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Review

A Comprehensive Review of Assessing Storm Surge Disasters: From Traditional Statistical Methods to Artificial Intelligence-Based Techniques

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Abstract: In the context of global climate change and rising sea levels, the adverse impacts of storm surges on the environment, economy, and society of affected areas are becoming increasingly significant. However, due to differences in geography, climate, and other conditions among the affected areas, a single method for assessing the risk of storm surge disasters cannot be fully applicable to all regions. To address this issue, an increasing number of new methods and models are being applied in the field of storm surge disaster risk assessment. This paper introduces representative traditional statistical methods, numerical simulation methods, and artificial intelligence-based techniques in this field. It compares these assessment methods in terms of accuracy, interpretability, and implementation difficulty. The paper emphasizes the importance of selecting appropriate assessment methods based on specific conditions and scientifically combining various methods in practice to improve the accuracy and reliability of storm surge disaster risk assessments.

Keywords: storm surge disaster; risks and economic losses; traditional statistical methods; numerical simulation methods; artificial intelligence-based techniques

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1. Introduction

Storm surges represent a natural phenomenon typically triggered by strong winds, low atmospheric pressure, and other meteorological elements, resulting in an abnormal rise in sea level that further invades coastal regions [1]. Such events not only impact the environment and ecosystems, but also exert far-reaching effects on economic activities and social structures. Dube et al. have indicated that storm surges have inflicted significant loss of life and property in the regions of the Bay of Bengal and the Arabian Sea [2]. Jin et al. have assessed the damages caused by storm surge disasters in specific areas of China through economic models, which included sectors such as agriculture, fisheries, human resources, engineering facilities, residential facilities, and direct economic losses. Their findings suggest that the model equations can intricately reflect the interrelations between storm surge losses and other related variables [3].

The impact of storm surges is not confined to coastal areas; they can also affect inland regions through various pathways. For instance, surges can lead to the elevation of river water levels, subsequently causing inland flooding [4]. This phenomenon has been recorded across multiple geographic locations and environmental conditions, notably in the Red River Delta region of Vietnam, where sea-level rise and storm surge disasters are considered key factors contributing to permanent and temporary flooding areas [5]. In New York City, factors such as changes in tropical storm climatic characteristics, sea-level rise, and coastal economic development have all been incorporated into the framework of assessing coastal flood risks [6]. Hurricane Ike in 2008 also triggered storm surges in the Mississippi River Delta area in the United States, leading to increased river water levels and causing inland flooding, severely affecting local agriculture and residents' lives [7]. Similarly, in the United States, a study on the economic losses from inland flooding caused by tropical cyclones showed that such events could directly lead to substantial economic losses [8].

The implications of storm surges can also be long-term. For example, surges may cause enduring damage to coastal ecosystems, affecting the development of the fisheries and tourism industries, which are major economic sources for many coastal regions [9]. Further research indicates that storm surges and other extreme hydrological events may accelerate the expansion of harmful algal blooms (HABs), further impacting the water supply of the affected areas and severely affecting the fisheries and tourism industries [10]. Additionally, storm surges may cause long-term damage to infrastructure, such as roads, bridges, and power facilities, necessitating significant local government investments of capital and time for repairs [6]. Some studies also point out that coastal vegetation, serving as 'biological barriers', can mitigate the impact of storm surges, but this approach may have long-term negative effects on biodiversity and human daily life [11].

Owing to global climate change and sea-level rise, the frequency and intensity of storm surges are expected to show a positive growth trend in the coming decades [12]. This underscores the importance of accurately assessing the economic impacts caused by storm surge disasters. However, given the complexity and diversity of the processes involved in storm surges becoming disasters, accurately assessing disaster impacts under different storm surge conditions is a highly challenging task. Notably, the choice of assessment methods can significantly affect the outcomes, thereby influencing policy decisions. For example, a particular method may be very effective in a specific geographic area but may not perform well elsewhere. Inaccurate or insufficient assessment methods could lead to the underestimation of storm surge risks, resulting in inadequate preparation for disaster prevention measures and potential catastrophic consequences. Conversely, overestimating risks could lead to the unnecessary allocation of resources, thus wasting them, which is also undesirable. Therefore, the importance of choosing appropriate and accurate assessment methods is self-evident.

