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Research on Port Risk Assessment Based on Various Meteorological Disasters

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Abstract: Within the framework of economic globalisation, ports serve as critical junctures in international trade and play a vital role. However, as infrastructure is closely linked to the natural environment, ports are highly susceptible to the impacts of meteorological disasters. Therefore, a comprehensive assessment of the risks posed by meteorological hazards to ports, establishing corresponding early warning mechanisms, and adopting reasonable response and recovery strategies, is paramount in ensuring the safe operation of ports and maintaining the stability of international trade. This study has comprehensively analysed historical data and identified the pre-established loss stratification system, improving the theoretical construct of "expected loss". Additionally, this research has innovatively integrated the idea of preventative factors aligned with risk indicators. A quantitative algorithm was used to factor in the preventative factors within the computational procedure, deriving the weights pertinent to each risk indicator. This research aimed to reduce the subjectivity inherent in the weighting assignment process through such an approach, thereby enhancing disaster risk assessment's scientific rigour and reliability. Moreover, it underscores the critical role of adaptive urban planning in enhancing the resilience of crucial economic nodes like ports, thereby contributing to the broader objectives of sustainable urban development.

Keywords: port meteorological disasters; risk assessment; weighting analysis

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1. Introduction

In the globalised trade system, ports act as crucial hubs, performing the pivotal function of transshipping and distributing maritime cargo. The efficient operation of ports is fundamental to facilitating the flow of goods between sea and land, enhancing global trade efficiency, and bolstering regional economic development. Because of the role of ports not just as trade facilitators but as integral components of urban development, climate adaptation and meteorological disaster prevention at these hubs is essential [1]. These measures impact urban resilience, safeguarding cities' economic continuity and development against increasing climate variability [2]. The role of ports in the global supply chain system is significant, contributing notably to the interconnectivity of global markets. However, the geographical location of ports often exposes them to the threats of meteorological disasters, which can jeopardise the integrity of port facilities and operational efficiency to varying extents. Ports are typically situated in low-lying coastal and riverine areas, making them particularly vulnerable to the physical impacts of natural disasters. The consequent damage has the potential to propagate through supply chains, leading to widespread economic losses [3]. Common meteorological disasters like typhoons and storm surges, characterised by their unpredictability and destructive power, can damage port infrastructure, cause logistics delays, and even cause trade disruption, thereby significantly affecting the stability of the global supply chain. Typhoon Maysak (Julian in the Philippines) was a powerful tropical cyclone that strongly impacted coastal regions of the Sea of Japan from 2 to 4 September 2020. Destructive winds, violent storm waves, and intense rainfall occurred in Japan, the Korean Peninsula, and Far-Eastern Russia. Devastating coastal floods caused severe damage to coastal infrastructure and ships and boats anchored in harbours and were responsible for numerous deaths [4]. Jihong's [5] research also indicates that the probability of susceptibility to failure in port oil pipelines increases concomitantly with the escalating intensity of typhoon categories. Lemmen et al. [6] highlighted the risk to maritime activities arising from storm waves in Canada's Pacific region, as demonstrated by five fatalities and the sinking of several fishing boats during a particularly severe storm in October 1984. More than 100 shipping containers were dislodged from a cargo ship off the coast of Victoria in October 2021, and stormy conditions hindered firefighting and recovery of the containers at the scene.

The studies mentioned above collectively demonstrate the considerable impact of meteorological disasters on ports and the maritime transport network. Given the critical role of ports in international trade and the ever-present threat that weather-induced disasters pose to port operational security, it becomes particularly imperative to conduct systematic risk assessments for meteorological disasters at ports. Nevertheless, Lau et al. [7] claimed that past research studies were only inclined toward theoretical or conceptual issues, proposing that their specific findings could not generate an objective vortex with visible reliability. Other scholars [8,9] concentrated on employing complex numerical weather models to predict weather impacts. Wang et al. [10] pointed out that insufficient knowledge of the thermodynamic mechanisms and typhoon system induces an incorrect elaboration of the structure and movement of a typhoon. In addition, Ng et al. [11] and Yang et al. [12] indicated the stakeholder viewpoints on the effectiveness of climate adaptation actions. To fill in the research gap, the risk assessment methodology presented in this paper is based on extensive analysis of historical data, characterising the nature of meteorological disasters, their probabilities of occurrence, and the potential impacts they may render. This facilitates the planning of preventive and recovery strategies to enhance the resilience of ports against such risks. Therefore, bolstering the disaster risk assessment and management strategies for ports is fundamentally significant in ensuring international trade stability and driving sustained global economic growth.

The remainder of this paper is organised as follows: Section 2 reviews foundational theories of risk assessment and the literature related to recent developments in port disaster risk evaluations; Section 3 details the specific assessment models employed in this study; Section 4 presents the results from numerical experiments conducted in case analyses; and Section 5 offers conclusions.

