Proc. of the European Safety and Reliability Conference (ESREL 2026)
Edited by José C. Matos, Paulo B. Lourenço, Michael Beer, Daniel Oliveira, Edoardo Patelli, Hélder S. Sousa, Rui A. Silva and Monica Santamaria

doi: 10.3850/ESREL2026061419_esrel26-p27805-cd

Dynamic Risk Assessment for Resilient Port Operations under Increasing Extreme Weather Conditions

Kwi Yeon Koo

Department of Microsystems, University of South-Eastern Norway, Norway. E-mail: kwi.y.koo@usn.no

Synnøve Sunne Hasslan

Department of Maritime Operations, University of South-Eastern Norway, Norway. E-mail: synnove.s.hasslan@usn.no

Gabriel Chikelu

Department of Energy and Mechanical Engineering, Aalto University, Finland. E-mail: Gabriel.chikelu@aalto.fi

Per Haavardtun

Department of Maritime Operations, University of South-Eastern Norway, Norway. E-mail: per.haavardtun@usn.no

Kenn Steger-Jensen[a, b]

[a]*Department of Maritime Operations, University of South-Eastern Norway, Norway. E-mail: kenn.steger-jensen@usn.no*
[b]*Department of Materials and Production, Aalborg University, Denmark*

In the last decade, many European ports are increasingly vulnerable to extreme weather conditions that disrupt logistics flows, reduce operational efficiency, and challenge safety management. As these disruptions become more frequent and less predictable, maintaining resilient port operations requires a shift from traditional static assessments toward more adaptive and time sensitive approaches.
This study presents a dynamic risk assessment approach that updates disruption estimates over time as weather conditions deteriorate and operational constraints tighten. The approach is illustrated using available operational information from the ports of Lisbon, Seville, and Dunkirk, and provides a reusable template intended for port specific instantiation under weather related disruption. To support this analysis, a Bayesian Network (BN) model is employed to represent probabilistic relationships between performance deviations, preparedness conditions, and disruption states. The BN outputs are passed to simulation models to assess the potential capacity impact of the relevant risk and to identify bottlenecks. These bottlenecks and capacity reduction are then used in the optimization models to support mitigation planning for capacity loss. Selected plans and resource allocations can then be fed back to the risk layer as updates to controllable conditions for the next update step. Through this interaction among risk assessment, simulation, and optimization models, the overall decision-making process can become more adaptive and resilient to uncertain weather-related disruptions.
By combining operational conditions with simulation and optimization outputs, the proposed approach supports short-term actions such as traffic sequence adjustment and temporary capacity adjustments, while also supporting long-term planning related to operational preparedness and infrastructure robustness. Overall, the study contributes to efforts to enhance port operational resilience by providing probabilistic disruption estimates and a structured interface for scenario evaluation and resource allocation under extreme weather.

Keywords: Dynamic risk assessment, Resilience, port operations, extreme weather

1. Introduction

Ports function as critical interfaces in global logistics networks (United Nations Trade Development 2025; W. Li et al. 2023). Daily operations depend on available infrastructure, coordinated terminal activities, and stable hinterland connections. Under extreme weather, disruptions can lead to temporary capacity loss and cascading delays across connected flows (Chikelu et al. 2025; Zhao et al. 2024; Devendran et al. 2023).

Recent studies address weather related port disruption using several modelling perspectives. C. Li, Yang, and Yang (2025) quantify port vulnerability to natural disasters using daily shipping traffic data at a global port set, supporting large scale empirical assessment beyond single port case studies. Zhu et al. (2025) advance digital twin-based modelling for port operations, aiming to connect operational data with integrated simulation for resilience and sustainability assessment at terminal level. Yin et al. (2024) develop a Bayesian network-based disruption risk model to capture multi factor dependencies and produce probabilistic disruption estimates. Related Bayesian Network approaches have also been applied to dynamic port risk assessment (Gui, Wang, and Yu 2022; Hossain et al. 2019; Wang, Wu, and Yuen 2023). However, risk assessments are often reported as disruption probabilities, composite indices, or ranked factors, which may not directly indicate which mechanisms constrain operational capacity. Operational planning benefits from an interpretable mapping from environmental evidence to capacity limiting mechanisms, so that functional constraints can be diagnosed and tested under alternative scenarios rather than treated as standalone scores. This requirement aligns with recent digital twin-based decision support and resource optimization, where state or risk estimates are coupled with a virtual representation of port operations to run what if scenario evaluations and support operational choices (Zhu et al. 2025; Jayasinghe et al. 2024; Yang et al. 2024). In this context, a key need is a risk inference component that produces uncertainty aware and operationally interpretable outputs for scenario-based evaluation and planning.

