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A 10-year analysis of the global maritime accidents: from a spatial and temporal perspective

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Maritime accidents pose challenges to global shipping safety, affecting human lives and economic activities. Hotspot identification and analysis of maritime accidents is crucial for accident prevention, as it enables the identification of high-risk areas and supports targeted safety interventions. However, accurately pinpointing high-risk areas and implementing effective safety measures remain persistent challenges for the maritime industry worldwide. Based on the global ship accident data from 2013 to 2022, this study aims to employ advanced analytical techniques including Kernel Density Estimation (KDE) and Emerging Hot Spot Analysis (EHA) to identify maritime accident hotspots. The KDE method, which does not consider the temporal dimension, is used to explore the spatial distribution characteristics of ship accidents in two dimensions. In contrast, the GIS-based three-dimensional spatiotemporal analysis method (i.e., emerging hot spot analysis) considers both spatial and temporal factors, allowing for a dynamic analysis of the spatiotemporal evolution of hot spots. The combination of KDE and EHA enables a comprehensive analysis of accident hotspots. The results reveal that the Europe, the English Channel, and the Strait of Malacca have consistently been accident hotspot regions. Additionally, the Mediterranean, the Singapore Strait, and the waters around China and Japan are areas where shipping accidents have continued to emerge as significant safety concerns. These regions have been identified as requiring particular attention regarding maritime safety management. Bases on EHA, this study also provides a detailed classification of hotspot patterns, enabling a comprehensive understanding of the spatio-temporal evolution of these accidents. Moreover, the study highlights the importance of implementing precise, region-specific safety interventions to proactively prevent accidents and enhance overall maritime safety.

Keywords: Kernel Density Estimation, Emerging Hot Spot Analysis, Maritime Safety, GIS.

1. Introduction

The high incidence of maritime accidents poses a challenge to the safety, security of life and economic activities of shipping worldwide. According to the European Maritime Safety Agency (EMSA, 2024), a total of 2676 maritime casualties and other accidents were reported in 2023, which is an increase of 49 compared to 2022. As the shipping industry grows, so does the number of maritime accidents. In recent years, statistical analysis of ship accident data and risk assessment studies have shown an upward trend in accident frequency (Eliopoulou et al., 2016). More precise identification of accident hotspot areas has been made possible by combined temporal and spatial analysis methods such as Kernel Density Estimation (KDE) and Emerging Hot Spot Analysis (EHA) (Acharya et al., 2017; Zhang et al., 2021). These techniques not only reveal static spatial patterns, but also capture the temporal evolutionary trends of hotspot areas, providing data support for the development of maritime safety management measures.

Current studies show that the characteristics of hotspot areas are often closely related to the traffic density of the waterway, meteorological conditions and economic activities in the region. For example, regions such as the Mediterranean Sea, the North Sea and the Strait of Malacca have a high accident frequency due to intensive shipping activities and complex geographic conditions (Wang et al., 2022). In addition, these hotspot regions simultaneously reflect the need to focus on human operational errors and equipment failures, etc. in maritime safety management (Hashimoto et al., 2016). In addition, the spatial maritime risk analysis method based on the Discrete Global Grid System (DGGS) can effectively identify high-risk areas on a global scale and provide support for maritime decision-making (Rawson et al., 2022).

This paper takes the global maritime accident data from 2013 to 2022 as the research basis, and combines the KDE and EHA analysis methods to analyze the temporal and spatial characteristics of global maritime vessel accidents, so as to provide a theoretical basis for the assessment of the risk of maritime vessel navigation and improve the ability of maritime traffic safety and security.

2. Data and method

2.1. *Data*

The global maritime accident data was obtained from Lloyd's List Intelligence and the original dataset contained 28 fields. After screening and cleaning to remove data irrelevant or unusable for this study, a total of 29131 valid accident records were obtained, and the dataset contains eight fields, namely, accident longitude, latitude, time (year/month/day), type of incident, age of the vessel, number of accidental number of deaths and missing persons, number of injuries, and total number of casualties describing the incident and the vessel's relevant information. These data provide a basis for analyzing the spatial and temporal distribution characteristics of maritime accidents.

