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Article

Spatial-Temporal Evolution of Maritime Accident Hot Spots in the East China Sea: A Space-Time Cube Representation

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Abstract: As public concern for maritime safety grows, there is a pressing need to delve deeper into the root causes of maritime accidents and develop effective preventive strategies. Spatial-temporal analysis stands out as a powerful approach to pinpointing accident hot spots. While previous research has shed light on the spatial aspects of these incidents, a comprehensive understanding of their temporal dimensions remains elusive. This paper bridges this gap by leveraging the Space-Time Cube tool in conjunction with traditional Kernel Density analysis to chart the spatial-temporal dynamics of maritime accident hot spots. Focusing on the East China Sea, a region notorious for its high incidence of maritime accidents and home to numerous world-class ports, we present a case study that offers fresh insights. Data spanning from 1994 to 2020, sourced from the Lloyd's List Intelligence (LLI) database, reveal the evolving landscape of maritime accidents in the area. Notably, since 2005, the Yangtze River Delta Region in China has emerged as a persistent hot spot for accidents, underscoring its significance in maritime safety discourse. Furthermore, our analysis from the 2010s detects a new hot spot expanding towards the southwest of Kaohsiung Port, China, signaling a burgeoning area of concern for maritime safety. While the Fujian coast of China has seen its share of accidents, it is not qualified as a hot spot zone. The Space-Time Cube proves to be an indispensable tool in unraveling the progression of maritime accidents, and our findings indicate that maritime accidents in certain areas may not be merely random occurrences but exhibit intricate patterns.

Keywords: maritime accidents; space-time cube; the East China Sea; kernel density analysis

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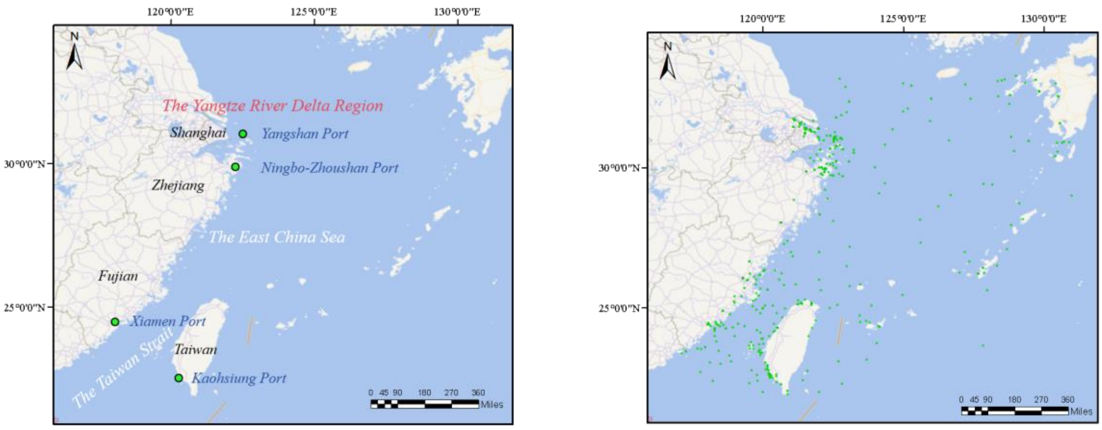
1. Introduction

The shipping industry is responsible for approximately 80% of the transportation of international trade cargoes [1]; the losses caused by maritime accidents are not what stakeholders in trade activities would like to see [2]. Despite the maritime community's efforts to enhance shipping safety, maritime transportation still faces the serious threat of maritime accidents, especially within busy waterways [3]. Undoubtedly, maritime accidents could lead to significant loss of life and property and marine environment pollution [4,5]. Exploring the spatial-temporal evolution of maritime accident hot spots could significantly contribute to maritime safety. It provides valuable references and cautions for decision-makers regarding the safe carriage of goods by sea, as well as insurance and port construction, etc.

The East China Sea was chosen as the research area in this research, a hot spot of marine accidents in the world [6,7]. The East China Sea is also a busy area with several of the world's largest ports, such as China's Yangshan Port and Ningbo-Zhoushan Port [8]. According to the Lloyd's List Intelligence (LLI) database, there are over 900 maritime accidents that occurred in the East China Sea from 1994 to 2020. A visual representation of the spatial distribution of these accidents, as depicted in Figure 1, underscores the Yangtze River Delta and the Taiwan Strait as zones of heightened vulnerability to maritime accidents. This spatial distribution corroborates the findings of the reference by Deng et al. in 2023 [9], whose research also identified hot spots of maritime accidents along the coast of China.



(**a**) Port distributions

(**b**) Accident distributions

Figure 1. The spatial distributions of maritime accidents in the East China Sea.

In the research of maritime accidents in the East China Sea, Gan et al. used knowledge graph construction to explore ship collision accidents along the coast of China, and the East China Sea is one of the important points [10]. Most researchers who study accidents in the East China Sea have paid attention to the "Sanchi" event in various ways [11,12]. The East China Sea is a bustling maritime corridor teeming with a multitude of vessels. Despite the dense maritime traffic, comprehensive studies on accidents in this region are scarce. The lack of research in this area is notable, given the importance of understanding the dynamics and risks associated with such a heavily trafficked waterway.

Furthermore, existing maritime accident studies have predominantly concentrated on spatial aspects [6,13], often neglecting the intricate spatial-temporal evolution. This study diverges from precedents by employing a Space-Time Cube tool, offering a novel perspective on the evolution patterns of maritime accidents in the East China Sea over recent years. The incorporation of case studies serves as an effective method to uncover detailed patterns.

The remainder of the study is structured as follows: Section 2 summarizes the literature in the area of maritime accident analysis based on GIS. Section 3 processes and analyzes the data. The Space-Time Cube analysis and Kernel Density analysis are illustrated in Section 4. Then, the results are shown in Section 5. Finally, discussions and conclusions are presented in Sections 6 and 7, respectively.

2. Literature Review

With the surge in trade volume, maritime safety challenges are escalating. The consequences of maritime accidents can be devastating, as exemplified by the persistent environmental pollution following the explosion of the cargo ship X-Press Pearl, which continued a year later [14]. The infamous "Sanchi" incident resulted in intolerable casualties, persistent environmental degradation, and substantial economic losses [12]. Consequently, enhancing maritime safety and mitigating the occurrence of maritime accidents have become pressing concerns.