This paper addresses this need by proposing a dynamic and modular risk assessment approach for port operations under extreme weather conditions. A Bayesian Network (BN) is specified as the risk inference component. It represents probabilistic dependencies between hazard drivers, infrastructure impacts, operational constraints, and mitigation actions. The BN is updated sequentially as new evidence becomes available. The output formulation is designed for operational use. It includes the disruption posterior, compact summary indicators, and a bottleneck profile that supports mechanism-based diagnosis. The same outputs are formatted for integration with external simulation and optimization modules. This supports an iterative decision support workflow in which risk inference informs scenario exploration and resource allocation, and selected plans update controllable conditions in subsequent BN updates.

The approach is illustrated using the information from three European ports: Port of Lisbon, Port of Seville, and Port of Dunkirk. These cases are used to ground the parameter choices and evidence design in realistic contexts, while the model is intentionally formulated as a generic structure with configurable components, so that it can be adapted to other terminals facing weather driven operational disruption by re specifying port specific inputs and thresholds rather than redesigning the full model.

2. Background

2.1.Extreme weather and port operation

Ports are particularly exposed to extreme weather because of their coastal location and dependence on outdoor operations (Verschuur et al. 2023; Verschuur, Koks, and Hall 2020). Infrastructures are not always the first element affected during extreme weather, but once degradation occur, it can drive large capacity loss by creating bottlenecks in cargo handling, nautical access, and landside access. This operational sensitivity is consistent with recent port resilience research that increasingly emphasises adaptation and resilience, with key themes including sea level rise, port vulnerability, climate adaptation, and emission reduction (Türkistanlı et al. 2025).

2.2.Motivation for a dynamic and modular approach

Extreme weather impacts are time varying. Evidence also arrives over time, through forecasts, sensor streams, incident reports, or operational status updates. Dynamic risk assessment allows risks to be updated as operating conditions change (Feng et al. 2025). This is important in ports because relevant data are often fragmented across organisations and systems, and direct statistics on disruption outcomes may be limited (He, Wan, and

Jiang 2021). The key need is therefore a model structure that can combine heterogeneous evidence and express uncertainty in an interpretable form.

A modular approach is also motivated by data and decision constraints. When disruption outcome data are sparse, scenario-based evaluation helps test the operational implications of risk assumptions and identify sensitive bottlenecks. Simulation can explore operational consequences under alternative disruption conditions, while optimization can translate scenario performance into resource allocation or prioritisation decisions. Feedback from evaluated scenarios can then support iterative refinement of controllable operational conditions in subsequent updates. Building on these needs, this study treats resilience as an operational concept and links sequential risk inference with iterative simulation and optimization-based evaluation.

3. Methodology

This study proposes a transferable Bayesian Network (BN) structure for dynamic risk assessment of resilient port operations under extreme weather conditions. Its top node represents the disruption state in probabilistic terms.

Proposed BN templet is intended to serve as a risk inference component within an integrated decision support system. Therefore, the resulting posterior disruption probabilities are provided to external simulation and optimization modules.

3.1.Modelling s*cope and outputs*

The modelling scope is defined at terminal or operational management unit level. It covers terminal processes and the enabling infrastructure that shapes operational capacity and safe execution of terminal activities. To support a transferable BN template, infrastructure assets inventories were reviewed for three representative ports (Dunkirk, Lisbon, and Seville), and the assets were grouped into eight functional infrastructure categories. These categories were then used to define the corresponding nodes in the BN.

The model output is a posterior distribution over ordered disruption states that represent levels of capacity loss over a defined decision time window. The output package also includes compact indicators that summarise the disruption posterior and operational bottleneck conditions for external simulation and optimization modules.

3.2.Evidence processing and BN evidence entry

The BN is updated sequentially as time indexed evidence becomes available. Continuous and heterogeneous observations are transformed into a compact set of discrete indicators to support stable inference and transparent evidence entry. Two evidence classes are used for BN updating. The first class captures discretised weather hazard intensity. The second class captures observed port operational conditions that reflect how operations respond to changing weather conditions. Plan feedback is treated separately as updates to controllable conditions, for example preparedness and mitigation states, rather than as observational evidence.