2. Literature Review

Risk assessment is the process of identifying, analysing, and evaluating potential risks and serves as a fundamental tool for risk management, risk prevention, and decision-making. Risk refers to the likelihood of an undesirable event occurring under specific conditions and its consequences. Risk assessment constitutes a series of systematic methodologies to identify and analyse potential risks, providing decision-makers with clear information on the level of risk through quantitative or qualitative means.

The theoretical foundation of risk assessment has continually evolved in response to practical application needs and the evolution of academic thought. In their research, Aven and Renn [13] emphasised the necessity for modern risk assessments to transcend traditional quantitative analysis models, considering the uncertainties and diversities of risks more significantly. Kaplan and Garrick [14] proposed the well-known risk triplet model earlier, providing a structured analytical framework for risk assessment. Bier [15], through an extensive literature review, underscored the introduction of decision analysis perspectives as significantly improving the practice of risk assessments. Andretta [16], based on systems theory and fundamental concepts of probability, aimed to construct basic concepts and principles applicable to various risk assessment domains within a single, extensive, and general theoretical context. Fischer et al. [17], in the earthquake risk assessment for urban areas, associated the three elements of "hazard", "exposure", and "vulnerability". Hazard measures the likelihood of earthquakes causing damage; exposure denotes the population size at risk of such damage; vulnerability refers to the extent of destruction experienced by buildings considered in seismic events. In many risk assessment cases, numerous researchers have conducted comprehensive analyses of the degree of risk both qualitatively and quantitatively from the perspectives of "hazard", "exposure", and "vulnerability". Sicari et al. [18] utilised risk assessment techniques to evaluate the reliability and robustness of components belonging to internet of things (IoT) platforms against malicious attacks. Zhang et al. [19] proposed a risk assessment method for risks with various associated factors, constructing a comprehensive correlation matrix to identify the interrelationships between risks and thus determine a risk hierarchy. Based on the determined categorised or uncategorised risk hierarchy structure and the probabilities and losses of risks provided by an expert panel, each risk value is computed using knowledge related to probability theory. Huang et al. [20] pointed out that methods such as the Monte Carlo simulation, Bayesian networks, Markov models, and others represent the most powerful analytical tools in maritime transport risk assessments, with fuzzy logic being the most commonly used auxiliary analysis tool. Furthermore, data mining and machine learning algorithms used for cluster analysis, association rule mining, and the like have also become significant players in risk assessment. Wang et al. and Wang et al. adopted Bayesian network models for in-depth tunnel risk assessments, a method effective in predicting risk levels during tunnel construction [21,22]. Hou and Du et al. conducted risk assessment studies using a combination of entropy weighting and extension theory, with the former focusing on tunnel-surrounding rock and the latter on the suspension system of railway vehicles [23,24]. Despite the considerable differences in their research domains, both studies highlight the broad applicability of entropy weighting and extension theory in risk assessments.

Port risk assessment is the systematic process of analysing, identifying, evaluating, and controlling safety risks encountered during port operations. Such assessments are crucial in ensuring the smooth conduct of international trade and maritime safety. They involve various possible risk elements, including but not limited to natural disasters (such as storms, floods, and earthquakes), human errors, acts of terrorism, technological failures, operational mistakes, and supply chain disruptions. Scholars have extensively researched port risk assessment methods in recent years. In particular, in a port supply chain, more resilient management should be adopted to address the risks posed by natural disasters. The two types of supply chain risks were defined as "parametric perturbations" and "external disturbances" [25]. Prominent methods include Bayesian networks, fuzzy logic theory, event tree analysis (ETA), fault tree analysis (FTA), multi-criteria decision analysis (MCDM), etc. These methodologies can reveal potential risks at ports from different perspectives and provide quantitative evaluations. Bayesian networks, for example, can flexibly handle uncertainty and incomplete information through probabilistic reasoning, making them highly suitable for risk assessments that deal with complex conditional dependencies. Fuzzy logic theory can address vague and uncertain systems, providing reasonable inferences for the typically imprecise data found in ports. Bellsolà Olba et al. [26] developed an assessment method that evaluates the overall potential risk of accidents occurring in port areas by creating a navigational port risk index (NPRI). Sihem and Robert [27] employed a multi-step process for evaluating and analysing port risks, which includes system identification, risk identification, risk assessment, risk control options, and decision-making. Alyami et al. [28] developed new methods based on a combination of a fuzzy rule-based Bayesian network (FRBN) and evidential reasoning (ER) in a complementary manner. When applied to container port risk assessment, this method can deal with dynamic models under the constantly changing operational states of ports. Gui et al. [29] incorporated the synergistic use of fuzzy Bayesian inference, the analytical hierarchy process, and the coefficient of variation method to facilitate handling uncertainties and quantitative analysis of congestion under different impacts of port risk factors. Cuong et al. [30] examined effective decision-making strategies for indicating dynamic interactions between seaports and regulating port productivity through the case of ports where productivity was impacted by the COVID-19 pandemic. Furthermore, they investigated the profits of the supply chain under environmental disruptions, incorporating risk assessment methodologies to analyse the costs associated with hinterland shipments and transshipment, as well as port profits under stochastic disruptions [31].