In the quest to bolster maritime safety, extensive research has been undertaken. Coraddu et al. developed a data-driven predictive model to categorize maritime accidents stemming from diverse human factors [15]. Huang et al. used a weighted association rule to find characteristics of intercontinental maritime accidents in the Mediterranean Sea and Black Sea [16]. Ma et al. mapped a complex network of maritime accidents attributable to human factors and, through the computation of PageRank values, identified four unsafe behaviors that directly influence the likelihood of grounding accidents [17]. Li et al. employed a Bayesian Network model to dissect the pivotal risk factors in maritime accidents [18]. Munim et al. utilized Automated Machine Learning to predict maritime accident risk in Norwegian waters over 40 years [19]. Wang et al. proposed a multi-factor time series prediction model with eight influencing factors based on global maritime accidents [20]. Kim et al. utilized logistic regression to assess the risk levels associated with near-miss accidents [21]. It is worth noting that research on maritime accidents often requires substantial data support.

Research also suggests a correlation between maritime accidents and geographical locations [6]. Accordingly, studies have been conducted with a focus on various locations. Some researchers have taken a global perspective on maritime accident analysis. Zhou et al. used machine learning and density analysis to study the global maritime accident spatial patterns and environmental factors over a 20-year period [22]. Li et al. have developed an innovative, data-driven model for the analysis of collision risk from a global perspective [23]. Others have honed in on specific maritime areas for more detailed insights. Uddin et al. investigated the Inland Waterways of Bangladesh, identifying high-risk locations and routes by analyzing accident frequency [24]. Yang et al. conducted an analysis of the Fujian sea area in China, leveraging Kernel Density Estimation and spatial auto-correlation techniques to predict maritime risks through machine learning methodologies [25]. Overall, areas with high accident rates consistently attract researchers' attention.

GIS has emerged as a powerful instrument for spatial analysis and visualization. Huang et al. examined the spatial distribution of global maritime accidents using cluster and buffer analyses [6]. Zhang et al. introduced Kernel Density Estimation (KDE) and K-means clustering methods to study maritime accidents [7]. Wang et al. employed density analysis and clustering analysis to examine the spatial patterns of frequency and severity of global maritime accidents [13]. This literature primarily focuses on spatial characteristics. Despite the limited literature on the spatial distribution of maritime accidents, the existing studies effectively demonstrate the spatial characteristics of these incidents.

In conclusion, while previous studies have delved into the spatial characteristics, influencing factors, risk levels of accidents, and so on, there is a little research on the temporal aspects of accidents [26]. Although researchers have made concerted efforts to integrate temporal and spatial factors in accident analysis [7,22], the representation of time has been imprecise, and time factors have not been given equal consideration alongside spatial factors; a reasonable method combining space and time factors is necessitated to learn the evolution patterns of the maritime accidents. This study aims to bridge this gap by introducing the Space-Time Cube method, offering a solution that enables a more nuanced visual representation of both spatial and temporal features. Such an approach will be instrumental in elucidating the patterns of maritime accidents and devising effective preventive strategies.

3. Data Processing and Analysis

3.1. Accident Datasets

A comprehensive database of maritime accidents compiled in the East China Sea was carefully gathered from the reputable Lloyd's List Intelligence (LLI), a leading provider of maritime business intelligence. After a thorough screening process, a total of 915 recorded accidents from over 70,000 global incidents from 1994 to 2020 were identified by the authors in 2020, when we had free access to this database, excluding those with missing information. This extensive collection of incidents offers a rich source for in-depth analysis, with potential applications ranging from academic research to informing policy-making. The data are formatted in ArcGIS 10.8, which is a product designed by Environmental Systems Research Institute (ESRI) in California, USA a leader for the design and development of ArcGIS 10.8 software [27], and which ensured the correct projection and accurate locational positioning of the accident points. Subsequently, the incident point data are transformed into an analyzable Object-ID field. The final dataset encompasses records of time, incident type, human and property loss, as well as the latitude and longitude of each accident site, as detailed in Table 1.

Table 1. Data structure of the data.

Data Attribute	Description
Casualty Date	The time when the accident happened
No. Injured/Missing/Fatality	Loss of persons
Loss Type	Actual total loss or constructive total loss
Latitude	The exact latitude of the accidents
Longitude	The exact longitude of the accidents

3.2. Descriptive Statistics

In our rigorous analysis of the maritime accident dataset from the East China Sea, the temporal distribution and the geographical occurrence of these incidents are specifically investigated and presented in Table 2. As described in the Introduction section, the East China Sea's high maritime accident zones are segmented into northern and southern regions. The northern region predominantly encompasses the Yangtze River Delta Region, while the primary areas of the southern region are around the Taiwan Strait. Our data analysis reveals that 642 maritime accidents have spread within these zones, representing about 70% of all incidents in the East China Sea. Figure 2 illustrates the annual distribution of these accidents across the specified timeframes. Within the Yangtze River Delta, there was a notable surge in maritime accidents from 2001 to 2010, with a particularly sharp increase occurring in 2006. However, this trend has stabilized, with the number of accidents remaining relatively constant from 2011 to 2020. Conversely, the Taiwan Strait exhibited a slow consistent upward trajectory in maritime accident frequency, but accelerated the rate of increase around 2013 to 2014.

The 20th century marked a significant turning point in the social-economic trajectory of the Yangtze River Delta Region. It is also the special time period when the Yangtze River Delta Region experienced a significant reversal in maritime safety, with the number of maritime accidents substantially surpassing those in the Taiwan Strait. This pattern persisted for approximately five years, from 2005 to 2009. A pivotal moment occurred in December 2005 with the opening of the Yangshan Port in Shanghai, which propelled the Shanghai Port to become the world's leading port in terms of container throughput. Additionally, the official adoption of the "Ningbo-Zhoushan Port" on 1 January 2006 marked a significant step in the integration of regional ports. These developments brought satisfactory business volumes and, however, a price to pay. The sharp increase in accidents during this period may be attributed to these developments. Figure 3 provides good evidence. Four major ports, Shanghai and Ningbo in the Yangtze River Delta Region and Xiamen and Kaohsiung around the Taiwan Strait were chosen to describe the port activity. The data of container throughput come from Clarkson in the UK. The rapid increase in container throughput in the representative ports of the Yangtze River Delta region, Shanghai and Ningbo, at the beginning of the 20th century signifies busier operations and more challenging management tasks. The subsequent reduction in the number of maritime accidents may indicate that the region has since adapted to these changes.

