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A Dynamic Bayesian Network Probability Framework for Typhoon Risk Analysis in the Land-sea Regions

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Abstract: The life cycle of a typhoon is mainly divided into three stages: far away from the coast, offshore, and on land. The disaster bodies and typhoons affected are different at every stage. The traditional assessment methods could not consider the risk from the complete typhoon life cycle to cover the effects of both land and sea. This paper proposes a Bayesian network risk assessment model to evaluate the navigational ship risk and damage risk of coastal structures during the different typhoon life cycles. The disaster memory database of the typhoon is also constructed in this paper, which deconstructs the typhoon risk factors and forms a unified description semantics.

Keyword: Case-based reasoning; Dynamic Bayesian Network; Land-Sea Coordination; Scenario-response; Typhoon accident.

1.0 Introduction

Typhoon storm surge is a kind of catastrophic natural phenomenon that causes the abnormal rise and fall of seawater due to the violent disturbance of the atmosphere and makes the tidal level of the affected sea area greatly exceed the normal tidal level (Zhang et al., 2016). As one of the major disasters on the sea in China, the economic losses caused by typhoon storm surge events are only up to hundreds of millions of yuan per year on the southeast coast and up to tens of billions of yuan per year (Liang et al., 2022). Therefore, how to effectively deal with typhoon surge emergencies is one of the urgent problems to be solved.

Storm surge events have the characteristics of occurrence uncertainty, unknown development path, and unpredictable evolution path, as well as the'scenario dependence'of g general unconventional emergencies, which lead to the additional' forecast-response' method g gradually not being applicable and cannot carry out efficient response assessment. It is necessary to shift to the 'scenario-response' emergency decision paradigm (Hu Jun. et al., 2013). The so-called'scenario-response'model requires decision-makers to judge, analyse, and predict the changes of uncertain events in different periods quickly and accurately to make scientific decisions and corresponding emergency management decisions (Pang et al., 2011).

In recent years, people have paid more and more attention to the important role of the "scenario-response" mode in the face of major emergencies, and some research progress has been made in fire accidents (Zhou et al., 2022), earthquake disasters (Chen et al., 2021), epidemic spillover (Fang et al., 2023), and other aspects. For example, Zhou et al. (2022) conducted accident dynamic risk analysis based on a dynamic Bayesian network for petrochemical plant fire accidents and combined scenario evolution with the Bayesian network to conduct scenario path analysis for possible petrochemical plant accidents. Chen et al. (2021) established a connection between earthquake disasters and coping strategies to generate emergency plans corresponding to scenarios. Fang et al. (2023) constructed the epidemic spillover event model of large-scale events, analysed the development trajectory of the epidemic by scenario inference, and made necessary epidemic prevention policies accordingly. While applying the "scenario-response" mode to deal with emergencies, new research models are constantly produced. For example, Zhong et al. (2012) proposed a scenario concept model based on knowledge elements and constructed the model through specific scenario cases for the deduction. Qi Kai et al. (2022) used evolutionary game theory to build a multi-scenario evolutionary game model of network public opinion and conducted scenario inference analysis of multiple research cases. Yuan (2011) established a system dynamics model based on the entropy principle and dissipative structure theory and analysed the temporal framework and mechanism of emergency decision-making.

The above research progress provides a good reference for storm surge scenario response. However, there are great differences between disasters in different scenarios. As the whole life cycle of storm surge spans three different geographical scenarios, namely ocean, ocean-land, and land, it has different spatio-temporal distribution characteristics and evolution patterns in different stages, so it is particularly important to focus on the study of different scenarios (Yang, 2000). At present, most of the research on storm surge focuses on prediction and response, including numerical simulation (Yuan, 2011), inundation simulation (Yin et al., 2013), disaster risk assessment, forecast models, and other main research directions. Although there is a clear understanding of the mechanism of storm surge, there is little research progress focusing on the effective suppression of overall disaster scenario development. This article will "scene-response" model into the storm surge case analysis, combined with geographical seven elements and geographical seven dimensions for the typhoon storm surge disaster scene building and the deduction of time and space and structured data storage. Through dynamic Bayesian network disaster risk in the situation of real-time supervision, dynamic real-time will calculate the best plan to deal with emergency situations.