When evidence is missing at an update step, the corresponding nodes are left unobserved. The network then updates using the available evidence and the current priors. This avoids introducing arbitrary values and keeps uncertainty explicit.

3.3.Bayesian network design and parameterisation

3.3.1.*BN structure and node groups*

The BN is organised into five node groups as follows:

- Weather nodes represent discretised hazard intensity, including wind, precipitation, and temperature extremes.
- Preparedness and mitigation nodes represent the availability and readiness of measures that can moderate hazard impacts or limit disruption propagation.
- Infrastructure category impact nodes represent functional constraints at the level of the eight functional categories.
- Status nodes represent operational bottlenecks as observable constraint signals.
- Disruption state node represents ordered capacity loss states at the terminal or operational unit level.

In the weather nodes group, wind, precipitation, and temperature extremes were selected because they are broadly monitored across ports and have clear, direct links to operational constraints such as crane restrictions, access limitations, and heat related work reductions. Flooding and storm surge are not modelled as primary weather nodes; instead, their effects are represented in the CPTs linking wind and precipitation to the relevant impact.

The preparedness and mitigation nodes were derived from a structured assessment of port level response, adaptation, and mitigation practices documented for three representative ports. A separate screening and classification step then abstracted the documented practices into four transferable capability nodes: monitoring and warning capability (P1), response governance and coordination readiness (P2), physical protection and redundancy readiness (P3), and resource mobilisation and recovery capacity (P4). These nodes are included as contextual modifiers that can alter hazard to impact relationships and the propagation from infrastructure category impacts to operational bottlenecks.

Infrastructure category impact nodes were derived from a review of infrastructure asset inventories from the three representative ports, as described in Section 3.1. In the BN, these nodes group represent short term functional constraints at category level and provide the main bridge between weather driven hazards, operational bottleneck status nodes, and the terminal level disruption state.

The status node group was introduced to aggregate category level constraints into a small set of operational bottlenecks. Directly connecting all eight category impact nodes to the disruption state can create large conditional probability tables (CPT) and reduce interpretability. An intermediate status layer is therefore used to aggregate category level constraints into a small set of operational bottlenecks.

3.3.2.Parameterisation strategy and constraints

Parameterisation follows a staged approach that matches typical data availability in ports. Initial CPTs can be set using structured expert judgement and prior vulnerability profiling, then refined when operational records become available. Directional constraints are enforced to avoid implausible behaviour, for example higher hazard intensity should not reduce the probability of severe category impact. Assumptions and parameter choices are documented as design outputs to support review and iterative revision.

3.4.Dynamic updating and risk indicator formulation

In this paper, the term risk indicator refers to a posterior based decision support signal derived from the BN. At each update step, the BN returns a posterior distribution over disruption states. For compact exchange and interpretation, the posterior is accompanied by three summary indicators as follows:

- The probability mass assigned to the high-capacity loss states.
- The expected disruption level computed from an ordinal representation of the disruption states.
- The bottleneck profile defined as posterior probabilities that each status node is in a restricted state.

Status nodes can be used as evidence entry points when bottleneck conditions are directly observed from operational monitoring. In such cases, the corresponding status node is entered as evidence, while upstream category impact nodes are left unobserved unless independent evidence is available. This supports consistent updating and reduces the risk of double counting when observations are correlated.

3.5.Interface specification to external modules

The disruption posterior and its indicator set are provided to external simulation and optimization modules. Within the decision support platform, the simulation module represents terminal process flows and queues as an agent-based discrete event simulation, including gate operations, yard handling, and quay operations. The BN posterior conditions the next run by updating scenario weights and capacity parameters, and the optimization module selects actions from the resulting performance summaries and feeds back updates to controllable condition nodes in the next BN step.

The interface specification is introduced to make the coupling explicit and repeatable across ports and platform implementations. It defines what information is exchanged, at which decision time step, and with which operational meaning, so that the BN remains a probabilistic inference layer rather than an embedded simulator. Simulation outputs provide the performance summaries required for optimization, while disruption probabilities may also enter optimization directly as scenario weights, objective penalties, or probability-based constraints. Feedback from the selected plan is restricted to updates of controllable condition nodes, which preserves separation of roles and prevents implicit double counting between the BN and the external models.

4. Results: framework artefacts and design outputs

4.1.BN template and node definitions

The reusable BN template is specified as node groups, node state definitions, and dependency rules. Table 1 summarises the BN node groups, inference roles, and evidence sources. In an instantiated BN, each node is discretised into a small number of ordered states, typically around three, to keep updating stable and interpretable.