Table 2. Cross-tabulation table of accident time and location.

			Area			
			The Yangtze River Delta Region	The Taiwan Strait	Others	Total
Casualty Date	1990s	Number Percentage	8 0.87%	43 4.70%	34 3.72%	85 9.29%
	2000s	Number Percentage	212 23.17%	87 9.51%	153 16.72%	452 49.40%
	2010s	Number Percentage	147 16.07%	145 15.85%	86 9.40%	378 41.31%
	Total	Number Percentage	367 40.11%	275 30.06%	273 29.84%	915 100%

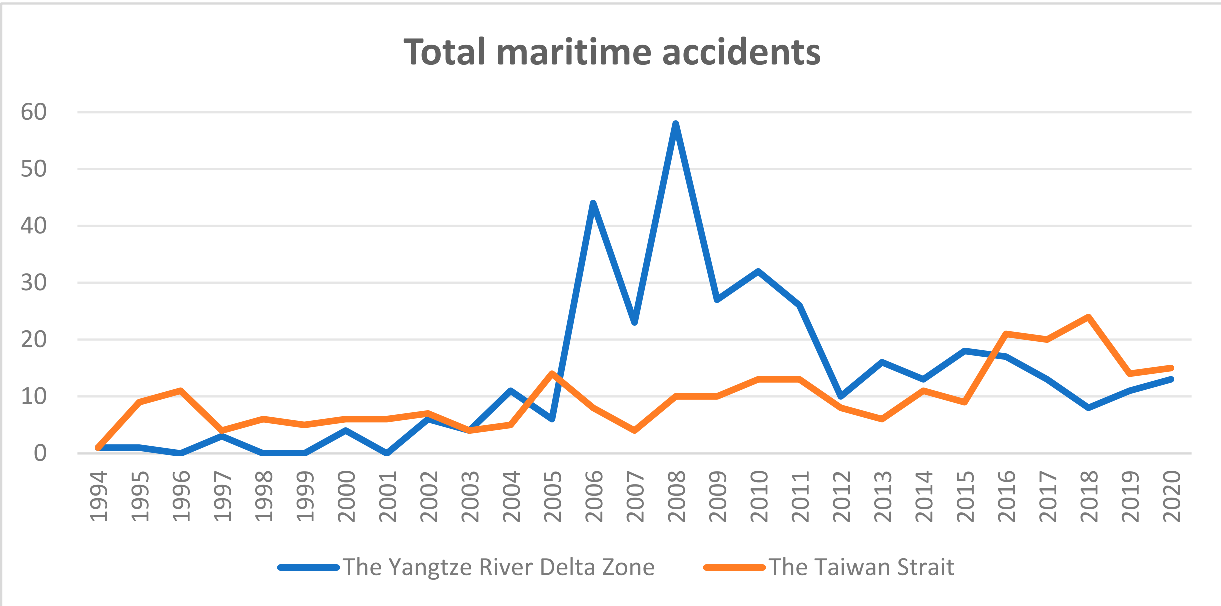


Figure 2. Trend of maritime accidents in two main areas from 1994 to 2020.

It is also notable that from 2011 to 2020, an interesting phenomenon emerged: the number of maritime accidents in the Yangtze River Delta Region was on par with those in the Taiwan Strait, despite a significant disparity in port throughput, as shown in Figure 3. This could be attributed to two primary factors. Firstly, there has been a continuous and satisfactory improvement in the management of the major ports within the Yangtze River Delta Region. Secondly, different sea states and weather conditions could play an integral role in this pattern.

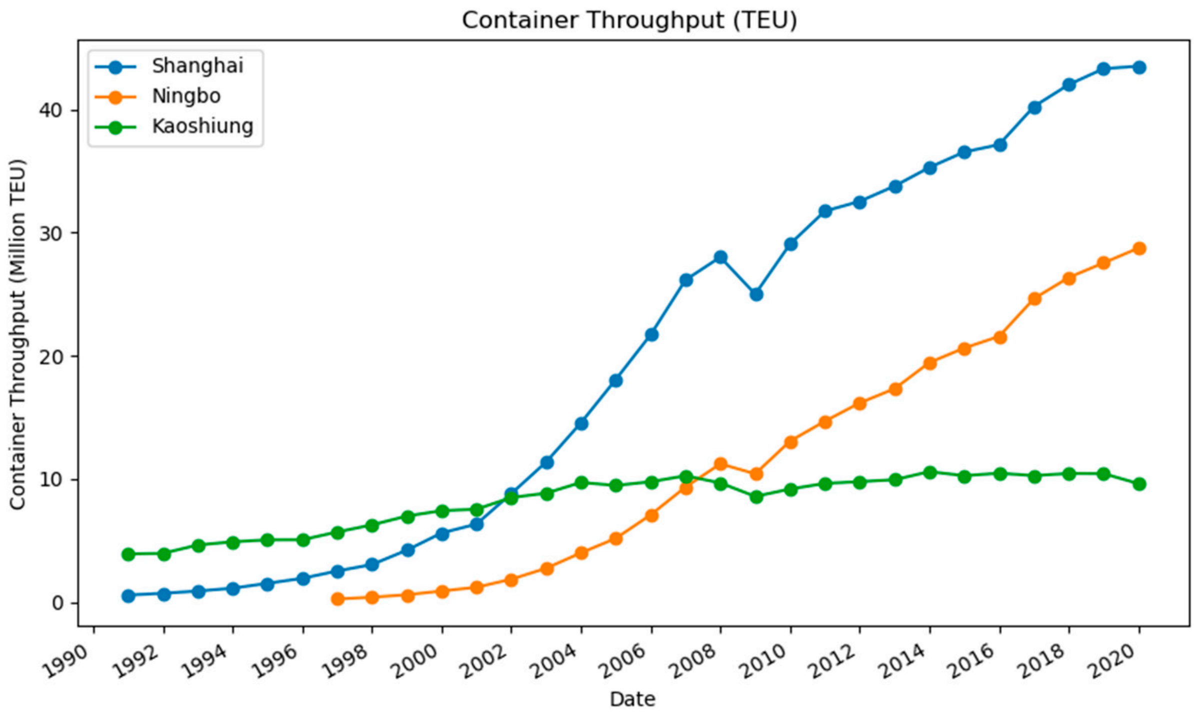


Figure 3. Container throughput of four major ports on the East China Sea.