2.0 Research Methodology

The process is shown in Figure 1. Firstly, multi-source heterogeneous data such as meteorological data, typhoon forecasts, statistical yearbooks, and accident plans are taken as input, and the above multi-source heterogeneous data are fused through the unified space-time framework of land and sea coordination. Disaster characteristics such as time, place, and process are extracted by NLP natural language processing and knowledge graphs, thus forming a disaster causal chain, disaster loss chain, and disaster plan chain. The typhoon accident construction is structured and formally expressed by geographical elements and geographical dimensions, thus forming a disaster classification and disaster memory library. The disaster memory database construction chain is used as the accident access source, the sample organisation is used as the training data, and the real detection data is used as the detection data. The dynamic Bayesian network is used for real-time risk monitoring. Taking the output probability of the dynamic bayesian network as the probability of disaster occurrence, and based on the accident plan in the construction chain of the disaster memory database, the dynamic analysis is carried out to quantify the numerical and logical indexes of the plan. Finally, the case reasoning is carried out through similarity calculations to calculate the plan evaluation, and finally, the plan is dynamically output.

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A typhoon accident is an accident scenario under the interaction of multi-factor, multi-process, multi-factor, and multi-system. The current accident state is affected by the previous moment and will affect the latter moment. Therefore, a dynamic Bayesian network is constructed to establish a real-time monitoring model of typhoon accident risk, and the dynamic verification and feedback assimilation between real-time observation data and mechanism process simulation data is completed.

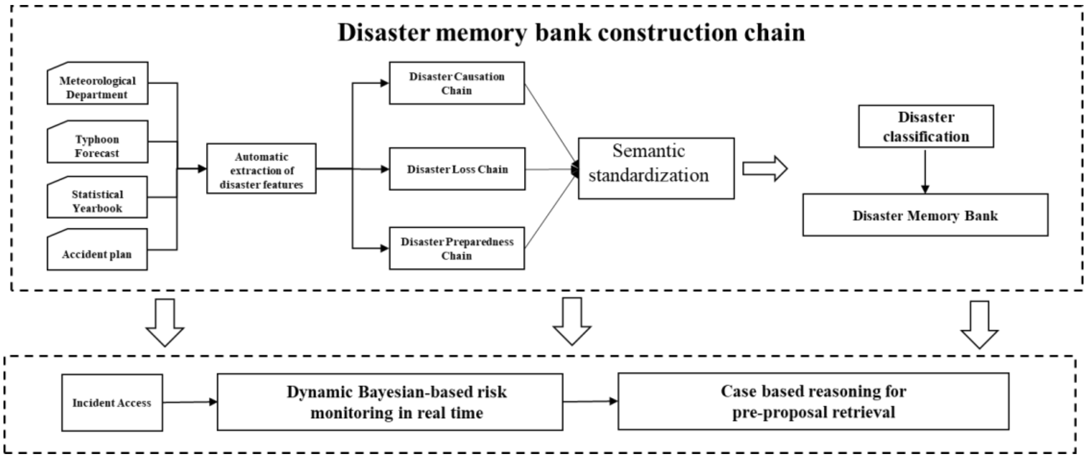

Figure 1: Typhoon accident life cycle evolution pattern.