The latitude and longitude data of the accidents in this study are in degree-partitioned format, for example, 37° 55' 59" N and 23° 37' 59" E, corresponding to the ArcGIS standardized coordinate format of +37.9331 and +23.6331, and all data formats are converted to locate the accident points on the map base layer of ArcGIS in order to obtain the global distribution map of maritime accidents.

2.2. *Kernel Density Analysis*

Kernel Density Estimation (KDE) has been widely used in the analysis of transportation accidents, and in this study, kernel density analysis is used to reveal the spatial distribution characteristics and risk areas of maritime accidents (Hashimoto et al., 2016). Kernel density estimation (KDE) is a nonparametric method designed to estimate the probability density function of a random variable and solve the problem of poor performance of parametric estimation results. Unlike traditional parametric estimation methods, KDE does not require assumptions about the density function of the dataset; KDE is based directly on the data itself, thus reflecting more accurately the actual distribution of the data (Zhang et al., 2021). The advantage of this method is that it characterizes the distribution of accident risk and can avoid estimation bias due to inaccurate parameter assumptions. The mathematical expression for kernel density estimation (KDE) is as follows (Anderson, 2009):

$$f(x, y) = \frac{1}{nh^2} \sum_{i=1}^{n} K\left(\frac{d_i}{h}\right) \tag{1}$$

where $f(x, y)$ is the estimated density at location (x, y); n denotes the number of locations, h denotes the bandwidth, K denotes the kernel function, and d_i denotes the distance from location (x, y) to the ith location. In this paper, the kernel density estimation method is used to visualize the spatial hotspot distributions of different accident factors for ships at sea for the period from 2013 to 2022.

2.3. *Emerging Spatiotemporal Hot Spot Analysis*

Emerging Spatiotemporal Hot Spot Analysis (EHSA) is an analytical technique based on the Getis-Ord Gi* spatial statistical method, designed to identify the spatial distribution characteristics of variable data. It calculates the average value (local mean) for a single bin and the spatiotemporal neighborhoods of the bin, then compares it with the global average to determine the "hotspot" and "coldspot" regions (Cuba et al., 2022). The goal of analyzing emerging hot and cold spots is to identify trends in the data, such as detecting new hot (cold) spots, consecutive hot (cold) spots, and intensifying hot (cold) spots (Zhao et al., 2024). The Mann-Kendall trend test is used to assess the trends of hot and cold spots.

First, spatio-temporal cubes were created by aggregating points, setting the time step to 1 year and analyzing the neighborhood distances using the default hotspots of ArcGIS Pro in order to generate the corresponding bar columns (Cheng et al., 2018). Subsequently, the Getis-Ord G* statistic is computed for each cube in the spatio-temporal cube. In this process, the local Gi* statistic generates trend z-scores and p-values as well as hotspot z-scores and p-values for each bar-column based on the location of each containing data, with statistically significant hotspots having higher z-scores and smaller p-values. Conversely, higher negative z-scores and smaller p-values indicate significant cold spots. The function of the Getis-Ord Gi* statistic is shown below (Xu et al., 2021):

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

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (3)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\bar{X}\right)^2} \quad (4)$$

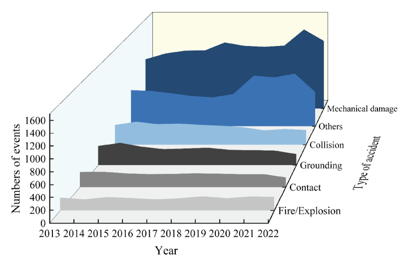
where x_j is the observed value of cell j, X is the global mean, S is the global standard deviation, $w_{i,j}$ is the weight matrix, and n is the total number of cells.