4. Methodology of Space-Time Cube Representation

The Space-Time Cube has been predominantly utilized within the meteorological and environment community. For example, Allen et al. applied Kernel Density and Space-Time Cube analysis to study the occurrence of Virginia tornadoes from 1960 to 2019 [28]. Cao et al. used the Space-Time Cube to describe coupling relationships between basin ecological quality and water eutrophication upstream of the Han River basin [29]. More recently, this analytical tool has been adopted in traffic accident research. Yoon and Lee utilized the Space-Time Cube to examine vehicle accidents involving pedestrians [30]. Soltani et al. analyzed the trends and locations of accidents in the Greater Melbourne Area during a 15-year period [31]. The Space-Time Cube has been well utilized in road accidents, but there is no literature using this method for spatial and temporal analysis of maritime accidents. The application of the Space-Time Cube in the maritime accident community holds the potential to unlock new avenues for interpreting the complex interplay of spatial-temporal patterns, thereby enriching our understanding and response to maritime safety challenges.

Figure 4 delineates the framework of our research. After the preliminary stages of data processing and analysis, the Space-Time Cube is utilized to explore the spatial-temporal dynamics of maritime accidents within the East China Sea. This methodology represents an innovative approach in maritime accident research. To verify the findings, both descriptive statistical analysis and Kernel Density Estimation are carried out in the study. These tools serve to evaluate the coherence and dependability of the dataset. Any inconsistencies that emerge will be investigated and dealt with and subsequently discussed within the context of the study.

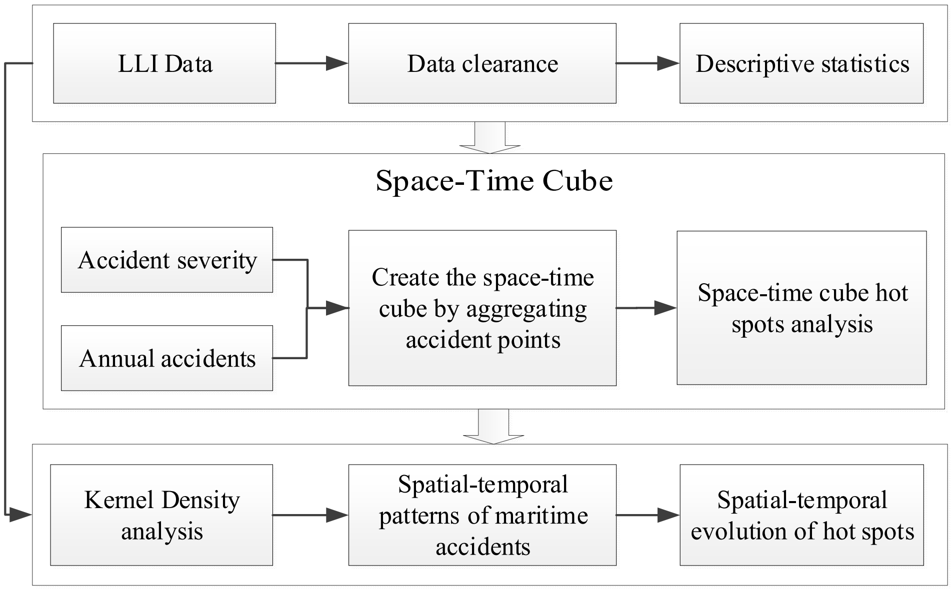


Figure 4. Framework of spatial-temporal evolution analysis.

4.1. Space-Time Cube Analysis

The analysis employs a Space-Time Cube to investigate the spatial-temporal patterns of maritime accidents. This approach involves consolidating all maritime accident data into the network common data form (NetCDF), a data abstraction for storing and retrieving multidimensional data [32]. Time, latitude, and longitude are selected as three dimensions. To ensure the interconnectivity of the grids used for aggregating accidents, a fishnet grid with a range of 50 nautical miles is selected, and 915 accidents are aggregated into 118 grids. Each accident in the grid every year constitutes a bin in the Space-Time Cube. The standard deviation is applied to quantify the variability in the annual number of accidents within each grid cell. Subsequently, the emerging Hot Spot Analysis tool within ArcGIS 10.8 is utilized to assess trends. ArcGIS employs the Getis-Ord Gi* method to identify clusters of high numbers of traffic accidents that are statistically significant. Furthermore, the results of Space-Time Cube should pass the confidence test. Each bin will be analyzed to measure the density of high or low cluster values. The test of this analysis is based on Z-scores and *p*-values. The Z-score represents a multiple of the standard deviation, and the *p*-value represents the probability. When the Z-score is very high or low and the *p*-value is small enough, it implies that the observed spatial pattern is unlikely to have arisen from a random process, and therefore we can reject the null hypothesis. The underlying formula for conducting Space-Time Cube analysis within GIS is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{1}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2} \tag{2}$$

where G_i^* equals the Z-score, x_j is the weighted impact of maritime accidents related to area j, $w_{i,j}$ is the spatial weight between area i and area j, $\overline{X}$ is the average impact of all maritime accidents, and n is the total number of the accidents.

At each location with data, we conducted the Mann–Kendall trend test as an independent bar time series test [33]. The Mann–Kendall statistic is a rank correlation analysis of the bar counts or values and their time series. The bar values are compared at the first time period with those of the second time period. If the former are less than the latter, the result is +1. If the former are greater than the latter, the result is −1. If they are equal, the result is 0. Then, they are summed to judge the characteristic. The rules of the characteristic are listed in Table 3 [34]. The analysis identifies various categories of hot spots, including new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, as well as historical hot and cold spots. In this paper, high-accident area means a location with a lot of accidents from a spatial view.

Table 3. Rules for accident characteristics.