Table 1. Node groups, inference roles, and evidence sources.

Node group	Purpose in inference	Evidence source
Weather	Hazard intensity drivers	Weather forecast
Preparedness and mitigation	Context modifiers that reduce impact or propagation	Plan and resource updates
Infrastructure category impact	Functional constraints for infrastructure	Inferred or assessed
Status	Operational bottleneck constraints	Direct monitoring or inferred
Disruption state	Terminal level capacity loss	Inferred

4.2.Status nodes and mapping from infrastructure categories to operational bottlenecks

To avoid a large parent set, an intermediate operational bottleneck layer is introduced. The eight category constraints are grouped into four operational bottleneck constraints that represent where capacity limitations manifest in terminal operations:

- Nautical access (Nautical)
- Landside access (Landside)
- Cargo handling capacity (Cargo)
- Yard operability and congestion (Yard/Cong.)

Table 2 summarises the mapping from infrastructure category impact nodes to the four operational bottleneck status nodes.

The mapping rule targets the bottleneck where degradation is expected to materialise most directly in day-to-day terminal operations. Secondary links are used only when a stable coupling is expected across terminals, to avoid unnecessary CPT growth.

Table 2. Mapping from infrastructure categories to operational bottlenecks.

Infrastructure category impact node	Primary bottleneck status node	Secondary bottleneck status node (optional)
Marine Structures	Nautical	None
Cargo Handling Equipment	Cargo	Yard/Cong.
ICT & Port Operations Systems	Yard/Cong.	Cargo
Energy Infrastructure and Distribution System	Cargo	Yard/Cong.
Access Infrastructure (Road/Rail)	Landside	None
Storage Support Facilities	Yard/Cong.	None
Environmental Protection Systems	Yard/Cong.	Landside
Utilities and Drainage Systems	Yard/Cong.	Landside

4.3.Risk indicator package and interface artefacts

At each update step, the BN produces the posterior distribution over the disruption states. This posterior is summarised into a compact indicators package so that the simulation and optimization module can use it.

Let S denote the disruption state with ordered levels of capacity loss. From the posterior $P(S)$, the following risk indicators are derived:

- High disruption probability

$$P(S \in S_{high}) = \sum_{s \in S_{high}} P(S = s)$$

This is the probability mass assigned to the high capacity loss states.

- Expected disruption level

$$E[S] = \sum_{s} Score(s) P(S = s)$$

Here, $Score(s)$ is an ordinal severity score assigned to each disruption state (for example Low, Moderate, High mapped to 1, 2, 3). This gives a single severity score.

- Bottleneck constraint profile

$$P(B_j = Restricted)$$

The posterior probability of being in a restricted state is provided for each bottleneck status node B_j.

Table 3 defines a minimal record schema for exchanging information between the BN and external simulation and optimization modules. The interface specification is designed to preserve uncertainty while keeping the interface compact and easy to implement.

Table 3. Minimal interface records for iterative updates.

Record	Key fields
Risk-Record	Time, unit id, disruption posterior, high disruption probability, expected disruption level, bottleneck profile, update availability flags
Scenario-Record	Scenario id, assumptions, feasibility flags, performance summaries
Plan-Record	Selected actions, resource allocation, operational configuration, expected capacity under plan

The Risk Record carries the disruption posterior and compact risk indicators from the BN. Update availability flags are included to make data missingness explicit at each update step, so that posterior changes can be interpreted in light of which input classes informed the update and to avoid over confidence when key inputs are absent. It is classified into the following three classes:

- Weather inputs available
- Operational status or bottleneck signals available
- Plan or control updates available

The Scenario Record carries simulation-based scenario assumptions, feasibility flags, and performance summaries for consistent comparison across candidate scenarios. The scenarios are in most cases conditioned on the BN disruption posterior, while the record itself is not entered as BN evidence but supports plan selection and subsequent feedback updates.

The Plan Record carries the selected actions and expected operating outcomes and is used to update preparedness and mitigation states, in the next BN update step. Expected capacity under plan is reported on the same reference as the BN disruption states, using the same decision time window. It can be expressed either as a capacity fraction relative to nominal operation or as the corresponding ordinal capacity loss level using the BN state bins. This interface specification supports iterative coupling across modules by separating outputs and feedback into lightweight records.