In the quest to better assess the extent of storm surge disasters, researchers have adopted a variety of different approaches. Traditional statistical methods and numerical simulation methods, as well as the emerging artificial intelligence-based techniques, have all played significant roles in this domain. To better address the disaster risks posed by storm surges, the advantages and disadvantages of different methods are urgently in need of in-depth study and comparison. This article aims to comprehensively explore these methods and provide guidance for policymakers and researchers on how to select appropriate assessment methods to tackle the challenges of diverse and complex disaster losses brought by storm surges. In the following, we delve into the application of traditional statistical methods, numerical simulation methods, and artificial intelligence-based techniques in the assessment of storm surge disaster risks, as well as their comparison and integration.

2. Traditional Statistical Methods

Currently, a multitude of methods are extensively applied and studied in the realm of assessing the risks of storm surge disasters. Foremost among these are traditional statistical analysis methods, which have long served as the foundation for assessing the impact of natural disasters. These methods are straightforward and principally reliant on historical data and empirical models, analyzing past natural disaster events and their effects on affected areas to predict future occurrences.

Applications of Traditional Statistical Methods

These traditional statistical methods have low data requirements, high computational efficiency, and good adaptability and comparability. Thus, they have been validated and tested in various contexts. Over time, traditional statistical methods have evolved from simple statistics to complex probability models. In the mid-20th century, researchers began using extreme value theory to analyze storm surge data, with Gumbel's work being one of the pioneering studies in the field of extreme value statistical analysis [13]. His proposed Gumbel distribution has been widely applied in the extreme value analysis of storm surges. Subsequently, Jenkinson improved Gumbel's method, proposing a more suitable approach for analyzing extreme storm surge data [14]. These early studies laid the foundation for using statistical methods to analyze extreme storm surge data; in the 21st century, with the development of computer technology and improved data collection capabilities, traditional statistical methods have become more widely used and refined in storm surge analysis. Pugh in his research utilized a variety of statistical methods to assess the long-term trend of the impact of sea-level rise on storm surges, providing important information for understanding storm surge risks under global warming [15]; Ji et al., based on the general form of disaster loss indicators, provided a disaster grade calculation formula for single factors of storm surge disaster losses, and proposed a fuzzy comprehensive judgment method for the quantitative assessment of storm surge disaster losses based on fuzzy mathematics theory [16]; Zhao et al. used a multi-indicator grading method to divide the natural intensity of storm surges into two aspects: the intensity of over-warning water level intensity, and wave intensity, and established a joint prediction equation for storm surge grades based on these two factors [17]. Moreover, in 2012, Shepard et al. studied the quantitative methods for assessing future storm surge risks, specifically the impact of sea-level rise on the storm surge risk to the south shore of Long Island, New York, using tidal gauges to measure sea water changes since 1856 and predict future storm surge disaster risks [18]; Hsu et al. used a combined probability approach and a hurricane storm surge risk assessment framework describing the relationship between storm surge height and other factors, such as wind speed, wind direction, and atmospheric pressure [19].

Through the application of traditional statistical methods, we can gain a better understanding of the risk impacts of storm surge disaster events and provide robust support for the formulation of corresponding risk management and disaster reduction strategies. However, traditional statistical methods only quantify storm surge disaster risks from a linear relationship perspective, while the genesis, development, and disaster process of storm surges represent a non-linear, complex, dynamic process. Therefore, relying solely on simple linear relationships fails to accurately comprehend the risks associated with storm surge disasters. Therefore, addressing the challenge of simulating the dynamic process of storm surges, numerical simulation methods have been increasingly applied as computer technology has evolved. In the following section, we explore in greater detail the utilization of numerical simulation methods in the assessment of storm surge disasters.

3. Numerical Simulation Methods

With the advancement of technology, the widespread application of large-scale computers has precipitated a leap forward in the development of numerical modeling, thereby enhancing the application of numerical simulation methods in assessing the severity of storm surges. Numerical simulation is a computational method based on physical and mathematical models that predicts the impact of storm surges on coastal areas by simulating the development and disaster-forming process of such events.

Deterministic simulation, a common form of numerical simulation, operates on the basis of known physical parameters and environmental conditions of storm surges. It simulates the development of storm surge events to predict the potential extent and depth of seawater intrusion. This method is of significant importance in the prediction and risk assessment of storm surge events.

