t)$	Performance during the recovery period at time t

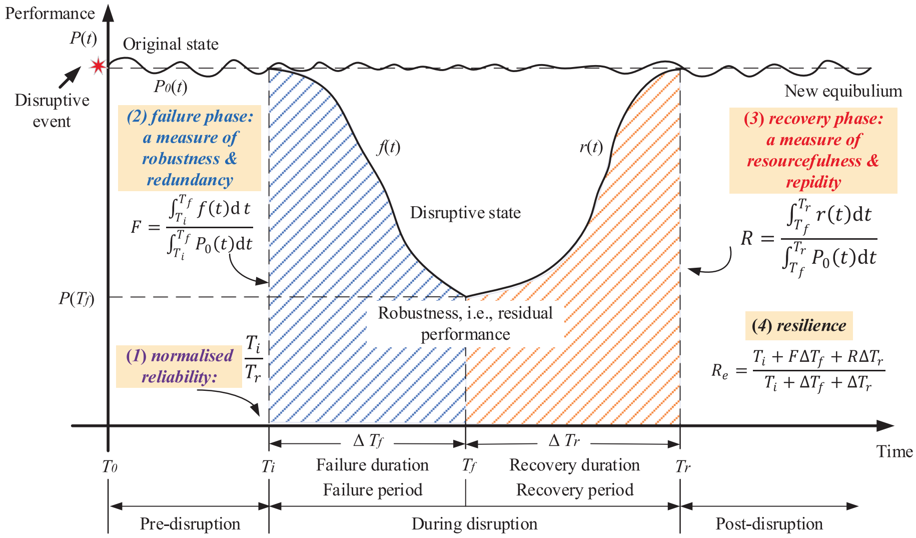


Fig. 3. Resilience quantification based on port performance. (Adapted from Zhang et al., 2025a)

$$R = \frac{\int_{T_f}^{T_r} r(t)\mathrm{d}t}{\int_{T_f}^{T_r} P_0(t)\mathrm{d}t}$$

In Fig. 3, $\frac{T_i}{T_r}$ is the normalised reliability, illustrating the system's capacity to maintain normal operation by postponing disruptive impacts. The failure profile F reflects both robustness and redundancy, while the recovery profile R measures resourcefulness and response speed. Together, these three components form the foundation of overall resilience R_e, in accordance with the definition of a resilient system outlined earlier.

3.1.3. KPIs aggregation model based on ER

As key nodes in multimodal transport networks, ports consist of diverse subsystems, each exhibiting unique resilience capacities when confronted with disruptions. Moreover, the resilience of these subsystems can be represented using a set of specific KPIs.

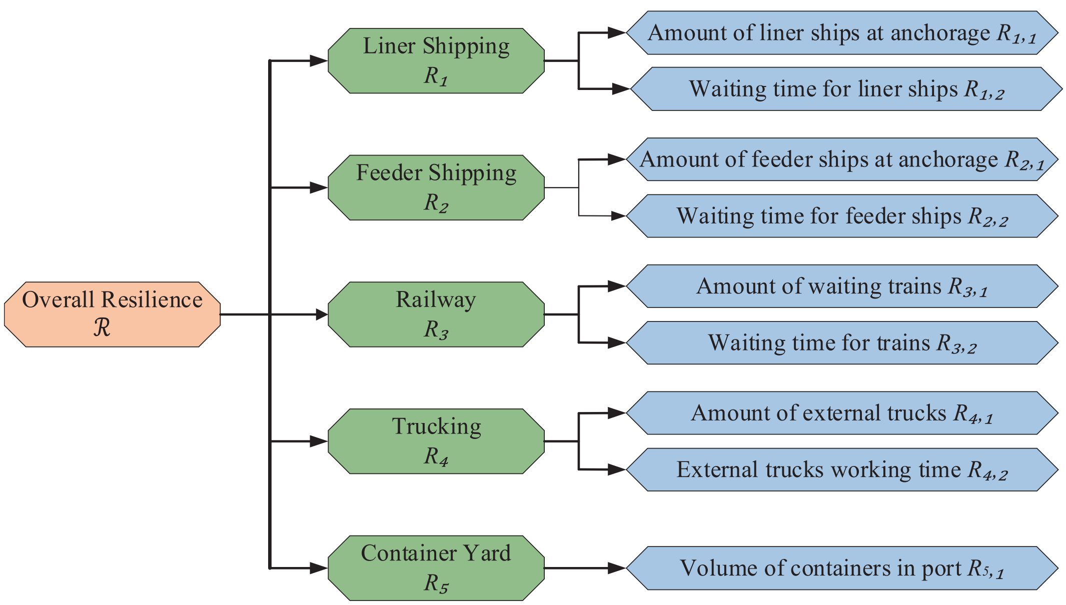


Fig. 4. Hierarchy structure of the ER model. (Adapted from Zhang et al., 2025a)

Following the approach in Section 3.1.2, each resilience value R_e is obtained from each KPI. To impartially and precisely aggregate these indicators into an overall resilience value $\mathscr{R}$, this study implements a scientifically rigorous, three-tiered approach based on ER. ER is selected over other methods due to multiple benefits: (1) it avoids subjective bias in quantification; (2) it enables the clear presentation of middle-level results; and (3) it translates the likelihood of each disruption type into belief distributions, thereby setting the groundwork for subsequent SA (Yang and Singh, 1994; Yang and Xu, 2013). It is structured in four distinct parts, outlined as follows:

(1) Hierarchical structure: A three-tiered structure is established to assess port resilience, as shown in Fig. 4. The bottom tier comprises KPIs that measure performance across different transportation modes, focusing on both temporal and quantitative dimensions. These KPIs are expressed by $R_{(w,v)}$ where w corresponds to the mode of transportation and v reflects its temporal or quantitative attribute. The selection of these KPIs is grounded in expert judgment and reinforced by prior literature (Liu et al., 2023c; Jin et al., 2021; Schulz et al., 2021; Li et al., 2018; Sun et al., 2020; Wan et al., 2018). The time-related yard efficiency indicator is not introduced independently, as its effects are already captured in the SD model through intermediate variables and its interactions with other transport subsystems. Interview-based expert validation was adopted following an established protocol applied in previous research (Zhang et al., 2025b; Zhang et al., 2025a) where the detailed backgrounds, areas of expertise, and interview questions are provided. The middle tier assesses the resilience of the various subsystems indicated by R_w, and the top tier measures the overall port resilience.
(2) Resilience value and the mapping of belief distribution: Based on past research, resilience can be categorised into four levels: strong, moderate, minimal, and weak (Gu and Liu, 2023). Each potential scenario generates a corresponding resilience value. If this value does not correspond exactly to an established category, it is linearly allocated a belief distribution to determine a Degree of Belief (Dof).
(3) Weight determination: In this hierarchy, each tier's influence on its upper tier is captured through weight assignment, whose fairness is critical for the integrity of the overall outcome. Consequently, the weights across $R_{(w,v)}$ are equal to reflect their equivalent relevance to R_w. The weight of R_w to the top level, which reflects the impact of different transportation subsystems on overall port resilience, is proportional to the container throughput of various transportation modes.
(4) Overall resilience integration: Based on the defined belief distribution and the established hierarchical structure, ER integrates KPIs from diverse transportation subsystems to calculate the overall resilience value. ER is a well-established method, and its computational process is well documented in previous studies (Yang and Singh, 1994; Wen et al., 2024; Jiang et al., 2021).

3.2. Sensitivity analysis

3.2.1. UQ of input variables

Reliable GSA results depend on the appropriate selection of input variables and their probability distributions, underscoring the necessity to accurately characterise them to reflect real-world conditions (Schmitz et al., 2023). The objective of this study is to analyse how different disruptions affect port resilience. The inputs, therefore, should be distinctly categorised by disruption severity (Chen et al., 2022) and duration (Cao and Lam, 2018; Taghizadeh et al., 2021), and the resulting output is an assessment of the port's resilience in the face of these disruptions. Drawing on expert insights and historical records, this research identifies significant representative and prevalent disruptions in port operations. For more details, refer to Section 4.2.

Following the selection of input variables, it is essential to specify their range of variation and associated probability distributions. Historical data is used to establish the maximum and minimum values for disruption severity and duration. Regarding probability distributions, multiple methods are available to quantify them depending on data availability: maximum likelihood estimation is generally used for extensive datasets, Bayesian inference is suitable for more limited data, and expert judgment can guide the definition of a plausible distribution when data are particularly sparse (Schmitz et al., 2023). Uniform disruption is adopted after careful consideration of the dataset's characteristics and past literature (Lu and Borgonovo, 2023). Although port accident records are available, the relative infrequency of such incidents over the observation period limits the reliability of traditional statistical models. Moreover, the highly unpredictable nature of these events further challenges efforts to derive precise parametric or probabilistic inferences about future disruptions. Under these circumstances, a uniform distribution offers a more robust and unbiased approach to capturing uncertainty, thereby avoiding overfitting of sparse data.

3.2.2. Sampling method

This process is typically realised using Monte Carlo simulations (Pohya et al., 2022), during which multiple iterations are performed with input variables created based on their designated probability distributions. Although increasing the number of simulations improves the convergence of statistical moment estimates, such as mean and variance, it also makes the traditional Monte Carlo method computationally costly due to the extensive combination of input variable combinations, rendering it practical only for models with rapid processing capabilities (Schmitz et al., 2023). Consequently, the adoption of an advanced sampling method that minimises the number of iterations yet comprehensively explores the sampling space and preserves statistical accuracy is essential.

Parameter exploration is conducted through the Sobol quasi-random cross-sampling scheme (Sobol sequence), which provides uniform sampling across the probability space, something not guaranteed by traditional random number generation. The distribution, while seemingly random, is methodically directed toward regions of the probability space that have not yet been sampled (Cohen et al., 2024). Another common sampling method is Latin Hypercube Sampling (LHS), which partitions the range of each input variable into equal-probability intervals and generates samples accordingly. However, LHS may produce biased sampling results, leading to overrepresentation in some dimensions and omission in others (Pang et al., 2020). To address this challenge, the Sobol sequence employs sampling based on the (t, m, s)-net and has been validated for its uniform distribution characteristics (Niederreiter, 1988).

3.2.3. Determination of output variables

Through sampling, various combinations of input variables are generated, each forming a distinct disruptive scenario. As described in Section 3.1, the SD simulator receives these scenario settings as inputs, which include the type or types of disruption, as well as their intensity and duration. Subsequently, an overall port resilience value is generated as output.

3.2.4. Sobol SA

The model $Y = f(X_1, X_2, \cdots, X_k)$ is defined over Ω, which specifies the range of all possible values of the disruptive variable X. Y represent the port resilience under a given disruptive scenario $(X_1, X_2, \cdots, X_k)$. The first-order contribution of X_i can be formulated as $V_{X_i}(E_{X_{\sim i}}(Y|X_i))$, in which $E_{X_{\sim i}}(Y|X_i)$ represents the expected port resilience Y obtained by averaging over all other disruptive variables other than X_i (denoted by $X_{\sim i}$) while X_i is fixed. Consequently, $V_{X_i}(E_{X_{\sim i}}(Y|X_i))$ quantifies the variability of these expectations. A large variance suggests a more significant impact of a particular disruptive factor X_i on Y. The notation for SA is presented in Table 4.

The associated first-order SI, which measures the individual effect of a single disruptive variable X_i on Y can be presented as:

$$S_i = \frac{V_{X_i}\left(E_{X_{\sim i}}(Y|X_i)\right)}{V(Y)} \tag{2}$$

where $V_{X_i}(E_{X_{\sim i}}(Y|X_i))$ denotes the first-order variance contribution of X_i. The $V(Y)$ is the overall variance of port resilience Y. The inner expectation, $E_{X_{\sim i}}(Y|X_i)$ represents the port resilience Y under fixed disruption X_i, averaged over all other disruptive factors. The outer variance then quantifies how this conditional expected resilience varies as X_i changes across its range.