In Table 1, we integrate previous risk assessment studies and compare the similarities and differences with this study from various perspectives.

Table 1. Comparative analysis of risk assessment methods.

	Previous Studies	**This Research**
Quantitative and qualitative analysis	Most of them adopt the qualitative analysis method (Aven and Renn 2009 [13])	It utilises data analysis to determine the weights rather than expert ratings.
Risk identification and analysis	Risk sources are identified, and risk factors are analysed (Bier 2020 [15]; Fischer 2022 [17])	It targets the local natural disasters for risk assessment.
Research field	The traditional field of risk assessment is broad and general (Kaplan and Garrick 1981 [14]; Zhang 2016 [19])	It focuses on the risk assessment of port natural disasters.
The validity and applicability of the method	It connects the theory of risk assessment with practical application (Sicari 2018 [18]; Wang 2020 [22])	The research method is more adaptable and can adjust the weight allocation according to different types and intensities of disasters.

Recent advancements in port risk assessment have shifted focus from traditional methods, emphasising the importance of addressing uncertainties and the multifaceted nature of risks. This field has evolved to prioritise quantitative over qualitative analyses, encouraging a more nuanced understanding of port operations' inherent dangers. Researchers aim to enhance maritime safety and facilitate seamless international trade by adopting a comprehensive approach that integrates various risk factors. However, a notable research gap persists in developing a cohesive, multidimensional risk assessment framework that effectively synthesises these diverse methodologies, underscoring the need for further exploration to refine and unify the existing theoretical and practical approaches.

3. Methodology

The research introduces a pioneering risk assessment methodology for natural disasters at ports, focusing specifically on heavy fog, storm surges, and typhoons. This approach utilises historical climate data from the China Meteorological Network, the National Centers for Environmental Information, and the National Marine Science Data Center to quantify risks accurately. By harnessing these data, the study diverges from traditional methods that typically rely on subjective expert judgments, thereby enhancing the objectivity and precision of the assessments.

This methodology employs a detailed analysis to assign objective weights to various risk indicators, enabling a customised evaluation of port vulnerabilities that considers each disaster type's specific nature and severity. The innovative use of empirical data to define the impact levels of different disaster indicators allows for a more scientific and accurate prediction of future risks, promoting more effective preparation and prevention measures at ports. It also introduces the concept of "loss expectation", calculated from historical loss data, which forms the basis for risk assessment and is integrated with a "prevention factor" that adjusts for a port's existing disaster mitigation capabilities.

Such a data-driven approach ensures consistency and predictability in evaluations and establishes a new standard in port risk assessment. This unique focus and methodology highlight a significant gap in existing research, pointing to the need for further development towards a cohesive and unified risk assessment framework. The study's rigorous, data-centric strategy marks a substantial advancement in the field, setting a benchmark that makes direct comparisons with previous studies challenging due to their varying methodologies and broader focus areas.

The Section 3 delineates a structured approach to port risk assessment through four interconnected subsections: loss severity categorisation, which defines the impact of climatic risks like storm surges, typhoons, and heavy fog, using international standards to assess potential losses uniformly; calculation of loss expectation, focusing on quantifying risks via statistical analysis of historical data to calculate expected losses for different disasters; introduction of preventive capability factors, which integrates the inherent disaster reduction capabilities of port infrastructures into the risk model to refine assessments; and computation of indicator weights, concluding with a formula that combines expected losses and preventive capacities to derive comprehensive risk assessment scores for ports, showcasing the synergy between theoretical insights and practical applications in optimising risk management strategies.

3.1. Loss Severity Categorisation

Weights can be recognised as the degree of influence each indicator exerts on the object of assessment. Based on risk loss theory and the concept of weight, the impacts of three climatic risk indicators on the same port are reflected uniformly as the potential loss consequences that hazardous factors may impose on the disaster-bearing entity, with a categorisation of the loss severity being conducted, as shown in Table 2.

Table 2. Classification of port losses.

Type	Classification of Port Damage
Minor loss	Part of the port was closed, and fishing boats stopped entering the port.
General loss	All port functions were closed, and the motor sailboats were suspended.
Heavy loss	Extensive loading and unloading machinery in port was easily damaged, communication was interrupted, and ships were prone to collision.

The impact of climatic risks of varying intensities on ports differs, and for the three risk indicators addressed in this article, international standards were adopted to classifying the intensities of these risk indicators.