Development and Applications of Numerical Simulation Methods

The development of numerical simulation methods in the field of storm surge disaster assessment marks a significant advancement in the understanding and predictive capability of this natural phenomenon. Since the late 20th century, with the rapid development of computer technology, numerical simulation methods have become an essential tool for studying the dynamics of storm surges and assessing their potential impacts. These methods, by simulating the interactions among the atmosphere, ocean, and land, offer a means to accurately predict storm surge events. In the early stages of numerical simulation method development, research primarily focused on enhancing the physical foundation of models and their computational efficiency. For instance, the SLOSH (Sea, Lake, and Overland Surges from Hurricanes, SLOSH) model developed by Jelesnianski et al. (1992) was one of the early significant tools for simulating storm surges [20]. This model simulated the generation and propagation of storm surges using simplified physical equations. In 2002, Zerger et al. utilized GIS (Geographic Information System, GIS) technology to verify the effectiveness of the model and evaluated the comprehensive risk of storm surge disasters in Cairns [21]. Subsequently, more sophisticated three-dimensional models such as ADCIRC (Advanced Circulation Model, ADCIRC) [22], Delft3D [23] and SCHISM (Semi-implicit Cross-scale Hydroscience Integrated System Model, SCHISM) [24] were developed to simulate storm surges and their impacts on coastal regions with greater precision. In 2010, Lin et al. improved the ADCIRC by enhancing its applicability for assessing the risk of storm surge disasters in coastal areas under the influence of climate change, thereby providing a reference for disaster prevention and mitigation decision-making [25]. Lara Santos et al. employed the Delft3D model to evaluate storm surge risks along the Portuguese coastline. They simulated historical storm surge events and reconstructed the genesis, development, and disaster processes of storm surges, while also assessing changes in water levels and flood inundation extents for various storm surge cases, offering a scientific basis for local disaster prevention and mitigation planning [26]. In 2023, Mentaschi et al. conducted a global-scale simulation of storm surges and waves using the SCHISM model. This research established a high-resolution, global coastal ocean dynamics simulation system, simulated numerous storm surge and wave processes over a period of 73 years [27]. The simulation results were compared with satellite altimetry, tide gauge, and buoy observation data to verify the model's accuracy and reliability. This work not only enhanced our understanding of the risks associated with storm surges and wave disasters in global coastal areas but also contributed to assessing coastal disaster risks under climate change. With the development of numerical simulation methods has increasingly emphasized the comprehensiveness and multi-scale modeling capabilities of models. In 2013, Kiren et al. presented at the EGU (European Geosciences Union, EGU) conference that the combination of the SWAN (Simulating Waves Nearshore, SWAN) and the ADCIRC could enhance resolution, thereby facilitating the assessment of typhoon-induced storm surge risks in the Martinique region of France [28]. By integrating multiple numerical models with GIS and marine meteorological datasets, and accounting for a variety of variables and parameters, such as wind speed, sea level height, population density, as well as geographic information, it becomes feasible to precisely simulate the propagation of the storm surges and the extent of their impacts, and thus to generate a more comprehensive and accurate risk assessment system.

The advantage of numerical simulation methods lies in their ability to simulate the complex dynamics of the formation and dissipation of storm surges and the resulting disaster processes from a nonlinear perspective. These methods enable the precise prediction of the impacts of storm surge events, providing a scientific basis for relevant departments to quickly make disaster prevention and mitigation decisions. However, numerical simulation methods require extensive input data and computational resources, making extensive simulations using these methods potentially costly. Additionally, these methods present a considerable barrier to entry for users, requiring a specific knowledge background and computational skills for effective implementation. Furthermore, translating complex simulation results into actionable guidance for decision-making also poses a challenge for relevant departments in affected areas.

4. Artificial Intelligence-Based Techniques

Recently, artificial intelligence-based technologies, particularly machine learning and deep learning, have begun to play a role and are increasingly being recognized in the assessment of storm surge disaster risks. Compared to traditional methods, artificial intelligence is capable of processing larger and more complex datasets, thereby enhancing the accuracy and efficiency of assessments. For instance, neural network models can be trained to identify and predict different types of economic losses caused by storm surges, including those to agriculture, real estate, and infrastructure.