3. Results

3.1. *Temporal characteristics of global ship accidents*

Based on the global maritime accident data, the temporal characteristics of ship accidents are analyzed. The distribution of the six types of accidents by year and month is shown in Fig. 1.The number of accidents of ship mechanical damage shows a rising trend from 2013 to 2022, with an average number of accidents per year of 1182.The number of collision accidents stays relatively stable from 2013 to 2022, with an average number of accidents per year of 336, and the probable causes of accidents are failure to keep regular lookout, failure to take collision avoidance measures and failure to navigate at a safe speed. causes are failure to maintain a formal lookout, failure to take effective collision avoidance measures, failure to navigate at a safe speed, and ultimately the determining factor in accidents is the human factor. The number of groundings, contact and fires/explosions shows a relatively small trend and is generally stable, with an average annual number of accidents of 282, 219 and 199, respectively, while the number of accidents of the "Other" type starts to rise sharply in 2017, reaches a peak in 2021, and then declines significantly, with an average annual number of accidents of 696. The volatility of "Other" accidents implies increased uncertainty in the shipping environment. Overall, the distribution of accidents is relatively even across the months of the year, but specific periods, such as the summer (June-August) and the end of the year (November-December), show a slight increase in the number of accidents, which calls for enhanced safety management during high-risk periods.

Fig.2.shows the distribution of the different initial events leading to global maritime accidents from 2013 to 2022, with the most common initial events being mechanical failure, collision, and grounding, accounting for 40.56%, 11.52%, and 9.67%, respectively. In addition, factors such as sinking, hull damage (perforation, cracks, structural failure), missing/overdue, arrest/seizure, etc. are categorized as "other", accounting for 23.9%, which reflects the diversified trend of maritime accidents, and should be paid attention to this type of "other" accidents when researching the types of major accidents. When studying the types of major accidents, attention should also be



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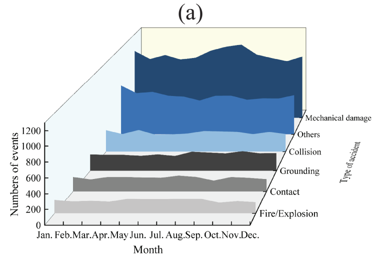


(b)

Fig. 1. Distribution of accident types: (a) by year (b) by month.

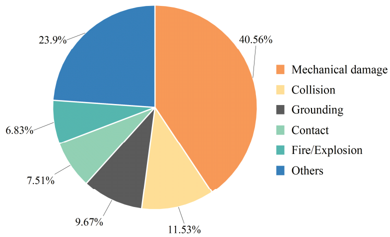


Fig. 2. Global distribution of initial events at sea.

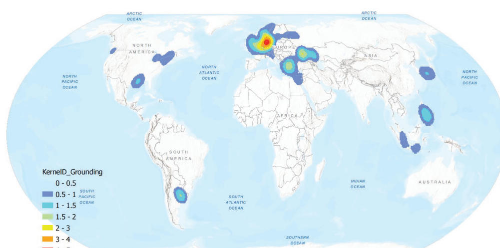
paid to these types of "other" accidents in order to comprehensively assess the risk of maritime accidents (Ventikos et al., 2018).

3.2. *Spatial characteristics of global ship accidents*

In this study, the ArcGIS online map-Terrain with Labels was used as the map base layer, and the processed accident data were imported to obtain the global distribution map of maritime accidents from 2013 to 2022.

