Resilience framework for seaport infrastructure under extreme wind

Balbi, A.; Kammouh, O.; Cimellaro, G. P.; Repetto, M. P.

DOI
10.1016/j.rcns.2025.09.001

Publication date
2025

Document Version
Final published version

Published in
Resilient Cities and Structures

Citation (APA)
Balbi, A., Kammouh, O., Cimellaro, G. P., & Repetto, M. P. (2025). Resilience framework for seaport infrastructure under extreme wind. *Resilient Cities and Structures*, *4*(3), 99-116. https://doi.org/10.1016/j.rcns.2025.09.001

4 (2025) 99–116

Contents lists available at ScienceDirect

Resilient Cities and Structures

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

Full Length Article

Resilience framework for seaport infrastructure under extreme wind

A. Balbi [a], O. Kammouh [b,*], G.P. Cimellaro [c], M.P. Repetto [a,*]

[a] University of Genoa, Italy
[b] Delft University of Technology, the Netherlands
[c] Politecnico di Torino, Italy

ARTICLE INFO

Keywords:
Extreme events
Infrastructure performance
Natural disaster
Port infrastructure
Resilience
Wind

ABSTRACT

The efficient transportation of goods is vital for the economic growth of communities, making developing and maintaining seaport infrastructure an essential component of the marine transportation system. Given their geographic locations, ports are consistently at risk from natural hazards, making the resilience of port infrastructure an essential goal.

Despite considerable progress in resilience research, there remains a gap in methods tailored explicitly to assessing port resilience, particularly under extreme wind events. Current approaches often do not capture the full complexity of port systems, as they tend to focus on isolated aspects, such as structural resilience.

This paper introduces the PORT Resilience Framework, addressing these gaps by evaluating resilience through a comprehensive list of indicators gathered from various legitimate sources. The indicators are then organized under four comprehensive resilience dimensions: Physical Infrastructure, ICT (i.e., Information and Communication Technology) and Equipment; Organization and Business Management; Resources and Economic Development; and Territory, Environment, and Stakeholders. This classification is summarized under the acronym "PORT."

This paper also introduces a method for aggregating resilience indicators by considering their performance before and after a specific hazard, transforming the data into a quantifiable Loss of Resilience index. The approach is applied to a case study, assessing the resilience of a real Terminal against wind action using real data sourced from the port management.

The case study analysis revealed that human resources and quay operations were the most critical factors affecting recovery, with insufficient staffing leading to prolonged recovery periods. The study further demonstrated that post-disruption activity surges, captured by different serviceability function methodologies, often created operational bottlenecks, challenging the port's overall recovery.

1. Introduction

Ports are one of the main components of the physical infrastructure within coastal communities, serving as fundamental elements for marine transportation at both local and national levels. Due to their natural location, ports are continuously threatened by natural hazards [1–3], necessitating ongoing monitoring to guarantee efficient terminal management and increased safety levels [4,5].

Among the various natural hazards, wind intensity has the most significant influence on port operations. Wind velocity is monitored to guarantee safe working conditions and prevent extreme weather disasters [6]. Typically, port authorities and private companies monitor wind intensity using local anemometers, applying restrictions or even suspending activities if wind speed increases over certain thresholds [7]. Closing port terminals due to wind alerts safeguards workers, which is the primary scope of the alert systems; however, it can also result in severe economic and performance losses, regardless of whether wind-induced damages occur. Moreover, the restart phase after the port closure or damage event is characterized by a transient period of recovery, a delicate phase with increased risk for non-standard operational conditions. This complex and interconnected problem necessitates advanced management procedures, calling for methodologies that assess the resilience and performance of port infrastructure. Such methodologies should enable proper management of closure conditions and extreme disruptive events, aiming to reduce overall risk and economic losses on a rational basis.

* Corresponding authors.
E-mail address: o.kammouh@tudelft.nl (O. Kammouh).

https://doi.org/10.1016/j.rcns.2025.09.001

Available online 19 September 2025

The concept of resilience is defined as the ability of social units (e.g., organizations, communities) to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways to minimize social disruption and mitigate the effects of further earthquakes [8]. Although substantial effort has been made to boost research on resilience measurement across multiple domains—including community and urban resilience frameworks [8–10], infrastructure and transport system assessments [11–14], and country/state-level resilience evaluation methods [15–19], there still exists a lack of operative methods tailored explicitly to comprehensive port infrastructure systems that integrate physical, organizational, and territorial dimensions.

Existing approaches have limitations; some focus on specific scenarios, such as quays' destruction under seismic events [20], while others center on identifying port performance indicators [21], leading to the development of performance evaluation frameworks [22–25]. These approaches do not capture the full complexity of port systems, resulting in a restricted view of the elements essential for an in-depth analysis of port operations. As of now, none of the methods developed recently have been able to assess the overall resilience of ports.

In addition to the general approaches to resilience in critical infrastructures, several studies have focused explicitly on the resilience of port infrastructure, offering varied methodologies and frameworks to assess and enhance resilience under different risks. Kong, et al. [26] addressed the structural resilience of core port infrastructure in the context of climate change, highlighting the increasing vulnerability of ports to extreme weather events. Similarly, Yang, et al. [27] developed an indicator-based resilience assessment model for critical infrastructures, which provides a comprehensive tool for evaluating resilience but lacks specific tailoring to the unique challenges of port environments. Expanding on this, Panahi, et al. [28] proposed a model for resilience assessment that captures the systemic nature of critical infrastructures but did not focus on specific sectoral applications such as ports. Cho and Park [29] introduced a resilience model using system dynamics, which offers valuable insights into how port infrastructure components interact dynamically during disruption events, though the application remains limited to structural factors. Several works also emphasize the need for scenario-based frameworks to address specific hazards, such as Modarres and Kruse [30], who examined seismic resilience in ports, and Marroni, et al. [31], who focused on LNG carriers in vulnerable port areas. Other studies, such as Hsieh, et al. [32], explored port vulnerabilities from the perspective of critical infrastructure interdependencies, underscoring the cascading effects that disruptions in interconnected systems can have on port operations.

Moreover, while much of the literature on infrastructure resilience addresses seismic hazards, extreme wind conditions have not yet been thoroughly analyzed. This represents a significant shortcoming, as wind poses the most disruptive natural risk for port areas. Adam, et al. [33] found that 48 % of maritime disruptions in the United Kingdom from 1950 to 2014 were due to wind storms and storm surges. Such damages include but are not limited to derailed or collapsed cranes, damaged warehouse rooftops, and overturned containers [34], along with indirect losses and reduced reliability within the connected industrial clusters [35].

Despite these advancements, a unified framework that integrates these various approaches and thoroughly addresses the full spectrum of port resilience—from physical infrastructure to operational and environmental factors—that focuses on extreme wind events remains underdeveloped. These gaps indicate the need for a comprehensive approach that encapsulates the dynamic and interdependent nature of ports in response to extreme natural events, as discussed by recent works on resilience evaluation along the maritime Silk Road [36] and the overall vulnerability of ports within supply chain systems [37].

This paper presents an advanced and comprehensive framework, the PORT Resilience Framework, designed to holistically assess the resilience of port infrastructures, particularly in the face of extreme wind events. The PORT Resilience Framework is developed to address existing gaps in current methodologies by integrating structural, operational, and environmental dimensions of port systems. Unlike previous models that focus predominantly on specific hazards such as seismic events [20] or provide isolated assessments of individual port components [26,31], the proposed framework captures the full complexity of port systems, emphasizing the interdependencies between physical infrastructure, business operations, and external environmental factors.

The PORT Resilience Framework offers a dual-stage approach. The first stage introduces a novel indicator-based resilience assessment model that evaluates the vulnerability of port terminals, operational efficiency, and systemic interdependencies under normal conditions and during wind-related disruptions. The indicators span multiple dimensions, including physical infrastructure, ICT systems, human resources, and environmental sustainability. The second stage focuses on real-time monitoring and post-event analysis, providing a dynamic evaluation of port recovery processes after severe wind events. Drawing on approaches from system dynamics [29] and risk assessment methodologies [30], this stage measures not only the immediate impacts of wind disruptions but also the longer-term implications on port functionality, business continuity, and economic stability.

The paper is structured as follows: Section 2 details the PORT framework, including the resilience dimensions, components, and indicators. Section 3 describes the methodology for quantifying these indicators and their consolidation into a singular serviceability function for the port infrastructure. Section 4 presents a case study of a real port infrastructure in northwest Italy, assessing its resilience against extreme wind events using real-time data provided by the Port management. Section 5 concludes with a summary and discusses directions for future research.

2. PORT framework structure

This section outlines the conceptual structure of the PORT Resilience Framework. It begins with a schematic representation of a typical container terminal to contextualize key port functions and components. A structured literature review, complemented by expert consultations, is then used to identify relevant indicators of resilience. These indicators are organized into a hierarchical framework consisting of dimensions and components, summarized under the acronym "PORT."

2.1. Port schematic representation

The initial step of this research involves identifying a general schematic representation of the port infrastructures within a typical container terminal. Fig. 1 provides a straightforward depiction of the port area, delineating the principal activities and key components involved in port operations.

Within this schematic, three main port cycles (train, quay, and truck cycles) are highlighted, along with the yard, which collectively form the intermodal areas of the port. These areas are where the most crucial activities of port operation occur. Containers are strategically moved from the quay cycle to the yard and then from the yard to the truck and train cycles for shipment outside the port. Conversely, the reverse of this process is executed for goods arriving from locations outside the port area.

Warehouses and administrative offices, though not directly involved in the movement of goods, play vital supporting roles in port operations and are considered complementary elements of a port. Their functions can include storage, record-keeping, and coordination among various port activities, contributing to the overall efficiency and effectiveness of the port infrastructure.

2.2. PORT framework structure: indicators, components, and dimensions

The methodology begins by identifying and gathering port-specific resilience indicators. Though indicators are valuable tools for

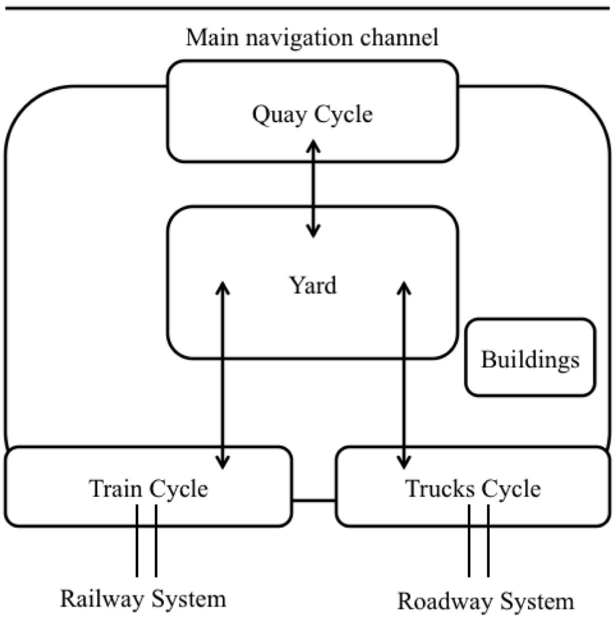

Fig. 1. Schematic representation of different port areas and their interconnections.

measuring resilience, formulating a standardized set of resilience indicators is challenging due to port environments' dynamic, ever-changing, and context-sensitive nature. The procedure followed three steps: i) collecting indicators, ii) identifying and assigning measures, and iii) clustering indicators.

2.2.1. Collecting indicators

The process of identifying and selecting resilience indicators for seaport infrastructure followed the PRISMA framework to ensure scientific rigor and representativeness. The methodology comprised four key stages: systematic literature review, expert validation, stakeholder consultation, and iterative refinement.

The initial stage involved a systematic search across leading scientific databases, including Scopus, Web of Science, and Google Scholar, using predefined search terms such as "infrastructure," "seaport," "resilience," "port," and "indicator." Boolean operators (AND/OR) and filters (e.g., publication years 2000–2023, English language) were applied to ensure relevance and breadth. The search yielded 2,512 articles, which were screened for relevance based on titles and abstracts. Inclusion criteria required that articles:

- Propose indicators for measuring the resilience of seaport infrastructure.
- Be peer-reviewed and published in English between 2000 and 2024.

The identified indicators were systematically evaluated for relevance, validity, and potential redundancy using established resilience frameworks [32,38–46]. A checklist mapped each indicator to core resilience attributes, such as robustness, redundancy, resourcefulness, and rapidity, and to the four PORT dimensions.