The typhoon paths around China are shown in Figure 2. Although typhoon paths vary greatly, there are still common characteristics in similar situations and conditions. Based on their main features, the basic paths of western Pacific typhoons can be summarised into the following three categories:

1. Category I is the westward path: Typhoons move westward from the sea east of the Philippines, pass through the South China Sea, and make landfall in the coastal areas of southern China, such as Hainan Island and the coast of Vietnam. Typhoons on this path have a greater impact on southern China.
2. Category II is the north-westward path: Typhoons move north-westward from the sea east of the Philippines, cross Taiwan and the Taiwan Strait, and make landfall in the coastal areas of Fujian and Guangdong provinces, or pass through the Ryukyu Islands and make landfall in the coastal areas of Jiangsu and Zhejiang. Typhoons on this path often affect mainland China and have a significant impact on both eastern and southern China; hence, it is known as the "landing-type typhoon path".
3. Category III is the turning path: Typhoons move north-westward from the sea east of the Philippines, then turn north-eastward and form a parabolic path. This is the most common path, where some typhoons turn and mainly hit Japan or disappear at sea. If typhoons turn near the coast, they mostly move north-eastward and affect North Korea, but a small part will turn north-westward in the later stages and make landfall in the coastal areas of Liaoning and Shandong in China. In winter, the turning point of such typhoons is often southward, which may affect the Philippines and Taiwan.

The above typhoon paths are typical paths obtained from many years of average data, reflecting the general regularity of typhoon movement. However, in reality, no typhoon path has ever appeared exactly the same twice, and some typhoons may even exhibit abnormal paths such as circling, swinging, quasi-stationary, or even retrograde movements..

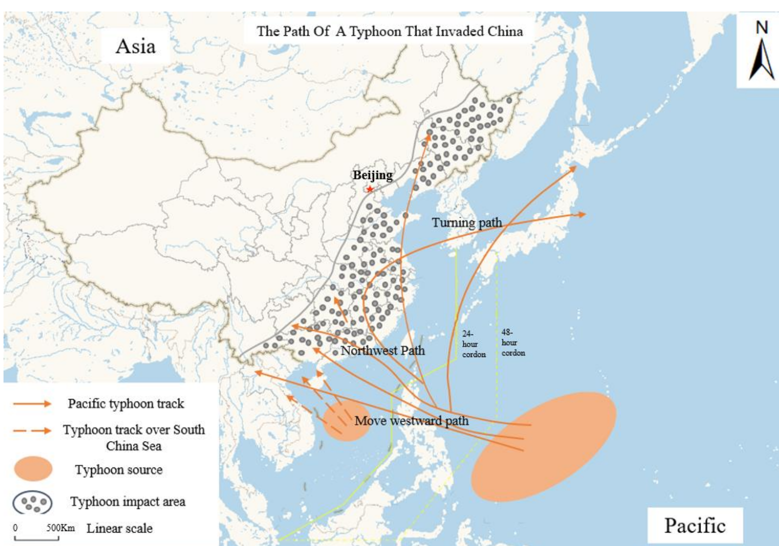

Figure 2: Land and Sea Areas Affected by Typhoons in China.

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2.1 Real-time monitoring of risk based on dynamic Bayesian

The life cycle of a typhoon accident sequence goes through n different states at different times from creation to extinction, as shown in Figure 3. Later, as time progresses, the typhoon scenario shifts to the coastal zone where the land and sea meet, and the affected bodies are mainly estuaries and other facilities. Finally, in the extinction stage of the typhoon, the scenario is on land, and the affected bodies are facilities such as power grids.

Therefore, the typhoon accident sequences are recorded as $S_0, S_1, S_2, \dots, S_{n-1}, S_n$, corresponding time points, carriers, and emergency management $(S_0, S_1, S_2, \dots, S_{n-1}, S_n), (A_0, A_1, A_2, \dots, A_{n-1}, A_n), (D_0, D_1, D_2, \dots, D_{n-1}, D_n)$