The established variance decomposition formula indicates that the total variance $V(Y)$ can be split into the first-order effect of the disruptive variable X_i and the interactive effects between X_i and all remaining inputs $X_{\sim i}$:

$$V(Y) = V_{X_i}\left(E_{X_{\sim i}}(Y|X_i)\right) + E_{X_i}\left(V_{X_{\sim i}}(Y|X_i)\right) \tag{3}$$

where $E_{X_i}(V_{X_{\sim i}}(Y|X_i))$ is also referred to as residual, representing the effect which could be traced to $X_{\sim i}$ on $V(Y)$ under fixed X_i. The total-order sensitivity index is defined as:

$$S_{T_i} = \frac{E_{X_{\sim i}}\left(V_{X_i}(Y|X_{\sim i})\right)}{V(Y)} = 1 - \frac{V_{X_{\sim i}}\left(E_{X_i}(Y|X_{\sim i})\right)}{V(Y)} \tag{4}$$

where S_{T_i} considers the overall influence of X_i on port resilience Y including its direct (first-order) and interactive (higher-order) effects. $E_{X_{\sim i}}(V_{X_i}(Y|X_{\sim i}))$ represents the expected conditional variance of port resilience Y if only X_i can be changed and $X_{\sim i}$ are fixed. Dividing it by the total variance $V(Y)$ obtains the fraction of the total variance $V(Y)$ that could be explained by the changes in X_i (including both its individual and joint variance). From another perspective, it can be interpreted that $V_{X_{\sim i}}(E_{X_i}(Y|X_{\sim i}))$ is the first-order contribution of $X_{\sim i}$, which means the contribution of other disruptive variables to port resilience except X_i. Then subtracting this from the total variance $V(Y)$ will give the contribution of all variances that is due to the changes of X_i.

According to Hoeffding decomposition (Sobol', 1990) where $f_i = f_i(X_i), f_{ij} = f_{ij}(X_i, X_j)$ and so forth, yielding 2^k terms in total, the resilience function f can be decomposed in different dimensions, including individual impact and joint disruptions across all scenarios:

Table 4
Notation for SA.

Notation	Description
N	The number of sampled disruptive scenarios, where each scenario is a combination of disruptive variables
k	Number of disruptive variables
$X_i, i \in \{1, 2, \cdots, k\}$	The i-th disruptive variable
$X = \{X_1, X_2, \cdots, X_k\}$	$N \times k$ matrix, representing all sampled combinations of disruptive variables (theoretical representation)
$\Omega = \{(X_i \mid 0 \le X_i \le 1)\}$	k dimensional hypercube representing all potential disruptive scenarios
$Y = f(X_1, X_2, \cdots, X_k)$	Model output, representing the overall port resilience under a certain disruptive scenario
$X_{\sim i}$	$N \times (k-1)$ matrix of all disruptive variables except for X_i
$E_{X_i}(\bullet)$	Expectation of $(\bullet)$ taken over X_i, representing the expected port resilience value under variation of X_i
$V_{X_i}(\bullet)$	Variance of argument $(\bullet)$ taken over X_i, representing the variability of port resilience under variation of X_i
S_i	First-order SI of X_i, representing the variance in the port resilience attributable solely to X_i
S_{T_i}	Total-order SI of X_i, representing the variance in the port resilience due to both X_i and its interactions with other variables
$S_{i,j}$	Second-order SI of X_i and X_j, representing the variance in the port resilience due to the interaction between X_i and X_j
A, B	$N \times k$ sample matrix of disruptive variables generated through simulation (realisations of X through simulation)
$A_B^{(i)}$	$N \times k$ matrix where column i is from B and all other $k-1$ columns are from A
$B_A^{(i)}$	$N \times k$ matrix where column i is from A and all other $k-1$ columns are from B

$$f = f_0 + \sum_i f_i + \sum_i \sum_{i<j} f_{ij} + \cdots + f_{1,2,\cdots,k} \tag{5}$$

where f_0 is a constant, which is the expected value of port resilience when all disruptive variables are certain. $f_i(X_i)$ is the isolated effect of the disruptive variable X_i to port resilience, $f_{ij}(X_i, X_j)$ is the interactive contribution of X_i, X_j to port resilience, and higher-order terms $f_{1,2,\cdots,k}$ represent the joint contribution among three or more disruptive variables. Eq. Eq. (6) breaks down the function into a constant, the contributions of individual variables and their combinations. Based on the concept mentioned in Eq. (2), the specific calculation of each term is as follows:

$$f_0 = E(Y) \tag{6}$$

$$f_i = E_{X_{\sim i}}(Y|X_i) - E(Y)$$

$$f_{ij} = E_{X_{\sim ij}}(Y|X_i, X_j) - f_i - f_j - E(Y)$$

where f is the expected port resilience, f_i is the deviation in the expected port resilience resulting solely from variations in the disruptive factor X_i, aligning with the first-order effect. f_{ij} is the deviation in expected port resilience attributable to simultaneous variations in both X_i and X_j, corresponding to the interaction effect. $E_{X_{\sim i}}(Y|X_i) - E(Y)$ isolates the part of the resilience variation that can be uniquely attributed to the influence of X_i alone, excluding contributions from other variables or interactions. When disruptive variables X_i and X_j are varied at the same time, $E_{X_{\sim ij}}(Y|X_i, X_j) - f_i - f_j - E(Y)$ represents the non-additive interaction between X_i and X_j, such as synergy or interference, where the joint effect is not simply the sum of individual effects. Based on Eq. (6), similarly, the partial variance formula can be determined by finding the variance:

$$V_i = V(E_{X_{\sim i}}(Y|X_i)) \tag{7}$$

$$V_{ij} = V\left(E_{X_{\sim ij}}(Y|X_i, X_j)\right) - V_i - V_j$$

where V_i is the first-order contribution of the disruptive variable X_i and V_{ij} is the second-order contribution of the interaction between X_i and X_j. By adding the effect across all orders, the overall variance can be decomposed:

$$V(Y) = \sum_i V_i + \sum_{i<j} V_{ij} + \cdots + V_{1,2,\cdots,k} \tag{8}$$

By dividing both sides by $V(Y)$, the decomposed form of the SI can be obtained:

$$\sum_i S_i + \sum_{i<j} S_{ij} + \cdots + S_{1,2,\cdots,k} = 1 \tag{9}$$

Manual resolution of these decompositions is feasible for small-scale basic analytical models. However, SI can be approximated through iterative sampling for large complex models using estimators. The Sobol method, which utilises Monte Carlo simulations, is detailed below. It computes an individual resilience value Y based on a sampled dataset of k disruptive factors $X_1, X_2, \ldots, X_k$. Numerous studies across various fields have shown that Sobol's method provides higher accuracy compared with other GSA methods (Pohya et al., 2022).

$$V_{X_i}(E_{X_{\sim i}}(Y|X_i)) = \frac{1}{N} \sum_{j=1}^{N} f(A)_j f\left(B_A^{(i)}\right)_j - f_0^2 \tag{10}$$

The variance in port resilience Y caused by a specific disruptive factor X_i is obtained by measuring the changes of Y when X_i is fixed and can be further achieved by comparing the output from two different matrices A and $B_A^{(i)}$. $A = [a_{ij}]$ where $i \in (1, k)$ indicating the index of disruptive factors and $j \in (1, N)$ indicating the index of simulation scenarios. $B_A^{(i)}$ is constructed by substituting the i-th column of A with that of matrix B. Other matrices of similar structure are constructed accordingly.

Eq. (10) was proposed by Sobol in 1993 and then improved to a more computationally efficient form using a strategy called winding stairs in 2010 (Saltelli et al., 2010), as shown in Eq. (11):

$$V_{X_i}(E_{X_{\sim i}}(Y|X_i)) = \frac{1}{N} \sum_{j=1}^{N} f(B)_j \left(f\left(A_B^{(i)}\right)_j - f(A)_j\right) \tag{11}$$

For the total-order effect, Jansen's method (Jansen, 1999) is adopted. The efficiency and superiority have been proven by numerous literature (Saltelli et al., 2009; Sobol', 2001):

$$E_{X_{\sim i}}(V_{X_i}(Y|X_{\sim i})) = \frac{1}{2N} \sum_{j=1}^{N} \left(f(A)_j - f\left(A_B^{(i)}\right)_j\right)^2 \tag{12}$$

The approach used to calculate the total-order effect can be applied to compute the interactive effect between a pair of disruptive variables X_i and X_j, so Jensen's estimator can be generalised into:

$$E_{X_{\sim ij}}\left(V_{X_i,X_j}\left(Y|X_{\sim ij}\right)\right)=\frac{1}{2N}\sum_{w=1}^{N}\left(f\left(A_B^{(i)}\right)_w-f\left(A_B^{(j)}\right)_w\right)^2 \tag{13}$$

Eq. (13) calculates the squared difference of port resilience Y between two disruptive scenarios $A_B^{(i)}$ and $A_B^{(j)}$. It is used to estimate the variation in Y when X_i and X_j are varied while keeping other disruptive variables constant. Therefore, Eq. (11), Eq. (12) and Eq. (13) are selected to obtain the first-order, total-order and second-order SI accordingly.

From the estimation approach above, the calculation of S_i and S_{T_i} requires matrices A and B, which involve $2N$ simulations. Besides, each disruptive variable requires k simulations for $A_B^{(i)}$, resulting in a computational cost of $N(k+2)$. For the second-order effect, an additional kN simulations are needed to obtain $A_B^{(j)}$, thus the total computational efforts should be $N(2k+2)$.

3.2.5. Consistency test between different SA

While Sobol SA has been proven to produce higher accuracy compared to other methods, this study enhances the validation of result accuracy by integrating two additional GSA methods and performing consistency checks using the ICC method. ICC is a statistical metric utilised to evaluate the consistency, reliability, or concordance of ratings among multiple assessors or across multiple evaluations (Shrout and Fleiss, 1979). It is frequently used in reliability research to measure the level of agreement in ratings assigned to the same subject by different assessors, or by the same assessor at different times.

The foundation of the ICC is based on ANOVA, and its formula is outlined as follows:

$$r=\frac{k}{k-1}\cdot\frac{P^{-1}\sum_{p=1}^{P}\left(\overline{s_p}-\overline{s}\right)^2}{d^2}-\frac{1}{k-1} \tag{14}$$

where k is the number of disruptive variables for which SI are calculated, P is the number of different SA approaches, and s_p is the SI obtained through the p-th approach, forming a dataset of $S=\{s_1,s_2,\cdots,s_P\}$. $\overline{s_p}$ is the average value of s_p, $\overline{s}$ and d^2 are the mean and deviation of the entire dataset. The ICC introduced is the most common form. Additionally, five other classes of ICC can be derived based on the randomness of evaluator selection and the number of measurements. These are summarised in Table 5.

4. Results and visualisation

This section first introduces the data collection process and then details the identification of disruptive factors, along with their value ranges and probability distributions. To ensure a comprehensive coverage of the input space, simulation samples are generated using Sobol sequences. Convergence is verified by increasing the sample size and checking for result stability. Upon confirming convergence, the total-order, first-order, and second-order SI of the disruptive factors are estimated. Finally, consistency tests are applied to cross-validate the SI derived from multiple SA approaches, reinforcing the reliability of the results.

4.1. Data collection

The effectiveness and applicability of the proposed framework are examined through a case study conducted on a port with significant international influence, advanced multimodal transport facilities, and representative risk profiles. Therefore, a world-leading multimodal container port is chosen as the research site. According to the Container Port Performance Index (CPPI) , the case port has an outstanding ranking in recent years, handling more than 10 million TEUs annually. It is equipped with deep-water container terminals, rail-sea intermodal facilities, and well-developed highway connections to inland logistics hubs. The port serves both international liner routes and regional feeder services, acting as a transhipment hub that connects cities, countries, and continents. Moreover, given the high standardisation of container ports in terms of layouts, equipment, and even operation procedures, the nature of accidents shares common features (Alyami et al., 2019), which means that lessons learned from one port will generate useful insights for other ports, demonstrating the generality of the model and its findings.

Table 5
ICC types and their definitions.