Characteristic	Score	Illustration
New hot spot	1	This location is a statistically significant hot spot in the final time step and has never been a statistically significant hot spot before.
Consecutive hot spot	2	This location has a single uninterrupted run of at least two statistically significant hot spot bars in the final time-step interval. The location has never been a statistically significant hot spot prior to the final hot spot run, and less than ninety percent of all bins are statistically significant hot spots.
Intensifying hot spot	3	This location has been a statistically significant hot spot for 90% of the time-step intervals, including the final time-step. Additionally, the intensity of the larger clusters in each time-step has generally increased, and this increase is statistically significant.
Persistent hot spot	4	This location has been a statistically significant hot spot for 90% of the time-step intervals, with no clear trend indicating that the clustering intensity has changed over time.
Diminishing hot spot	5	This location has been a statistically significant hot spot for 90% of the time-step intervals, including the final time-step. Furthermore, the clustering intensity in each time-step has generally decreased, and this decrease is statistically significant.
Sporadic hot spot	6	The hot spot in the last time-step interval is statistically significant and has historically been a recurring hot spot. At most 90% of the time-step intervals have been statistically significant hot spots, and none of the time-step intervals have been statistically significant cold spots.
Oscillating hot spot	7	The hot spot in the final time-step interval is statistically significant, while this interval has a history of being a statistically significant cold spot in previous time-steps. At most 90% of the time-step intervals have been statistically significant hot spots.
Historical hot spot	8	The most recent time period is not a hot spot, but at least 90% of the time-step intervals have been statistically significant hot spots.
No pattern detected	0	This location does not belong to any defined patterns.
Cold spot	<0	The same illustration rules as hot spots; the scores of the cold spots are opposite numbers.

Greater emphasis is placed on accidents with significant human casualties and substantial property damage. For example, Severity 1 will be given a weight of 1 in the Space-Time Cube and Severity 2 will give a weight of 2, the same principle as Severity 3. While the Severity judgment may not fully follow the conventional way due to data limitations, these incidents warrant heightened scrutiny and attention. Table 4 shows the classification of the maritime accident severity. A formula is introduced to calculate the x_j of each accident based on its accident severity. The results of the Weighted Impact will be imported into the Space-Time Cube. The formula is as follows:

$$x_{\mathrm{j}} = \text{Base Impact} \times \text{Severity} \tag{3}$$

where Base Impact is a constant value assigned to each accident, representing its initial impact before severity weighting. Firstly, we suppose all the Base Impacts are equal to 1; this means all the accidents play equal roles in the model, just like previous accident projection studies. Severity is a factor that corresponds to the severity level of the accident, with levels 1, 2, and 3 having multipliers of 1, 2, and 3, respectively.

Table 4. Classification of maritime accident severity.

Severity	Description	Number
1	Less serious	694
2	Accident involves either loss of life or (constructive) total loss [1]	147
3	Accident involves both loss of life and (constructive) total loss	74
	Total	915

[1] (Constructive) total loss: Actual total loss or constructive total loss. Actual total loss means the ship is so damaged it ceases to be a ship. Constructive total loss means the ship is reasonably abandoned on account of its actual total loss appearing to be unavoidable.

4.2. Kernel Density Analysis

In GIS, Kernel Density analysis stands as a pivotal spatial analysis technique. This method is instrumental in ascertaining the density of point or line elements within a given area, thereby assigning relative weights to these elements based on their spatial distribution. Kernel Density analysis effectively captures the spatial clustering of objects under study, offering insights into areas of high or low concentration. The underlying formula for conducting Kernel Density analysis within GIS is as follows:

$$f(x) = h(x) \times K((x - x_0)/h) \tag{4}$$

where $f(x)$ is the Kernel Density function, $h(x)$ is the smoothing function, K is the kernel function, x is the spatial position, x_0 is the sample point position, and h is the bandwidth. If density values are selected, these values represent the Kernel Density values per unit area per pixel. In this study, h is set to default in ArcGIS 10.8; this methodology for choosing the search is based on Silver's Rule-of-thumb bandwidth estimation formula, and it has been adapted for two dimensions [35], which can correct spatial outliers based on spatial configuration. A range of maritime accident points will be aggregated and colored.

5. Results

5.1. Space-Time Cube Analysis of the East China Sea

Space-Time Cube analysis is utilized to examine the spatial-temporal evolution of maritime accident hot spots, treating the dimensions of space and time with equal importance. The accident points are counted and aggregated. Furthermore, the severity of accidents can be identified, allowing for the weighting of each incident. With a systematic understanding of the regional distribution of accidents, the severity factor is integrated into the model to enhance its comprehensiveness and reliability. Although the severity factor is not the focus of this study, its inclusion ensures that severe accidents are represented with greater intensity in the model compared to less severe ones. This approach allows us to illustrate the spatial-temporal patterns of maritime accidents in the East China Sea within a single, consolidated figure. Figure 5 shows the outcomes of the Space-Time Cube analysis.

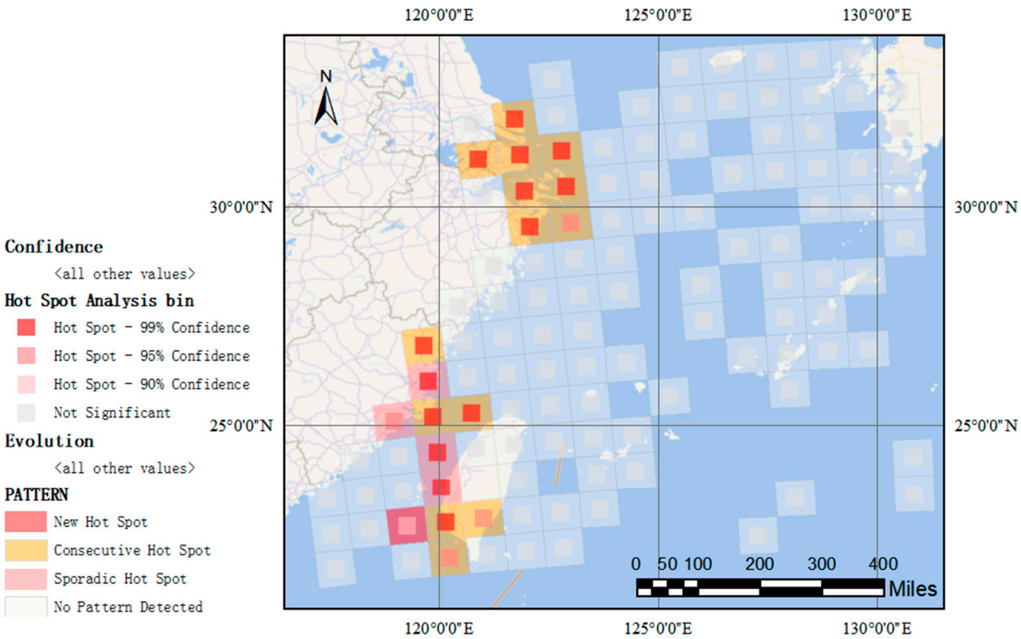


Figure 5. Results of the Space-Time Cube in the East China Sea.