3.2.1. *Kernel density estimation analysis*

Kernel density analysis was used to visualize the initial event distribution of global maritime accidents, as shown in Fig. 3. The kernel density level is classified into seven levels, with darker colored regions indicating denser accidents. The unit of measurement is "points per square degree", where "point" represents the location of the maritime accident and "square degree" refers to the area of each 1° x 1° area in the geographical coordinate system. Points per square degree" represents the location of an accident at sea, and 'square degrees' refers to the area of a 1° x 1° area in the geographic coordinate system. The results of the kernel density analysis indicate the number of accidents per 1° x 1° geographic area, by which the spatial distribution of maritime accidents is demonstrated and areas with a high frequency of accidents are identified. In Fig. 3(a), the highest density of grounding accidents is found in narrow straits and coastal zones like the English Channel, North Sea, Skagerrak, Baltic Sea, and Mediterranean, areas with complex shipping routes, drastic water depth changes, and high traffic. In Fig. 3 (b), fire/explosion accidents are most concentrated around the English Channel, North Sea, Ionian Sea, Aegean Sea, and Black Sea, typically linked to hazardous material transport in trade-intensive regions. In Fig. 3 (c), mechanical failures occur frequently in high-density areas such as the Skagerrak, Irish Sea, English Channel, and Aegean Sea, and the waters off Shanghai and Japan are also accident-prone areas. Mechanical damage are often related to aging equipment and inadequate maintenance on older ships. In Fig. 3 (d), the area with the highest density of touch-and-go accidents is located in the Skagerrak, followed by the Baltic Sea, the Aegean Sea, the St. Lawrence River and the Strait of Georgia, and the area with a lower density of accidents is located in the Sea of Marmara, the Singapore Straits, and the sea area near Japan. These hotspot areas are usually characterized by the presence of topographic features such as reefs and shoals. In Fig. 3(e), the concentration of collisions is reflected in the Singapore Strait, the Malacca Strait, the waters off Hong Kong, China, the Taiwan Strait, the waters off Japan, the Korea Strait, the waters off Shanghai and Ningbo. Most of the collisions occurred in the area of shipping lanes with very high vessel traffic. The Singapore Strait and the Malacca Strait are the busiest shipping lanes in the world, with extremely high ship densities and narrow shipping lanes, increasing the risk of collision. In Fig. 3 (f), the "other" accident types show a dispersed pattern, particularly in the Gulf of Guinea, the Aegean Sea, the North Sea, the English Channel, the Singapore Strait and the Malacca Strait.



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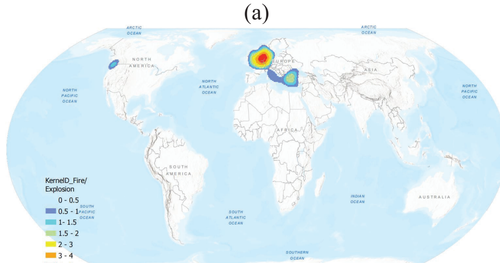

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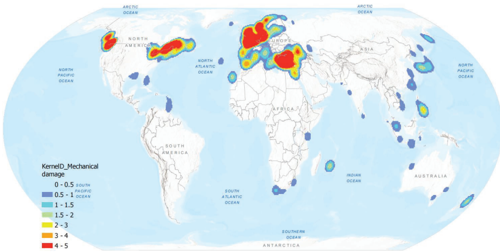

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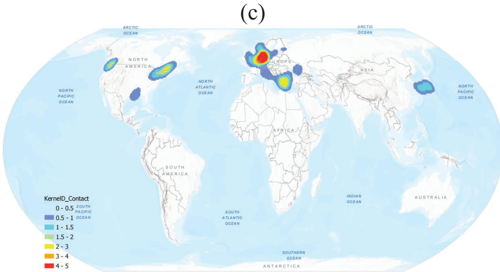

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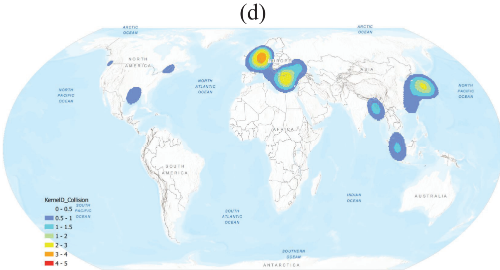