It is important to note that the PORT Framework is designed with a practical emphasis on real-world implementability. Indicators requiring unavailable or confidential data—such as structural typologies or detailed fragility curves—were excluded in favor of measurable, routinely collected operational metrics. This ensures the framework remains usable by port authorities across diverse contexts. To further refine the set of indicators, The indicators were reviewed for operational relevance, measurability, and redundancy by port operators and infrastructure experts, ensuring their applicability across diverse global seaport contexts. Interviewees have also proposed additional indicators that were not covered by the literature review.

2.2.2. Identifying and assigning measures

The measure $m_i(t)$ of an indicator i provides a quantitative or measurable parameter that can be used to assess the port's performance and compare the effect of different disruptions to ultimately evaluate the system's resilience objectively. The indicator is classified as static (S) if its measure is a constant value and as dynamic (D) if the measure varies over time [8,47,48]. In this study, each indicator was assigned a measure derived from the literature or, in some instances, based on the authors' expertise and knowledge of infrastructure resilience. These proposed measures were then reviewed and discussed with seaport experts to ensure their validity and to confirm that values exist in the port terminals' databases and current monitoring systems

2.2.3. Clustering indicators

The collected indicators were clustered under components and dimensions to make them more organized and easier to understand. Adopting a hierarchical approach, indicators are first grouped into components, representing homogeneous categories of indicators. These components are further grouped into dimensions, which are broader categories containing similar components. The dimensions, summarized under the acronym "PORT," are as follows:

1. Physical infrastructure, ICT (i.e., Information and Communication Technology), and equipment;
2. Organization and business management;
3. Resources and economic development;
4. Territory, environment, and stakeholders.

A detailed description of these Dimensions (Dn) and Components (Cn.m) can be found in Table 1 and the complete list of dimensions, components, and indicators is provided in Appendix A, together with the proposed measure, the literature reference (if any) and the static/dynamic nature of the indicator.

While the framework employs quantitative metrics, several indicators implicitly capture qualitative human resource aspects through their operational manifestations. For instance, 'Manning of Company' reflects operator efficiency, which naturally decreases due to fatigue or skill degradation, while workforce availability indicators capture effective availability as determined by management considering operator capability under stressed conditions

The modular design of the PORT framework allows for various approaches to indicator measurement, including integration of Structural

Table 1
Port Framework Components and Dimensions.

D1- Physical infrastructure, ICT, and equipment	D2- Organization and business management	D3- Resources and economic development	D4- Territory, environment, and stakeholders
C 1.1- Quay Cycle	C 2.1- Terminal Policy	C 3.1- Financial Flows	C 4.1- External Physical Access
C 1.2- Trucks Cycle	C 2.2- Internal and External Communication	C 3.2- Financial Services	C 4.2- Environment Sustainably
C 1.3- Train Cycle	C 2.3- Human Resources	C 3.3- Port Business and Costs	C 4.3- Reputation
C 1.4- Yards	C 2.4- Resources Planning	C 3.4- Employment Services	
C 1.5- Port Buildings			
C 1.6- Containers			
C 1.7- Port Utilities			
C 1.8- Technical Services			

Health Monitoring (SHM) data when available [49].

In the following subsections, the dimensions and components will be introduced and detailed.

2.3. Physical infrastructure, ICT, and equipment (D1)

The first dimension brings together eight components related to physical infrastructure, ICT (Information and Communication Technology), and equipment. *Quay Cycle* refers to the area near the dock where quay cycle cranes manage the loading and unloading goods from ships. *Trucks Cycle* is the area dedicated to loading and unloading containers to and from trucks, featuring rubber-tired gantries used for stacking containers in the Yard. *Train Cycle* is located near the port's railroad tracks and involves rail-mounted gantries that load and unload freight trains. The *Yard* is dedicated to terminal container storage and movement between cycles, usually involving equipment like Prime Movers and Reach Strakes. *Port Buildings* include structures such as offices that help organize port activity or function as warehouses to store equipment and facilitate container operations such as customs clearance and consolidation. *Containers* can be of various types (such as International Maritime Organization IMO Goods, Reefer, Empty container, and Full Container Load (FCL), and may be full or empty, stacked in piles in the Yard. *Port Utilities*, including gas and electricity, are crucial for operating port cranes and ICT equipment. Finally, *Technical Services* represent the facilities necessary for vessel entry and mooring operations. These components collectively provide a comprehensive view of the physical elements crucial for port functioning, setting the stage for understanding how resilience can be assessed and maintained within these critical areas

2.4. Organization and business management (D2)

Port organization activity is divided into two main categories: ordinary organizational practices and extraordinary organizational practices. Ordinary practices include terminal policies, internal and external communications, human resources, and resource planning.

Terminal Policy encompasses Health and Safety Executive (HSE) measures, evaluating the impact of disturbances on workers' safety and health, the Information Technology system, and terminal security. *Internal and External Communication*, including details like location, destination, and container contents, plays a vital role in port organization and logistics. The *Human Resources* component includes Company workers, such as operational personnel, staff planning operational activities, and supervisory staff, as well as the Manning of dockers, which is highly sensitive to fluctuations in workload. *Resources Planning* involves factors such as berth window occupancy delays, average container turnaround time in the yard, and berth occupancy rate.

2.5. Resources and economy development (D3)

Investments and economic planning are vital for maintaining port competitiveness and serviceability. Within this dimension, four main components are considered. *Financial Flows* is a crucial aspect that measures money movement within the port system, essential for evaluating serviceability and potential upgrades, such as maintenance, drainage, and building new infrastructure. *Financial Services* considers the various banking and financial solutions, such as loans and investment strategies, that support the port's growth and development. *Port Business and Costs* encompasses a broad range of indicators representing the current status of port performance, including tonnage moved, annual revenue, growth, and business continuity. Assessments in this area help understand the port's financial health and operational efficiency. Lastly, *Employment Services* includes all aspects of labor within the port, such as hiring practices, workforce planning, and employment laws, ensuring that the port maintains a skilled and compliant workforce.

Investments are fundamental for ports to ensure their competitiveness and serviceability. Measuring the *Financial flow* is crucial to evaluate the serviceability of a port system and its potential to upgrade. *Financial investment* is often needed for maintenance and drainage, expanding the storage space, or building new superstructures (e.g., cranes). *Port Business and Costs* includes a wide range of indicators that represent the current status of port performance and achievements in terms of tonnage moved, annual revenue, growth, and business continuity.

2.6. Territory, environment and stakeholders (D4)

This dimension focuses on the external aspects of the port that intersect with the surrounding community, environment, and stakeholders. *External Physical Access* pertains to the serviceability and integrity of access routes leading to the port terminal, including roadway systems, railway systems, and the main navigation channel. This component ensures smooth transportation and connectivity between the port and other key locations. *Environment Sustainability* is a critical aspect that measures the port's impact on the environment, including aspects like air and water quality, noise pollution, and adherence to environmental regulations and practices. This component emphasizes the port's responsibility towards maintaining ecological balance. *Reputation* considers the social image and credibility of the port in the eyes of various stakeholders, including citizens, businesses, and governing bodies. It encompasses factors like community engagement, adherence to ethical practices, and the overall impact of port activities on the lives of surrounding inhabitants. Together, these components provide a well-rounded perspective of how the port interacts with its surrounding territory, the environment, and stakeholders, ensuring a harmonious and responsible presence in the region.

3. PORT framework methodology for loss of resilience (LOR) evaluation

This section presents the methodology used to quantify resilience through the computation of the Loss of Resilience (LOR). It introduces the formulation of serviceability functions, indicator weighting techniques, and the aggregation process leading to the overall resilience metric. Different implementation strategies and methodological considerations are also discussed.

3.1. Loss of resilience (LOR)

The methodology presented in this section aims to calculate the port's resilience during a disruption event in terms of Loss of Resilience (LOR). According to Bruneau, et al. [10], LOR is calculated as the area between the aggregated serviceability function and the 100% serviceability level (Fig. 2) and is expressed as:

$$LOR = \int_{t_e}^{t_e+T_c} 1 - Q(t)dt \tag{1}$$

where $Q(t)$ is the aggregated serviceability function of the port; t_e is the time at which the disruptive event occurs (often set to 0); T_c is the control time.

LOR can also be normalized with respect to T_c to allow comparing events of different time scales, as follows:

$$LOR_{nor} = \frac{\int_{t_e}^{t_e+T_c} 1 - Q(t)dt}{T_c} \tag{2}$$

Currently, there is no universally agreed-upon choice for T_c in existing research. This time interval should be selected in a consistent

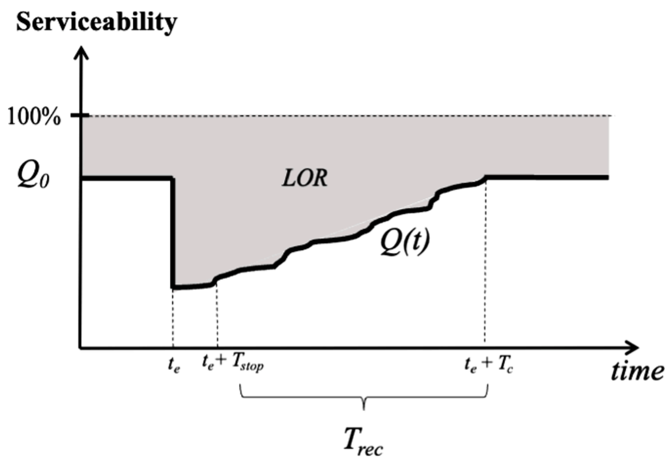

Fig. 2. Aggregated serviceability function $Q(t)$.

manner to enable comparison between various events. In this study, the control time T_c is identified by:

$$T_c = T_{stop} + T_{rec} \tag{3}$$

where T_{stop} is the port activities closing time, T_{rec} is the recovery time which is required to restore the serviceability function to a state unaffected by the event.

3.2. Serviceability functions

Serviceability is adopted as the primary performance criterion due to its direct observability and data availability across operational records. Although safety and structural damage metrics are essential, such data were not consistently accessible.

The aggregated serviceability function, *Q(t)*, in Eq. (1) represents the port's capability to perform its operations effectively. As the port consists of highly heterogeneous elements, as discussed in the previous section, its overall serviceability is determined by combining the performance measures of each indicator. To this end, the aggregated serviceability function *Q(t)* is defined as:

$$Q(t) = \sum_i w_i \cdot q_i(t) \tag{4}$$

where $q_i(t)$ is the serviceability function and w_i is the weight factor of the i^{th} indicator.

The serviceability function $q_i(t)$ for each indicator is strictly related to the measure $m_i(t)$ assigned to each indicator. Due to the heterogeneity of the indicators, the measures of different indicators differ in nature and measurement units. Therefore, each measure is transformed into a dimensionless function, $q_i(t)$, normalized with respect to a Target Value TV_i, as follows:

$$q_i(t) = \frac{m_i(t)}{TV_i} \tag{5}$$

TV_i is a metric that sets the baseline for assessing a system's resilience. The system's performance at any given time is compared with the corresponding TV_i to determine the extent of serviceability deficiency experienced by the system. It is important to note that this does not necessarily mean that the indicator measure should match the TV_i under normal conditions before the disruptive event, as the TV_i represents an ideal target.

Using the indicator serviceability function q_i, rather than the indicator's measure prior to the disruptive events, $m_i(t_e)$, allows for a consistent comparison of resilience indicators across different ports.

3.3. Indicator weighting

The weighting factor w_i in Eq. (4) represents the *i-th* indicator's contribution to the overall aggregated serviceability function. Determining the values of w_i is critical for evaluating resilience and must consider the interdependence of the indicators. Various weighting methods are discussed in the literature. In this study, two specific techniques are considered:

- the Importance-based weighting technique, following the procedure proposed by [8];
- the Time-Series weighting technique, based on the analytical time series analysis proposed by Shumway, et al. [50] and Dueñas-Osorio and Kwasinski [51].

3.3.1. Importance-based weighting technique

The Importance-based weighting technique assumes that a variable's significance is closely linked to the number of other variables in the same group that depend on it. From this perspective, the PORT structure outlined in Section 2.2. is considered a classification derived from an analysis of interdependencies: interdependent indicators are grouped into components; interdependent components are then assembled into dimensions, forming the topology of the PORT framework. The interdependency analysis is conducted hierarchically (as shown in Fig. 3), assigning an importance factor I_i to each element within its respective group. The importance factor evaluates the significance of an element in relation to other elements in the same homogeneous group. The weighting factor is then calculated as follows:

$$w_i = \frac{I_i}{\sum_k I_k} \tag{6}$$

where I_i is the importance factor of the *i*-th element in the group, *k* is the number of elements in the homogeneous group. The value of the importance factors is assigned based on the experience of the port experts. Each expert assigns a score or value to the indicators, reflecting their perceived importance. These scores are then aggregated to determine the importance factor I_i for each indicator. The aggregation method may vary, but it often involves averaging the scores or using a consensus-building process to ensure that the final importance factor represents a balanced view of all operators' inputs.