ICC type	ICC name	Randomness	Number of measurements
ICC(1, 1)	Single raters absolute	Each disruptive variable is evaluated through a different random subset of k methods	Single measures
ICC(2, 1)	Single random raters	k methods are randomly selected, then each disruptive variable is measured by the same set of k methods	Single measures
ICC(3, 1)	Single fixed raters	k fixed methods are defined. Each disruptive variable is measured by the k methods	Single measures
ICC(1, k)	Average raters absolute	Each disruptive variable is measured by a different set of k randomly selected methods	Average measure
ICC(2, k)	Average random raters	k methods are randomly selected, then each disruptive variable is measured by the same set of k methods	Average measure
ICC(3, k)	Average fixed raters	k fixed methods are defined. Each disruptive variable is measured by the k methods	Average measure

The dataset for this research is split into two groups: (1) operational data under normal conditions at the port, collected via detailed field investigations and interviews with experts, and (2) accident data, which is determined by reviewing the port accident reports of 14 years from 1998 through 2021.

4.2. Disruptive factors and identification

Statistical data and expert opinions are combined to select variables that affect port resilience and to determine their value ranges, as shown in Table 6. Expert input was obtained through structured interviews with port managers, selected for their extensive risk management expertise and over 10 years of experience in port operations. Additionally, it identifies the KPIs as depicted in Table 6.

4.3. Model convergence using different samples

Employing a range of sample sizes and monitoring their convergence areessential for checking the stability of GSA methods (Cheng et al., 2023; Cohen et al., 2024). To this end, four sample sizes, 64, 128, 256, and 512, are chosen, corresponding to simulation runs of 768, 1536, 3072, and 6144, respectively. The selection of these sample sizes is justified by the optimal performance of the Sobol sequence when applied to powers of two (Schmitz et al., 2023), while the number of simulation runs is further specified according to the computational demand required for estimating S_i, S_{T_i} and $S_{i,j}$ as outlined in Section 3.2.4. Fig. 5 indicates that variable rankings can be initially established with very few simulations and stabilise after 3072 runs, thus validating the sufficiency of the selected sample sizes.

To rigorously demonstrate the convergence of the results, a numerical experiment is conducted alongside the graphical analysis, showing that variability declines with increasing numbers of simulations. The Coefficient of Variation (CV) is widely adopted as an indicator of stability. Given the significant variation in the magnitude of the results, the relative percentage change is not appropriate as it overemphasises fluctuations in small-magnitude values. Therefore, a three-point sliding window CV is used to quantify and illustrate the stabilisation, as shown in Table 7.

The CVs associated with nearly all disruptive factors decline steadily as the sample size increases, indicating convergence. While minor fluctuations are observed for X_1 during the second sampling window and for X_8 during the third, small variations of CV (X_1) and in low-SI factors (X_8) are generally acceptable in convergence assessment. Based on this evidence, the model can be considered to reach a satisfactory level of convergence.

4.4. Visualisation of the results

This section examines the results obtained from Sobol SA, chosen for its ability to compute total-order, first-order, and second-order effects. Additional experiments are conducted to assess robustness across various sample sizes and methods, with further details provided in the subsequent section. The SALib package in Python, Vensim DSS for simulating port operations, and IDS software for implementing the ER algorithm are used.

Based on Section 3.2.2, a quasi-random sampling is performed to explore the multidimensional space involving 10 identified input variables, all of which are uniformly distributed. To present the sampling results visually, the ten-dimensional array is transformed into a two-dimensional array of sampling points, as shown in Fig. 6. The total number of simulations is 6144.

The generated samples are subsequently introduced into the SD model as disruptive scenarios for simulation. The resulting time-series KPIs are converted into resilience values and then integrated using ER to determine the overall port resilience.

In the Sobol SA process, the generated samples are used as input to quantify the variance of the output, which is the overall port resilience. The analysis identifies and categorises SI into total-order, first-order, and second-order, as demonstrated in Figs. 7 and 8. The aggregate height represents the total-order effect, encompassing first-order effects and interaction contributions. A Sobol SI value above 0.1 signals high sensitivity of influencing factors. Indices from 0.01 to 0.1 reflect moderate sensitivity, whereas values below 0.01 are classified as insensitive (Yan et al., 2023).

Regarding the first-order SI, which illustrates the individual contribution of each disruptive variable on port resilience, the results indicate that the variation is predominantly driven by the number of liner quay cranes and the duration of their downtime, with S_i of

Table 6
Input disruptive factors and their range of variability.

Accident type	Input variables	Notation	Lower bound	Upper bound	Unit
Liner quay crane	Number of equipment	X_1	1	3	Cranes
	Duration	X_2	12	120	Hours
Feeder quay crane	Number of equipment	X_3	1	2	Cranes
	Duration	X_4	12	120	Hours
Rail crane	Number of equipment	X_5	1	3	Cranes
	Duration	X_6	12	120	Hours
Yard crane	Number of equipment	X_7	4	24	Cranes
	Duration	X_8	12	120	Hours
Traffic congestion	Increase in truck density	X_9	0.2	1.0	–
	Duration	X_{10}	12	120	Hours

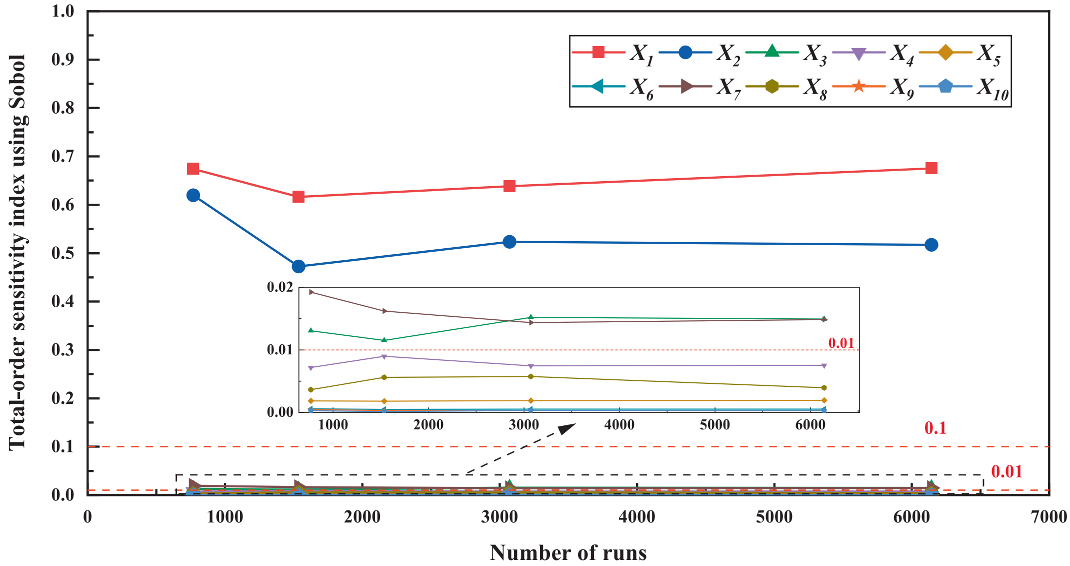


Fig. 5. Total-order Sobol SI under various sample sizes.

Table 7
CV based on three-point sliding windows for each factor across different sampling sizes.

Factor	CV (sample 768–1536)	CV (sample 1536–3072)	CV (sample 3072–6144)
X_1	0.045255	0.049032	0.022456
X_2	0.139075	0.052926	0.011616
X_3	0.139006	0.138308	0.04005
X_4	0.12053	0.097191	0.023316
X_5	0.023408	0.03857	0.015731
X_6	0.076683	0.052403	0.056687
X_7	0.1482	0.070467	0.018589
X_8	0.234081	0.065434	0.230014
X_9	0.210875	0.086787	0.067073
X_{10}	0.362652	0.364194	0.057019

0.45 and 0.37, respectively (see Fig. 7). These are followed by the number of feeder quay cranes and yard cranes, which also exhibit notable contributions, with S_i of 0.013 and 0.011, respectively. The occurrence of disruptions associated with these variables can lead to substantial fluctuations in port resilience. It is worth noticing that traffic congestion in the yard, which naturally receives the same amount of attention as crane failure in port management, does not appear to significantly influence port resilience uncertainty, at least not through a direct effect. Other variables in feeder shipping, railway, and yard area demonstrate relatively low first-order effects, indicating that their individual impact on port resilience is limited and therefore may not require prioritisation in targeted adjustment strategies. From a broader perspective, approximately 80% of the overall variation in port resilience can be explained by disruptions occurring directly within the liner operation area, while the remaining portion stems from disruptions in other transport subsystems.

The total height of each bar in Fig. 7 reflects the total-order S_{Ti}, which includes both the individual contribution of a variable and its interactions with others. Eq. (2) indicates that the sum of first-order indices equals 1, while it does not apply to total- or second-order SIs. Overall, the trends in total-order SI are largely consistent with those of the first-order effects, suggesting that direct impacts rather than complex interactions primarily drive the port's resilience. Specifically, the total-order indices for the number of liner quay crane failures and their downtime duration are 0.67 and 0.51, respectively. Among all variables, the number of liner quay crane failures has the largest total effect, underscoring its pivotal role in sustaining port operational stability. The downtime duration follows closely, reinforcing the critical importance of maintaining high availability of liner quay cranes to enhance port resilience. Feeder quay cranes and yard cranes also contribute to port resilience through both direct and indirect effects, with total-order indices of 0.015 for both. These results underscore the importance of ongoing attention to their preventive maintenance and rapid recovery capabilities. In contrast, the remaining variables show relatively minor influence on port resilience. Therefore, in resource-constrained scenarios, these factors may be deprioritised without significantly compromising overall system resilience.

Interaction effects are illustrated by the dark blue bar in Fig. 7, and the specific variable pairs responsible for each interaction can be examined in greater detail in Fig. 8. There is a substantial interaction between the number and the downtime duration of liner quay crane failures, contributing approximately 16% and 14% to the total-order effects, respectively. This indicates that a significant portion of their influence on port resilience arises from their interactions with other variables, rather than from their individual effects alone.

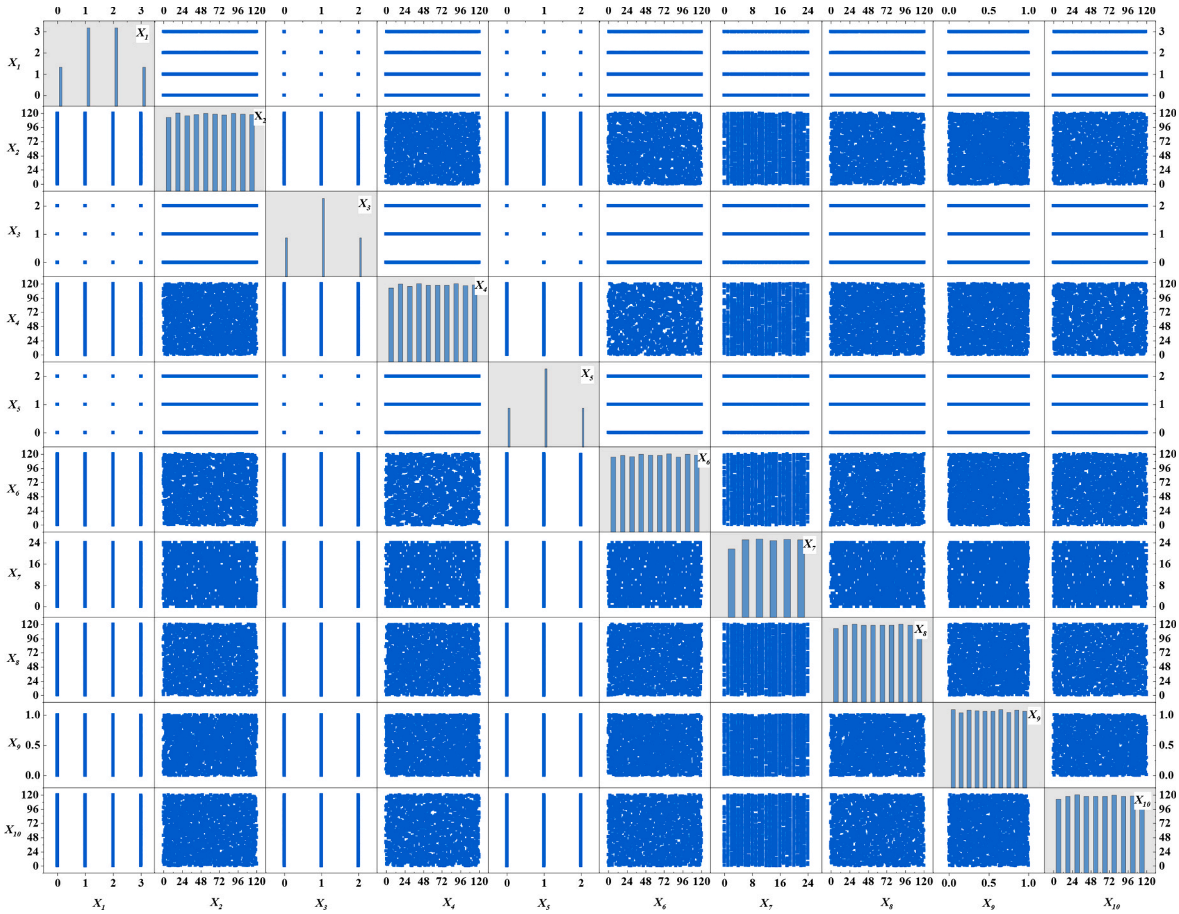


Fig. 6. Sobol sampling results of 6144 samples.