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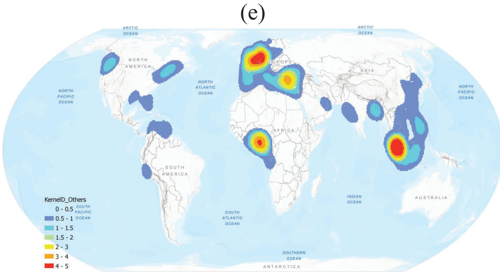
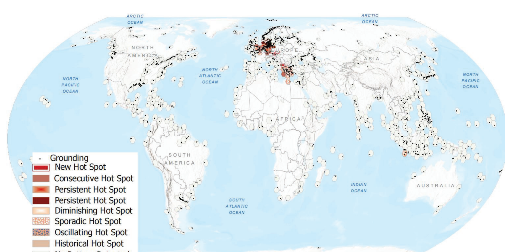


(f)

Fig. 3. KDE results for marine accidents: (a) Grounding (b) Fire/Explosion (c) Mechanical damage (d) Contact (e) Collision (f) Others.

3.2.2. *Emerging Hot Spots Analysis*

The results of the spatio-temporal hotspot analysis of global ship accidents are shown in Fig. 4. Warm colors represent high-frequency areas of accidents, indicating that these areas are high-risk zones for maritime accidents. The cold color represents the lower frequency areas of accidents, and no accident cold spots appear in the figure, indicating that the study mainly focuses on the high-frequency areas of accidents. In addition, the emerging spatio-temporal analysis method is used to identify accident hotspots and classifications, and compared with the nuclear density results, with the aim of using different analysis methods to reveal the accident distribution patterns and trends. In Fig. 4(a), continuous hotspots for stranding accidents are found in the English Channel, Strait of Dover, and western European waters, with enhanced hotspots in the southern North Sea and Rhine River. In Fig. 4(b), fire/explosion hotspots extend to southern European seas, with continuous hotspots in western European seas and the Mediterranean. The southern European waters, being key energy transport routes, are particularly hazardous due to oil and chemical shipments. In Fig. 4(c), mechanical failures are concentrated in the North Sea, English Channel, and North American waters, with persistent hotspots around southern European waters, especially the Strait of Istanbul. These are often linked to aging equipment and poor maintenance in high-traffic regions. Fig. 4(d) shows the Baltic Sea as a continuous hotspot for touch-and-go accidents, with intensified hotspots in the Skagerrak and scattered hotspots in the English Channel. Fig. 4(e) highlights collision hotspots in the Baltic Sea and waters near Japan, with the English Channel and Cretan Sea also showing dispersed incidents. Collisions are mainly caused by narrow channels, high vessel traffic, and operational errors. In Fig. 4(f), the continuous hotspot areas are in Northwest Europe, Singapore Strait, and Malacca Strait, with decentralized hotspots in the North Sea, Aegean Sea, and Malaysia's waters. These areas are the accident areas that ships at sea need to focus on in recent years. In order to reduce the risk of accidents, ships should avoid routes to these high-risk areas as much as possible during route planning, or when ships are traveling to the area, they should remind crews in a timely manner of the high rate of accidents in the area and the need to drive with caution.



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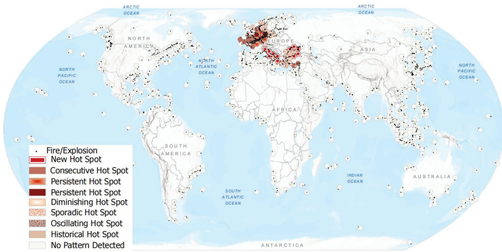

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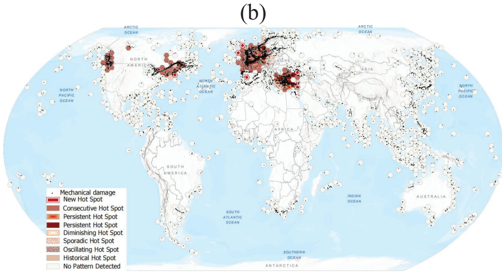