4.1. Machine Learning and Deep Learning Techniques for Storm Surge Assessment

Machine learning, a critical branch of artificial intelligence, learns patterns and rules from data to make autonomous decisions and predictions. In assessing the economic losses from storm surges, machine learning methods can leverage historical data and environmental information to establish predictive models estimating the impacts of future storm surge events. For example, by analyzing historical data from multiple storm surge events, machine learning algorithms can identify key factors affecting economic damages and predict the extent of losses under various scenarios. Deep learning, a specialized form of machine learning, uses artificial neural networks to emulate the neural structure and functioning principles of the human brain. With its strength in handling complex non-linear relationships and large-scale data, deep learning can play a significant role in storm surge risk. Deep learning algorithms allow for the construction of more intricate models that capture the complex interactions between different factors, thereby predicting the disaster impact of storm surge events more accurately.

4.2. Recent Studies Using Artificial Intelligence-Based Techniques

There are numerous studies utilizing artificial intelligence for storm surge disaster risk assessment. In their study, Lin et al. employed ANN (Artificial Neural Networks, ANN) for the prediction of typhoon-induced storm surges, demonstrating the potential of artificial intelligence-based techniques in enhancing the accuracy of storm surge forecasts [29]. Zhao Xin, Wang Baosong, et al. proposed a storm surge disaster loss measurement method based on the RS-SVM (Rough Set-Support Vector Machine, RS-SVM) model by constructing an assessment indicator system. Their data fitting analysis with this model yielded promising results [30]. Wang Tiantian, Liu Qiang established a BP (Back Propagation, BP) neural network model optimized by beetle antennae search based on existing storm surge disaster research, creating a predictive indicator system for storm surge disaster losses for 29 storm surges in Fujian Province, and found that the BAS (Beetle Antennae Search, BAS)-BP regression prediction model had good applicability in predicting storm surge disaster losses [31]; Zhao Xin, Wang Xiaohan introduced the POT (Peak Over Threshold, POT) model based on extreme value theory to perform distribution fitting on direct economic loss data from storm surge disasters between 1989 and 2014. They found that the POT model could aptly describe the tail loss distribution of storm surge disasters in China, achieving the research goal of reasonably calculating the risk value of storm surge disasters in China [32]; Hao Jing, Liu Qiang, et al. used 50 sets of typhoon storm surge data from Guangdong Province for research, quantified climate change data, and employed the sparrow search algorithm to optimize the extreme learning machine to establish a pre-assessment model. Their predictions for typhoon storm surge loss levels, affected population, and direct economic losses showed improved accuracy in the optimized model [33]; Jiang and Liu used the beetle antennae search algorithm to optimize a BPNN (Back Propagation Neural Network, BPNN) based on 20 predictive parameters to forecast the next moment's storm surge, demonstrating that the combination of BAS and BPNN yielded more accurate and reliable results than a single BPNN [34]. Zhang and Jiang employed four optimization algorithms (including genetic algorithm, particle swarm optimization, beetle antennae search, and beetle swarm optimization) to optimize Back Propagation Neural Networks, proposing four optimized BPNN for predicting storm surge disaster risk [35]. Lockwood et al. found that ANN models trained on synthetic datasets could predict storm surge levels along the eastern United States and the Gulf of Mexico, providing scientific support for relevant departments to take preventative and disaster mitigation measures [36].

The advantage of artificial intelligence-based techniques is their ability to process large amounts of data and variables and to automatically identify patterns and trends, thereby offering more accurate and comprehensive assessment outcomes. However, AI (Artificial Intelligence, AI)-based approaches not only face challenges such as substantial data requirements and insufficient model robustness but also necessitate addressing a series of issues related to model parameter selection and training. Addressing these challenges requires considerable time investment and human resources. Moreover, models that have been fine-tuned may not exhibit high applicability across all scenarios. These issues necessitate rational solutions and adjustments in practical applications to ensure the effective utilization of AI-based methods in diverse contexts.