Variables X_5(number of train crane failures), X_7 (number of yard crane failures), and X_9 (yard congestion) are noteworthy for their disproportionately large interaction effects, which exceed their relatively small first- and total-order contributions. This suggests that while these variables may have limited standalone influence on port resilience, their combined impact with other variables could be considerable. These interaction effects indicate that port resilience is shaped by the combined effects of multiple disruptions, rather than by their individual contributions. Moreover, the combined impact of multiple disruptions may exceed the sum of their individual effects, forming a nonlinear $1 + 1 > 2$ effect. This highlights the need for more detailed analyses to understand these risk interactions and to develop flexible, adaptive mitigation strategies that go beyond linear, single-variable interventions. Conversely, variables such as X_3 (number of feeder quay crane failure) and X_7 (number of yard crane failures) demonstrate high first-order and total-order indices (both exceeding 0.1), yet exhibit relatively low interaction effects. This implies that their impact on port resilience is primarily mediated by direct mechanisms.

In summary, despite their limited standalone influence, variables with high interaction but low first-order effects can significantly affect port resilience through co-occurrence with other risks. This underscores the need for detailed data collection and additional interaction-focused analysis. In risk prevention and response planning, special consideration should be given to the joint effects of train crane failures, yard crane disruptions, and yard traffic congestion. The co-occurrence of these risks is likely a consequence of ripple effects, through which disturbances propagate across interconnected port subsystems and amplify their overall impact on resilience. While the thresholds of 0.1 and 0.01 help identify the sensitivity level, it should be emphasised that the actual impact of variables with limited first-order effects may change under dynamic conditions or in response to unexpected events. Such behaviours may arise from external factors or environmental changes that the current model does not fully capture.

While first- and total-order analyses highlight individual and overall influence, second-order analysis further uncovers key combinations between variable pairs. It is important to recognise that Sobol SI only quantifies the level of influence and does not distinguish between the positive or negative impacts of variable interactions. The percentages in the figures denote the extent of the interaction effect between two variables, relative to the sum of all possible effects across all variables.

Overall, interaction effects are generally weak, with a few notable exceptions. As shown in Fig. 8, the interaction effects for most variable pairs fall below 1%, indicating that port resilience is predominantly driven by first-order (individual) effects. However, several combinations exhibit interaction effects exceeding 1%, and in some cases surpassing 10%, suggesting a substantial influence of

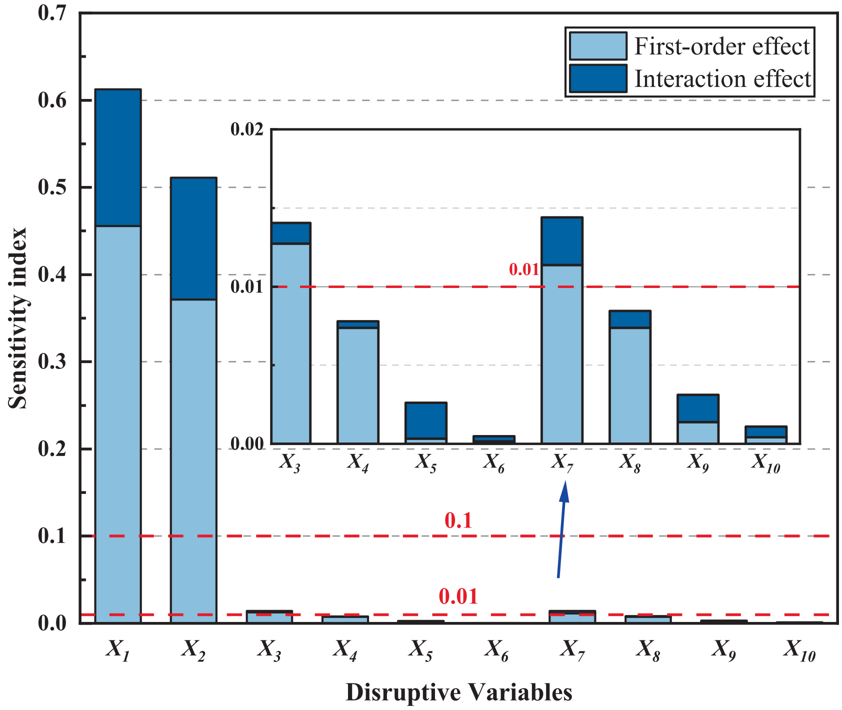


Fig. 7. Sobol first-order (S_i) and total-order (S_{Ti}) SI under 6144 simulation runs.

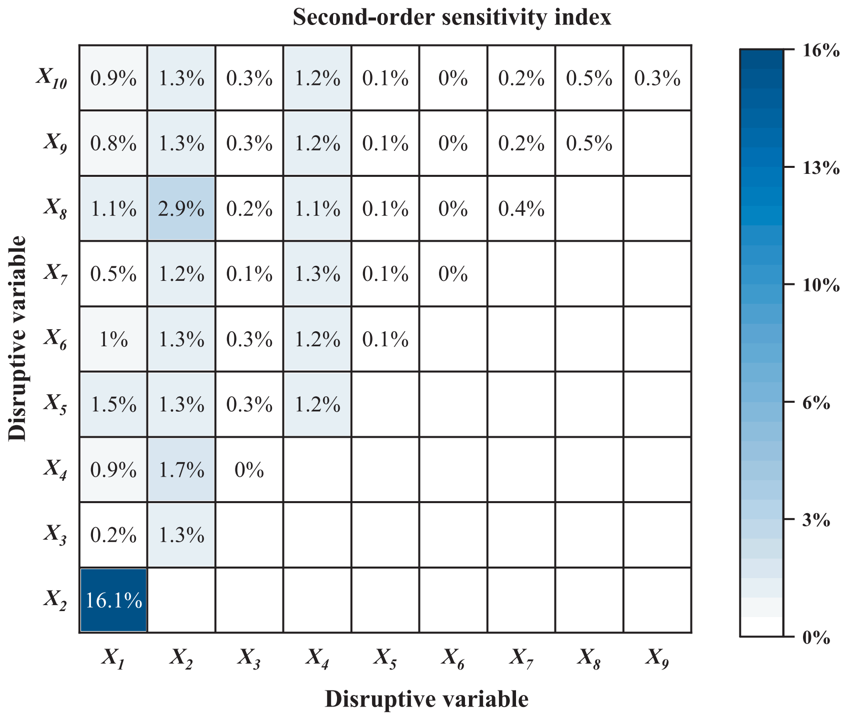


Fig. 8. Sobol second-order SI under 6144 simulation runs.

interaction effects on resilience. The majority of low interaction effects among variable pairs implies that the port operates with a relatively modular structure, where localised disruptions can be effectively contained within individual subsystems due to their inherent recovery capacity. However, this low level of interconnectivity also implies that, if a local failure intensifies, the lack of strong cross-mode support may impose higher recovery burdens.

The most significant interaction effect is identified between the number and duration of liner quay crane failures. When these two factors co-occur, their combined impact on port resilience is substantially amplified, far exceeding the additive effects of each variable in isolation. Under such conditions, higher severity is often accompanied by prolonged failure durations, resulting in a non-linear and disproportionately greater degradation of port resilience. The result implies a systemic bottleneck, possibly stemming from the functional interdependence of the two variables within the same operational subsystem. The exceptionally strong interaction between variables X_1 and X_2 may therefore reveal a latent vulnerability within the port's operation. X_2(duration of liner quay crane failure) shows notable interaction effects with X_8 (duration of yard crane failure) and X_4 (duration of feeder quay crane failure), indicating its strong potential to amplify the overall impact of disruptions on port resilience. Similarly, variable X_8(duration of yard crane failure) also demonstrates strong interaction effects with several other factors, including X_2(duration of feeder quay crane failure), X_1(duration of liner quay crane failure) and X_4 (duration of feeder quay crane failure) respectively. This suggests that X_8 may serve as a key node that influences or is influenced by other variables. This observation aligns with the operational role of yard cranes, which are essential for supporting various modes of transport. Variables like X_2 and X_8 can be considered as key connectors within the network of interdependent disruptions. Their impact is not primarily exerted through direct effects, but through their interactions with other variables. The interaction effects of rail operations, container trucks, and container volume with other disruptive factors are minimal, indicating that these factors function largely as independent inputs within the port system.

The variables X_1, X_2, and X_8 collectively form a high-interaction cluster, with interaction indices consistently above 0.1, indicating a tightly coupled subsystem that plays a critical role in reinforcing disruptions. Such a structure significantly increases the likelihood and severity of compound disruptions.

4.5. Comparison with other GSA methods

This section confirms the SI results through cross-method consistency checks. It is crucial to understand that variations in outcomes are a natural consequence of the fundamentally different logical reasoning of SA methods, which means these methods are complementary rather than competitive (Garcia et al., 2019; Ligmann-Zielinska et al., 2024). Additionally, acknowledging that results are heavily influenced by the sampling techniques, and some sensitivity techniques require particular sampling methods, only methods that are compatible with the Sobol sequence are selected, thereby removing external interferences. The FAST-RBD method, known for its broad recognition and usage (Cukier et al., 1973), is chosen for comparative analysis. Additionally, the PAWN method, which is better suited for handling asymmetric result distributions, is increasingly preferred to traditional Sobol methods (Coppola et al., 2023). Accordingly, this study employs PAWN as one of the comparative methods. The results of all three methods, along with the rankings of each disruptive factor, can be seen in Fig. 9.

The figure shows that the outputs from the Sobol and FAST-RBD methods align closely, following the same trends with slight variances. Evidence from other studies supports the consistency between these methods (Pohya et al., 2022). For future applications with limited computational resources, it is recommended to prefer the Sobol method for its ability to compute higher-order SI effectively. Additionally, the PAWN method is observed to compress larger values and amplify smaller ones, thereby narrowing the discrepancies among them. As previously discussed, the Sobol method was chosen as the primary approach due to its superior performance in low-sample environments and its capacity to quantify higher-order interaction effects. However, all methods reveal similar patterns, where liner quay crane disruptions are notably impactful, in contrast to the minimal influence of other variables.