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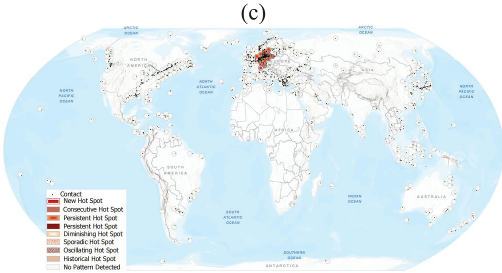

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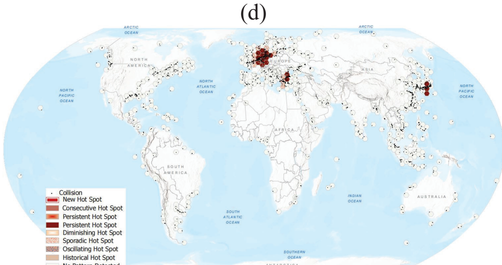

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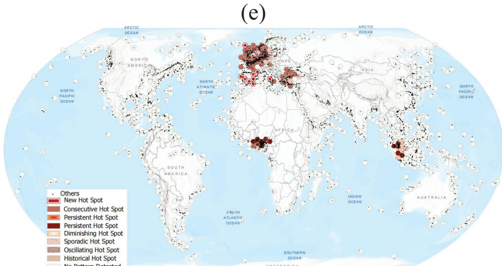

(f)

Fig. 4. Results of hotspot analysis of marine accidents: (a) Grounding (b) Fire/Explosion (c) Mechanical damage (d) Contact (e) Collision (f) Others.

3.3.*Spatial and temporal characteristics of global ship accidents*

In order to reveal the spatial and temporal trends of global maritime accidents from 2013 to 2022, this paper adopts the emerging spatial and temporal hotspot analysis combined with three-dimensional visualization method to analyze the representative accident types of collision accidents for the following main reasons: collision accidents are closely related to high-density shipping activities, have obvious regional distribution characteristics and strong spatial dependence, and are more frequent in busy shipping lanes and crowded port areas. As shown in Fig. 5, the three-dimensional bar chart shows the hotspot regional trends of global collisions in a dynamic way by combining time and space. A persistent hotspot (indicated by a red fill) indicates a hotspot that persists as a hotspot for 90% of the time-step intervals studied, with no change in significance (Gudes et al., 2017). Each cube in a bar represents one year. For example, to view the dispersal hotspots (highlighted with blue circles), it is clear that they presented as hotspots in 2014-2015 (the 2nd and 3rd smallest cubes from the bottom), but then became non-significant, significant again in 2017-2019, then non-significant again, and significant again in 2021-2022. Therefore, these were categorized as decentralized hotspots. Overall, based on the spatio-temporal analysis, the persistent hotspots and dispersed hotspot areas then show the distribution of risk on emerging routes in shipping over the 10 years of the study, providing important support for future safety management policies.

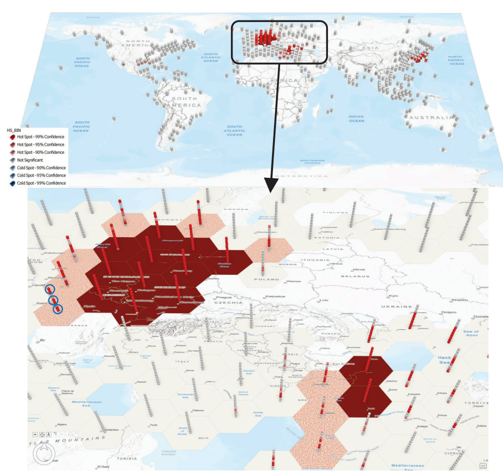

Fig. 5. Spatial and temporal hotspots of collisions at sea: 2013-2022.