Strong winds may lead to increased wave height, posing threats to the safety of vessels and potentially causing damage to port infrastructure, thereby increasing the cost and duration of repair and recovery work. The specific wind force level at which maritime operations are halted may differ across various ports and types of ships. Based on maritime engineering practices and safety experience, offshore operations are generally suspended when the wind force at sea reaches Beaufort scale 7. According to the newly revised National Standard for "Tropical Cyclone Categories" (GB/T19201-2006), tropical cyclones are classified and labelled according to the maximum wind force near the centre at the bottom, as indicated in Table 3 below.

Storm surges frequently have significant repercussions on port operations and maintenance. They can lead to coastal erosion, flooding, pollution dispersion, port and shipping limitations, and personnel safety risks. Storm surge disasters are primarily caused by severe local swells brought about by high tidal levels, which can readily result in inundation and damage to materials and infrastructure at the port. Consequently, the intensity of storm surges is classified based on their maximum water level rise, as shown in Table 4.

Table 3. Classification of tropical cyclones.

Rank Mark	Tropical Cyclone Classification	Maximum Wind Speed Near the Centre of the Bottom Layer/(m·s^{-1})	Maximum Wind Near the Centre of the Bottom Layer/Level
1	Tropical Depression (TD)	10.8~17.1	6~7
2	Tropical Storm (TS)	17.2~24.4	8~9
3	Severe Tropical Storm (STS)	24.5~32.6	10~11
4	Typhoon (TY)	32.7~41.1	12~13
5	Strong Typhoon (STY)	41.5~50.9	14~15
6	Super Typhoon (super TY)	≥51.0	≥16

Table 4. Classification of storm surge intensity.

Rank Mark	Name	Water Increase Amplitude/cm
1	Light storm surge	30~50
2	Small storm surge	51~100
3	General storm surge	101~150
4	Large storm surge	151~200
5	Huge storm surge	201~300
6	Extreme storm surge	301~450
7	Unusually large storm surge	>450

Fog-related disasters impact ports in multiple aspects. Firstly, reduced visibility due to fog makes it difficult for vessels to discern their position and surroundings, potentially increasing the risk of collisions and navigational errors and possibly restricting navigation. Additionally, port operators are unable to properly observe and manage loading and unloading equipment, leading to decreased cargo handling efficiency. Furthermore, due to operational delays at the port and ship postponements, fog can also affect supply chains and trade. Hence, in low-visibility conditions, ports generally adopt different navigation restrictions based on internal and external harbour planning, the type of cargo being transported (such as flammable chemicals), the tonnage of the ships, and the specific level of visibility to ensure the safety of navigation and docking. However, these measures inevitably result in certain economic losses.

By applying pertinent statistical methods to historical data, three categories of risk indicators can be defined on the same level of loss severity, allowing for the calculation of dimensionless results that are comparable among the three indicators. This determines the impact of the hazardous factor on the at-risk entity. In this process, the categorisation of internationally recognised hazard indicators and port navigational requirements, disaster prevention requirements, and related engineering indexes are referenced. Considering various navigational requirements under different visibility conditions, classifications of the port's hazardous water levels, and large cargo handling machinery specifications, the loss levels of each hazardous factor are categorised to reflect the different degrees of potential loss to the port, as detailed in Table 5.

Table 5. Classification of risk factors loss degree.

Risk Factor	Storm Surge	Typhoon	Heavy Fog
	Water Increase Amplitude/cm	Wind Speed/m·s^{-1}	Visibility/km
Heavy loss	>250	>35	<0.5
General loss	150~250	20.9~35	0.5~1
Minor loss	80~150	10.8~20.8	1~1.5

3.2. Calculation of Loss Expectation

The objective establishment of the weights of risk elements is contingent upon the judicious computation of the expected loss associated with disasters. For this purpose, the present paper adopts the subsequent computational method for the estimation of expected losses predicated on a historical data sample.

Step 1: By conducting statistical analysis on historical data, it is possible to acquire the distribution sets $U_{ij}(a_1, a_2, \ldots, a_n)$ for each risk factor within various rating levels. Here, i indicates the rating level index, j denotes the risk factor index (with indices specified in Table 4), and a represents the statistical data value of each risk factor. In the context of this study, both i and j assume values ranging from 1 to 3, while the range for n depends on the count of statistical data sample instances. To assure the comparability of the resulting weights, initial data normalisation is conducted to transform the sample indicators into dimensionless figures with values between 0 and 1. Moreover, considering the necessity for convergence at either end of the chosen interval for the final quantification, the Z-score distribution method is selected. The Z-score analysis technique, rooted in the theory of standard scores, is a statistical method employed for identifying outliers within a dataset. This method quantifies the deviation of an individual data point from the mean value of the dataset, expressed in terms of standard deviations. The application of Z-score analysis requires that the dataset approximates a normal distribution and that the data points exhibit independence and identical distribution. This technique is widely used across various fields for purposes such as outlier detection, risk management, and quality monitoring, leveraging Z-scores to objectively assess the extremeness of data points. Its calculation approach is as delineated in Equation (1):

$$\mu = \begin{cases} 0,\ x > b \\ 2\left(\frac{x-b}{a-b}\right)^2,\ b > x > \frac{a+b}{2} \\ 1 - 2\left(\frac{x-b}{a-b}\right)^2,\ \frac{a+b}{2} \geq x > a \\ 1,\ x < a \end{cases} \tag{1}$$