5. Discussion

The preceding sections have outlined the main categories of methods used for storm surge disaster risk assessment, including traditional statistical approaches, numerical simulations, and emerging artificial intelligence techniques. Each methodology has its unique advantages and limitations. Figures 1 and 2 present the results of our statistical analysis on the number of articles from the ScienceDirect literature database from 2000 to 2023, focusing on the application of the three methods in assessing and predicting the impact of storm surges. It is evident that, over these years, the number of papers utilizing traditional statistical methods, numerical simulation methods, and AI-based technologies for storm surge assessment and prediction has significantly increased. Papers applied numerical simulation constitute the majority, accounting for 53% of the total, while AI, being an emerging technology, has the smallest share at only 8%. The number of articles employing AI-based technology has shown a positive growth trend starting from 2019. In contrast, the growth trend in the number of articles using traditional statistical methods is less pronounced.

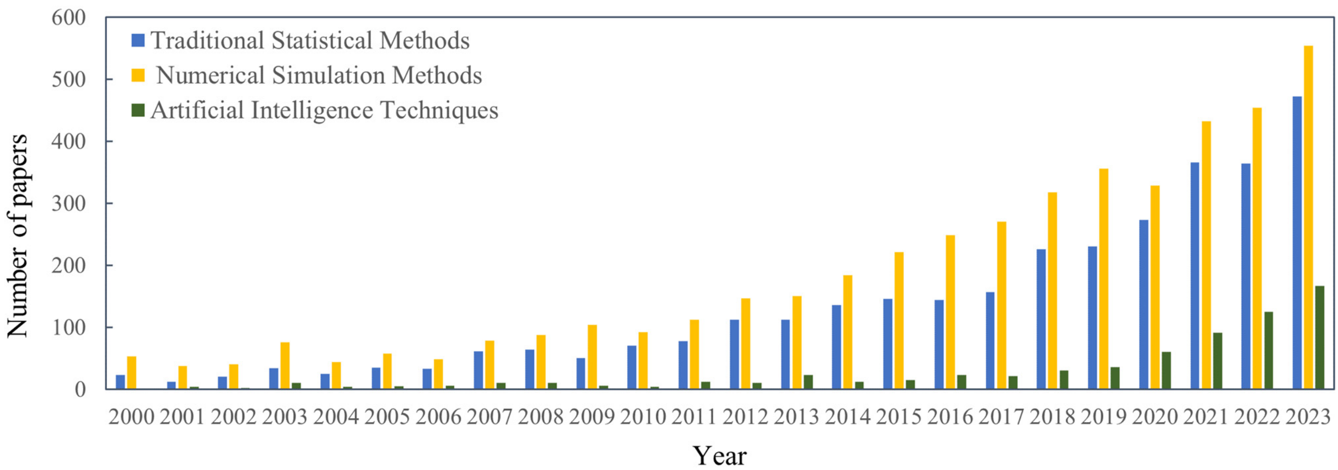

Figure 1. The number of papers in the ScienceDirect literature database from 2000 to 2023 on the application of traditional statistical methods, numerical simulation methods, and artificial intelligence techniques in storm surge assessment.

In assessing storm surge disaster risks, various methodologies exhibit distinct advantages and limitations. Hence, selecting an appropriate method necessitates comparative and integrative consideration. The following discussion compares and synthesizes traditional statistical methods, numerical simulation methods, and artificial intelligence-based techniques to clarify their respective advantages and limitations.