4. Discussion

In summary, the hotspots of the six initial accidents are mainly concentrated in Europe, the English Channel, North America, the Mediterranean Sea, the Aegean Sea, the waters around China and Japan, the Singapore Strait and the Malacca Strait, and the reasons for the regional concentration of accidents are as follows: (1) Europe is an important hub for global shipping and a key node in the global supply chain industry. The European coastal region is dotted with busy maritime ports with frequent ship entries and exits, and the ship berthing and departure process is prone to accidents (Giannousopoulou et al., 2023).

(2) The St. Lawrence Seaway, the Strait of Georgia and other important shipping lanes, as key waterways connecting the east coast of North America with the international shipping network, are characterized by dense ship traffic, narrow shipping lanes, overloaded transportation, and severe congestion in the shipping lanes, resulting in accident-prone areas.

(3) The Mediterranean Sea and the Aegean Sea area, as an important water area connecting Europe, Asia and Africa, has a highly developed shipping industry, dense shipping routes, and large ship traffic, which makes it easy for collision and grounding accidents to occur (Wang et al., 2022).

(4) The coasts of China and Japan, as hot spots of accidents, especially the ports of Shanghai, Ningbo and Tokyo, are characterized by high ship traffic and dense shipping lanes. Secondly, extreme weather phenomena such as typhoons, heavy rains, strong winds and high waves are frequent in the area.

(5) The Straits of Malacca and Singapore are narrow channels with limited space for ships to navigate. In addition, the frequent occurrence of piracy, robbery and maritime crime in the waters of the Straits of Malacca poses a threat to the safety of navigation.

The study reveals the characteristics of the spatial and temporal distribution of accidents in different regions, in particular the trends in the long-term risk distribution in hotspot regions such as Europe, the English Channel and the Mediterranean Sea. However, the results of the study are also affected by several limitations that deserve further discussion.

This study is based on global maritime accident data from 2013-2022, but underreporting may exist in certain regions, especially in developing countries or small port areas, where the completeness and accuracy of accident reporting is compromised (Hassel et al., 2011; Goerlandt et al., 2017). The current analysis mainly focuses on the distribution of the number of accidents without considering the severity of the accidents (e.g., number of casualties, economic losses, etc.). For example, the number of accidents in certain sea areas is low, but the severity of accidents may be higher, which requires different safety management strategies (Zhang et al., 2022). In addition, the effect of traffic density on accidents was not considered in this study. High traffic density areas tend to be more prone to accidents (Acharya et al., 2022), and analyzing traffic density data in combination with accident data may reveal new accident hotspot areas.

Future research can further combine this information to explore the diversity of accident causes and construct dynamic risk prediction models with climate change and other factors to provide decision support for safety management in high-risk areas.

5. Conclusions

Improving maritime safety is essential to facilitate global economic and trade development. In this study, we develop a new framework to examine the evolutionary patterns of global maritime accidents from 2013 to 2022. The results show an upward trend in machinery damage accidents, while collisions are relatively stable, suggesting that older ship equipment and inadequate maintenance may be the main risk factors. In addition, the high incidence of accidents during the summer months and at the end of the year suggests that increased seasonal activity is associated with an increased risk of accidents. Spatially, the high accident areas are concentrated in busy shipping lanes such as the English Channel, the North Sea, and the Malacca Strait, which are accident hotspots due to complex channel conditions and high traffic density. The study also found that accident hotspots changed over time, such as the increase in “other” types of accidents after 2017, reflecting rising uncertainty in the shipping environment.

In addition, the results analyzed in this study indicate that the distribution of accidents has a significant spatial and temporal clustering. Future maritime safety management should pay more attention to the construction of dynamic monitoring and early warning systems in order to assess accident risks in real time and take timely intervention measures.

Acknowledgement

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