The strength of this method is its simplicity and its direct link with port operators' local experience and knowledge. The weakness lies in the fact that it is subjective. This weakness can be mitigated by considering a broad and diverse group of operators with different roles, experiences, and lengths of service at the port.

3.3.2. Time-series weighting technique

The interdependencies between different indicators can generate detrimental or amplification effects, and therefore, they strongly influence operations. Continuous monitoring of these indicators enables the gathering of data over time. Analyzing these time-histories statistically can provide quantitative insights into their interdependencies. The method introduced by Dueñas-Osorio and Kwasinski [51] and further elaborated by Cimellaro, et al. [52] is employed to assess the extent of interdependency between different indicators through time series analysis. This interdependency analysis is then utilized to determine the weighting factor of each indicator.

Each indicator is recorded with a time series of *$m_i(t)$ measurements*. The data should be at least weakly stationary for conducting exploratory analyses in the time domain [50]. However, achieving this condition for a short time series of measurements can be challenging. The method suggested by Dueñas-Osorio and Kwasinski [51] is used to mitigate the effects of nonstationarity and ensure meaningful statistical analyses. In this method, the measured time-histories undergo a preliminary

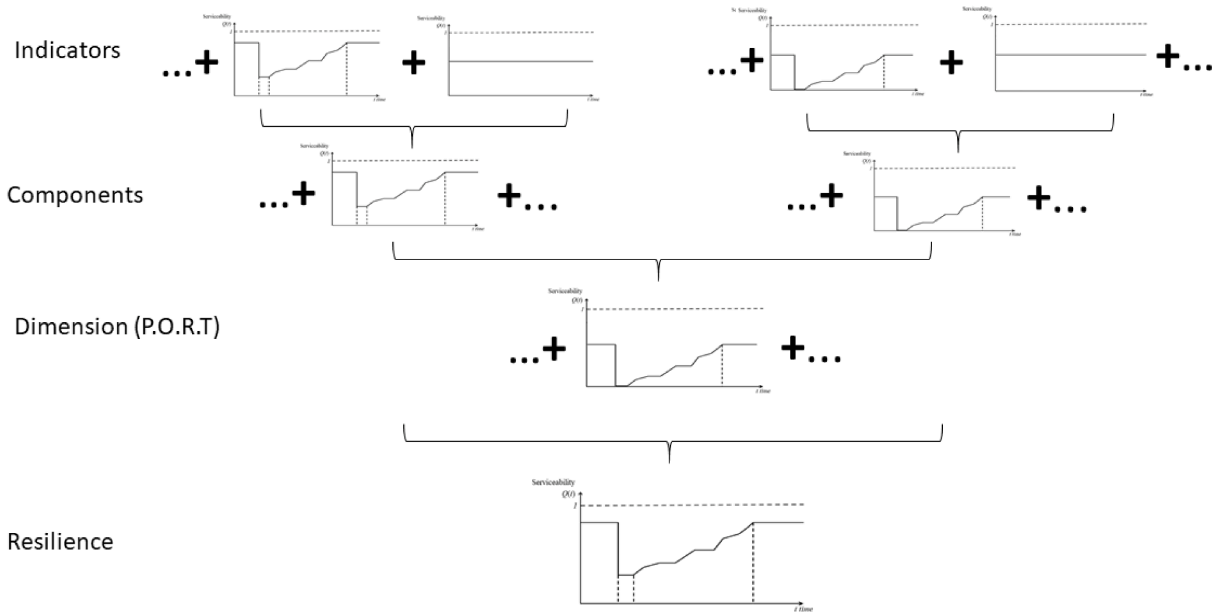

Fig. 3. Importance-based weighting technique and serviceability function aggregation.

transformation using logarithmic and second-time differencing transformations, as follows:

$$\widetilde{m}_i(t) = \frac{\partial^2 \ln(m_i(t))}{\partial t^2} \tag{7}$$

This transformation is aimed at stabilizing variability, ensuring constancy in the mean value of the time series at different times t, and achieving auto-covariance values that decay rapidly and are dependent only on the time-lag $\Delta t = t_1 - t_2$, where t_1 and t_2 are arbitrary points in time [50]. By discretizing time into constant intervals, typical in port organizations' working shifts, the time lag can be expressed in non-dimensional form as the number h of shifts between t_1 and t_2. The degree of interdependency between the time series of measurements for the *j-th* and *k-th* indicators is then determined through the coupling parameter $S_{j,k}$, as follows:

$$S_{j,k}(\widehat{h}) = \begin{cases} \dfrac{\rho^+_{j,k}(\widehat{h})}{1+\sqrt{|\widehat{h}|}} \operatorname{sgn}(\widehat{h}) \text{when} \widehat{h} \neq 0 \\ \rho^+_{j,k}(\widehat{h}) \text{when} \widehat{h} = 0 \end{cases} \tag{8}$$

where$\rho^+_{j,k}$ corresponds to the maximum positive cross-correlation function value $\rho_{j,k}(h)$, $\widehat{h}$ is the time lag at which the maximum positive cross-correlation function value between $\widetilde{m}_i(\mathrm{t}_1)$ and $\widetilde{m}_i(\mathrm{t}_2)$ occurs. The cross-correlation function effectively quantifies the predictability of one series as a function of another for a given lag time h between them. In the context of interdependency analyses, $\rho^+_{j,k}$values and associated $\widehat{h}$ levels can measure the strength of coupling between the two series, though this does not necessarily imply causation. The sign function (*sgn*) keeps track of the dominant coupled indicator. Therefore, if $S_{j,k}$ is positive, the *j-th* indicator conducts the trend of the *k-th* indicator; if $S_{j,k}$ is negative, the reverse is true. The maximum $S_{j,k} = 1$ can occur when two indicators are perfectly coupled at $\widehat{h} = 0$. Eq. (8) indicates a decreasing trend in the coupling between indicators for $\widehat{h} \neq 0$. The matrix $S_{j,k}$ is a square matrix where diagonal terms associated with autocorrelation are always equal to 1, while the off-diagonal terms can vary between -1 and 1.

The weighting coefficients are then defined as the ratio between the sum of the positive values $S^+_{i,j}$of each row i and the sum of all positive terms $S^+_{i,j}$ in the matrix, as follows:

$$w_i = \frac{\sum_j S^+_{i,j}}{\sum_i \sum_j S^+_{i,j}} \tag{9}$$

Note that the definition of the weighting coefficient in Eq. (9) does not require any hierarchical procedure. In this case, the PORT framework simply offers a structured approach to organizing infrastructural data, as outlined in Section 2.2. The primary advantage of this method is its reliance on objective, quantifiable data. However, a significant challenge arises in the data collection process, which is subject to Terminals' confidentiality policies. Additionally, the method faces limitations due to the variability of data; in particular, the outcomes can differ significantly based on whether correlations are assessed over the entire dataset or on a per-event basis, particularly when analyzing data within the recovery period (T_{rec}) following an event.

While the current correlation-based approach provides objective interdependency measures, it does not distinguish between causation and correlation. Causal inference methods such as Granger causality or structural equation modeling could be incorporated to better reflect directional influences between indicators. However, such approaches would require longer time series, increased computational complexity, and may not always be feasible in data-limited port environments

3.4. Serviceability function aggregation

Following the weighting of the elements, the serviceability functions are aggregated into a single serviceability, as illustrated in Fig. 3, using the weighted average method. This involves aggregating (i) the serviceability functions of indicators into those of components, (ii) the serviceability functions of components into those of dimensions, and (iii) the serviceability functions of dimensions into the overall aggregated serviceability function of the PORT, denoted as *Q(t)*. This aggregated serviceability function represents the collective impact of all indicators, reflecting the port's overall serviceability at any given time. The aggregated serviceability function is a tool for assessing the port's operational status and resilience. It gives the port operator a quick overview of its overall performance and identifies any issues or problems. If there are problems, one can look closer into the reasons by checking the serviceability functions of each indicator. This helps make informed decisions based on a holistic analysis of the port's serviceability, facilitating targeted interventions and strategic planning to enhance port performance.

3.5. Implementation considerations and methodological variability

The outcomes of the aggregated serviceability function $Q(t)$ and the consequent quantification of LOR or LOR_{nor}, theoretically defined in Eqs. (1,2, 4), can vary depending on the implementation details and choices made. Given the highly fluctuating nature of port activities, two primary sources of uncertainty must be considered: the assessment of indicator serviceability functions and the evaluation techniques for weighting factors.

Considering the serviceability function of indicators as defined in Eq. (5), $q_i(t)$ is expected to fluctuate between 0 and 1, with the maximum value of 1 corresponding to $m_i(t)=TV_i$. However, the TV_i value is not a theoretical maximum but a representation of ideal performance during normal operations. Notably, there can be instances of abnormal port operativity, occurring especially after disruptive events, where $m_i(t)$ exceeds TV_i, leading to $q_i(t)$ values greater than 1. Such occurrences of serviceability exceeding 100% can ostensibly increase resilience, thereby reducing the LOR. However, whether these abnormal peaks truly signify a favorable condition in the system's recovery phase is debatable. In reality, such surges in post-event activity are more often indicative of operational stress than true resilience. These peaks typically arise from the urgent need to clear backlogs and may lead to logistical bottlenecks, workforce fatigue, or unsafe operating conditions. Without careful treatment, such transient overperformance may be misinterpreted as a sign of enhanced resilience.

This research proposes three distinct approaches for calculating the serviceability function during the recovery time interval. The first approach (SF1) does not modify the indicator serviceability functions or the aggregation process, accepting transient situations where $q_i\ (t)$ exceeds 1. The second approach (SF2) caps the indicator serviceability functions at a maximum value of 1, ignoring any excess in calculating the aggregated serviceability function and LOR. The third approach (SF3) substitutes the indicator serviceability functions with their average value, calculated over a period deemed long enough for the stabilization of operations post-disruption, which in this study is evaluated to be 15 days.

The three serviceability function approaches serve as sensitivity analyses for different interpretations of post-event performance surges. Comparing LOR values across SF1 (uncapped), SF2 (capped), and SF3 (smoothed) reveals how methodological choices affect resilience quantification. The choice between allowing or capping performance above 100% reflects different conceptual frameworks: SF1 credits actual system dynamics and adaptive capacity, while SF2 maintains that resilience should be measured against normal operational expectations without crediting potentially unsustainable surge activities. Small differences between approaches suggest robust results, while large variations indicate sensitivity to surge interpretation, requiring careful consideration of which approach best represents operational reality in the specific port context.

Considering the weighting factors evaluation techniques, three possibilities can be adopted, as explained in Section 3.3. The first (WF1) uses the importance-based weighting factor technique obtained from expert knowledge (see Section 3.3.1). The second (WF2) adopts the time-series analysis technique, applied to the whole time history length (see Section 3.3.2). The third (WF3) applies the time-series analysis technique to time histories in the T_{rec} intervals after each event (see Section 3.3.2). Table 2 summarizes the implementation approaches described here.

In practical terms, the choice between the expert-based and time-series-based weighting approaches involves a trade-off between data availability and methodological objectivity. The expert-based method (WF1) is more broadly applicable, particularly in contexts where historical or real-time data are limited or unavailable. Although this approach introduces subjectivity, its reliance on domain expertise ensures that the most contextually relevant indicators are emphasized. In contrast, the time-series approaches (WF2 and WF3) offer a more data-driven and potentially reproducible mechanism but depend on consistent, high-resolution operational data, which may not be accessible in many port environments. Practitioners should thus select the method best suited to their context, balancing data limitations with the need for analytical rigor.

Table 2
Implementation strategies of the PORT framework.