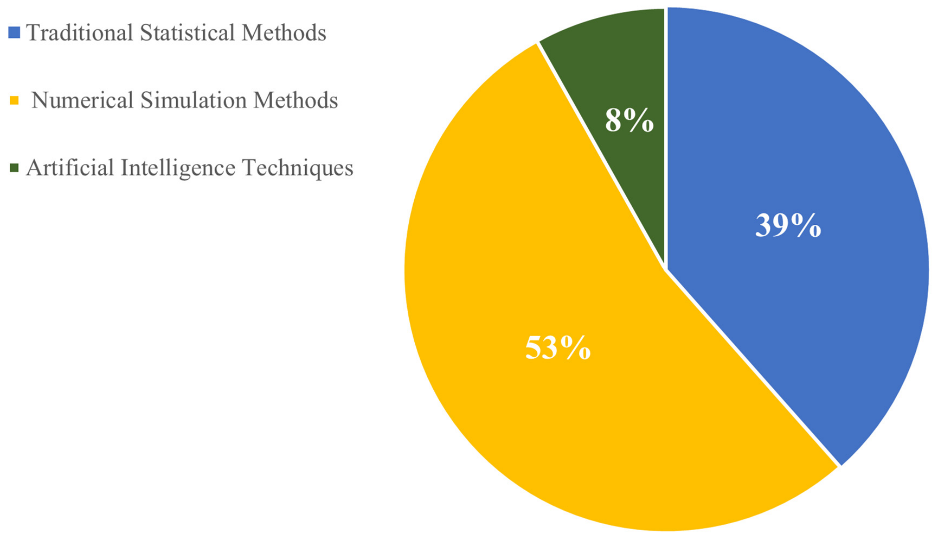

Figure 2. The proportion of papers in the ScienceDirect literature database from 2000 to 2023 on the application of traditional statistical methods, numerical simulation methods, and artificial intelligence techniques in storm surge assessment.

5.1. Comparison of Accuracy

Traditional statistical methods hold certain advantages in data analysis and summarization, reflecting the extent of storm surge disasters and economic losses through historical data. However, they may fail to capture complex nonlinear relationships and inter-variable interactions, limiting the accuracy of predictions.

Numerical simulation methods, utilizing physical models and environmental data, can predict the development and impact scope of storm surge events with greater precision. By considering multiple variables and parameters, these methods provide a more comprehensive loss assessment. However, they require extensive data and computational resources, and their accuracy is influenced by the model parameters and input data.

Artificial intelligence-based techniques, through machine learning and deep learning, can identify complex patterns and relationships, offering more accurate assessment outcomes. Nonetheless, these methods require substantial data for training samples, and the models' interpretability is relatively low, making it challenging to comprehend how predictions are derived. (From Table 1).

Table 1. Summary of research on storm surge disaster assessment methods.

Study	Methods	Accuracy	Advantages	Disadvantages
Li Peishun [37]	Stepwise Regression	Correlation coefficient = 0.99 S = 9.4	Low assessment error, uses historical data, high reliability.	Lower applicability of equations, higher limitations.
Zhao et al. [17]	Multi-indicator Grading	R-Squared = 80% RMSE = 1.7	Measures storm surge disaster levels from multiple perspectives.	Some variable coefficients in the equation are empirically determined.
Lin et al. [25]	ADCIR	Accuracy = ±80%	Improved model does not rely on historical data, suitable for prediction.	Longer simulation time, high computational cost, application to extensive simulations may be costly.
Lorenzo et al. [26]	SCHISM	Pearson correlation = 0.55	High nearshore spatial resolution captures local, short-term storm surge variations.	Model initialization has limitations, neglecting some nonlinear interactions.
Zhao xin et al. [32]	RS-SVM	Test Samples R-Squared = 0.7669	Small error; multidimensional factors assess storm surge disaster risk.	High data requirements; extensive training time.
Jiang and Liu [34]	BAS-BPNN	RMSE = 6.14 MSE = 5.19	BAS optimization of BPNN enhances accuracy of assessment results.	Model may not be universally applicable across multiple regions.

5.2. Comparison of Interpretability

The results of traditional statistical methods are typically transparent and understandable, clearly showing the impact of different variables on storm surge disaster risks and post-disaster economic losses. However, they may not adequately handle complex nonlinear relationships and interactions, limiting interpretability.

The outcomes of numerical simulation methods are often intuitive and can be visually displayed, such as the propagation paths and impact areas of storm surges. Yet, due to the high complexity of the models, interpreting and understanding the assessment results may require specialized knowledge.

Artificial intelligence-based techniques, compared to the aforementioned methods, may be more challenging to interpret because the models, although trained with complex learning methods on extensive data, do not explicitly explain the basis and reasons for the predictions. This limitation can restrict the application and dissemination of artificial intelligence techniques. (From Table 1).

5.3. Comparison of Implementation Difficulty

Traditional statistical methods are relatively straightforward, requiring only the collection and analysis of historical data without complex model building and computation. However, they may not capture intricate variable relationships, leading to less accurate predictions.

Numerical simulation methods necessitate constructing physical models, collecting vast environmental data, and performing complex numerical calculations. This requires specialized knowledge and substantial computational resources, presenting a higher difficulty level in implementation.