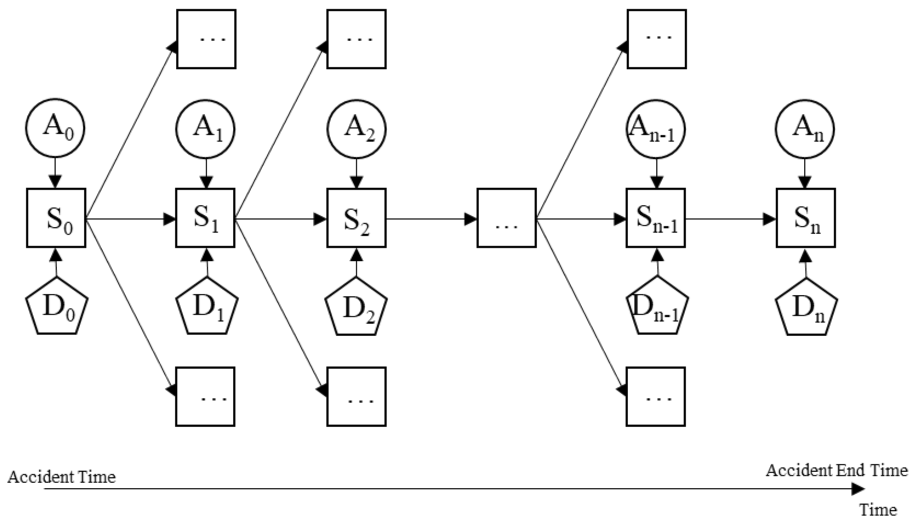

Figure 3: Typhoon accident life cycle evolution pattern.

The evolution law of the typhoon accident life cycle shown in Figure 2, S_0 is in the creation stage of the typhoon accident life cycle at a time t_0 , and its state is controlled by emergency management D_0 and has an impact on hazard bearing body A_0 . Due to the different emergency plans corresponding to the S_0 state, that is, the emergency control is different, and there are many possibilities when the typhoon accident S_0 evolves from time t_0 to time t_1 . At this time, the typhoon accident state is S_1 , and its state is controlled by emergency management D_1 , which has an impact on the hazard-bearing body A_1 . In the process of evolution, the current state is the input of the latter state. In the process of evolution, dynamic verification and feedback assimilation are carried out between the real-time observation data and the mechanism process simulation data, to further improve the accuracy of the results. The process is until the life cycle of the typhoon accident at time t_n dies out.

The evolution of storm surges is an uncertain problem, which contains some definite information, such as time, weather, sea conditions, and some unknown information. The bayesian network can update the node probability to ensure the reliability of inference results by using the relationship between random variables under incomplete or uncertain information. A time factor is added to the Bayesian network to form a system model that changes with time, namely a dynamic Bayesian network. The calculation formula is:

$$P(X_1,\cdots,X_n)=\prod_{1}^{n}P\left(X\mid P\left(\prod X_n\right)\right)$$

Where X represents the situation at a certain moment; $P(X_1,\cdots,X_n)$ represents the scenario state value under n scenarios; $P\left(\prod X_n\right)$ denotes the prior probability of network node variables; $P\left(X\mid P\left(\prod X_n\right)\right)$ represents the conditional probability of network node variables.

Based on the construction of the typhoon accident scenario and evolution scenario chain, key scenario elements at different times are extracted as node variables of a dynamic Bayesian network. The prior probability and conditional probability of time-varying and causal node variables are used as the input of the above formula to calculate the probability value of the scenario state and realize the scenario deduction of typhoon accidents.