Serviceability function (SF)	Implementation
SF1	Eq. (5) $q_i(t) = m_i(t)/TV$
SF2	Eq. (5) with limit to 1: $\begin{cases} q_i(t) = m_i(t)/TV \text{if} q_i(t) \leq 1 \\ q_i(t) = 1 \text{otherwise} \end{cases}$
SF3	Eq. (5) with the correction in the recovery interval: $q_i(t) = [\overline{q}_i(t \in [t_0, t_0 + 15 days])] \text{for} t \in [t_0, t_0 + T_c]$
Weighting factors (WF) evaluation	Approach
WF1	importance-based technique (Section 3.3.1)
WF2	time-series analysis (Section 3.3.2) over the whole time-history length
WF3	time-series analysis (Section 3.3.2) over T_{rec}

4. Case study: the resilience of terminal containers under extreme wind events

A case study was conducted in collaboration with the management authority of a large Terminal container. This case study serves as a complete application of the PORT Resilience Framework, demonstrating its operational implementation in a real-world port setting. It illustrates how the framework's steps—from indicator measurement, to weighting, serviceability calculation, and resilience assessment—can be applied using real data. The objective is to validate the feasibility and internal consistency of the framework under actual conditions, rather than tailoring the framework to fit the case. While the data are site-specific, the structure and logic of the framework are designed to be transferable to other port contexts.

The terminal spans an extensive area of 978,000 m^2 and features a quay length of 1,433 meters, accommodating three berths for unloading operations. The terminal includes a ship access channel protected by a breakwater, along with two land access routes: a railway line and a highway connection. It hosts a large yard where full containers are stored prior to shipping and has two designated areas for empty container storage. The terminal engages in various activities, including customs services, container freight station operations, warehouse management, storage of empty containers, quay cycle (QC) operations with 12 quay cranes, train cycle operations with three rail-mounted gantries (RMG), nine rail lines, and truck cycle operations with 20 rubber-tired gantries (RTG), 29 reach stackers.

Wind conditions significantly impact the terminal's operations, particularly affecting crane activities and the stability of stacked containers, which can lead to unsafe conditions for workers, damage to structures, and collapses of piled containers. The terminal is equipped with several anemometric stations that measure wind speed in real-time. An automatic system receives these measurements and issues operational alerts based on predefined limit thresholds. When wind speed exceeds the most critical threshold, port activities are halted, and the areas are evacuated. This analysis aims to quantify the terminal's resilience to extreme wind events, defined as port closures due to wind speeds exceeding the threshold, regardless of whether incidents or damages occur.

4.1. Data collection

The management of the terminal contributed to this study by providing two types of data:

1) Wind Interruption Data: A comprehensive list of 18 instances when port operations were halted due to wind conditions from 2015 to 2018 was supplied. Each closure event was detailed with its duration in hours. In some instances, these wind events were accompanied by damages, and in such cases, a quantification of the damage was also provided.
2) Operation Data: Continuous records relating to quay, truck, and rail cycles were provided. Using this data, it was possible to construct a time series for the main indicators within the "Physical Infrastructure" and "Organization and Business Management" dimensions of the PORT Framework.

The data spanned from January 2015 to April 2018, covering a total of 1,189 days. The sampling rate was aligned with the port's work shift level, which is every 6 hours, resulting in a total of 4,576 data points for each indicator. For each indicator, the corresponding measure m_i and target value TV_i were defined based on a literature review and the local management's experience. The chosen TV_is are consistent with the organizational, technical, and environmental conditions of the terminal and are based on those currently used to evaluate its performance by the company that manages the terminal.

These target values serve as ideal benchmarks representing full operability under normal, undisturbed conditions. Their derivation followed technical meetings with port experts, incorporating internal monitoring practices, operational standards, and expert judgment. This process ensured consistency with practical port operations and relevance to real-world performance targets. This paper, under a confidential agreement, does not disclose these values. The development of universally applicable TV_is presents an opportunity for future research.

It is important to note that extreme wind events impact only a select number of indicators. Only those indicators directly affected by the events are considered in this study. This approach means that post-event serviceability can drop to 0, which, in this context, signifies an interruption of operations rather than a total disruption of the port. In a multi-hazard framework where multiple types of risks are considered, it would be necessary to include all indicators to comprehensively assess the resilience and operational capacity of the port under various threat scenarios.

In Table 3 the analyzed indicators and the corresponding measures are summarized.

Table 3
Indicators and measure.

Dimension D	Component C	Indicator I	Measure
D1- Physical Infrastructure, ICT and Equipments	C1.1 Quay Cycle	QC Movements	n° of movements per crane per hour
		QC Cranes	n° of working cranes
	C1.2 Trucks Cycle	Rubber-tired gantries (RTG) Movements	n° of movements per crane per shift
		Trucks	n° of Trucks served
	C1.3 Train Cycle	Rail-mounted gantries (RMG) Movements	n° of TEUs loaded and unloaded
D2- Organization and Business Management	C2.3 Human Resources	Manning of Company (*)	QC movements per man per hour
		Manning of Dockers (*)	QC movements per man per hour

[*] due to a lack of information, Manning of Company and Manning of Dockers are considered together in this work and named "Manning."

Recovery time in this study is not analytically modeled but empirically derived from the observed time series of operational indicators (e.g., quay movements, manning). Specifically, for each closure event, recovery was defined as the time required for these indicators to return to their pre-event fluctuation patterns. Based on expert feedback and data review, this period was typically 16 shifts (96 hours). The 96-hour recovery period aligns with port operational cycles (16 shifts) and was validated through systematic analysis showing that most indicators returned to pre-event variability patterns within this timeframe. This period captures both immediate recovery and operational stabilization while avoiding contamination from unrelated subsequent events. A shorter period (e.g., 48-72 hours) would systematically increase LOR values by truncating the assessment before full recovery is achieved, potentially overestimating resilience loss and missing the benefits of effective recovery strategies. This could lead to misleading comparisons where events with similar disruption but different recovery speeds appear to have different resilience impacts. Conversely, a longer period (e.g., 120-168 h) would generally decrease LOR values by extending the assessment period, but risks including normal operational variability unrelated to the original disruption, potentially underestimating actual resilience loss. More critically, excessively long periods could contaminate results with subsequent minor events or seasonal operational changes.

Although detailed wind hazard modeling was not conducted, wind intensity is indirectly accounted for through closure records tied to measured wind speed thresholds. These operational shutdowns serve as real-world proxies for hazard impact, allowing the framework to evaluate functional disruption without requiring explicit hazard simulations.

4.2. Indicators data analysis

4.2.1. Indicators serviceability functions

The serviceability function $q_i(t)$ of each indicator was determined using Eq. (5). Fig. 4 shows the serviceability functions of the adopted indicators during a typical week of normal operations. The diagrams show the usual fluctuations in values due to the daily organization of work and the entrance/exit of ships.

The behavior of these indicators changes remarkably during a closure event caused by an extreme wind event. The following analysis focuses on the closure event that occurred on March 1, 2018. Specifically, Fig. 5 depicts the serviceability functions of indicators over a 124-hour period corresponding to the closure event. The segment of the serviceability functions within the red dotted line indicates the cessation of port activities; this period is denoted as T_{stop}. The duration of T_{stop} varies for different events and is specified as 48 hours for the case presented. The latter part of the serviceability functions represents the recovery phase. Based on the expertise of seaport managers and the analysis of the provided data, the recovery time, T_{rec}, is set at 16 shifts (96 hours or 4 days). This recovery period was determined by identifying the point at which indicator serviceability functions stabilized and resumed pre-event oscillatory patterns. No analytical damage-recovery models were applied; instead, real-world operational recovery behavior was used to construct the post-event serviceability curve.

The thin line (SF1) represents the $q_i(t)$ as calculated using Eq. (5) (see Table 2). It can be noted that several indicators exhibit peaks where $q_i(t)>1$ in the recovery curve. For example, the number of trucks significantly exceeds the corresponding TV, leading to safety and logistical issues within the port and affecting the surrounding city. The thick dashed line (SF2) shows $q_i(t)$ calculated using Eq. (5) but limiting $q_i(t)$ to a maximum of 1 (see Table 2). The thin dash-dotted line (SF3) represents $q_i(t)$ calculated using Eq. (5) with an adjustment based on the average value over 15 days (see Table 2).

4.2.2. Indicators weighting

The weight of each indicator was identified according to the three

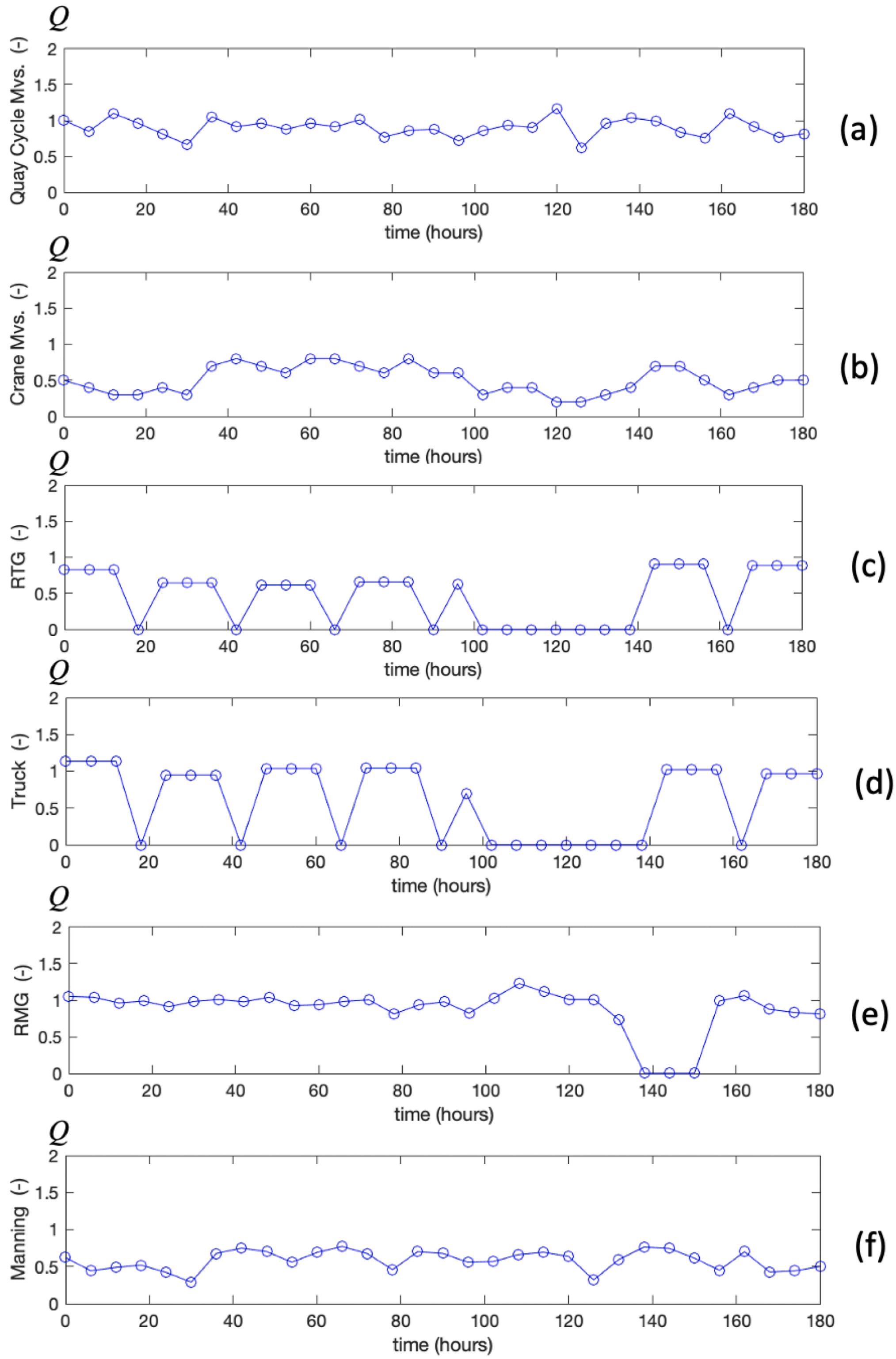

Fig. 4. Serviceability functions of indicators during normal operations: a) quay cycle movements, b) quay cycle cranes, c) rubber tired gantry RTG crane movements, d) number of trucks in/out, e) rail mounted gantry RMG crane movements, f) manning.

different methodologies presented in Section 3. The methodologies used complementarily can help better understand the behavior of such a complex system. The Importance factor Methodology (WF1) was implemented through technical interviews with several port experts. During these interviews, experts were given a scorecard to evaluate each set of homogeneous indicators. The scorecard required experts to assign a value between 1 and 3 to each indicator within a group of homogeneous indicators. The weighting factor for each indicator was then calculated using Eq. (6), as shown in Table 6. It is important to note that the resulting w_i value is influenced by the number of elements in the respective group of homogeneous indicators.