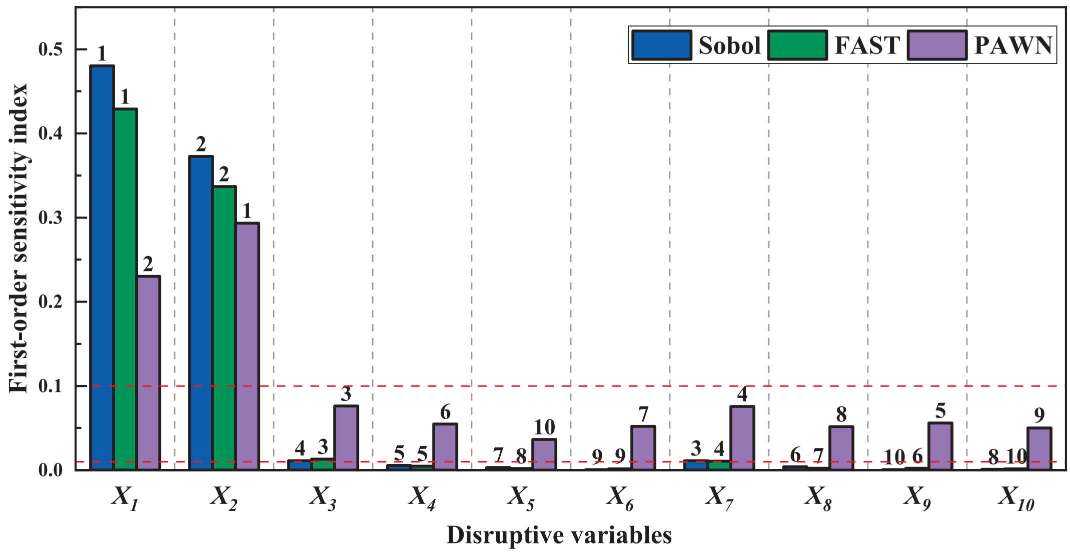


Fig. 9. Comparison of SI computed with Sobol, FAST-RBD and PAWN.

Despite minor methodological differences, all three approaches are consistent in recognising the liner quay crane to be the key component for port resilience. Such an analysis provides a basis for port operators to set priorities and optimise resource allocation toward key operational assets. Other critical elements, such as feeder quay crane and yard crane, possess an SI over 0.1, which confirms that those disruptions need to be considered essential as well.

For an in-depth validation of the SA's accuracy, the ICC consistency test is utilised, and the findings are shown in Table 8.

In the first and second columns, different types of ICC tests are detailed, with corresponding ICC values in the second column, where higher values signify greater consistency. The final column reveals the positioning of the consistency test outcomes within the 95% confidence interval. Analysis using 6 ICC tests indicates consistently high consistency. Such comparative analysis validates the results in identifying and quantifying influential factors for port resilience.

5. Discussion

The framework developed in this paper is designed to directly address the complex and evolving risk management requirements faced by port stakeholders operating in increasingly multimodal environments. Specifically, the framework targets container ports characterised by the presence of two or more transportation modes, standardised cargo handling processes, and essential operational equipment. By focusing on these criteria, the framework seeks to offer stakeholders a decision-support tool that is not only practical and user-friendly but also robust in its analytical foundation and broadly accessible across diverse operational contexts. In developing this framework, particular attention is given to the internal operational disruptions that most acutely affect port performance, such as equipment failures, process delays, and intra-terminal bottlenecks. While the primary emphasis is on internal dynamics, the framework acknowledges that external socio-economic factors and broader network-level interactions can play significant roles in shaping operational resilience. However, for analytical tractability and to ensure actionable insights for port managers, these externalities are deliberately held constant in the present model. This scoping decision enables greater specificity in modelling subsystem interdependencies and risk-propagation pathways within the port environment. A key strength of the proposed framework lies in its modular, parameterised structure, which enhances its adaptability across a wide range of container ports with similar multimodal characteristics. The framework can be recalibrated to suit ports with fewer transportation modes, different throughput capacities, or unique operational constraints by adjusting relevant parameters and subsystem couplings. This flexibility extends the model's practical applicability and supports its integration into existing risk management protocols at both established and emerging container ports. The preceding analysis has outlined the principal findings of this study and subjected them to rigorous robustness checks, including scenario-based sensitivity analyses and cross-validation against empirical data where available. These methodological steps underpin the credibility and generalisability of the results. The subsequent sections will further elaborate on the practical, policy, and stakeholder-specific implications of these findings, highlighting implementation pathways and areas for future research.

5.1. Implications for theory

This research advances the traditional resilience framework by integrating underexplored dimensions and providing a deeper theoretical interpretation, with particular focus on the structural and operational complexities of multimodal transport systems. Rather than confining resilience to conventional emphases on response speed and post-disturbance stability, this study broadens the conceptual landscape by explicitly introducing subsystem coupling relationships and mechanisms of risk propagation across interconnected modes, such as ripple effects. By foregrounding these elements, the research enriches the conceptual depth of resilience and aligns it more closely with the realities of modern transport systems, where tightly coupled subsystems and cross-modal dependencies are prevalent (Liu et al., 2023d; Wang et al., 2025; Li et al., 2022). Notably, this perspective challenges the prevailing tendency to treat resilience as a static or intrinsic attribute, instead framing it as an emergent and dynamic property shaped by evolving interdependencies among system components in multimodal environments. Furthermore, this study moves beyond conventional analyses that primarily address isolated or single-risk scenarios (Li et al., 2025) by investigating system behaviour under simultaneous and interacting disruptions. Through examining how key performance indicators and feedback structures respond to compound disturbances, the research extends the theoretical applicability of resilience to complex transportation networks characterised by nonlinearity and intermodal interactions. This approach underscores the need to capture cascading effects and cross-modal feedback when assessing system robustness and recovery potential, thereby advancing the adaptation of resilience concepts to the multifaceted risk landscape of contemporary multimodal transport systems.

Table 8
Result of the ICC consistency test between three sensitivity methods.

ICC Type	ICC	CI 95%
ICC(1, 1)	0.779	[0.51, 0.93]
ICC(2, 1)	0.779	[0.5, 0.93]
ICC(3, 1)	0.773	[0.48, 0.93]
ICC(1, *k*)	0.914	[0.76, 0.98]
ICC(2, *k*)	0.914	[0.75, 0.98]
ICC(3, *k*)	0.911	[0.74, 0.98]

5.2. Implications for the managers and the policymakers

This research establishes a quantitative foundation for prioritising disruptions and optimising emergency resource allocation, advancing port operations from experience-driven to evidence-based decision-making in areas such as maintenance, inventory, and contingency planning. The following recommendations are derived directly from the analytical findings.

The distinction between first-order and total-order sensitivity indices provides important insights into the structural nature of vulnerabilities and resilience within multimodal port systems. Disruptive factors with high first-order effects, such as liner quay crane failures, represent dominant single sources of uncertainty. This suggests that the resilience loss associated with these disruptions is primarily driven by their own features, rather than by complex propagation mechanisms. From a system perspective, such disruptions can be interpreted as locally critical components whose failure directly influences performance. Therefore, resilience improvements can be achieved through targeted, component-level interventions without necessarily requiring broader system intervention. Based on the previous results, liner quay crane malfunctions fall into this category of single-source dominant risks. Therefore, marginal improvements in their reliability can generate substantial system-wide benefits directly with highly effective and immediate rewards. Practical measures include the deployment of health monitoring sensors, optimised maintenance scheduling based on failure risk, ensuring the availability of critical spare parts, and establishing rapid replacement and repair protocols to minimise downtime. Compared with traditional experience-based approaches to emergency resource allocation and maintenance planning, such targeted, evidence-based allocation of emergency resources and maintenance scheduling enable resilience enhancement measures that not only improve operational resilience but also enhance cost-effectiveness.

Beyond liner operations, feeder quay crane failures emerge as a second tier but structurally essential disruption factor. Although their first-order effects are markedly lower than those of liner quay cranes, feeder crane disruptions still contribute non-negligibly to overall port resilience. This is because feeder operations constitute a critical link in multimodal transport, redistributing containers between international mainline services and regional networks. Moreover, despite differences in scale and capacity, feeder quay cranes share similar mechanical structures and operational workflows with liner quay cranes, implying comparable vulnerability mechanisms. Consequently, disruptions in feeder crane availability can propagate delays to yard operations and hinterland transport even when liner services remain stable. In summary, feeder operations do not emerge as a bottleneck issue; instead, they define port resilience under non-extreme disruption scenarios. Therefore, for ports that rely heavily on feeder-based transhipment, preventive maintenance and contingency plans should be in place.

In contrast, factors with relatively low first-order but high interaction effects represent systemic risks, whose influence on port resilience arises not from their standalone impact, but from their ability to amplify and propagate disruptions through interdependent subsystems. Such factors function as structural coupling points within the port system, and therefore require coordinated, cross-subsystem management strategies. For example, yard crane failures exemplify this interaction-dominant risk type. From an operational perspective, yard cranes serve as the interface between seaside and landside operations, linking vessel handling, trucking, and yard storage processes. Disruptions in yard crane operations can therefore magnify upstream and downstream delays, leading to disproportionate system-wide impacts. To mitigate these adverse interaction effects, yard management should not only focus on itself but also on its connection to other subsystems. Actionable measure includes dynamic storage allocation, coordinated and synchronised scheduling with seaside operations. In addition, it requires continuous situation monitoring and proactive preparation across other subsystems to mitigate the potential ripple effects.

Rail crane failures exhibit a similar but more latent risk profile. Individually, their influence on port resilience is modest. However, when rail crane disruptions coincide with failures in yard or quay crane operations, their combined effects become disproportionately large, often far exceeding their standalone contribution. This interaction-driven behaviour reveals a critical vulnerability of multimodal transhipment systems, in which simultaneous disruptions across multiple transport modes can rapidly overwhelm overall resilience. Such risks are particularly pronounced in ports with high rail modal shares, and hinterland connectivity plays a strategic role in sustaining throughput during disruption periods.

Traffic congestion exhibits a similar amplification mechanism. Despite its low individual sensitivity, congestion shows notable second-order interactions with other equipment failures (e.g., yard cranes, liner quay cranes, and feeder quay cranes), indicating its role as a temporal and spatial risk amplifier. When a disruption leads to traffic congestion, reliability and robustness across multiple subsystems are reduced, and recovery processes are prolonged, which in turn generates negative feedback loops that further intensify these negative effects. This finding underscores the necessity of integrating congestion management into recovery planning, including the design of emergency access routes, priority lanes with time windows, and nearby transfer hubs. Importantly, such measures require coordination beyond the port boundary, involving hinterland transportation authorities and multimodal logistics providers.

High second-order sensitivity indices between variables (e.g., X_1 and X_2, X_2 and X_8) indicate that simultaneous disruptions can cause a sharp and substantial loss of port resilience, even when each disruption alone appears to be insubstantial and practically manageable. This reflects the non-additive and nonlinear nature of ripple effect in multimodal container ports and explains why ports may experience sudden operational breakdowns without clear early warning signs. Therefore, it poses a significant challenge for experience-based decision-making, as it often contradicts intuitive expectations from traditional single-risk scenarios. From a preparedness and governance perspective, these findings suggest that ports should move beyond single risk decision-making and instead be aware and prepare for simultaneous multiple disruptions. Actionable measures should start from systematically recording, examining, and prioritising combinations of risks that are likely to cause severe damage, but are difficult to foresee based on past experience alone.

Taken together, these findings indicate that port resilience is shaped by a small number of dominant, standalone disruption risks, as well as by a much broader set of interaction-driven risks arising from the mutual reinforcement of multiple disruptions. While targeted

Table 9
Disruption strategies based on stakeholder responsibilities.

Stakeholders	Scope of control	Disruption impact	Disruption-based resilience strategy	Application of the proposed methodology	Contribution to port resilience
Port authority and terminal operator	Direct control (internal operations)	Degraded port operational performance and service reliability	Scheduling and design	Buffer zone design, coordinated scheduling, prioritising critical operations	Absorbs disruptions and reduces the influence of risk propagation
		Increased emergency costs and pressure	Disruption mitigation and response	Repair speed, emergency response plan, prioritised lane, emergency drill considering compounded disruptions	Improves response and recovery capability by enabling timely countermeasures that account for compound disruption effects.
		Equipment damage	Equipment maintenance	Predictive maintenance, health monitoring sensors, and spare parts inventory	Increases robustness and reliability by reducing the likelihood and severity of critical equipment failures
		Loss of shipping lines and reduced port competitiveness	Risk accountability	Clear definition of risk ownership, responsibility allocation, and accountability tracking	Strengthens governance and coordination
Government and public agencies	Policy-level and regulatory control	Reduced port throughput and hinterland connectivity	Port development direction	Strengthen policy guidance and funding in port infrastructure development and management, especially on resilience enhancement	Enhance long-term robustness by supporting resilience-oriented infrastructure investment
		Regional trade and supply chain continuity	Port functionality design against disruptions	Incorporate multi-disruption scenarios into port design and planning, set appropriate thresholds and implement risk decoupling strategies	Reduce the influence of cascading failures
		Economic and social risks	Collaboration within government bodies	Collaborate with the highway, railway, and surrounding authorities for disruption monitoring and coordinated response design	Enable coordination and reducing disruption propagation between the port and the hinterland
Logistics companies	Indirect control (dependent on port functionality for international trade)	Schedule unreliability, reduced service level and long-term customer relationships.	Risk prevention and preparedness, and responses	Staff training, risk prediction, information sharing, and collaborative rescheduling	Enhances robustness and response by improving decision-making, information sharing, and flexible rescheduling.

interventions on critical assets such as liner quay cranes can deliver immediate resilience gains, managing interaction-dominant factors such as yard crane downtime, rail operations, and traffic congestion requires coordinated, cross-subsystem strategies.