2.2 Plan retrieval based on case inference

Firstly, based on the real-time risk monitoring of the dynamic Bayesian network constructed in the accident chain, the output probability is the probability of disaster occurrence at this time. Through the disaster characteristics, disaster causal chain, disaster loss chain, and disaster plan chain constructed in the disaster memory database, the attribute quantification is provided for the case, so that the case numerical index and logical index can be expressed from the mathematical point of view. Therefore, this paper calculates the weight of each attribute in the case at different times through the dynamic network. When the plan is evaluated and generated automatically, the matching degree between the weight of each component input into the case reasoning and the attributes in the case base can be monitored in real-time according to the dynamic bayesian network risk, to obtain the relative weighted sum, and then the similarity of the plan is expressed according to the distance between the weighted sum and the matching degree of each attribute in the case. The formula is defined as follows. Firstly, the definition of the distance between cases (i.e., similarity) is given (which needs to reflect the weight of each attribute). According to this definition, the distance between the target case and all the cases in the disaster memory database is calculated, and then the minimum distance is selected. It is evaluated as the best plan and output, to complete the similarity calculation, plan evaluation, and plan generation in the planned retrieval based on case-based reasoning.

The usual formula of the nearest neighbour method is :

$$Similarity(T, X) = \sum_{i=1}^{n} f(T_i, X_i) * w_i$$

Where T represents the target case; X represents the original data case in the disaster memory database; n represents the number of features contained in each case in the disaster memory database, $i \in [1, n]$; f represents the similarity function of i features in the target case T and the original data case X ; w represents the weight of the attribute corresponding to feature i , $w \in [1, n]$, $\sum_{i=1}^{n} w_i = 1$. The higher the calculated $Similarity$, the better the matching degree with the corresponding plan in the disaster memory database.

In many nearest neighbour case retrieval algorithms, the traditional and most commonly used similarity calculation method is Euclidean distance. The Euclidean distance formula is expressed as:

$$d_{ti} = \{\sum_{j=1}^{n} w_j (x_{ij} - T_j)^2\}^{\frac{1}{2}}$$

In the formula, x_{ij} represents the j attribute value of the case i , and w_j represents the weight of the j attribute; n is the total number of attributes; T_j is the value of the j attribute of the target case T ; d_{ti} is the Euclidean distance between the target case T and i case in the source case base. The smaller the d_{ti} more similar they are. Select the case of minimum d_{ti} , which is the corresponding plan of the optimal case at this time.

3.0 Case Study

This paper collects typhoon data from 2000 to 2021 to build an accident memory database [http://www.ncei.noaa.gov.agora.ex.nii.ac.jp], where the typhoon data includes the maximum wind power and other attributes of each track point. The detailed source and data description of the overall data are shown in Table 1.

Table 1: Overall Data Description

Data	Data source	Describe	Data source URL
Hazard-affected body	Research Group Develops Coastal Zone Data	Shapefile: Names, categories, codes, locations, and vulnerability levels of various types of hazard-affected bodies including embankment projects in coastal cities, key protection targets, ecologically sensitive targets, population and houses in coastal communities, coastal inland areas, power facilities and high-risk areas of geological disasters.	NAN
Typhoon data	National Centers for Environmental Information Japan Typhoon Research Institute	GeoJSON, CSV format; including time, location, typhoon level, typhoon intensity, wind speed, central pressure, wind circle radius, etc.	http://www.ncei.noaa.gov agora.ex.nii.ac.jp
Typhoon forecast	National Hurricane Center	GeoJSON	http://www.nhc.noaa.gov
Base map	Map World remote sensing image	Map World	http://www.tianditu.gov.cn/
Emergency Management Data	Research group formulation	Excel format; contains name, category, code, number, etc.	From the network crawling