Time series analysis was performed using two different approaches: WF2, which analyzed the entire database, and WF3, focusing on individual time events. In both cases, the initial step involves assessing the

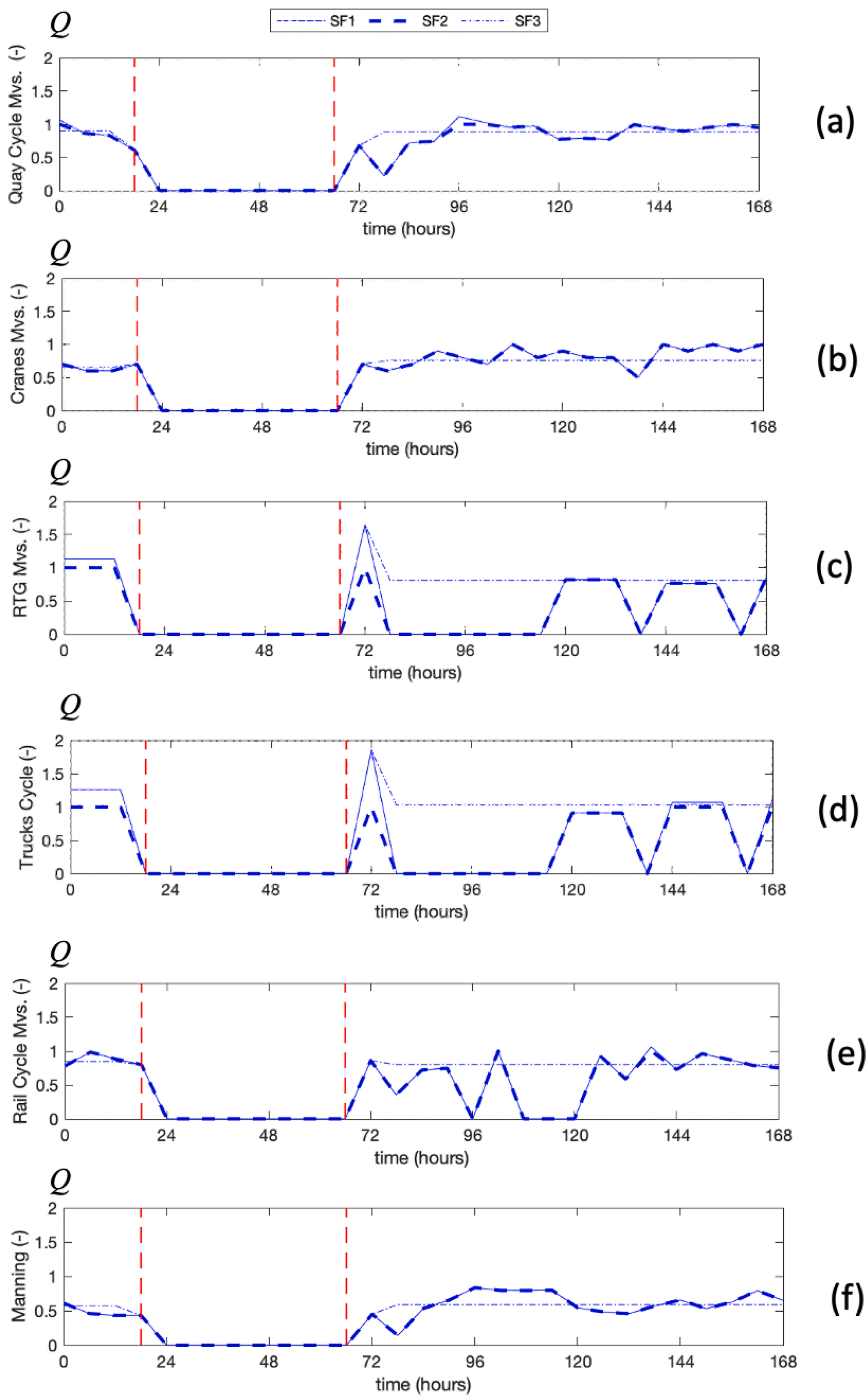

Fig. 5. Serviceability functions of indicators during the a) quay cycle movements, b) quay cycle cranes, c) rubber tired gantry RTG crane movements, d) number of trucks in/out, e) rail mounted gantry RMG crane movements, f) manning closure event that occurred on March 1, 2018:.

cross-correlation between pairs of indicators, j and k, and determining their coupling parameter $S_{j,k}$ (Eq. (8)), which captures the degree of interdependency between indicators.

As an illustrative example, Fig. 6 shows the cross-correlation (ρ) between two indicators: Quay Cycle Cranes and Mannings. This cross-correlation is plotted as a function of the time lag h, specifically for the March 1, 2018 closure event. The analysis reveals a maximum positive correlation of $\rho^{+}_{j,k}=0.6$, corresponding to a time lag $\widehat{h}$ of approximately ten hours. This finding indicates a significant interdependency between the two indicators within this specific time frame, providing valuable insights into how different elements of port operations are interconnected and influenced by external events like wind closures.

Table 4 illustrates the results of the interdependence matrix $S_{i,j}$, calculated based on the entire length of the time series (WF2). This provides insights into the long-term interdependencies and patterns between different indicators under normal operational conditions. Table 5 presents the outcomes of the interdependence matrix $S_{i,j}$, evaluated explicitly for the event of March 1, 2018 (WF3). This event-specific analysis offers a focused view of how various indicators interact and influence each other during and immediately after a significant disruption event.

The comparison between the values in the interdependence matrix considering the entire time series and those specific to the control time of a single event reveals notable differences. Specifically, when analyzing the interdependency values $S_{i,j}$ at the scale of a single closure event (WF3), there is generally an increase, especially noticeable between Quay Cycle indicators (i.e., QC mvs and QC Cranes) and both Truck and Train Cycle indicators (i.e., RTG mvs, Trucks, and RMG mvs). The rationale behind this is that under normal operational conditions, the yard serves as a buffer between the different cycles during daily activities. However, during events that lead to the closure of activities, followed by their reopening, the typical buffer role of the yard is diminished. This change results in a more direct and pronounced interaction between the cycles, thus increasing their interdependency values.

Based on the calculated interdependence matrix, the weights of the indicators are then determined using Eq. 9. Table 6 presents the results of applying the WF1, WF2, and WF3 approaches.

In contexts where such data are unavailable, weighting based on expert elicitation can be used, but may introduce subjectivity and uncertainty. In such cases, extensions of the framework using fuzzy logic or multicriteria decision-making (MCDM) approaches, such as fuzzy-AHP, can provide more robust estimates [53–57]. Future applications may

Table 4
Interdependency Matrix Whole Time Series (WF2).

$S_{i,j}$	QC_mvs	QC Cranes	RTG mvs	Trucks	RMG mvs	Manning
QC mvs	1	- 0,27	- 0,002	0,01	- 0,002	0,766
QC Cranes	0,27	1	0,004	0,004	- 0,001	0,726
RTG mvs	0,002	- 0,004	1	0,926	- 0,005	0,005
Trucks	- 0,01	- 0,004	0,926	1	- 0,019	0,006
RMG mvs	0,002	0,001	0,005	0,019	1	- 0,002
Manning	0,766	0,726	- 0,005	- 0,006	0,002	1

Table 5
Interdependency Matrix March 1, 2018 (WF3).

$S_{i,j}$	QC_mvs	QC Cranes	RTG mvs	Trucks	RMG mvs	Manning
QC mvs	1	- 0,16	0,221	0,283	- 0,782	0,938
QC Cranes	0,16	1	0,506	0,216	0,134	0,144
RTG mvs	- 0,221	0,506	1	0,759	- 0,176	- 0,108
Trucks	- 0,283	- 0,216	0,759	1	- 0,256	- 0,124
RMG mvs	0,782	- 0,134	0,176	0,256	1	0,643
Manning	0,938	- 0,144	0,108	0,124	0,643	1

Table 6
Weighting factors obtained with importance base methodology (WF1), time series analysis applied on the whole time-history length (WF2), time series analysis applied to the closure event of March 1, 2018 (WF3).

Indicator	WF1	WF2	WF3
QC mvs	0,13	0,18	0,21
QC Cranes	0,09	0,18	0,14
RTG mvs	0,09	0,17	0,15
Trucks	0,13	0,17	0,12
RMG mvs	0,08	0,09	0,19
Manning	0,50	0,22	0,19

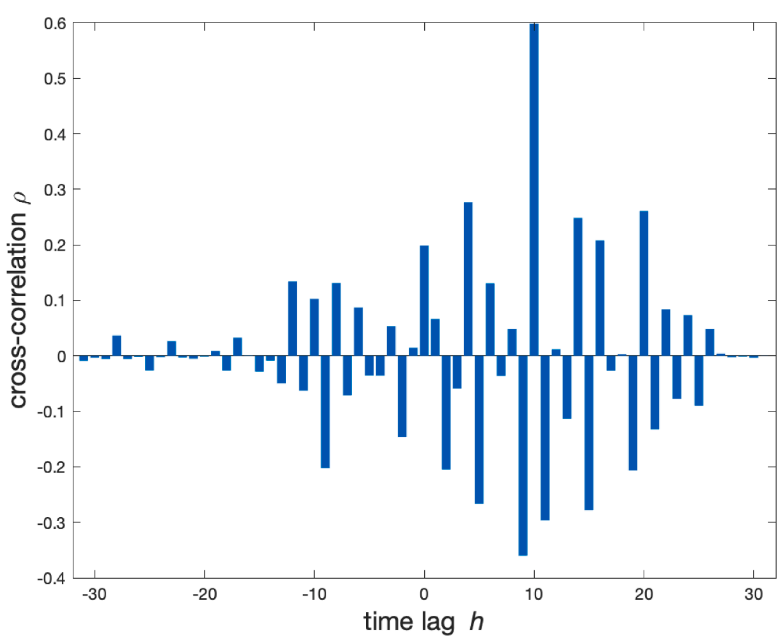

Fig. 6. Cross-correlation between QC Cranes and Manning indicators, evaluated during the closure event that occurred on March 1, 2018.

adopt such hybrid techniques depending on data availability and desired model fidelity.

4.3. Aggregated serviceability function

The overall serviceability function, $Q(t)$, was calculated for each of the 18 extreme wind events using Eq (2), adopting the aggregation approaches detailed in Chapter 3. Fig. 7 shows the aggregate serviceability function of the March 1, 2018, event for each of the three approaches.

The Aggregate Serviceability Function exhibits some common characteristics in its general shape, regardless of the methodology or approach used:

- Pre-Event Serviceability: prior to the closure of port activities, the initial serviceability of the terminal is always below the limit of 1. This indicates that the port's performance, when normalized against Target Values, does not reach the 100 % maximum level.
- Rapid Fall During Closure: a sharp decline in the serviceability function is observed due to the suspension of operations caused by the wind event. This decrease persists throughout the T_{stop} period, the duration when terminal activities are halted.
- Zero Serviceability During Stoppage: when port activities are stopped, serviceability drops to zero, highlighting the impact of closure events on port operativity.
- Post-Event Serviceability Peak: following the event, there is a noticeable peak in serviceability after the resumption of port activities. This spike is attributed to the urgent need to process the backlog of accumulated goods to avoid penalties and further delays.
- Subsequent Collapse: after this peak, serviceability experiences another downturn. This is due to the lack of incoming goods during the T_{stop} period when activities were suspended.
- Asymptotic Return: the serviceability function eventually shows an asymptotic return to its initial levels, characterized by the typical oscillatory pattern of port activities.

The three implementation techniques for evaluating serviceability functions post-event (SF1, SF2, SF3, as outlined in Table 2) each offer a distinct perspective on the recovery phase following an extreme event. These techniques mainly address the bounce-back peak often observed in port operations immediately after an event, provided there is no permanent structural damage to critical infrastructure like lifelines, yards, and dock equipment. SF1 captures the actual fluctuations in serviceability, including any extra work or surge in activity following the event. However, this increase in activity could potentially lead to unsafe conditions within the port area, making its impact on resilience complex to assess. SF2 approach moderates the impact of the post-event serviceability peak compared to SF1 and SF3. This is achieved by capping the serviceability function at 1, thus avoiding the representation of overcapacity or overactivity that could be misinterpreted as increased resilience. SF3 diminishes the effect of the subsequent decline in serviceability and eliminates the oscillatory trend resulting from work shifts. It focuses solely on the closure duration, providing a smooth-out view of the recovery phase.