The Space-Time Cube provides a visual representation of the spatial-temporal dynamics of maritime accidents. Trend attribution within this framework includes categorizing hot spot bins with varying levels of trend confidence, such as 99%, 95%, and 90%. These typical confidence values imply that the observed spatial patterns are unlikely to have occurred by chance, that is, as a result of random processes or low-probability events, thus allowing the rejection of the null hypothesis [34]. The 99% confidence will cover the true value of the maritime accident parameter 99%, allowing for a 1% chance of not capturing the true accident parameter, the same rules as for 95% and 90% confidence [36]. In this paper, "Not Significant" indicates that while an area has experienced accidents in the past, the number of accidents are not sufficient to demonstrate certain characteristics and patterns. The accident here is more likely to be a random occurrence. "New hot spot" indicates an emerging hot spot of accidents in an area in recent years. "Consecutive Hot Spot" means historically persistent hot zones of accidents till now, but this location is not always a hot spot area. "Sporadic Hot Spot" indicates that there have been hot spots historically, but they did not show continuity over time.

Upon examination of the figures, it is evident that in the Yangtze River Delta Region, there are consecutive hot spots identified along the coasts of Shanghai, Ningbo, and Zhoushan in China. Meanwhile, along the Taiwan Strait, Kaohsiung Port emerges as a new hot spot for maritime accidents, with three additional consecutive hot spots in its vicinity. Furthermore, four areas within the Taiwan Strait exhibit sporadic hot spots, all of which are located along the coast and near major ports. Three consecutive hot spots show scattered distribution. In addition, three consecutive hot spots are also observed dispersing in the central region of the strait. There is no cold spot in the East China Sea.

Figure 6 presents a three-dimensional (3D) perspective of the Space-Time Cube analysis. The three axes of the cube represent time, latitude, and longitude, respectively. Each small square within the figure signifies the annual aggregation results for various regions previously delineated, referred to as "confidence bins", which are calculated along the time axis. ArcGIS summarizes and evaluates the confidence bins that show hot spot confidence for each time axis and then derives the spatial-temporal patterns of maritime accidents within each grid, as shown in Figure 5.

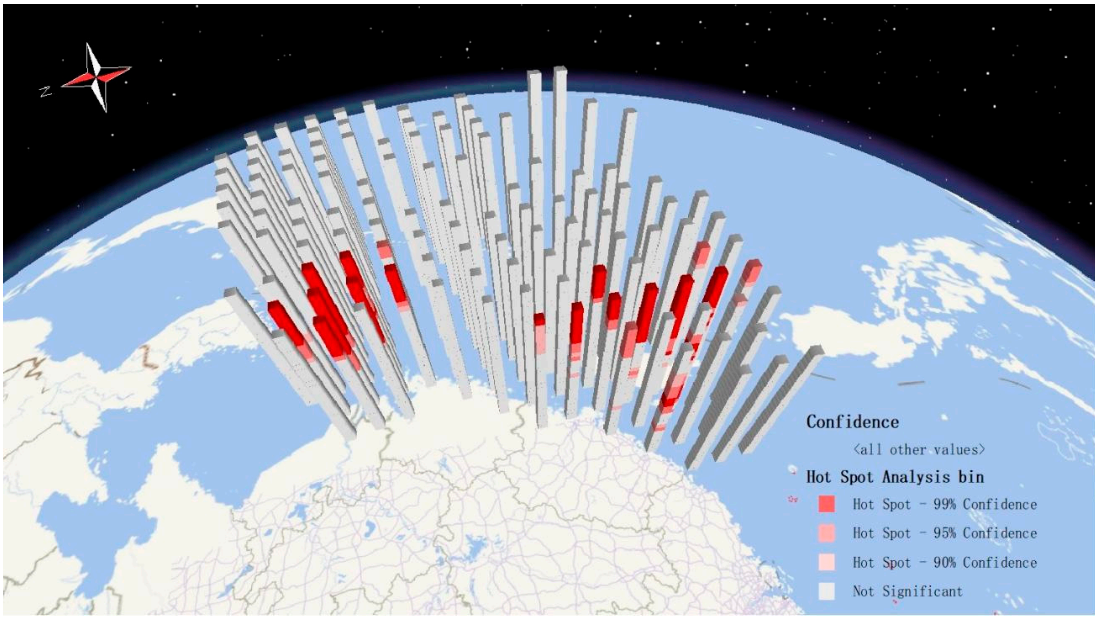


Figure 6. Space-Time Cube in 3D view.

In the Yangtze River Delta Region, confidence bins show clustering in both space and time. In the Taiwan Strait, it is observed that the confidence bins cover a large area of space, indicating a spatial dispersion of maritime accidents. However, in the southern region of Taiwan, the distribution of the confidence bins is particularly noticeable. This area is in close proximity to Kaohsiung Port. New confidence bins have appeared in the southwest in recent years. As inferred from both Figures 5 and 6, maritime accidents in this region may originate from Kaohsiung Port and subsequently spread towards the southwest.

5.2. Kernel Density Analysis in the East China Sea

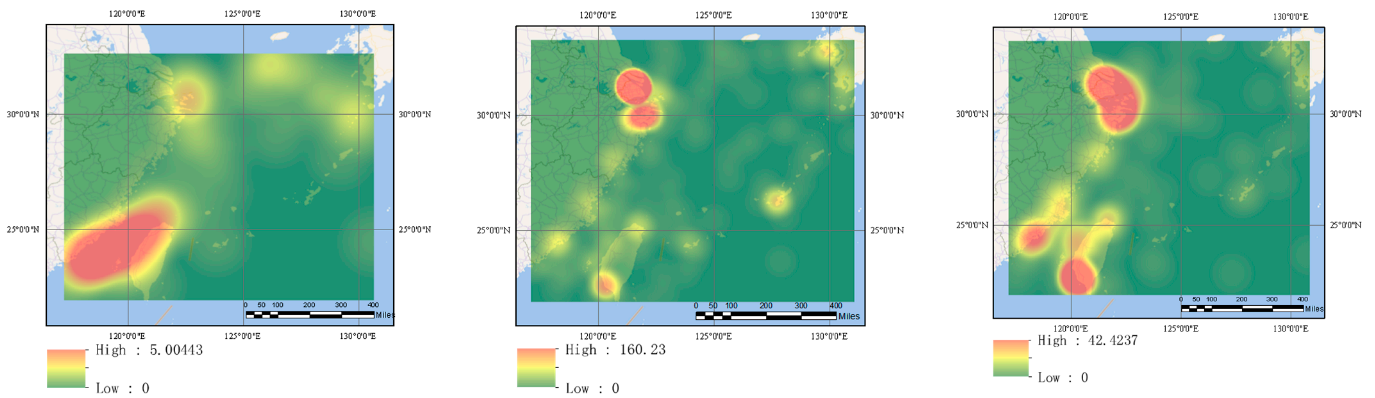
Kernel Density analysis is employed to investigate the spatial patterns within the East China Sea and serves as a validation for the findings from the Space-Time Cube analysis. It is a widely used tool to study maritime accidents. If the results of the Space-Time Cube method and the conventional Kernel Density analysis are not in conflict, this means the method proposed in this paper is reasonable. Given the substantial fluctuation in the annual number of maritime accidents, particularly the significant increase from 2001 to 2010, a straightforward temporal division has been implemented. Maritime accidents in the East China Sea are categorized into three distinct time periods.