Firstly, based on the dynamic Bayesian network, a three-level network structure of risk scenario-bearing body-disaster driving factor is constructed. The risk scenario mainly includes all kinds of secondary risks caused by the extension of the ocean to the inland from the perspective of the typhoon. Due to data limitations, this paper only discusses three types of risk scenarios: ship out of control, seawater intrusion, and shore-based damage. In these three types of risk scenarios, the main disaster-bearing bodies of ship out of control risk are ships and crews. This paper mainly discusses ships, which are roughly divided into small ships according to their tonnage (total tonnage < 1000ton). Medium-sized ships (1000ton < total tonnage < 10000ton), large ships (total tonnage > 10000ton), and the hazard-affected bodies of seawater intrusion and shore-based damage risk are coastal zones and coastal buildings. This paper mainly discusses three types: natural vegetation, earth-rock dams, and artificial dams. Different types of coastal buildings have different tolerance to typhoon disasters. Disaster driving factors are used to describe the intensity, range, and arrival time of typhoons, and multi-factor driving judgments are made on whether typhoons cause the risk of hazard-affected bodies. It is worth noting that for each risk scenario node and disaster driving factor node, because of its evolution process in time series, the node state of the previous moment will affect the state of the next moment, so it is set as a dynamic node, thus expanding the judgment basis of Bayesian network. The overall Bayesian network node and its discrete attributes are shown in Table 2.

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Table 2: Bayesian Network Nodes and Their Discrete Attribute Tables

Type	Node	Attribute
Risk scenarios	Ship out of uncontrol (SOU)	Low risk; Medium risk; High risk
	Indwelling (INW)	Low risk; Medium risk; High risk
	Buildings damaged (BD)	Low risk; Medium risk; High risk
hazard-bearing body	Ship	Small ships; Medium ship; Large ship
	Coastal zone construction (CZC)	Natural vegetation; earth-rock Dam; Artificial seawalls
Disaster driving factor	Typhoon intensity (TI)	TD; TS; STS; TY; STY; Super TY
	Maximum wind velocity (MWV)	Strong breeze; Strong gale; Whole gale; Force 12 wind; Force 14 wind; More than force 16 wind
	Sphere of influence (SOI)	Small; Moderate; Big
	Offshore distance (OD)	High sea; Offshore; Inshore; On land
	Precipitation (PRE)	Light; Moderate; Heavy; Torrential; Extraordinary
	Movement speed (MS)	Slow; Moderate; Fast; Very fast
	Temperature (TEM)	Low; Moderate; High
	Wave height (WH)	Wavelet; Moderate sea; Routh sea; Very rough sea

The training process of the Bayesian network needs to be combined with expert experience. The risk probability of the three types of scenarios is supplemented at each typhoon time node, and a complete disaster sample database is constructed. The conditional probability between different nodes is further counted, and the conditional probability table is calculated to obtain a complete Bayesian network.
Many ships had accidents such as grounding, wrecks, and rollovers in this typhoon. At the same time, the typhoon also caused serious damage to different shore-based areas. The dynamic Bayesian network proposed in this paper was used to deduce the three probabilities of the accident. Figure 4 shows the overall framework of the Bayesian network constructed in this paper and the probability value in the initial stage of the typhoon.

In dynamic Bayesian networks, SOU nodes are mainly affected by MediumRisk and HighRisk ; the influence weights of LowRisk, MediumRisk and HighRisk in INW nodes are similar ; BD nodes are mainly affected by LowRisk and MediumRisk ; the influence weights of SmallShips, MediumShip and LargeShip in Ship node are similar. CZC nodes are mainly affected by Artificial Seawalls ; WH nodes are mainly affected by ModerateSea ; the MWV nodes are mainly affected by StrongBreeze, WholeGale, Force12Wind ; OD nodes are mainly affected by Offshore ; PRE nodes are mainly affected by Heavy and Moderate ; TEM nodes are mainly affected by Low and Moderate ; the MS nodes are mainly affected by Moderate and Fast ; SOI nodes are mainly affected by Small ; The weights of TI nodes affected by each factor are close..