4.4. LOR and LOR_{nor} evaluation

As described in Section 3, resilience can be assessed in terms of Loss of Resilience (*LOR*, Eq.(1)) or in terms of Normalized Loss of Resilience (LOR_{nor}, Eq. (2)). Table 7 shows the *LOR* and LOR_{nor} values for the described event of March 1, 2018, calculated using the different weighting methodologies and serviceability function implementations outlined in Table 2. The mean values obtained from various approaches are 15,5 (*LOR*) and 0,55 (LOR_{nor}), respectively, with the maximum values always given by the WF1 weighting methodology and SF2

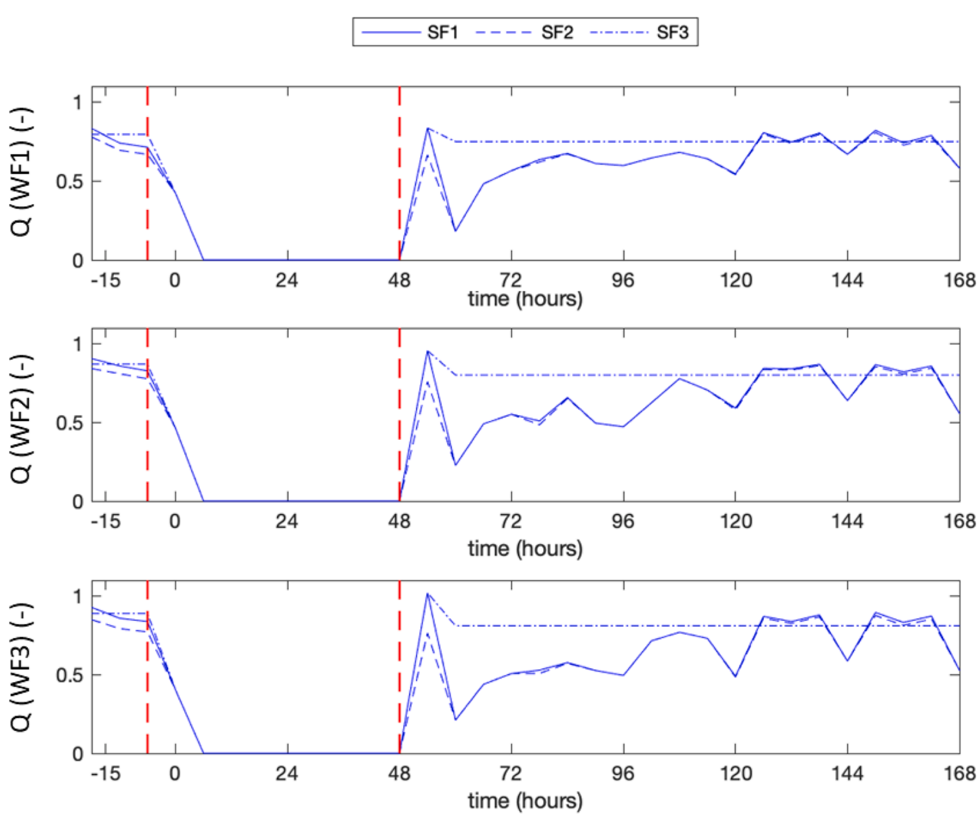

Fig. 7. Aggregate Serviceability Function of March 1, 2018, obtained with a) importance base methodology (WF1), b) time series analysis applied on the whole time-history length (WF2), c) time series analysis applied to the closure event (WF3).

Table 7
LOR and LOR_{nor} of March 1, 2018 event.

	LOR			LOR_{nor}		
	SF1	SF2	SF3	SF1	SF2	SF3
WF1	16,3	16,6	15,8	0,58	0,59	0,56
WF2	15,3	16,3	13,4	0,55	0,58	0,48
WF3	15,3	15,7	14,6	0,54	0,56	0,52

serviceability function technique.

Figs. 8 and 9 show the results of the un-normalized and normalized loss of resilience (*LOR* and LOR_{nor}) at the Terminal in the form of Box plots. The variability observed within each boxplot stems from the use of different methodologies (WF1, WF2, WF3) and serviceability functions (SF1, SF2, SF3) in calculating the LOR. Each box represents the middle 50% of the data for a specific date, with the horizontal line inside the box marking the median LOR value. The box's top and bottom edges signify the 75th and 25th percentiles, respectively. Whiskers extend from the boxes, showing the most extreme data points within a specific range.

The LOR outputs (Fig. 8) reveal variability in the port's operational impact across different wind events, with specific dates like 19/12/16 and 24/02/18 showing notably high resilience losses, hence a profound impact on port operations. This variability is further accentuated by the differences observed across various methodologies (WF1, WF2, WF3) and serviceability functions (SF1, SF2, SF3), indicating that the choice of assessment approach can influence the perceived impact of an event. Interestingly, there is no clear temporal trend in resilience loss over the years; instead, the impact seems event-specific, with some events causing more disruption than others.

Through normalization, the LOR_{nor} (Fig. 9) provides a relative measure of each event's impact, independently from the duration of the events and recovery phase. The LOR_{nor} outputs show an overall similar trend as the *LOR*, with the same key dates standing out, highlighting their significant relative disruption. This is mainly because all the events have a similar time scale.

For compound events the framework treats multiple closely-spaced closures as a single extended event to capture cumulative impacts without the complexity of overlapping recovery calculations. The January 2017 closures present a such a case. The terminal experienced numerous short but repeated closures due to frequent extreme wind events, significantly affecting business continuity and having cascading effects on the serviceability of subsequent events. This cannot be addressed solely at the scale of single events but must be considered cumulatively over a more extended period, such as a month. It is important to note that this monthly event should be compared in terms of LOR rather than the normalized LORnor, as the latter does not account for the compounded impact of these frequent closures.

Fig. 9 also shows the damage in the Port area during the wind events. Due to data sensitivity, damage is expressed as a percentage of disruption to total port operations, ranging from 0 (no damage) to 1 (highest recorded damage). It is worth noting that most closure events were not affected by damage, indicating that the current alert system is over-conservative. It is also interesting to note that the largest *LOR* and LOR_{nor} do not necessarily correlate with the highest damage situations.

Tables 8 and 9 illustrate how different weighting methodologies and serviceability function implementations influence *LOR* and LOR_{nor} outcomes based on the whole data set. The *LOR* data (Table 8) show a variation in resilience loss values, with mean values ranging from 9.12 (WF3_SF3) to 13.14 (WF1_SF2). This spread indicates variability in impact assessments across different weighting methodologies (WF1, WF2, WF3) and serviceability function implementations (SF1, SF2, SF3). Notably, WF1_SF2 returns the highest mean and maximum *LOR*, suggesting a greater sensitivity to extreme events. On the other hand, WF3_SF3 returns the lowest mean *LOR* and a smaller standard deviation, implying a more consistent and less severe assessment of events. The range of standard deviation values, from 2.84 to 3.32, further highlights the variability in *LOR* across different methodologies.

Similarly, LOR_{nor} data (Table 9) present a spread of mean values from 0.401 (WF2_SF3) to 0.578 (WF1_SF2). The pattern observed in WF1_SF2, with the highest mean and maximum *LORnor*, is consistent with the unnormalized data, indicating that certain events have a pronounced impact regardless of normalization. WF2_SF3, which sits in the mid-range in unnormalized data, is seen as having the least severe impact when normalized.

Overall, normalization in LOR_{nor} data appears to moderate the extremes seen in the unnormalized *LOR* data, leading to a more condensed range of values. This is particularly evident in the assessment of WF2_SF3. The choice of weighting methodology has an influence on how the impact of disruptive events is interpreted.

5. Discussions and conclusions

This paper introduces a comprehensive framework for measuring the resilience of seaport infrastructures to natural hazards, specifically focusing on the impact of extreme wind events on container terminals. This framework encompasses a broad array of resilience indicators that

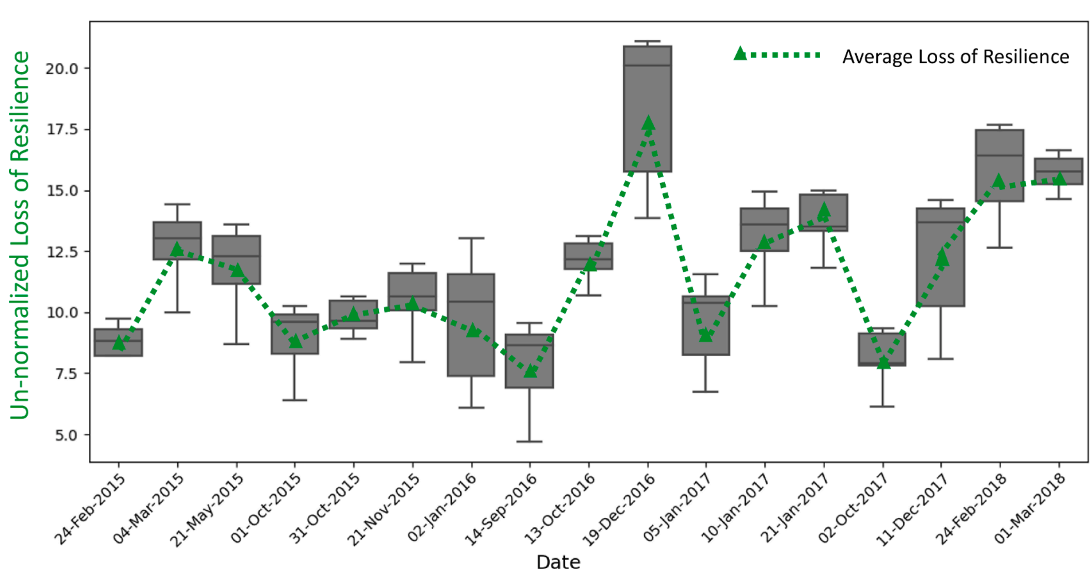

Fig. 8. Comparative analysis of un-normalized loss of resilience (LOR) at the Terminal by weighting methodology and serviceability function calculation technique.

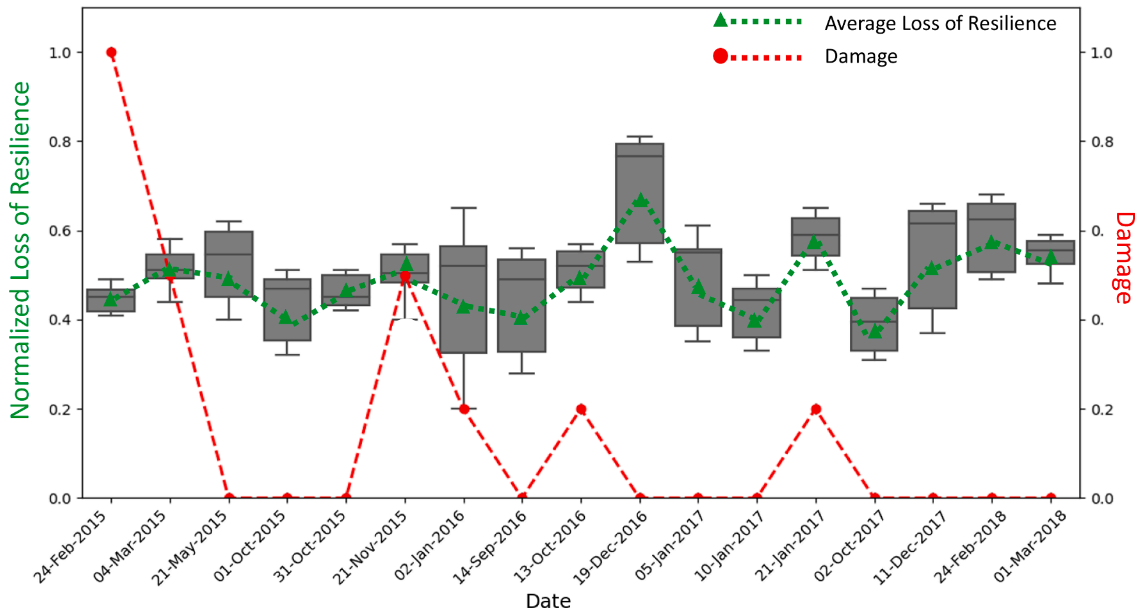

Fig. 9. Comparative analysis of normalized loss of resilience (LOR-nor) at the Terminal by weighting methodology and serviceability function calculation technique.

Table 8
Statistical Summary of LOR for Wind Events in the Terminal.

Methodology_Function	Mean LOR	Std. Dev.	Min LOR	Max LOR
WF1_SF1	12,8	3,3	9,1	20,9
WF1_SF2	13,1	3,3	9,3	21,1
WF1_SF3	10,8	2,8	6,9	15,7
WF2_SF1	12,3	3,1	7,8	20,4
WF2_SF2	12,8	3,3	9,1	20,9
WF2_SF3	9,2	2,8	4,7	14,5
WF3_SF1	11,9	3,1	7,8	19,8
WF3_SF2	12,4	3,1	8,1	20,1
WF3_SF3	9,1	2,8	5,1	14,6

Table 9
Statistical Summary LOR_{nor} for Wind Events in the Terminal.