In the 1990s, the East China Sea witnessed a relatively low total number of maritime accidents, with the highest Kernel Density value reaching 5.0044, indicating a very low clustering in this period because of small accident sample. During this decade, the Taiwan Strait exhibited a pronounced clustering of accidents, with the high-accident area encompassing nearly the entire strait. The maritime accidents during this period may not have significant reference value, not only because the total number of accidents during this time accounts for a very small proportion of the total accident data, but also because the coverage area of the hot spots in the Kernel Density picture is too broad to reflect the accurate hot spots of maritime accidents.

In the 2000s, the focal point of accident clusters shifted northward, predominantly along the coasts of Shanghai, Ningbo, and Zhoushan. The Yangtze River Delta Region is a high-accident area, with a high Kernel Density value reaching 160.2300. The apparent decline in Kernel Density intensity within the Taiwan Strait does not contradict the increase in maritime accidents in that region. The substantial rise in the overall number of maritime accidents in the East China Sea, particularly in the northern region, has led to a less pronounced aggregation of incidents in the Taiwan Strait.

Entering the 2010s, the aggregation of maritime accidents is more distinct, but the highest Kernel Density value decrease to a relatively low level recorded at 42.4237, reflecting the improved conditions in the Yangtze River Delta Region. The number of accidents in the Yangtze River Delta Region and the Taiwan Strait become similar. High-accident areas continue to be concentrated in the Yangtze River Delta. Additionally, high-accident areas have re-emerged in the vicinity of the Taiwan Strait, particularly around the Kaohsiung Port Area and the coast of Fujian Province.

Kernel Density analysis indeed offers an appealing representation of spatial distributions, yet it is not without its drawbacks. One such issue is the potential distortion caused by disparities in the number of data points. This can lead to misleading interpretations, as exemplified by Figure 7b. Despite the lack of a high-accident area in the Taiwan Strait, it does not necessarily indicate a lower incidence of accidents. The high concentration of accidents in the Yangtze River Delta Region skews the results, creating a false impression of safety in the Taiwan Strait.



(**a**) 1994 to 2000 (**b**) 2001 to 2010 (**c**) 2011 to 2020

Figure 7. Results of the Kernel Density analysis in the East China Sea.

Furthermore, the Kernel Density values exhibit significant variation across Figure 7a–c, which complicates the analysis of temporal trends. The obvious differences in these values make it challenging to draw definitive conclusions regarding the influence of time on the distribution of incidents.

6. Discussion

6.1. Verification of the Space-Time Cube

The Space-Time Cube represents an innovative tool in the analysis of marine casualties, with validation provided through Kernel Density analysis and descriptive statistical analyses. Initially, the outcomes from the Space-Time Cube successfully pass the confidence test, showing the reasonability of this tool. In the Yangtze River Delta Region, the spatial results derived from the Space-Time Cube are found to be largely consistent with the Kernel

Density analysis presented. When considering the temporal factor, it is observed that maritime accidents in the Yangtze River Delta Region began to exhibit distinct, patterned characteristics approximately 15 to 17 years ago. This observation is attributed to the majority of the confidence bins, which vertically display a red coloration that has persisted for about 15 to 17 years. These patterns started around 2006, which marks a significant year for the Yangtze River Delta Region, during which maritime accidents surged and then continued to occur with regularity.

In the Taiwan Strait, both the Space-Time Cube and Kernel Density analysis indicate that maritime accidents are predominantly concentrated along the coast of China's Fujian Province and in the vicinity of Kaohsiung Port. Regarding the temporal aspect, the Kernel Density analysis presents a challenge in drawing definitive conclusions. However, the results of the Kernel Density analysis do highlight hot spots around the Kaohsiung Port from the 2010s, a finding that is consistent with the Space-Time Cube results because of the number of confidence bins. The coast of China's Fujian Province, on the other hand, reveals a distinct yet non-contradictory pattern, which will be further elaborated upon in the subsequent discussions. In summary, the Space-Time Cube has been proven to be capable of yielding accurate conclusions and is deemed a valuable tool for use in maritime accident research.

6.2. Spatial-Temporal Evolution of Maritime Accidents

6.2.1. The Yangtze River Delta Region

Based on the findings from the Space-Time Cube and Kernel Density analysis, the evolution of maritime accidents in the Yangtze River Delta region can be delineated into three distinct phases. These phases may correlate with the actions of port authorities and the development of port infrastructure, as suggested by Cao's research in 2023 [37], which emphasized the role of port management. The first period spans from 1994 to 2005, during which time maritime accidents were more sporadic and fewer in number. This can be attributed to the relatively low volume of shipping traffic at that time, resulting in an insufficient accident base to be effectively represented by the Space-Time Cube. The second period, from 2006 to 2010, can be characterized as an anomalous phase. The pronounced increase in maritime accidents during this time reflects the impact of port development strategies. Significant growth occurred at the Shanghai Port and Ningbo-Zhoushan Port. This era also marks the onset of discernible spatial-temporal patterns in maritime accidents, as indicated by the emergence of red confidence bins, which eventually developed into successive hot spots. The third period, from 2011 to 2020, signifies a stabilization in maritime accident patterns. The low Kernel Density values and descriptive statistics indicate that the port has seemingly adapted to the increased volume of shipping traffic. However, the persistence of consecutive hot spots serves as a cautionary signal. It suggests that maritime accidents in the region retain a notable spatial-temporal aggregation effect, underscoring the need for continued vigilance in the face of heavy ship traffic.