Therefore, beyond management policies within the port, the establishment of a cross-agency collaborative response platform is essential for enhancing port resilience under compounded disruptions. In practice, operations such as railway dispatching, yard management, and berth scheduling are currently dealt with by separate departments and their holistic coordination and management are overseen. An integrated platform for cross-agency coordination, such as a joint monitoring centre or a collaborative emergency response hub, enables real-time data sharing, early detection of risk amplification, and coordinated decision-making. To further strengthen collaboration, incentive mechanisms can be introduced to reward operational adaptability during disruptions between stakeholders. Building on this work, the development of a digital twin architecture informed by the proposed SD-ER-GSA framework can enable an integrated approach that connects short-, medium-, and long-term resilience management within ports. Such a system would enable coherent support for risk identification, resilience assessment, consequence prediction, coordinated emergency scheduling, equipment maintenance planning, staff training, and strategic infrastructure investment, thereby ensuring that operational resilience is embedded throughout the port's life cycle.

While the proposed framework adopts a multimodal perspective, it is important to recognise that the scope of operational control of a container port operator is largely confined to internal terminal activities. Disruptions from external transportation, including rail and road connections, are typically managed by independent commercial groups or public agencies. Therefore, it is important to support a multi-stakeholder approach to port resilience enhancement. For port authorities and terminal operators, the sensitivity analysis provides evidence-based prioritisation of critical internal assets and recovery strategies. For external transport operators, such as railway and highway infrastructure management agencies, railway and trucking companies, the results highlight the conditions under which their disruptions may interact with terminal operations to amplify resilience losses, thereby informing coordinated response and information-sharing recovery. For shipping lines, the findings provide a clearer understanding of the underlying causes of port delays and support service recovery through informed rescheduling. Local and national government, maritime and coastal agency, urban and regional planning department, and budget planning office and other public agencies can use these insights to support cross-sectoral planning, regulatory alignment, and targeted infrastructure investment, particularly in ports with high reliance on hinterland connectivity. To ensure effective implementation, the proposed measures should be adapted according to the distinct roles and influence of each stakeholder group. Therefore, applicable disruption strategies are mapped against key stakeholder responsibilities, as shown in Table 9.

5.3. Limitations of the study and future research directions

While the proposed framework offers a systematic and practical approach to quantifying resilience and making risk-informed decisions, it also has certain limitations. One lies in addressing the substantial time and computational costs involved in simulating various disruption scenarios. To mitigate this, parameterised *meta*-models could be used to predict port resilience under various disruptions, thereby reducing simulation load. In particular, the present model does not capture fine-grained task-level operational decisions, such as assigning and sequencing specific internal trucks to quay or yard cranes. Future research will extend this work by developing more detailed and realistic simulation models. Moreover, other potential research areas include cost-benefit analysis of pre-disruption, maintenance, and resource allocation optimisation during or post-disruption.

6. Conclusion

A framework based on SD, resilience quantification, ER, and GSA is proposed to identify, prioritise, and quantify disruptive factors affecting port resilience and their interconnections, using real operational data and incident reports from port operations. The main contributions of this paper are as follows: (1) GSA is employed to determine the extent of the disruption's impact on port operational resilience. Consistency tests are conducted across three distinct GSA methods to ensure the accuracy of the findings and the robustness of the framework. (2) Drawing on real-world examples, this study employs Sobol's second-order SI to capture the compounded impact of concurrent disruptions on port resilience, which may be attributed to underlying ripple effects. (3) The SI obtained through the proposed framework, including total-order, first-order, and second-order, offers highly applicable guidance for risk-informed policymaking and operational planning aimed at enhancing resilience in multimodal port systems.

This study contributes to both theory and practice by providing a robust and transferable framework for analysing port operational resilience under complex and concurrent disruptions. Methodologically, the integration of SD, ER, and multiple GSA techniques advances resilience research and offers new insights into ripple effects that are often overlooked in existing studies. From a practical and policy perspective, the resulting first-order, total-order, and second-order sensitivity indices offer an interpretable and evidence-based foundation for prioritising risks, allocating resources, and designing targeted operational and regulatory interventions. As such, the proposed framework supports academics in advancing resilience modelling, assists port managers in tackling operational risks, and informs policymakers in addressing pressing challenges.

CRediT authorship contribution statement

Jinglin Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xuri Xin:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis. **Rameshwar Dubey:** Writing – review & editing, Validation, Supervision. **Trung Thanh Nguyen:** Supervision. **Xiaoning Shi:** Supervision. **Na Li:** Writing – review & editing, Validation, Methodology. **Zaili Yang:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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.

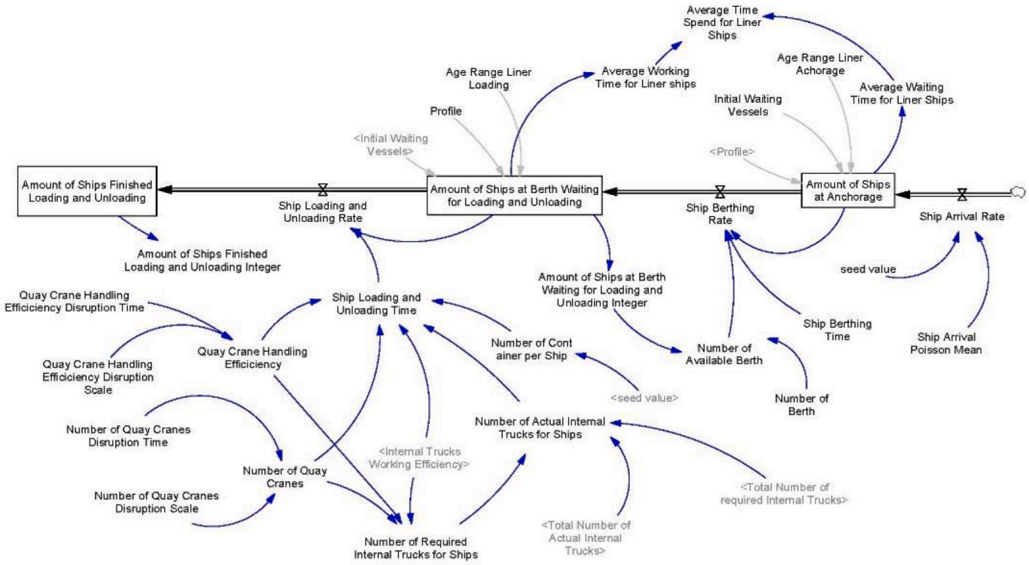
Acknowledgments

This research was funded by a European Research Council project under the European Union's Horizon 2020 research and innovation programme (TRUST CoG 2019 864724).

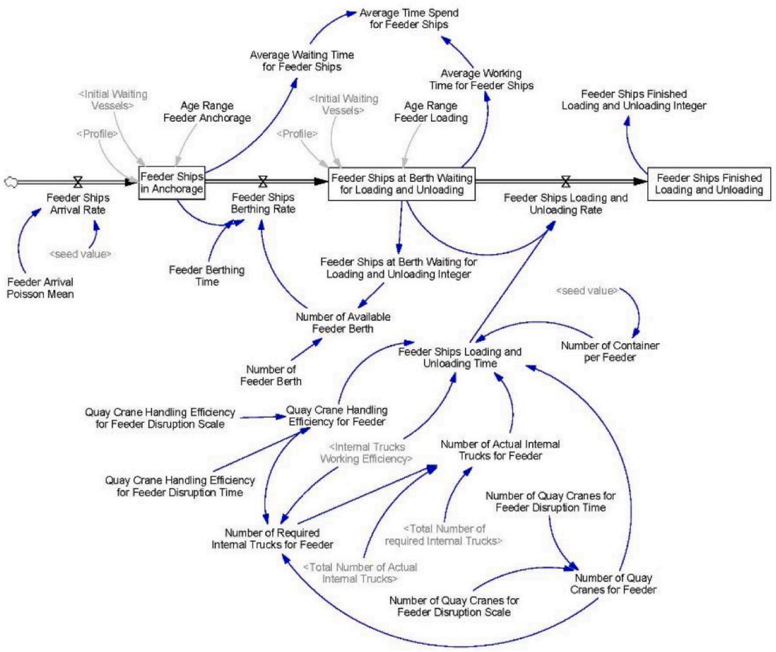
Appendix 1

Appendix A

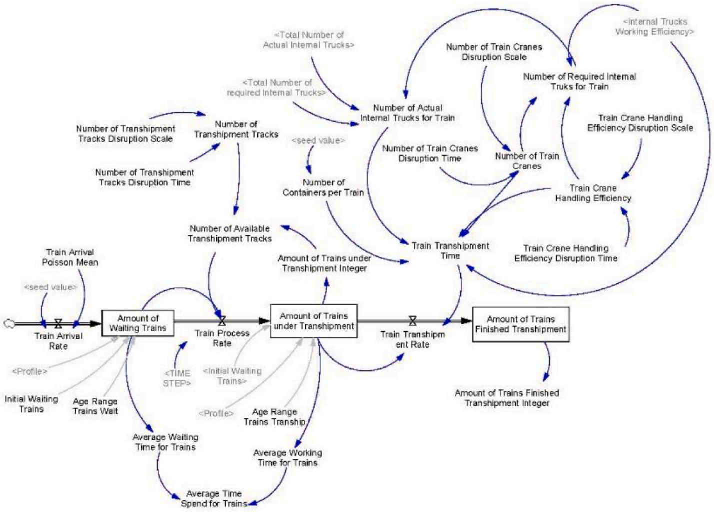
Elaborating on the causal loop diagram, the stock-flow diagram is also developed in a modular manner, encompassing five subsystems and various quantitative variables, as shown in Fig. A1.



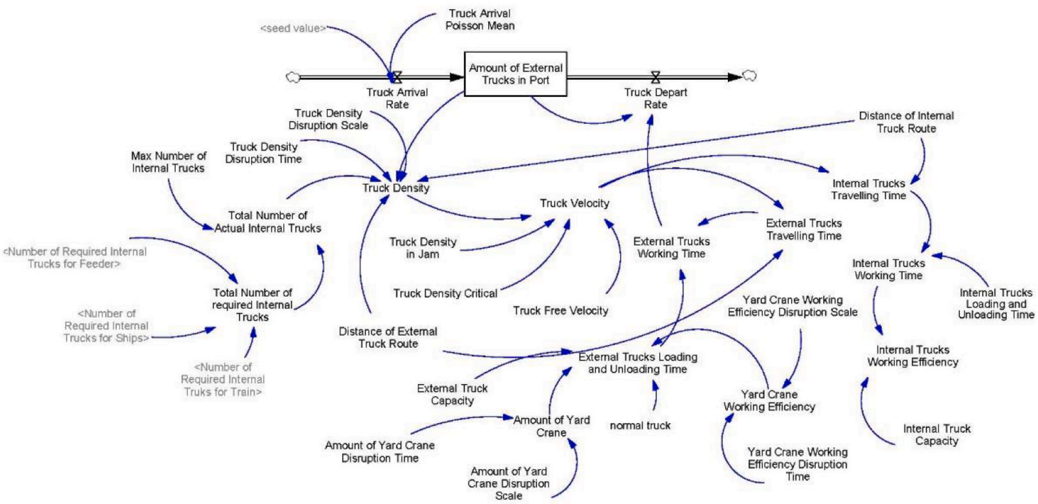
(a) Liner shipping system.