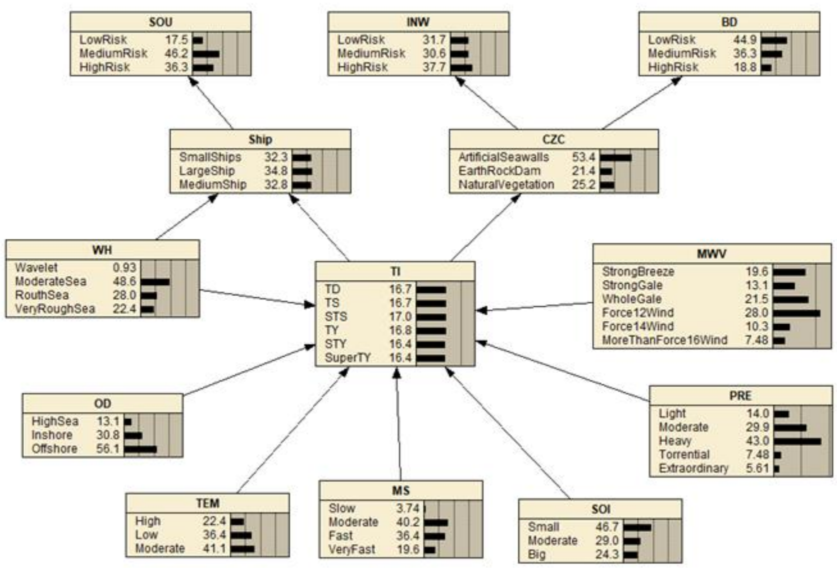

Figure 4: Bayesian Network and Its Node Probability.

4.0 Conclusions

Typhoon accidents are violent, fast, and destructive. They often bring secondary disasters such as winds, rainstorms, and storm surges, Typhoon accidents are violent, fast, and destructive. They often bring secondary disasters such as winds, rainstorms, and storm surges and have a strong scenario dependence. Therefore, the traditional "prediction-response" model has been difficult to deal with. At the same time, the study of storm surges is mainly focused on the analysis of influencing factors, risk assessment, numerical simulation, and so on. There is a lack of research on the development and control of the whole disaster situation.At the same time, the study of storm surges is mainly focused on the analysis of influencing factors, risk assessment, numerical simulation, and so on. There is a lack of research on the development and control of the whole disaster situation.

In traditional research methods, there is a lack of effective means to integrate the ocean scene, the land scene, and the land-sea handover scene, which leads to the inconsistency of the space-time framework in the three scenes. Therefore, based on the unified space-time framework of land-sea coordination, this paper effectively solves the above problems.

Compared to other methods, this paper utilises several distinctive approaches. Firstly, a risk assessment model based on Bayesian networks is employed in this paper, which can comprehensively consider the different stages and influencing factors throughout the typhoon's lifecycle, providing a more comprehensive evaluation capability. In contrast, traditional assessment methods often only consider a specific stage or influencing factor, resulting in less accurate evaluation results. Secondly, this paper establishes a typhoon disaster memory database, which decomposes the risk factors of typhoons and forms a unified description semantics, allowing for clearer descriptions and identification of the risk characteristics of different typhoons. Other methods may lack such a memory database or have less clear and accurate descriptions of risk factors, which makes effective risk assessment difficult. Furthermore, this study evaluates different types of affected objects, including navigational vessels and coastal structures, while other methods may only focus on one type of affected object, lacking comprehensiveness and diversity. In summary, the methods employed in this paper have advantages in evaluation capability, description semantics, and the scope of affected objects, which can provide more accurate and comprehensive support for related research and practice in this field.

A typhoon accident is an accident scenario under the interaction of multi-factor, multi-process, multi-factor, and multi-system. The current accident state is affected by the previous moment and will affect the latter moment. Therefore, the dynamic Bayesian network is constructed, the real-time monitoring model of typhoon accident risk is established, the dynamic verification and feedback assimilation between real-time observation data and mechanism process simulation data is completed, and the optimal plan retrieval based on case inference can effectively improve the ability to respond to typhoon accidents.