Artificial intelligence-based techniques involve preparing extensive training data, selecting appropriate algorithms, and conducting model training and adjustments. Although the implementation is challenging, once an effective model is established, it can yield substantial benefits in future applications. (From Table 1).

In summary, different methods have varying strengths and limitations depending on the context. In practice, the choice of method or a combination thereof can be guided by factors such as data availability, required prediction accuracy, and interpretability needs, aiming to produce more accurate and reliable assessments of storm surge disaster risks and economic losses. The selection process should also consider the purpose of the assessment and the practical application scenarios to ensure the results provide robust support for decision-making by relevant authorities. In the next section, we build upon the content previously discussed and offer recommendations on selecting suitable assessment methods.

6. Conclusions and Perspectives

Based on the comparison and integration of methods for assessing storm surge disaster risks and economic losses, we can draw several discussions and suggestions to enhance the accuracy and reliability of future assessment results.

6.1. Basis and Flexibility for Method Selection

As evident from the preceding sections of this article, different methods have their respective advantages and limitations in assessing the risk of storm surge disasters and economic losses. Traditional statistical methods are suitable for summarizing and analyzing historical data, revealing characteristics of past events. However, with increasing climate change and uncertainty factors, these methods may not effectively predict future storm surge disaster severity and economic loss. Numerical simulation methods can more precisely model the development process of storm surges and predict disaster extent, but their accuracy depends on model and parameter selection. Artificial intelligence-based techniques, particularly machine learning and deep learning, can process large amounts of complex data and uncover potential correlations and patterns, but they require substantial training data samples and appropriate feature selection.

Thus, when choosing an assessment method, one should weigh the pros and cons of different methods based on the specific context and determine the most suitable method considering the available data, complexity of the issue, and the temporal scale of the forecast. In practice, combining multiple methods can also be considered to enhance the accuracy and reliability of the predictions. For instance, Hashemi et al. (2016) utilized datasets derived from numerical simulations to train artificial intelligence models, significantly enhancing the efficiency and accuracy of storm surge predictions and providing more reliable tools for storm surge disaster assessment in coastal areas [38].

6.2. The Importance of Data and Handling Uncertainty

Whether traditional statistical methods, numerical simulation methods, or artificial intelligence-based techniques are used, data support is indispensable. In assessing storm surge disaster risks and economic losses, the quality and completeness of data are crucial for the accuracy of the predictions. Therefore, collecting and compiling accurate storm surge event data, economic loss data, and other relevant data significantly impacts the reliability of the assessment.

However, the uncertainty in data is also a challenge. There is inherent error in the acquisition and measurement of meteorological and oceanographic data, and future climate changes and sea-level rise add to this uncertainty. When using data for model training and prediction, these uncertainties must be considered, and appropriate measures should be taken to address them, such as introducing uncertainty ranges or conducting sensitivity analyses.

6.3. Summary

In this research, we have delved into the application of various methods in assessing the risks and economic losses from storm surge disasters. Through traditional statistical methods, numerical simulations, and artificial intelligence-based techniques, we have understood the diversity and variability of methods to assess the extent of storm surge disasters and post-disaster economic losses. We have summarized the strengths and weaknesses of these three methods and offered some thoughts and recommendations.

In the realm of traditional statistical methods, based on the results obtained by multiple researchers using this approach in the field of storm surge disaster risk and post-disaster economic loss, statistical methods mainly rely on historical data and empirical models. However, they also provide a novel perspective to understand the threat level of storm surges to affected areas, offering valuable quantitative information for decision-makers. The advent of numerical simulation methods has furnished us with more precise models of storm surge propagation and impact. Utilizing numerical models and Geographic Information System data, we can accurately simulate the intensity and impact range of storm surges, generating comprehensive and accurate loss assessment outcomes. The application of artificial intelligence-based techniques brings new opportunities to the assessment of storm surge disaster risks and economic losses. The use of machine learning and deep learning enables us to better uncover potential patterns within large datasets. The rapid development of these technologies provides us with deeper insights, facilitating a more comprehensive assessment of the impacts of storm surges.

In the comparison and integration section of methods, we discovered disparities among the different approaches regarding accuracy, interpretability, and implementation difficulty. Considering these factors, we can choose the most suitable method based on the specific context. Such integrative application can better meet diverse decision-making needs.

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