In the equation, a and b are each indicator's upper and lower threshold values, respectively. Due to the established loss grading system, in this experiment, a and b correspond to the threshold values of the loss gradings. The resultant post-standardisation computation yields the processed collection $U_{ij}(\mu_1, \mu_2, \ldots\ldots, \mu_\mathrm{n} \,|\, p_{ij})$, where p_{ij} signifies the annual mean number of sample instances for a risk factor labelled as j within the rating level denoted by i. The formula for its calculation is as indicated below:

$$p_{ij} = N_{ij}/m \tag{2}$$

In the expression, N_{ij} denotes the aggregate count of sample entries for the jth indicator within the ith grade, whereas m signifies the duration of the data sequence measured in years. The temporal scope of the historical climatic dataset amassed for this research extends from the year 1989 through 2019, thus, the value assigned to m is 30.

Step 2: Introducing the expected value in mathematical definition: Let be a discrete random variable, taking values corresponding to the probabilities. If the series converges absolutely, it is designated as the expected value. Owing to the inherent uncertainties associated with risk factors in risk theory and the application of the Z-score normalisation method to ensure that the standardised data converges at the endpoints of the value range, the primary conditions of this definition are satisfied. Smith [32] proposed the risk expressions (3) and (4):

$$\text{Risk level} = \text{probability} \times \text{loss} \tag{3}$$

$$\text{Risk magnitude} = \text{probability} \times \text{potential loss} \tag{4}$$

These expressions further encapsulate the essence of risk by integrating the probability of disaster occurrence with potential losses. Hence, following the theory of mathematical expectation and risk loss and synthesising the above studies, this paper will represent the total magnitude of loss potentially inflicted on the risk-bearing entity by hazardous factors in the form of expected value:

$$\text{Expected loss} = \text{probability} \times \text{severity of loss} \tag{5}$$

Based on the established loss gradation, the degree of loss for each level is represented by the standardised mean value of hazardous factors at that level. This approach eliminates the dimensional differences across various indicators and reflects the variation caused by different sample sizes within the same loss category. Considering only the frequency without accounting for the magnitude of hazardous factors fails to capture the differences between the various evaluation samples. In this context, the mean serves as a better choice to represent the overall distribution characteristics of the dataset.

In this experiment, the calculation method for the expected loss is as follows:

$$E_j = \sum_{i=1}^{3}\left(\frac{1}{n}\sum_{m=1}^{n}\mu_m^{(i)}\right)p_i^{(j)}; i = 1,2,3\ldots; j = 1,2,3\ldots; m = 1,2,3,\ldots\ldots n. \tag{6}$$

In the formula, i represents the loss grade, and j denotes the index of the risk factor.

3.3. Introduction of Preventive Capability Factors

In the risk management domain, the term "preventive capability" encompasses a compendium of actions, policies, and strategic measures adopted by entities exposed to risks to confront a spectrum of risks. Given the inherent disaster reduction and prevention capabilities encoded within the design and construction of port facilities, the computed weightings in this study are predicated upon the expected losses derived from the theory of risk-related losses. The mitigation capacity held by the insuring party will, to different degrees, diminish loss incurrence; this characteristic is consequently reflected in the ultimate results. However, traditional evaluation techniques, which comprise independent scoring of hazard and mitigation capacity indicators, tend to introduce subjectivity based on practical experience. Davidson et al. have introduced an approach known as the disaster risk assessment index method, which aims to provide a more systematic and objective evaluation of risk [33].

$$\text{Risk index} = \text{hazard} \times \text{vulnerability} \times (1 - \text{disaster prevention capacity}) \tag{7}$$

Consequently, based on this methodology, this paper does not take into account the vulnerability of the risk-bearing entity, and assuming that corresponding preventive capacity indicators can be identified for each hazard factor and can be linearly expressed, the weights of the indicators can be represented by Equation (8):

$$\text{Indicator weight} = \text{loss expectation} \times (1 - \text{preventive capacity of the indicator}) \tag{8}$$