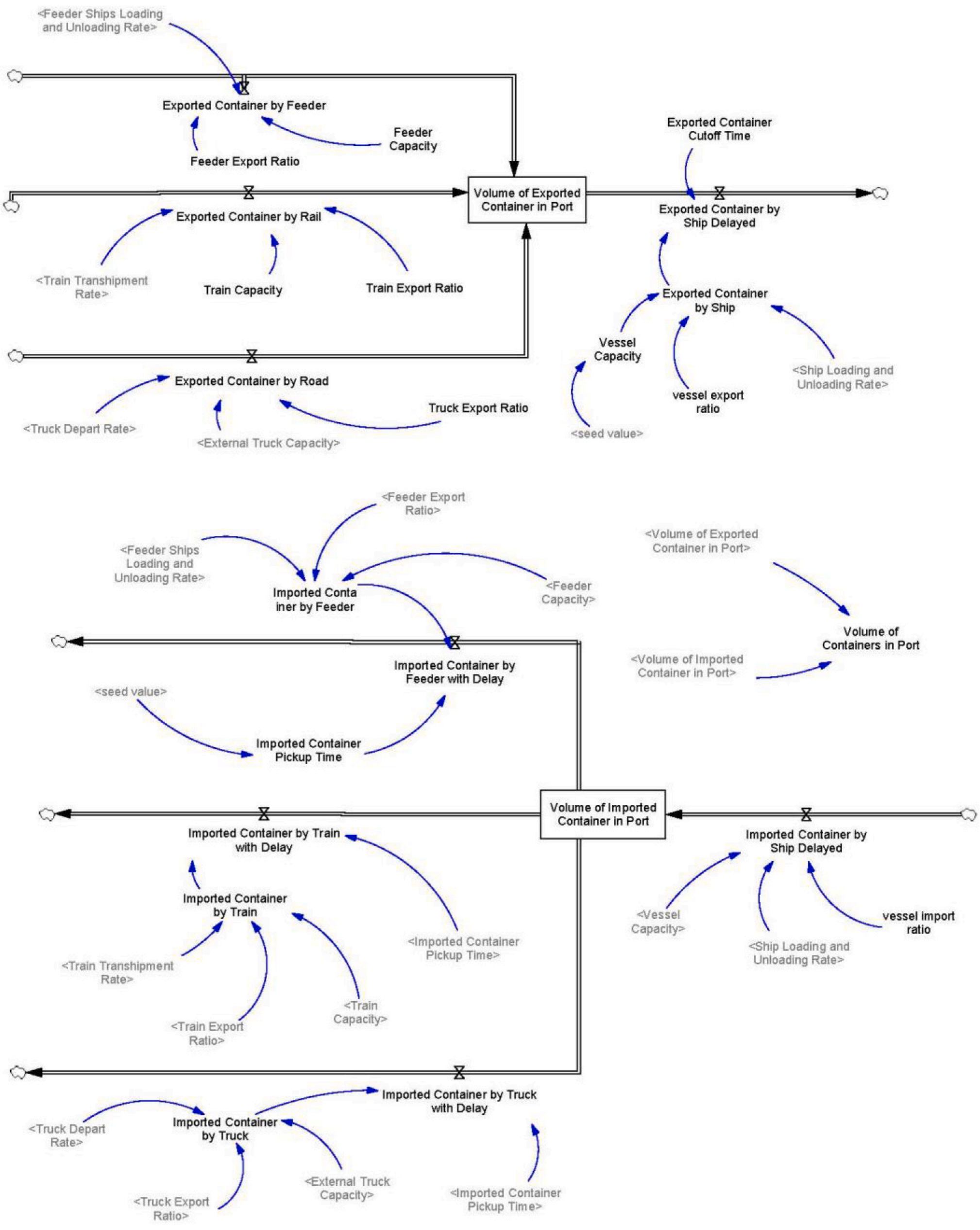
(b) Feeder shipping system.



(c) Railway system.



(d) Truck system.



(e) Container inventory system.

Fig. A1. Stock-flow diagram of multimodal container port (Adapted from Zhang et al., 2025b).

Data availability

Data will be made available on request.

References

Alyami, H., Yang, Z., Riahi, R., Bonsall, S., Wang, J., 2019. Advanced uncertainty modelling for container port risk analysis. Accid. Anal. Prev. 123, 411–421.
Ayaz, İ.S., Bucak, U., Mollaoğlu, M., Esmer, S., 2022. Resilience strategies of ports against covid-19 in terms of chaos theory. Mar. Policy 146, 105323.
Ayyub, B.M., 2014. Systems resilience for multihazard environments: definition, metrics, and valuation for decision making. Risk Anal. 34, 340–355.
Bai, X., Xu, M., Han, T., Yang, D., 2022. Quantifying the impact of pandemic lockdown policies on global port calls. Transp. Res. A Policy Pract. 164, 224–241.

Bell, M.G.H., Wang, Z., Cheung, K.-F., Zhu, S., 2023. A system dynamics analysis of the trans-pacific trade lane during the pandemic. Transp. Res. A Policy Pract. 176, 103802.
Bruneau, M., Chang, S.E., Eguchi, R.T., Lee, G.C., O'Rourke, T.D., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W.A., von Winterfeldt, D., 2003. A framework to quantitatively assess and enhance the seismic resilience of communities. Earthq. Spectra 19, 733–752.
Cai, L., Li, W., Zhou, B., Li, H., Yang, Z., 2024. Robust multi-equipment scheduling for u-shaped container terminals concerning double-cycling mode and uncertain operation time with cascade effects. Transp. Res. Part C Emerging Technol. 158, 104447.
Cao, X., Lam, J.S.L., 2018. Simulation-based catastrophe-induced port loss estimation. Reliab. Eng. Syst. Saf. 175, 1–12.
Chen, J., Liu, J., Du, B., Peng, Q., Yin, Y., 2022. Resilience assessment of an urban rail transit network under short-term operational disturbances. IEEE Trans. Intell. Transp. Syst. 23, 24841–24853.
Chen, W., Zhang, L., 2021. Resilience assessment of regional areas against earthquakes using multi-source information fusion. Reliab. Eng. Syst. Saf. 215, 107833.
Cheng, Y., Elsayed, E.A., Huang, Z., 2022. Systems resilience assessments: a review, framework and metrics. Int. J. Prod. Res. 60, 595–622.
Cheng, Y., Xia, J., Zhou, M., Deng, S., Wang, Z., Lu, J., 2023. Parameter sensitivity and uncertainty of a one-dimensional morphodynamic model in the lower yellow river. J. Hydrol. 625, 130016.
Cohen, M., Schwartz, N., Rosenzweig, R., 2024. Identification of parameter importance for benzene transport in the unsaturated zone using global sensitivity analysis. Hydrol. Earth Syst. Sci. 28, 1585–1604.
Collins, M., Chandler, R.E., Cox, P.M., Huthnance, J.M., Rougier, J., Stephenson, D.B., 2012. Quantifying future climate change. Nat. Clim. Chang. 2, 403–409.
Coppola, A., D'Aniello, C., Pariota, L., Bifulco, G.N., 2023. Assessing safety functionalities in the design and validation of driving automation. Transp. Res. Part C Emerging Technol. 154, 104243.
Cukier, R.I., Fortuin, C.M., Shuler, K.E., Petschek, A.G., Schaibly, J.H., 1973. Study of the sensitivity of coupled reaction systems to uncertainties in rate coefficients. I theory. J. Chem. Phys. 59, 3873–3878.
Dempster, A. P. 2008. Upper and lower probabilities induced by a multivalued mapping. In: YAGER, R. R. & LIU, L. (eds.) Classic works of the Dempster-Shafer theory of belief functions. Berlin, Heidelberg: Springer Berlin Heidelberg.
Dolgui, A., Ivanov, D., 2021. Ripple effect and supply chain disruption management: New trends and research directions. Int. J. Prod. Res. 59, 102–109.
Dolgui, A., Ivanov, D., Sokolov, B., 2018. Ripple effect in the supply chain: an analysis and recent literature. Int. J. Prod. Res. 56, 414–430.
Fisher, R.A., 1970. Statistical methods for research workers. *Breakthroughs in statistics: Methodology and distribution*. Springer.
Garcia, D., Arostegui, I., Prellezo, R., 2019. Robust combination of the morris and sobol methods in complex multidimensional models. Environ. Model. Software 122, 104517.
Ghadge, A., Er, M., Ivanov, D., Chaudhuri, A., 2022. Visualisation of ripple effect in supply chains under long-term, simultaneous disruptions: a system dynamics approach. Int. J. Prod. Res. 60, 6173–6186.
Gonçalves, L.A.P.J., Ribeiro, P.J.G., 2020. Resilience of urban transportation systems. Concept, characteristics, and methods. J. Transp. Geogr. 85, 102727.
Gu, B., Chen, J., Haralambides, H., Liu, J., 2025. A novel method of assessing port resilience and its positive ramifications. Marit. Policy Manag. 1–24.
Gu, B., Liu, J., 2023. Port resilience analysis based on the HHM-FCM approach under COVID-19. Ocean Coastal Manag. 243, 106741.
Gu, B., Liu, J., Ye, X., Gong, Y., Chen, J., 2024. Data-driven approach for port resilience evaluation. Transp. Res. ELogistics and Transportation Review 186, 103570.
Guo, S., Wang, H., Wang, S., 2023a. Network disruptions and ripple effects: Queueing model, simulation, and data analysis of port congestion. Journal of Marine Science and Engineering 11, 1745.
Guo, T., Liu, P., Wang, C., Xie, J., Du, J., Lim, M.K., 2023b. Toward sustainable port-hinterland transportation: a holistic approach to design modal shift policy mixes. Transp. Res. A Policy Pract. 174, 103746.
Ha, M.-H., Yang, Z., 2017. Comparative analysis of port performance indicators: Independency and interdependency. Transp. Res. A Policy Pract. 103, 264–278.
Ha, M.-H., Yang, Z., Lam, J.S.L., 2019. Port performance in container transport logistics: a multi-stakeholder perspective. Transp. Policy 73, 25–40.
He, B., Gilligan, J.M., Camp, J.V., 2023. An index of social fabric for assessing community vulnerability to natural hazards: Model development and analysis of uncertainty and sensitivity. Int. J. Disaster Risk Reduct. 96, 103913.
He, B., Guan, Q., 2024. Investigating the effects of spatial scales on social vulnerability index: a hybrid uncertainty and sensitivity analysis approach combined with remote sensing land cover data. Risk Anal. 44, 2723–2739.
Hossain, N.U.I., Amrani, S.E., Jaradat, R., Marufuzzaman, M., Buchanan, R., Rinaudo, C., Hamilton, M., 2020. Modeling and assessing interdependencies between critical infrastructures using bayesian network: a case study of inland waterway port and surrounding supply chain network. Reliab. Eng. Syst. Saf. 198, 106898.
Iman, R.L., Johnson, M.E., Watson Jr., C.C., 2005. Sensitivity analysis for computer model projections of hurricane losses. Risk Anal. 25, 1277–1297.
Ivanov, D., 2017. Simulation-based ripple effect modelling in the supply chain. Int. J. Prod. Res. 55, 2083–2101.
Jansen, M.J.W., 1999. Analysis of variance designs for model output. Comput. Phys. Commun. 117, 35–43.
Jaxa-Rozen, M., Pratiwi, A.S., Trutnevyte, E., 2021. Variance-based global sensitivity analysis and beyond in life cycle assessment: an application to geothermal heating networks. Int. J. Life Cycle Assess. 26, 1008–1026.
Jiang, M., Lu, J., Qu, Z., Yang, Z., 2021. Port vulnerability assessment from a supply chain perspective. Ocean & Coastal Management 213, 105851.
Jiang, X., Jia, R., Yang, L., 2024. Assessing the economic ripple effect of flood disasters in light of the recovery process: Insights from an agent-based model. Risk Anal. 44, 203–228.
Jin, J.G., Meng, Q., Wang, H., 2021. Feeder vessel routing and transshipment coordination at a congested hub port. Transp. Res. B Methodol. 151, 1–21.
Lai, X., Chen, Z., Wang, X., Chiu, C.-H., 2023. Risk propagation and mitigation mechanisms of disruption and trade risks for a global production network. Transportation Research Part e: Logistics and Transportation Review 170, 103013.
Li, C., Yang, X., Yang, D., 2025. Port vulnerability to natural disasters: an integrated view from hinterland to seaside. Transp. Res. Part D: Transp. Environ. 139, 104563.
Li, N., Chen, G., Govindan, K., Jin, Z.H., 2018. Disruption management for truck appointment system at a container terminal: a green initiative. Transportation Research Part D-Transport and Environment 61, 261–273.
Li, N., Haralambides, H., Sheng, H., Jin, Z., 2022. A new vocation queuing model to optimize truck appointments and yard handling-equipment use in dual transactions systems of container terminals. Comput. Ind. Eng. 169, 108216.
Liang, X., Fan, S., Lucy, J., Chen, J., Coleman, J., Li, Y., Qu, Z., Li, H., Yang, Z., 2025. Quantitative sustainability assessment of freeports: Hybrid model evidence from the uk. J. Clean. Prod. 487, 144521.
Ligmann-Zielinska, A., Jankowski, P., Najwer, A., Zwoliński, Z., 2024. A streamlined approach to uncertainty and sensitivity analysis for models with spatial outputs with an example from geodiversity assessment. Int. J. Geogr. Inf. Sci. 38, 1531–1554.
Liu, A., Li, Z., Shang, W.-L., Ochieng, W., 2023a. Performance evaluation model of transportation infrastructure: Perspective of COVID-19. Transp. Res. A Policy Pract. 170, 103605.
Liu, J., Gu, B., Chen, J., 2023b. Enablers for maritime supply chain resilience during pandemic: an integrated mcdm approach. Transp. Res. A Policy Pract. 175, 103777.
Liu, J., Wang, X., Chen, J., 2023c. Port congestion under the COVID-19 pandemic: the simulation-based countermeasures. Comput. Ind. Eng. 183, 109474.
Liu, Q., Yang, Y., Ng, A.K.Y., Jiang, C., 2023d. An analysis on the resilience of the european port network. Transp. Res. A Policy Pract. 175, 103778.
Liu, X., Titheridge, H., Yan, X., Wang, R., Tan, W., Chen, D., Zhang, J., 2020. A passenger-to-driver matching model for commuter carpooling: Case study and sensitivity analysis. Transp. Res. Part C Emerging Technol. 117, 102702.
Lu, B., Sun, Y., Wang, H., Wang, J.-J., Shuai Liu, S., Cheng, T.C.E., 2024. Dynamic resilience analysis of the liner shipping network: from structure to cooperative mechanism. TransportationResearch Part e: Logistics and Transportation Review 191, 103755.
Lu, X., Borgonovo, E., 2023. Global sensitivity analysis in epidemiological modeling. Eur. J. Oper. Res. 304, 9–24.
Mizgier, K.J., 2017. Global sensitivity analysis and aggregation of risk in multi-product supply chain networks. Int. J. Prod. Res. 55, 130–144.
Morris, M.D., 1991. Factorial sampling plans for preliminary computational experiments. Technometrics 33, 161–174.