Methodology_Function	Mean LOR_nor	Std. Dev.	Min LOR_nor	Max LOR_nor
WF1_SF1	0,56	0,09	0,46	0,8
WF1_SF2	0,58	0,08	0,47	0,81
WF1_SF3	0,48	0,07	0,37	0,61
WF2_SF1	0,54	0,10	0,39	0,78
WF2_SF2	0,56	0,09	0,46	0,8
WF2_SF3	0,40	0,08	0,28	0,56
WF3_SF1	0,53	0,09	0,39	0,76
WF3_SF2	0,55	0,08	0,41	0,77
WF3_SF3	0,40	0,08	0,3	0,53

collectively address the key aspects of port activities and management. A thorough literature review was conducted, and insights were gathered from several port experts and port authority personnel to finalize the list of indicators presented in this study. Moreover, each indicator is associated with a measure, which facilitates the quantification of the indicator in a rational manner. The proposed indicators are then categorized into four dimensions—Physical Infrastructure, ICT and Equipment; Organization and Business Management; Resources and Economic Development; Territory, Environment, and Stakeholders—collectively encapsulated under the acronym "PORT." A serviceability function is defined for each indicator, showing their performance before, during, and after a hazard event. The serviceability functions of the indicators are weighted according to their importance and then aggregated into a single serviceability function, which represents the port infrastructure's performance across different phases of a disruptive event.

As a case study, we explored the resilience of a real terminal container under extreme wind events. Data for the case were supplied by Port management, covering the period from January 2015 to April 2018, and focused on the main indicators identified. Additionally, 16 wind-induced interruptions of port activity were analyzed. For each of these instances, the corresponding indicator serviceability function was determined, adopting two methodologies to calculate the weights of each indicator. The various approaches were then utilized to derive the aggregated serviceability function.

Our findings reveal several insights into the port's operational resilience. Applying different serviceability function methodologies (SF1, SF2, and SF3) and weighting factor approaches (WF1, WF2, WF3) demonstrated varied impacts on the port's resilience assessment. Specifically, we found that the approach accounting for average serviceability values post-restoration provided a more stabilized and less fluctuation-prone perspective on the port's resilience. Conversely, techniques focusing on expert subjective opinion showed an increased Loss of Resilience, particularly the larger weight of human resource indicators, emphasizing the critical role of human resources in port operations.

The recovery modeling approach adopted here relies directly on real performance data rather than assumed fragility-recovery functions. As such, it captures both direct disruption and the cascading effects of organizational and human resource constraints. However, future work could validate this approach by comparing PORT-derived recovery trajectories with independent historical case studies, particularly in contexts with more complete damage data.

The discussion on the Loss of Resilience due to port activity closures and the actual damage during the extreme wind events shows a discrepancy between the two outcomes. This raises a question regarding the potential overconservativeness of the alert system.

It is important to note that the PORT framework is designed to be flexible with respect to the level of uncertainty in input data. While the present implementation adopts deterministic values derived from available records, the framework can accommodate uncertainty through methods such as fuzzy logic, probabilistic (Bayesian) modeling, or multicriteria decision analysis. These tools can be employed in future applications to reflect data vagueness, expert disagreement, or variability in hazard exposure and system response.

The framework's flexibility extends to the incorporation of advanced measurement technologies such as Structural Health Monitoring, which can provide more accurate and reliable indicator values when such systems are available, demonstrating the framework's adaptability to evolving data collection capabilities. It also enables integration with weather forecasting systems through Territory dimension indicators. This capability allows for prospective LOR simulation under different operational strategies, transforming the framework from retrospective assessment into proactive decision support for optimizing alert system thresholds

It is possible to include new indicators in the existing list. The process is straightforward. However, when introducing new indicators with potential non-linear or time-delayed relationships, a gradual integration is recommended. New indicators can initially use importance-based weighting until sufficient data are available for time-series analysis. For complex relationships, the cross-correlation approach can be extended to include higher-order correlations or alternative dependency measures, though this may increase computational complexity

Future research should tackle the following aspects:

1. Refine and expand the PORT framework, especially in the context of diverse port environments and under different types of disruptive events.
2. Explore more dynamic, real-time data integration for resilience assessment instead of relying solely on expert opinions and historical data.
3. Explore causal inference methods to enhance the time-series weighting approaches, potentially providing more accurate representations of operational interdependencies and improving weighting factor reliability.
4. Explore explicit modeling of qualitative human resource aspects such as fatigue and skill degradation.
5. Incorporate mechanisms for detecting and adapting to shifting baselines in port performance, ensuring that Target Values remain relevant as operational contexts evolve over time. *We suggest two* approaches: (1) Periodic TV recalibration based on rolling averages of recent performance; (2) Trend analysis to detect systematic changes in baseline performance
6. Emphasize disaggregated LOR presentation by dimension, providing actionable insights for targeted resilience improvements rather than single aggregated metrics alone. Implementation would involve calculating partial LOR values for each dimension and presenting results as both absolute and relative contributions

Based on our findings, we recommend that port authorities and policymakers prioritize data-driven decision-making and resilience building. The simulation of realistic scenarios can improve the knowledge of hazards [58] and vulnerability [59,60]. Implementing robust data analysis techniques and considering various resilience assessment methodologies can support decision-making and significantly enhance a port's preparedness and response to extreme weather events.

Relevance to resilience

This work contributes to resilience practices by offering a measurable and actionable methodology for port authorities and stakeholders to improve the resilience of seaport infrastructure under challenging conditions.

The findings from this research emphasize critical aspects of port resilience by analysing how seaports perform under extreme wind events. The study provides a structured approach to identify vulnerabilities and improve recovery processes of seaport infrastructure. The proposed framework allows for a more comprehensive evaluation of port performance during disruptions considering both physical and operational dimensions. The case study highlights the use of real-world data to guide practical decision-making, demonstrating how targeted actions can enhance recovery and preparedness.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to improve the grammar and readability of the text. After using this tool, the authors reviewed and edited the content as needed, and take full responsibility for the content of the publication.

CRediT authorship contribution statement

A. Balbi: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **O. Kammouh:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization. **G.P. Cimellaro:** Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **M.P. Repetto:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interests

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.

Acknowledgement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors

Appendix A. - PORT Framework indicators

Dimension/ component/indicator	Measure (0 ≤value ≤1)	Ref	Nat***
1. Physical Infrastructure, ITC, Equipments			
1.1 Quay Cycle			
- QC Movements	n° of movements per crane per hour ÷ TV	[46]	D
- QC Cranes	n° of working cranes ÷ TV	[38, 46]	D
1.2 Trucks Cycle			
- Trucks	n° of Trucks Served ÷TV	[44]	D
- Rubber-tired gantries (RTG) Movements	n° of movements per crane per shift ÷ TV	[46] [38]	D
1.3 Train Cycle			
- Trains	n° of train operated ÷ TV	[44]	D
- Rail-mounted gantries (RMG) movements	n° of TEUs loaded and unloaded ÷ TV	[46] [38]	D

(continued on next page)

(*continued*)

Dimension/ component/indicator	Measure (0 ≤value ≤1)	Ref	Nat***
1.4 Yard			
- Reach Stackers	n° of TEUs loaded and unloaded ÷ TV	[46]	D
- Prime mover	n° of TEUs carried ÷ TV	[46]	D
1.5 Port Buildings			
- Docks	Resistance of the structure	[44] [38]	D
- Administration buildings office	Resistance of the structure	[44]	D
- Operation Control Room	Resistance of the structure	**	D
- Maintenance buildings	Resistance of the structure	**	D
- CFS	Resistance of the structure	[41]	D
1.6 Containers			
- IMO Goods	n° of IMO TEUs handled ÷ TV	**	D
- Reefer	n° of Reefer TEUs handled ÷ TV	[44]	D
- Empty Containers	n° of undamaged empty TEUs stored ÷ TV	**	D
- FCL	n° of FCL handled ÷ TV	[44]	D
1.7 Port Utility Systems			
- Power line/Electricity sub-station	1 (if it is active), 0 (otherwise)	[45]	S
- Liquid fuel system	1 (if it is active), 0 (otherwise)	[43]	S
- Fiber Optics	1 (if it is active), 0 (otherwise)	[45]	S
- Phone lines	1 (if it is active), 0 (otherwise)	[45]	S
- Sewer lines/(wastewater system)	1 (if it is active), 0 (otherwise)	[45]	S
- Water Utility	1 (if it is active), 0 (otherwise)	[45]	S
- Fire-fighting plant	1 (if it is active), 0 (otherwise)	[43]	S
1.8 Technical Services Availability			
- Pilots	1 (if it is active), 0 (otherwise)	[45]	S
- Thug Boats	1 (if it is active), 0 (otherwise)	**	S
- Mooring	1 (if it is active), 0 (otherwise)	**	S
Organization and Business Management			
2.1 Terminal Policy			
- HSE	n° of professional Illnesses ÷ TV	[39]*	D
- IT Policy	n° of events stopped operations ÷ TV	[32]	D
- Security organization (International Ship and Port Facility Security ISPS Code)	n° of monthly security incidents ÷ TV	[39]	D
- Delegation of authority	1 (if there is), 0 (otherwise)	[39]	S
	2.2 Internal and External Communication		
- Terminal and Shipping Companies Communication	1 (if there is), 0 (otherwise)	[42]	S
- Terminal and Port Authority Communication/Coast Guard	1 (if there is), 0 (otherwise)	[42]	S
-Terminal and Trucks Company Communication	1 (if there is), 0 (otherwise)	[42]	S
- Terminal/Shipper&Forwarders Communication	1 (if there is), 0 (otherwise)	[42]	S
- Internal Terminal Communication (Electronic Data Interchange EDI connectivity)	1 (if there is), 0 (otherwise)	[39]	S
	2.3 Human Resources		
- Company Workers	n° of TEUs handled per time unit]per unit of Company Worker÷ TV	[42]*	D
- Planning of ops staff	n° of personnel supervising terminal÷ TV	[42]*	D
- Supervising of ops staff	n° of personnel responsible for managing and performing trans-loading operations ÷ TV	[42]*	D
- Manning of Dockers and Company (to cover peaks)	QC movements per man per hour ÷ TV	[42]*	D
	2.4 Resources Planning and Location		
- Delays	1- ((n° of ships arrived at port at the berthing window - n° of ship allowed to enter into the port) ÷ n° of ships arrived at port)	[45]	D
- Turnaround time	TEUs average warehousing time ÷ TV	[39]	D
- Berth occupancy rate	n° of vessel ÷ n° of quay location available	[39]	D
	Resource and economic development		
	3.1 Financial Flows		
- Access to capital and investment for dredging, safety measures, and expansion	capital accessed/ capital needed	[42]	D
- Revenues, access to capital, and liquidity to invest in warehouses, storage yards, and connecting infrastructure	capital accessed ÷ capital needed	[42]	D
- Access to capital, liquidity, and revenue to fund operations and investments in superstructure	capital accessed ÷ capital needed	[42]	D
- Access to capital, liquidity, and revenue to fund operations and expansion of infrastructure	capital accessed ÷ capital needed	[42]	D
3.2 Financial Services			
- Difficulties in obtaining insurance	0 (if there are), 1 (otherwise)	**	S
- Hazard Insurance Coverage (Risks uninsurable)	% of port elements covered by an insurance program	[40]	S
3.3 Port Business and Costs			
- Tonnage	total of goods tons moved ÷ TV	[45]	D
- Revenue to Terminal	revenue to port ÷ TV	[45]	D
- Operations continuity	1 (if there is), 0 (otherwise)	[45]	S
- Respect for pre-storm business plans	1 (if there is), 0 (otherwise)	[45]	S
- Investment growth	% of investment growth ÷ TV	**	D
	Territory Environment and Stakeholders		
	4.1 External Physical Access		
- Roadway Systems	1 (if there is), 0 (otherwise)	[43]	S
- Railway Systems	1 (if there is), 0 (otherwise)	[43]	S
- Main Navigation Channel	1 (if there is), 0 (otherwise)	[45]	S

(*continued on next page*)

(*continued*)

Dimension/ component/indicator	Measure (0 ≤value ≤1)	Ref	Nat***
	4.2 Environment Sustainably		
- Noise pollution	1-(noise pollution index (NPI) ÷ TV)	[61]	D
- Air quality	air quality index (AQI) ÷ TV	**	D
- Water Quality	water quality index (WQI) ÷ TV	**	D
- Waste management	1 (if there is), 0 (otherwise)	**	S
- Debris field cleaning	0 (if there is), 1 (otherwise)	**	S
	4.3 Reputation		
- Social image of the port	Social Image Index (SII) ÷ TV		D

* Indicator found in the literature but strongly modified after meetings with port experts
** Indicator found after interviews with port experts and port management personnel
*** Nat describes the nature of the indicator: The indicators can be either Static (S) or Dynamic (D).