In the context of ports, the influence of storm tide surges is primarily evidenced by the threat that excessively high water levels present to coastal engineering projects. As such, the inherent ground elevation of the port dictates its disaster mitigation capability in response to precipitously increasing water levels. Consequently, a ground elevation index is incorporated as a preventative factor against storm surge hazards. The ground elevation of the major ports of Shanghai port was collected through the National Marine Science Data Center. These data, combined with the water increase amplitude caused by the above storm surge, allowed us to calculate the storm surge index prevention capability using Equation (9).

$$R_1 = \begin{cases} 0.1, & h < 0; \\ 0.3, & 0 < h \le \Delta h; \\ 0.6, & T < h \le \Delta h + T; \\ 0.7, & T_{max} < h \le \Delta h + T_{max}; \\ 0.8, & h + T_{max} < h \le \Delta h + T_{max} + 10; \\ 0.9, & h > \Delta h + T_{max} + 10. \end{cases} \quad (9)$$

In the formula, h represents the elevation above sea level; Δh represents the relative rise in sea level during the assessment period; T is the commonly observed tidal level for the evaluation unit, which in this experiment is substituted by the mean tidal level; T_{max} is the highest historical storm surge for the evaluation unit. A critical value of 10 m is set for the vulnerability of the elevation above sea level.

The menace of robust winds to harbours extends beyond generating wind waves and storm surges; it principally involves the risk that extreme wind loads may cause displacement, detachment, or even damage to sizable crane and cargo handling apparatus. Therefore, the self-weight and stability of the cargo handling equipment are critical in determining its preventative capabilities against vigorous winds. We obtained the design and use standard of Shanghai Port infrastructure through the industry standard of construction machinery along the port issued by the Ministry of Transport, introducing the port's ship unloader design for wind resistance at 35 m/s as a measure of defensive capacity. Its formulation is as shown in Equation (10):

$$R_2 = \begin{cases} 0.1\,, & t < 50 \\ 0.3\,, & 50 < t < 100 \\ 0.5\,, & 100 < t < 150 \\ 0.7\,, & 150 < t < 200 \\ 0.9\,, & t > 200 \end{cases} \quad (10)$$

Since operations of vessels under low visibility conditions can only be guided by navigational and harbour-avoiding technical standards, and it is impossible to implement physical or technical fog-prevention measures, this study does not quantify the defensive capability ($R_3 = 0$) for this risk indicator. Instead, it directly employs the expected loss as a basis for calculating the degree of membership.

In conclusion, the computation of the weights for the indicators in this experiment is displayed in Equation (11):

$$W_j = \frac{E_j\left(1 - R_j\right)}{\sum_{j=1}^{3} E_j\left(1 - R_j\right)} \qquad j = 1, 2, 3 \quad (11)$$

4. Results

This investigation conducted an in-depth analysis of historical data and considered the pre-established loss stratification system, advancing the theoretical construct of "expected loss". The crux of this construct lies in the quantitative estimation of the anticipated value for potential losses. Moreover, this research innovatively incorporated the notion of preventative factors aligned with risk indicators. To materialise a quantifiable risk assessment process, the study utilised standardisation methodologies on the data to guarantee comparability among distinct risk indicators. Subsequently, a quantitative algorithm was deployed by factoring in the preventative factors within the computational procedure, deriving the weights pertinent to each risk indicator. This methodology bolstered the scientific and systemic aspects of the risk evaluation and amplified the practicability of the risk management strategies. The detailed procedure is delineated in Figure 1.