Mustafa, F.S., Khan, R.U., Mustafa, T., 2021. Technical efficiency comparison of container ports in asian and middle east region using dea. The Asian Journal of Shipping and Logistics 37, 12–19.
Niederreiter, H., 1988. Low-discrepancy and low-dispersion sequences. J. Number Theory 30, 51–70.
Pang, Z., O'Neill, Z., Li, Y., Niu, F., 2020. The role of sensitivity analysis in the building performance analysis: a critical review. Energ. Buildings 209, 109659.
Pianosi, F., Wagener, T., 2015. A simple and efficient method for global sensitivity analysis based on cumulative distribution functions. Environ. Model. Software 67, 1–11.
Pohya, A.A., Wicke, K., Kilian, T., 2022. Introducing variance-based global sensitivity analysis for uncertainty enabled operational and economic aircraft technology assessment. Aerosp. Sci. Technol. 122, 107441.
Praharsi, Y., Jami'I n, M.A., Sari, D.P., Isti'Anah, P.R., Wee, H.-M., 2025. Developing key performance indicators for a port in Indonesia. Sustainability 17, 4664.
Punzo, V., Montanino, M., Ciuffo, B., 2015. Do we really need to calibrate all the parameters? Variance-based sensitivity analysis to simplify microscopic traffic flow models. IEEE Trans. Intell. Transp. Syst. 16, 184–193.
Qazi, A., Dickson, A., Quigley, J., Gaudenzi, B., 2018. Supply chain risk network management: a bayesian belief network and expected utility based approach for managing supply chain risks. Int. J. Prod. Econ. 196, 24–42.
Razavi, S., Jakeman, A., Saltelli, A., Prieur, C., Iooss, B., Borgonovo, E., Plischke, E., Lo Piano, S., Iwanaga, T., Becker, W., Tarantola, S., Guillaume, J.H.A., Jakeman, J., Gupta, H., Melillo, N., Rabitti, G., Chabridon, V., Duan, Q., Sun, X., Smith, S., Sheikholeslami, R., Hosseini, N., Asadzadeh, M., Puy, A., Kucherenko, S., Maier, H.R., 2021. The future of sensitivity analysis: an essential discipline for systems modeling and policy support. Environ. Model. Software 137, 104954.
Razavi, S., Sheikholeslami, R., Gupta, H.V., Haghnegahdar, A., 2019. Vars-tool: a toolbox for comprehensive, efficient, and robust sensitivity and uncertainty analysis. Environ. Model. Software 112, 95–107.
Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., Tarantola, S., 2010. Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Comput. Phys. Commun. 181, 259–270.
Saltelli, A., Campolongo, F., Cariboni, J., 2009. Screening important inputs in models with strong interaction properties. Reliab. Eng. Syst. Saf. 94, 1149–1155.
Schmitz, V., Arnst, M., El Kadi Abderrezzak, K., Pirotton, M., Erpicum, S., Archambeau, P., Dewals, B., 2023. Global sensitivity analysis of a dam breaching model: to which extent is parameter sensitivity case-dependent? Water Resour. Res. 59, e2022WR033894.
Schulz, A., Fliedner, M., Fiedrich, B., Pfeiffer, C., 2021. Levelling crane workload in multi-yard rail-road container terminals. Eur. J. Oper. Res. 293, 941–954.
Shrout, P.E., Fleiss, J.L.J.P.B., 1979. Intraclass correlations: Uses in assessing rater reliability. Psychol. Bull. 86, 420–428.
Sobol', I.M., 2001. Global sensitivity indices for nonlinear mathematical models and their monte carlo estimates. Math. Comput. Simul 55, 271–280.
Sobol', I.Y.M., 1990. On sensitivity estimation for nonlinear mathematical models. Matematicheskoe Modelirovanie 2, 112–118.
Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M., Xu, C., 2015. Global sensitivity analysis in hydrological modeling: Review of concepts, methods, theoretical framework, and applications. J. Hydrol. 523, 739–757.
Spear, R.C., Grieb, T.M., Shang, N., 1994. Parameter uncertainty and interaction in complex environmental models. Water Resource Research 30, 3159–3169.
Sun, H., Liu, J., Han, Z., Jiang, J., 2021. Stochastic petri net based modeling of emergency medical rescue processes during earthquakes. J. Syst. Sci. Complex. 34, 1063–1086.
Sun, H., Yang, M., Zio, E., Li, X., Lin, X., Huang, X., Wu, Q., 2024. A simulation-based approach for resilience assessment of process system: a case of lng terminal system. Reliab. Eng. Syst. Saf. 249, 110207.
Sun, W., Bocchini, P., Davison, B.D., 2020. Resilience metrics and measurement methods for transportation infrastructure: the state of the art. Sustainable and Resilient Infrastructure 5, 168–199.
Taghizadeh, E., Venkatachalam, S., Chinnam, R.B., 2021. Impact of deep-tier visibility on effective resilience assessment of supply networks. Int. J. Prod. Econ. 241, 108254.
Valaei Sharif, S., Habibi Moshfegh, P., Kashani, H., 2023. Simulation modeling of operation and coordination of agencies involved in post-disaster response and recovery. Reliab. Eng. Syst. Saf. 235, 109219.
Verschuur, J., Pant, R., Koks, E., Hall, J., 2022. A systemic risk framework to improve the resilience of port and supply-chain networks to natural hazards. Maritime Economics & Logistics 24, 489–506.
Wan, C., Yan, X., Zhang, D., Qu, Z., Yang, Z., 2019. An advanced fuzzy bayesian-based fmea approach for assessing maritime supply chain risks. Transportation Research Part e: Logistics and Transportation Review 125, 222–240.
Wan, C., Yang, Z., Yan, X., Zhang, D., Blanco-Davis, E. & Ren, J. Risk-based resilience analysis of maritime container transport networks. Proceedings of the 29th European Safety and Reliability Conference, ESREL 2019, 2020. ESREL.
Wan, C., Yang, Z., Zhang, D., Yan, X., Fan, S., 2018. Resilience in transportation systems: a systematic review and future directions. Transp. Rev. 38, 479–498.
Wang, N., Wu, M., Yuen, K.F., 2025. Dynamic enterprise resilience assessment for port systems: a framework integrating bayesian networks and Dempster-Shafer evidence theory. Reliab. Eng. Syst. Saf. 262, 111105.
Wang, N., Yuen, K.F., 2022. Resilience assessment of waterway transportation systems: Combining system performance and recovery cost. Reliab. Eng. Syst. Saf. 226, 108673.
Wang, T., Ng, A.K.Y., Wang, J., Chen, Q., Pang, J., Tang, J., 2024. Adaptation planning of container ports in the context of typhoon risks: the case of Ningbo-Zhoushan port in China. Ocean & Coastal Management 257, 107303.
Wen, T., Chen, Y.-W., Syed, T.A., Wu, T., 2024. Eriue: Evidential reasoning-based influential users evaluation in social networks. Omega 122, 102945.
Wu, J., Liu, J., 2025. Cooperation strategies for competing ports considering risk linkages. Comput. Ind. Eng. 200, 110796.
Xiao, Z., Bai, X., 2022. Impact of local port disruption on global container trade: an example of stressing testing chinese ports using a D-vine copula-based quantile regression. Ocean & Coastal Management 228, 106295.
Yan, J., Chen, J., Zhang, W., 2023. A new probabilistic assessment process for human health risk (hhr) in groundwater with extensive fluoride and nitrate optimized by non parametric estimation method. Water Res. 243, 120379.
Yang, J.-B., Singh, M.G., 1994. An evidential reasoning approach for multiple-attribute decision making with uncertainty. IEEE Trans. Syst. Man Cybern. 24, 1–18.
Yang, J.-B., Xu, D.-L., 2013. Evidential reasoning rule for evidence combination. Artif. Intell. 205, 1–29.
Zhang, J., Xin, X., Dubey, R., Nguyen, T.T., Shi, X., Li, N., Yang, Z., 2025a. Impact of the ripple effect on the resilience of multimodal container port operations: a system dynamics simulation approach. Risk Anal. 45, 4903–4932.
Zhang, J., Xin, X., Liao, Z., Dubey, R., Nguyen, T.T., Li, N., Yang, Z., 2025b. Analysis of the ripple effects of disruptions on multimodal container terminals operations: a system dynamics approach. Transportation Research Part e: Logistics and Transportation Review 202, 104264.
Zhang, J., Yang, D., Luo, M., 2024. Port efficiency types and perspectives: a literature review. Transp. Policy 156, 13–24.
Zhao, C., Peng, L., Dong, K., Yang, H., 2024. Government policies on port resilience amid strike events—a two-stage van damme based tripartite evolutionary game. Transp. Res. A Policy Pract. 188, 104196.
Zhao, Y., Guo, Z., Niu, F., Yu, Y., Wang, S., 2019. Global sensitivity analysis of passive safety systems of fhr by using meta-modeling and sampling methods. Prog. Nucl. Energy 115, 30–41.
Zohoori, S., Jafari Kang, M., Hamidi, M., Maihami, R., 2023. An ais-based approach for measuring waterway resiliency: a case study of Houston ship channel. Marit. Policy Manag. 50, 797–817.