Regarding future research directions, this study proposes the following suggestions: Firstly, further research should be conducted on the construction of dynamic Bayesian networks in different typhoon lifecycles to meet the risk assessment demands in different contexts. Specifically, different dynamic Bayesian network nodes should be introduced in different lifecycles to more accurately describe the changes in risk factors. Secondly, the accuracy of risk assessment can be improved by adding more dynamic Bayesian network nodes, which can be updated based on previous research results and real-time observation data to reflect the dynamic changes of typhoon events. These suggestions are expected to provide useful guidance and support for future research and practices in related fields.

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References

Chen Bo, Wang Fang, & Xiao Benfu. (2021). The Development of Scenario-response Theoretic System and Its Application in Earthquake Disaster Emergency Management. Technology for Earthquake Disaster Prevention, 16(4), 605–616.

Fang Danhui, Xu Simin, & MI Wenzhong. (2023). Analysis of COVID-19 Spillover Risk of Major Sports Events Based on Scenario Deduction. Journal of Catastrophology, 04(37), 85–91.

Hu Jun, Lu Qingyi, Chen Lei, Wang Yunhua, & Chen Shihong. (2013). Harmfulness Assessment and Trend Monitoring Model in Unconventional Emergency. Journal of Wuhan University(Natural Science Edition), 59(4), 381–387. https://doi.org/10.14188/j.1671-8836.2013.04.015

Liang Haiping, LI Tuanjie, LIANG Haiyan, & GAO Lu. (2022). Distributional characteristics and influencing factors of storm surge in Haikou. Journal of Marine Sciences, 40(2), 83–92.

Pang, J., Liang, L., & Li, S. (2011). A Comparative Study between Prediction-Response and Scenario-Response in Unconventional Emergency Decision-Making Management. Computational Sciences and Optimization (CSO), 2011 Fourth International Joint Conference on. https://xueshu.baidu.com/usercenter/paper/show?paperid=083e7753405c67d3a3bf58e3c6fd1c8b&site=xueshu_se

Qi Kai, Peng Cheng, Yang Zhi, & Li BinGxue. (2022). Research on Network Public Opinion Governance of Emergent Crisis Events Based on the SEIR Evolutionary Game Model. Journal of Modern Information, 42(4), 120–133.

Yang Guishan. (2000). Historical change and future trends of storm surge disaster in China's coastal area. Journal of Natural Disasters, 9(3), 23–30. https://doi.org/10.14188/j.1671-8836.2013.04.015

Yin Jie, YIN Zhane, YU Dapeng, & XU Shiyuan. (2013). Flood Simulation Study of Typhoon Storm Surge Based on Scenarios in Shanghai. Scientia Geographica Sinica, 01(33), 110–115.

Yuan Xiaofang. (2011). Research on Key 'Technologies of Emergency Decision-makingfor Unconventional Emergency Based on Scenarioanalysis and CBR [Ph.D, Xi'an University of Science and Technology]. https://kns.cnki.net/kcms2/article/abstract?v=3uoqIhG8C447WN1SO36whHG-SvTYjkCc7dJWN_daf9c2-IbmsiYfKpO9fwS6OrJIIBREhl-QwQYL74TVIQMDm1se5X76Cgr4&uniplatform=NZKPT

Zhang, M., Huang, Y., & Bao, Y. (2016). The mechanism of shallow submarine landslides triggered by storm surge. Natural Hazards, 81(2), 1373–1383. https://doi.org/10.1007/s11069-015-2112-0

Zhong Qiuyan, Guo Yanmin, Wang Ning, Xue Huifang, Cui Li, & Wang Yanzhang. (2012). Research on unconventional flood emergency evolution risk analysis based on knowledge element. Information Science, 30(1), 115–120. https://doi.org/10.13833/j.cnki.is.2012.01.029

Zhou Ning, Wu Kejian, Li Xue, Liu Xuanya, Yuan Xiongjun, Li Xuwei, Cao Linlin, & Qiao Shiwei. (2022). Dynamic risk analysis of petrochemical plant fire accident based on dynamic Bayesian network. Industrial Safety and Environmental Protection, 48(2), 6-10+21.