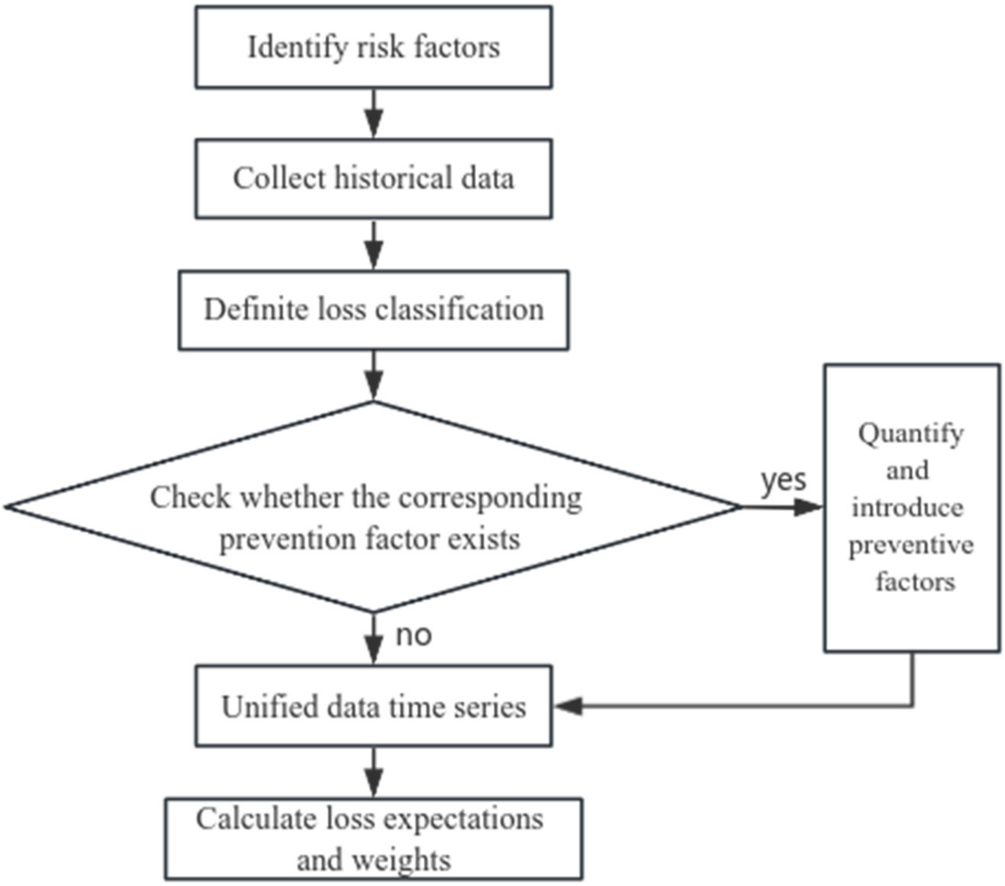

Figure 1. Flow chart of indicator weight determination.

In adherence to the computational protocol elucidated by Equations (1) through (11), this study selected Shanghai Port as a case study exemplar. To ensure that the weighting results were comparable across distinct inquiries, a rigorous organisation of historical climatic datasets was mandatory, complying with the following standardisation prescriptions: primarily, congruence in the temporal sequence of data was paramount, signifying that all datasets employed should span identical periods, thereby enabling vertical comparative and analytical endeavours. Secondly, datasets that differed in sampling frequencies necessitated judicious conversion during data processing and analytical stages to uphold chronological uniformity across datasets. In this study's data collection, typhoon wind speed metrics were catalogued with a regularity of an 8 h interval. In contrast, storm surge and fog visibility parameters corresponding to individual sampling events were logged. Hence, a recalibration of these frequencies to an annual scale was carried out, ensuring that data derived from disparate temporal frames were aggregated for an integrative annual risk assessment and analysis.

In summary, the expected losses, defensive capabilities, initial weights, and the ultimate normalised weights for the three climatic indicators of Shanghai Port could be derived. The results are displayed in Figure 2.