5. Discussion

A clear separation is maintained between infrastructure category impact nodes and bottleneck status nodes. Infrastructure category nodes represent where functional degradation is expected to occur, while bottleneck nodes represent how that degradation becomes visible as actionable operational constraints. This intermediate bottleneck layer improves CPT tractability and interpretability, but it may introduce an aggregation trade off. For instance, secondary cross bottleneck effects may be omitted, and results can become sensitive to category to bottleneck parameterisation, especially when direct status observations are sparse. To address these limits, the mapping and CPTs can be refined in future work using targeted sensitivity checks and available operational logs.

Preparedness and mitigation nodes act as contextual modifiers that can change hazard to impact relationships and the translation from category impacts to bottlenecks. This provides a compact way to represent differences in protection and response capability across ports without introducing asset level detail, and it also creates explicit handles for reflecting selected actions and resource activation in the next update step. These nodes typically change on slower time scales than weather and operational evidence, and are updated when measures are activated or resources are reallocated.

For integration with external modules, the risk output package retains the full disruption posterior while providing a small set of summary indicators. High disruption probability and expected disruption level can support screening and ranking, and the bottleneck profile can support diagnosis and targeted operational response. This package supports scenario exploration and resource allocation by providing uncertainty aware disruption estimates together with bottleneck level diagnostics.

The proposed BN structure is intentionally transferable and does not represent asset level degradation mechanisms or detailed physical processes. This choice supports portability and interpretability at terminal level, but it may reduce diagnostic resolution for compound hazards and for ports with strong local protection features. When local pathways are particularly dominant or site-specific effects are pronounced, this limitation can be mitigated by adding a small number of port specific hazard or impact refinements for dominant local pathways and by updating the relevant CPTs using local event logs and structured operator elicitation.

Parameterisation is constrained by port data availability, so initial CPTs rely on structured expert judgement and vulnerability profiling rather than statistical calibration. Recovery dynamics are not yet represented as explicit state variables. These limitations motivate the planned stakeholder workshops and scenario exercises, which will identify degradation pathways and recovery requirements to refine state definitions, thresholds, and CPTs, and to update preparedness and mitigation node settings in a transparent way.

Future work will use structured stakeholder workshops with terminal operators to strengthen operational grounding where empirical data are limited. The workshops will identify stepwise changes in feasible activities under deteriorating weather, together with recovery needs such as additional tasks, backlog formation, and resource requirements. The identified information will be used to refine state definitions and thresholds, update hazard to impact and impact to bottleneck parameterisation, and adjust preparedness and mitigation node settings. Scenario based exercises can then test whether inferred bottleneck profiles match operator expectations and whether the risk output package supports scenario comparison and resource allocation decisions.

6. Conclusions

This paper presents a transferable Bayesian Network (BN) template for dynamic risk assessment of port operations under extreme weather. The template is informed by infrastructure asset inventories from three representative ports, Dunkirk, Lisbon, and Seville. The BN is positioned as a risk inference component that can support a generic digital decision support platform, rather than as a port specific calibrated model. The modelling scope is defined at terminal or operational management unit level. Disruption is represented as ordered levels of capacity loss over a defined decision time window.

The main contribution is a reusable BN structure that translates weather hazard intensity into infrastructure category impact states and operational bottleneck constraints, and then infers disruption state probabilities. This layered abstraction supports operational interpretability and feasible parameterisation while avoiding asset level modelling. A second contribution is the inclusion of preparedness and mitigation nodes as slow varying contextual modifiers. These nodes represent differences in protection and response capability across ports and provide explicit levers for reflecting selected actions and resource activation in subsequent update steps. A third contribution is a compact risk output package designed for operational use. It preserves uncertainty through the disruption posterior while providing summary indicators for screening and bottleneck-oriented diagnosis. Lightweight interface records are specified to support integration with external simulation and optimization modules. This design supports iterative use in which risk outputs inform scenario evaluation and resource allocation, and selected plans are reflected as updates to controllable conditions in the next BN update.

Further work should strengthen credibility through structured instantiation and evaluation. Priority areas include refining CPTs using operational records and event logs where available, and conducting stakeholder workshops to identify feasible actions, degradation pathways, and recovery resource needs. These steps can improve state definitions, threshold choices, and parameter settings while retaining the transferability of the core template.

Acknowledgement
This paper is based on work carried out in the SAFe, climAte Resilient Infrastructure (SAFARI) project funded by the European Union's Horizon Europe Programme (Grant No. 101147432).