References

[1] Kron W. Coasts: the high-risk areas of the world. Nat Hazards 2013;66(3):1363–82.
[2] Verschuur J, Koks EE, Hall JW. Port disruptions due to natural disasters: Insights into port and logistics resilience. Transp Res Part D 2020;85:102393.
[3] León-Mateos F, Sartal A, López-Manuel L, Quintás MA. Adapting our sea ports to the challenges of climate change: development and validation of a Port Resilience Index. Mar Policy 2021;130:104573.
[4] Solari G, Repetto MP, Burlando M, De Gaetano P, Pizzo M, Tizzi M, Parodi M. The wind forecast for safety management of port areas. J Wind Eng Ind Aerodyn 2012; 104-106:266–77.
[5] Repetto MP, Burlando M, Solari G, De Gaetano P, Pizzo M. Integrated tools for improving the resilience of seaports under extreme wind events. Sustain Cities Soc 2017;32:277–94.
[6] Amini K, Padgett JE. Probabilistic risk assessment of hurricane-induced debris impacts on coastal transportation infrastructure. Reliab Eng Syst Saf 2023;240: 109579.
[7] Repetto MP, Burlando M, Solari G, De Gaetano P, Pizzo M, Tizzi M. A web-based GIS platform for the safe management and risk assessment of complex structural and infrastructural systems exposed to wind. Adv Eng Softw 2018;117:29–45.
[8] Cimellaro GP, Renschler C, Reinhorn AM, Arendt L. PEOPLES: a framework for evaluating resilience. J Struct Eng ASCE 2016.
[9] Kammouh O, Cimellaro GP. PEOPLES: a tool to measure community resilience. In: Soules JG, editor. Proceedings of 2018 Structures Congress (SEI2018). Fort Worth, Texas: ASCE- American Society of Civil Engineering; 2018. p. 161–71. Editor. 2018April 19–21.
[10] Bruneau M, Chang SE, Eguchi RT, Lee GC, O'Rourke TD, Reinhorn AM, Shinozuka M, Tierney K, Wallace WA, von Winterfeldt D. A framework to quantitatively assess and enhance the seismic resilience of communities. Earthquake Spectra 2003;19(4):733–52.
[11] Kammouh O, Chahrour N. Indicator-based framework to evaluate the resilience of transport infrastructure systems. Sustain Resilient Infrastruct 2025:1–27.
[12] Vugrin ED, Camphouse RC. Infrastructure resilience assessment through control design. Int J Crit Infrastruct 2011;7(3):243–60.
[13] Francis R, Bekera B. A metric and frameworks for resilience analysis of engineered and infrastructure systems. Reliab Eng Syst Saf 2014;121:90–103.
[14] Hein C, Schubert D. Resilience, disaster, and rebuilding in modern port cities. J Urban Hist 2021;47(2):235–49.
[15] De Iuliis M, Kammouh O, Cimellaro GP. Resilience assessment at the state level using the sendai framework. In: Eslamian S, Eslamian F, editors. Disaster Risk Reduction for Resilience: Disaster and Social Aspects. Springer International Publishing: Cham; 2022. p. 3–23.
[16] Kammouh O, Dervishaj G, Cimellaro GP. A new resilience rating system for countries and states. Procedia Eng 2017;198(Supplement C):985–98.
[17] Kammouh O, Dervishaj G, Cimellaro GP. Quantitative Framework to Assess Resilience and Risk at the Country Level. ASCE-ASME J Risk Uncertainty Eng Syst, Part A 2018;4(1):04017033.
[18] Cutter SL. The landscape of disaster resilience indicators in the USA. Nat Hazards 2016;80(2):741–58.
[19] Kammouh O, Noori AZ, Taurino V, Mahin SA, Cimellaro GP. Deterministic and fuzzy-based methods to evaluate community resilience. Earthquake Eng Eng Vib 2018;17(2):261–75.
[20] Shafieezadeh A, Burden LI. Scenario-based resilience assessment framework for critical infrastructure systems: case study for seismic resilience of seaports. Reliab Eng Syst Saf 2014;132:207–19.
[21] Pant R, Barker K, Ramirez-Marquez JE, Rocco CM. Stochastic measures of resilience and their application to container terminals. Comput Ind Eng 2014;70: 183–94.
[22] Barker K, Ramirez-Marquez JE, Rocco CM. Resilience-based network component importance measures. Reliab Eng Syst Saf 2013;117:89–97.
[23] Gharehgozli AH, Mileski J, Adams A, von Zharen W. Evaluating a "wicked problem": a conceptual framework on seaport resiliency in the event of weather disruptions. Technol Forecast Soc Change 2017;121:65–75.
[24] Liu X, Chen Z. An integrated risk and resilience assessment of sea ice disasters on port operation. Risk Anal 2021;41(9):1579–99.
[25] McIntosh RD, Becker A. Expert evaluation of open-data indicators of seaport vulnerability to climate and extreme weather impacts for U.S. North Atlantic ports. Ocean Coast Manag 2019;180:104911.
[26] Kong D, Setunge S, Molyneaux T, Zhang G, Law D. Structural resilience of core port infrastructure in a changing climate. Work Package 2013:3.
[27] Yang Z, Barroca B, Weppe A, Bony-Dandrieux A, Laffréchine K, Daclin N, November V, Omrane K, Kamissoko D, Benaben F, Dolidon H, Tixier J, Chapurlat V. Indicator-based resilience assessment for critical infrastructures – a review. Saf Sci 2023;160:106049.
[28] Panahi R, Sadeghi Gargari N, Lau Y-Y, Ng AKY. Developing a resilience assessment model for critical infrastructures: the case of port in tackling the impacts posed by the Covid-19 pandemic. Ocean Coast Manag 2022;226:106240.
[29] Cho H, Park H. Constructing resilience model of port infrastructure based on system dynamics. Disaster Manag 2017;7:245–54.
[30] Modarres M, Kruse H. Scenario-based resilience assessment framework for seismic resilience of seaports. Reliability Engineering & System Safety 2014.
[31] Marroni G, Casson Moreno V, Ovidi F, Chiavistelli T, Landucci G. *B.* Ocean Eng 2023;273:114019.
[32] Hsieh C-H, Hui-Huang T, Lee Y-N. Port vulnerability assessment from the perspective of critical infrastructure interdependency. Maritime Policy Manag 2014;41(6):589–606.
[33] Adam EF, Brown S, Nicholls RJ, Tsimplis M. A systematic assessment of maritime disruptions affecting UK ports, coastal areas and surrounding seas from 1950 to 2014. Nat Hazards 2016;83(1):691–713.
[34] Cao X, Lam JSL. Simulation-based catastrophe-induced port loss estimation. Reliab Eng Syst Saf 2018;175:1–12.
[35] Athanasatos S, Michaelides S, Papadakis M. Identification of weather trends for use as a component of risk management for port operations. Nat Hazards 2014;72(1): 41–61.
[36] Lin W, Liu W. Resilience evaluation of ports along the maritime silk road from the perspective of investment and construction. J Adv Transp 2023;2023(1):8818667.
[37] Jiang M, Lu J, Qu Z, Yang Z. Port vulnerability assessment from a supply chain perspective. Ocean Coast Manag 2021;213:105851.
[38] Thoresen CA. Port designer's handbook: recommendations and guidelines. Thomas Telford; 2003.
[39] De Langen P, Nidjam M, Van der Horst M. New indicators to measure port performance. J Maritime Res 2007;4(1):23–36.
[40] Cutter SL, Barnes L, Berry M, Burton C, Evans E, Tate E, Webb J. Community and Regional Resilience Initiative (CARRI) Research Report. 2008. p. 1.
[41] Na UJ, Shinozuka M. Simulation-based seismic loss estimation of seaport transportation system. Reliab Eng Syst Saf 2009;94(3):722–31.
[42] Berle Ø, Asbjørnslett BE, Rice JB. Formal vulnerability assessment of a maritime transportation system. Reliab Eng Syst Saf 2011;96(6):696–705.
[43] Kyriazis, P., Sotiris, A., Kalliopi, K., Anastasia, A., Helen, C., *Systemic seismic vulnerability and risk analysis for buildings, lifeline networks and infrastructures safety gain. SYNER-G synthetic document.* 2013.
[44] Southworth, F., Hayes, J., McLeod, S., Strauss-Wieder, A., *Making US ports resilient as part of extended intermodal supply chains*. 2014.
[45] Becker AH, Matson P, Fischer M, Mastrandrea MD. Towards seaport resilience for climate change adaptation: stakeholder perceptions of hurricane impacts in Gulfport (MS) and Providence (RI). Prog Plann 2015;99:1–49.
[46] Morris, L., *Ports resilience index: participatory methods to assess resilience*. 2017.
[47] Kammouh, O., Marasco, S., Noori, A.Z., Cimellaro, G., Mahin, S., *PEOPLES: indicator based tool to compute community resilience*, in *the 11 national conference on earthquake engineering*. 2018, the 11 national conference on earthquake engineering: Los Angeles, USA.
[48] Kammouh O, Noori AZ, Cimellaro GP, Mahin SA. Resilience assessment of urban communities. ASCE-ASME J Risk Uncertainty Eng Syst, Part A 2019;5(1): 04019002.
[49] Radicioni L, Giorgi V, Benedetti L, Bono FM, Pagani S, Cinquemani S, Belloli M. On the performance of data-driven dynamic models for temperature compensation on bridge monitoring data. J Civ Struct Health Monit 2025;15(6):1957–72.
[50] Shumway RH, Stoffer DS, Stoffer DS. Time series analysis and its applications, 3. Springer; 2000.

[51] Dueñas-Osorio L, Kwasinski A. In: Quantification of Lifeline System Interdependencies after the 27 February 2010 Mw 8.8 Offshore Maule, Chile, Earthquake. 28. Earthquake Spectra; 2012. p. 581–603.

[52] Cimellaro GP, Solari D, Bruneau M. Physical infrastructure interdependency and regional resilience index after the 2011 Tohoku Earthquake in Japan. Earthq Eng Struct Dyn 2014;43(12):1763–84.

[53] De Iuliis M, Kammouh O, Cimellaro G, Tesfamariam S. Resilience of the built environment: a methodology to estimate the downtime of building structures using fuzzy logic. In: Resilient Structures and Infrastructure. Springer; 2019. p. 47–76.

[54] De Iuliis M, Kammouh O, Cimellaro GP. Measuring and improving community resilience: a fuzzy logic approach. Int J Disast Risk Reduct 2022;78:103118.

[55] De Iuliis M, Kammouh O, Cimellaro GP, Tesfamariam S. Downtime estimation of building structures using fuzzy logic. Int J Disast Risk Reduct 2019;34:196–208.

[56] De Iuliis M, Kammouh O, Cimellaro GP, Tesfamariam S. Quantifying restoration time of pipelines after earthquakes: Comparison of Bayesian belief networks and fuzzy models. Int J Disast Risk Reduct 2021;64:102491.

[57] Kammouh O, Zamani Noori A, Domaneschi M, Cimellaro GP, Mahin S, et al. A fuzzy based tool to measure the resilience of communities. In: Powers N, et al., editors. 9th International Conference on Bridge Maintenance, Safety (IABMAS2018). Melbourne, Australia: CRC Press; 2018. p. 588.

[58] Ricci A, Burlando M, Repetto MP, Blocken B. Simulation of urban boundary and canopy layer flows in port areas induced by different marine boundary layer inflow conditions. Sci Total Environ 2019;670:876–92.

[59] Torre S, Burlando M, Ruscelli D, Repetto MP, Camauli G. Wind tunnel experimental investigation of the aerodynamic coefficients reduction due to sheltering surroundings on a cruise ship moored in port. J Wind Eng Ind Aerodyn 2021;218:104731.

[60] Ricci A, Vasaturo R, Blocken B. An integrated tool to improve the safety of seaports and waterways under strong wind conditions. J Wind Eng Ind Aerodyn 2023;234:105327.

[61] Molavi A, Lim GJ, Race B. A framework for building a smart port and smart port index. Int J Sustain Transp 2020;14(9):686–700.