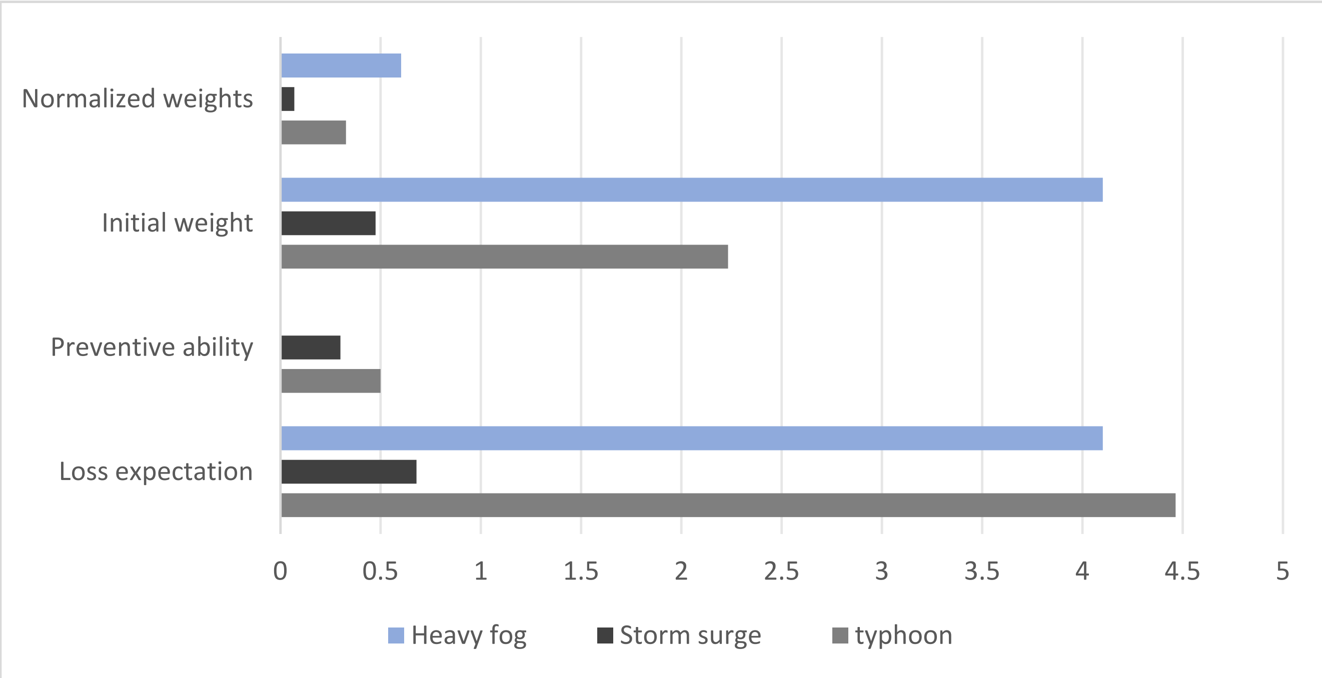

Figure 2. The calculation result of Shanghai Port index.

5. Discussion and Conclusions

Thorough data collection and statistical processing were undertaken in this chapter, encompassing the historical meteorological information relating to typhoons, dense fogs, and storm surges that affected the Shanghai Port from 1989 to 2019. The indicators mentioned above were quantitatively processed at an equivalent level of loss severity through pertinent statistical methods. Centring on the expected value of risk loss, the factor of preventive capacity was introduced to establish a weight standard that differentiated the impact of the three risk categories, defining potential losses they might cause to the port. Hence, the resulting dimensionless outcomes possessed fair comparability, enabling the measurement of the varying impacts of different risk factors on the disaster-bearing body and facilitating the practical assessment and subsequent formulation of disaster prevention strategies for the port.

In the context of urban development, ports serve as vital arteries that fuel cities' economic and logistical vitality. Coastal urban regions are more vulnerable to diverse climate hazards, such as flooding, storm surges, and rising sea levels [34]. On the other hand, urban resilience to climate change has increasingly attracted attention as functional urban units and resources to adapt to climate risks are usually skewed towards metropolitans [35], where port cities occupy a high proportion. Thus, the study's emphasis on integrating preventive capabilities into risk assessment frameworks speaks volumes about the need for urban systems to adopt flexible and forward-thinking strategies in disaster risk management. This approach aligns with urban science's goals of creating sustainable, resilient urban environments that withstand and adapt to changing climatic conditions. By applying the Shanghai Port analysis insights, urban planners and policymakers can better understand the complex interplay between natural hazards and urban infrastructures. Consequently, this knowledge can guide the formulation of comprehensive urban development strategies that prioritise resilience, ensuring cities are better prepared to mitigate the impacts of meteorological disasters. This proactive stance safeguards critical infrastructure like ports and contributes to the broader objective of securing urban economic stability and quality of life in the face of increasing climate variability and environmental challenges.

Due to seaports being increasingly critical and becoming operationally complicated regarding the sustainability of cargo operations, there is an urgency to create and adopt appropriate port risk assessment tools and methodologies that will systematically evaluate and manage risks. The suggested port risk assessment approach constructs its functionality and structure, which are employed in the existing literature, to tailor its suitability within the port area. Additionally, the suggested port risk assessment approach assessed environmental and human risk events [36]. The findings address that the port risk assessment method may be a feasible solution to attain continuity of port operations and generate a substantial decrease in the risks influencing port operations under extreme weather circumstances. In addition, the study addressed the priority for designing and implementing valuable resilience strategies via the proposed port risk assessment against possible effects that heavy fog, storm surges, and typhoons may create. Many port sector and related industrial practitioners remain unaware of the significant port risk assessment method and resilience strategies because they lack awareness of possible threats that may result from heavy fog, storm surges, and typhoons. As such, innovative port risk assessment methods should be delivered to foster awareness concerning the potential results of heavy fog, storm surges, and typhoons. Human health risks and threats can be mitigated in the forthcoming years.

The case study findings highlight that the original expectations of loss for both typhoon and heavy fog weather disasters are similar for Shanghai Port, yet they significantly differ from the loss expectations caused by storm surges—the latter being merely 15% of the former. This observation suggests that, from a historical data analysis perspective, storm surges have a comparatively smaller real-world impact on the port's operations. However, after incorporating the preventive capacity factor into the quantitative analysis of the risk indicator weights, a substantial divergence was observed between the final normalised weights of typhoons and heavy fogs—almost an order of magnitude. This indicates the indispensable role of preventive capabilities in the port's response to meteorological disasters. Moreover, there is a clear disparity in the prevention capability levels against various disasters for specific conditions of the Shanghai Port. The research presented herein offers critical guidance for the ongoing management and formulation of port disaster prevention strategies.

Nevertheless, the current study used Shanghai Port as a single case study. To the best of our knowledge, Shanghai Port is one of the leading ports in the world. As such, the study may provide a guide, workable example, and research model for the other ports in the following research. To improve the methodology, we may conduct an in-depth semi-structured interview with key stakeholders to further test the viability of the established port risk assessment method.

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