References

Chikelu, G., M. Chaal, S. Hirdaris, N. Papadopoulou, A. Nazemian, O. Tzoraki, E. Boulougouris, and O. A. V. Banda. (2025). Vulnerability and Recovery Co-Analysis to Enhance Resilience of Ports Impacted By Extreme Weather Events - Preliminary Results from EU Project Safari. International Conference on Civil, Structural and Transportation Engineering.

Devendran, Lishalini, Masha Menhat, Rudiah Md Hanafiah, Norhafiza Ilyana Yatim, Nora'aini Ali, and Izyan Munirah Mohd Zaideen. (2023). Adapting to the impacts of climate change on port operation. Australian Journal of Maritime & Ocean Affairs 15 (2): 107-126.

Feng, Lihe, Binyue Xu, Chaojun Ding, Hongxiang Feng, and Tianshou Liu. (2025). Dynamic Risk Assessment Framework for Tanker Cargo Operations: Integrating Game-Theoretic Weighting and Grey Cloud Modelling with Port-Specific Empirical Validation. Systems 13 (8): 697.

Gui, Dongping, Haiyan Wang, and Meng Yu. (2022). Risk assessment of port congestion risk during the COVID-19 pandemic. Journal of Marine Science and Engineering 10 (2): 150.

He, Ruhai, Chengpeng Wan, and Xinchen Jiang. (2021). Risk management of port operations: A systematic literature review and future directions. 2021 6th International Conference on Transportation Information and Safety (ICTIS).

Hossain, Niamat Ullah Ibne, Farjana Nur, Seyedmohsen Hosseini, Raed Jaradat, Mohammad Marufuzzaman, and Stephen M Puryear. (2019). A Bayesian network based approach for modeling and assessing resilience: A case study of a full service deep water port. Reliability Engineering & System Safety 189: 378-396.

Jayasinghe, SC, M Mahmoodian, A Sidiq, TM Nanayakkara, A Alavi, Sam Mazaheri, F Shahrivar, Z Sun, and S Setunge. (2024). Innovative digital twin with artificial neural networks for real-time monitoring of structural response: A port structure case study. Ocean engineering 312: 119187.

Li, Chengkun, Xiyi Yang, and Dong Yang. (2025). Port vulnerability to natural disasters: An integrated view from hinterland to seaside. Transportation Research Part D: Transport and Environment 139: 104563.

Li, W., X. Bai, D. Yang, and Y. Hou. (2023). Maritime connectivity, transport infrastructure expansion and economic growth: A global perspective. Transportation Research Part A: Policy and Practice 170.

Türkistanlı, Taha Talip, Nergis Özispa, Gökçe Tuğdemir Kök, Ünal Özdemir, and Davut Pehlivan. (2025). Exploring Research Trends on Climate Change: Insights into Port Resilience and Sustainability. Sustainability 17 (8): 3542.

United Nations Trade Development. (2025). Review of Maritime Transport 2025: Staying the Course in Turbulent Waters. Stylus Publishing, LLC.

Verschuur, J, EE Koks, and JW Hall. (2020). Port disruptions due to natural disasters: Insights into port and logistics resilience. Transportation research part D: transport and environment 85: 102393.

Verschuur, J, EE Koks, S Li, and JW Hall. 2023. Multi-hazard risk to global port infrastructure and resulting trade and logistics losses, Communications Earth & Environment, 4, 5.

Wang, Nanxi, Min Wu, and Kum Fai Yuen. (2023). Assessment of port resilience using Bayesian network: A study of strategies to enhance readiness and response capacities. Reliability Engineering & System Safety 237: 109394.

Yang, Wenqiang, Xiangyu Bao, Yu Zheng, Lei Zhang, Ziqing Zhang, Zhao Zhang, and Lin Li. (2024). A digital twin framework for large comprehensive ports and a case study of Qingdao Port. The International Journal of Advanced Manufacturing Technology 131 (11): 5571-5588.

Yin, Jingbo, Rafi Ullah Khan, Xinbo Wang, and Mujtaba Asad. (2024). A data-centered multi-factor seaport disruption risk assessment using Bayesian networks. Ocean Engineering 308: 118338.

Zhao, C., Y. Yin, K. Dong, C. Yang, and K. Wang. (2024). How does port alliance survive extreme weather? Analysis using stochastic evolutionary game. Transportation Research Part D: Transport and Environment 133.

Zhu, Mingyu, Carlos Calderon, Alistair Ford, Craig Robson, and Jiayi Jin. (2025). Digital Twin for resilience and sustainability assessment of port facility. Sustainable and Resilient Infrastructure: 1-34.