6.2.2. The Taiwan Strait

In the Taiwan Strait, maritime accidents are primarily concentrated in two regions: the coast of Fujian and southern Taiwan. Analysis through Kernel Density analysis has revealed that there was a hot spot along the coast of China's Fujian Province from 1994 to 2000, with a resurgence observed from 2011 to 2020. However, it is suggested that the reliability of a hot spot should be reconsidered. Kernel Density analysis reflects the spatial aggregation of incidents, and a high total number of accidents may lead to the appearance of a hot spot. That means if the accidents in an area are temporally and spatially numerous and evenly distributed, this area may have exhibited as a high-accident area in

Kernel Density analysis and was curtly judged as a hot spot, yet the actual situation might not be so severe. For the time factor, the Space-Time Cube divides the accidents every one-year, which weakens the impact of time accumulation. For the space factor, Yang's research in 2022 suggests that the distribution of accident areas in the Fujian maritime region is relatively uniform [25]; the 3D results of the Space-Time Cube also demonstrated this pattern. These explain the presence of Kernel Density hot spots along the coast of Fujian Province but almost no hot spots in Space-Time Cube. In addition, the results of the Space-Time Cube show a significant number of "Not significant trend" and "Sporadic Hot Spot".

In contrast, the situation in southern Taiwan is clearer. The area has consistently shown hot spots of accidents and has exhibited continuity, with distinct persistent red confidence intervals in both space and time. It is noteworthy that a new hot spot has emerged near the port of Kaohsiung. Research by Ung in 2021 indicates that maritime accidents in Taiwan have been on an upward trend since 2013 [38]. The results of the Space-Time Cube and Kernel Density analysis in this research demonstrate hot spots since the 2010s. Yang's research in 2020 suggests that the causes of these accidents may be related to weather conditions [39].

6.2.3. Discussion on the Spatial and Temporal Evolution Patterns of Maritime Accidents

This paper investigates the distribution patterns of the maritime accidents in the East China Sea, revealing the spatial and temporal evolution characteristics of maritime accidents. The case studies of maritime accidents in the East China Sea indicate that the maritime accidents may exhibit certain patterns in both time and space, rather than being entirely random [6,26]. The discussion on the Yangtze River Delta region and the Taiwan Strait in this section implies that the evolution of the maritime accidents varies across different regions. Additional evidence is that the global accident type changed from collision to capsize because of industrial progress [40], while other research shows that collision accidents in the East Asia region have always been the most frequent due to the large cargo volume, and mechanical accidents are predominant in South America and West Africa for unexplored reasons [7]. The same principle is true for the accident causes, for example, weather factors are the main causes of accidents in Arctic waters [41], while in the Mediterranean Sea and Black Sea, the large volume of ship traffic is the main reason [16]. In summary, the spatial and temporal evolution patterns and causes of maritime accidents vary from place to place, making it difficult to summarize a systematic nature. However, there is no doubt that maritime accident patterns have correlations in both time and space. This paper provides an effective method for studying maritime accidents, which helps us to gain a detailed understanding of the temporal and spatial evolution characteristics of maritime accidents.

6.3. The Comparison Between Space-Time Cube and Kernel Density Analysis

Regarding the calculation methodology, the Kernel Density analysis, which calculates the sum of accident data, may obscure temporal patterns. This limitation is exemplified by the accident in 2006, which is not clearly delineable through Kernel Density analysis mapping. The analysis of the Space-Time Cube will be affected by the size of the database. In this study, maritime accidents in the 1990s consistently presented "Not Significance", a result that can be attributed to the limited database. Of course, a sufficient database can show certain features, and small datasets may not produce reliable overall features, as with the "Not Significance" results of the Space-Time Cube along the coast of China's Fujian Province.

The Space-Time Cube represents a pioneering approach in the analysis of maritime accidents, offering distinct advantages over traditional Kernel Density analysis. Unlike Kernel Density, which amalgamates incidents and may obscure temporal patterns, the Space-Time Cube consolidates the spatial-temporal dynamics of maritime accidents into a singular, comprehensive visualization. This method foregoes the need to segment accidents into several periods, thereby providing a more lucid depiction of their temporal evolution. Moreover, the Space-Time Cube enhances the interpretability of the time factor, overcoming certain limitations inherent in Kernel Density analysis. This is particularly evident in the Fujian coast, where the nuances of temporal patterns are critical to understanding. On the other hand, an area with few accidents is not worth further discussion from an overall perspective. The accident in the Taiwan Strait in the 1990s is a typical example.

Nevertheless, it is also important to acknowledge that the Space-Time Cube methodology has its drawbacks. One such limitation is the potential for spatial ambiguity, as the technique may blend coastal areas with adjacent landmasses in its visualizations. In such cases, Kernel Density analysis can serve as a beneficial adjunct, offering a more refined resolution of spatial data, complementing the insights provided by the Space-Time Cube.

7. Conclusions

This study constitutes the pioneering effort to evaluate maritime accidents within the East China Sea by employing the Space-Time Cube in conjunction with Kernel Density analysis. The contributions of this study are as follows:

(1) Spatial and temporal distribution characteristics of maritime accidents in the East China Sea.

The accidents in the Yangtze River Delta Region exhibit continuity totally since 2005. The Kaohsiung Port in Taiwan China merits close monitoring, for its hot spots have continued spreading towards the southwest since the 2010s. The coast of China's Fujian Province no longer qualifies as a hot spot.

(2) Reflections on the causes of spatial and temporal evolution hot spots

The persistent nature of the accident hot spots in the Yangtze River Delta region is due to the large volume of cargo traffic, which leads to an increase in the number of ships. Port management has improved the accident situation, but it remains a hot spot area. The emergence of new hot spots in the Kaohsiung Port may be related to weather changes in the Taiwan Strait. This implies that the evolution patterns and causes of spatial and temporal hot spots vary across different regions, with significant differences even in such a small area like the East China Sea. The Space-Time Cube provides a systematic framework for analyzing maritime accident hot spots, yet the causes of the spatial and temporal evolution of hot spots for specific regions still require dedicated research and discussion.

This paper provides a detailed explanation of the spatial and temporal characteristics of maritime accidents in the East China Sea and offers an effective method for studying such incidents. This will assist governments, businesses, and other stakeholders in enhancing maritime safety levels.

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