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GIS-based analysis on the spatial patterns of global maritime accidents

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ABSTRACT

Based on the global maritime accident data from 2010 to 2019, density analysis and clustering analysis have been used to analyse the spatial patterns of maritime accidents in terms of accident frequency and severity. The North Sea, the Baltic Sea and the Mediterranean Sea form low severity accident clustering. More than 60% accidents are found within the sea areas less than 30 nm to the coastline. As to the spatial characteristics of maritime accident severity, the coastal waters surrounding China, Japan, South Korea, Vietnam and the Philippines, the Singapore-Malacca Strait and the Bay of Biscay form high severity accident clustering. The North Sea, the Baltic Sea and the Mediterranean Sea form low severity accident clustering in the clustering analysis although they have medium and high densities of accident severity in the density analysis. Almost 60% of serious accidents and very serious accidents are found within 30 nm to the coastline. The comparison of the results of density analysis and clustering analysis indicate that the latter can provide more abundant spatial characteristic information, while the former is superior in terms of simplicity and computational efficiency. This study provides useful information to assist the relevant maritime authorities in improving maritime traffic management.

1. Introduction

According to the statistics of the United Nations Conference on Trade and Development (UNCTAD, 2019), the global seaborne trade volume in 2018 was 11 billion tons, accounting for 80%–90% of the world's total merchandize trade. However, with the increasing prosperity of the shipping industry, the number of maritime accidents remains high (Hassel et al., 2011; Jiang, 2020; Zhang et al., 2019). According to Allianz Global Corporate & Specialty's *Safety and Shipping Review 2020* (AGCS, 2020), 2,815 shipping casualties or incidents were reported in 2019, up 5% year-on-year. The *Annual Overview of Marine Casualties and Incidents* published by European Maritime Safety Agency EMSA (2019) also indicates an average of 3,239 marine casualties or incidents per year during the 2011–2018 period. The influences of maritime accidents, such as the sinking of M.V. Grande America (Ivorra et al., 2019) and the explosion and sinking of M.T. Sanchi (MSA, 2018), could be high in terms of loss of life and property and damage to the marine environment. Therefore, much research has been conducted on the analysis of maritime accidents, which can provide effective and reliable information for decision makers to take effective measures to reduce the probability of maritime accidents.

In general, most of the research on maritime accidents focuses on the number (Bye and Almklov, 2019; Hassel et al., 2011; Psarros et al., 2010), the consequences (Park et al., 2019; Weng et al., 2018), or the risk assessment (Antão and Soares, 2019; Fan et al., 2020; Goerlandt and Montewka, 2015) of accidents, while the research on the spatial distribution of maritime accidents is relatively rare. An in-depth study of the spatial distribution of maritime accidents will help maritime authorities to more intuitively understand the traffic safety conditions of ships within their jurisdiction and take targeted measures to improve navigational safety. The research methods of the spatial distribution characteristics of maritime accidents mainly include the traditional data statistical analysis and the spatial analysis based on Geographic Information System (GIS). The former determines the sea areas where maritime accidents occur frequently by statistical analysis according to the accident locations in the collected accident information, while the latter presents accidents visually on the map through GIS technology and analyses their spatial distribution characteristics (*e.g.* spatial

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relationships among different accidents) by means of spatial analysis from different perspectives.

This study utilizes 3,484 accident records from the Global Integrated Shipping Information System (GISIS) to analyse the spatial patterns of maritime accidents by a new framework of combining density analysis and clustering analysis in terms of accident frequency and severity. The remainder of the study is structured as follows. Section 2 provides a brief review of the past research and analyses the research gaps. Section 3 introduces the spatial analysis methods proposed to use in this study. Section 4 introduces the data sources and makes necessary pre-processing of the data. The results of the spatial analysis of the world-wide maritime accidents are presented in Section 5 with brief discussions. Section 6, finally, summarizes the conclusions with recommendations for further research.

2. Literature review

GIS is an emerging spatial data processing and analysis technology, which is based on geographic information and adopts the method of geographic model analysis to provide the spatial relationship between objects, and serves for geographic research and geographic decision-making (Maguire, 1991). GIS has been widely used in resource exploration (Ahmad et al., 2020; Nguyen et al., 2020), environment assessment (Parlato et al., 2020; Singh, 2019), transportation (Goralski and Gold, 2007; Hu et al., 2020), agricultural land availability assessment (Ahmad et al., 2020; Pilehforooshha et al., 2014), urban planning (Badach et al., 2020; Terh and Cao, 2018) and many other fields (Valiente et al., 2020; Wang et al., 2019).

In the field of maritime affairs, GIS was first applied to maritime spatial planning and management (Castro-Santos et al., 2020; Stelzenmüller et al., 2010; Van Zuidam et al., 1998) and oil spill monitoring and management (Fustes et al., 2014; Kulawiak et al., 2010; Martin et al., 2004). Some studies (Jiang et al., 2012; Martin et al., 2004) were also carried out on the development of a GIS-based decision support system for chemical pollutant emissions generated by maritime traffic. Moreover, GIS is also widely used for the monitoring of marine ecosystems (Furlan et al., 2020; Guzman et al., 2020; Mazaris, 2017) and fishing activities (Perzia et al., 2016; Stelzenmüller et al., 2008).

In the maritime traffic sector, the application of GIS in the support of maritime surveillance can provide the typical trajectory information of ships along the main traffic routes, thus some studies were carried out to identify ship behaviours by visualizing ship trajectory by GIS. Tsou (2010) explored the visualization of ship trajectory and density maps in ArcGIS by integrating GIS and datamining in the analysis of AIS data. Vettor and Guedes Soares (2017) studied the coastal maritime traffic patterns in the main European coastal traffic routes and identified the sea areas with high traffic density. Wu et al. (2015) analysed the effectiveness of maritime safety control along the Yangtze River by incorporating spatial sequential frontiers and grey relational analysis. In the study of Rong et al. (2020), a data mining approach was developed to determine shipping route characteristics and detect anomalies of ships. Applying the GIS technology to identify past shipping route patterns and their changes was also conducted in many studies (Giguère et al., 2017; Gustas and Supernant, 2017; Leidwanger, 2013).

Many studies were conducted to evaluate and map maritime transportation risk by using GIS technology. Zhou et al. (2020) developed a spatial fuzzy multi-criteria evaluation method and applied it to maritime transportation risk assessment and mapping in the South China Sea. In the study of Zhen et al. (2017), encountering vessels were grouped by Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and the real-time multi-vessel collision risk assessment and ranking were conducted based on AIS data analysis. Wang et al. (2014) analysed the spatial variation of shipping route risk using a fuzzy analytic hierarchy process method. Zhang et al. (2019) produced shipping risk maps using the navigation risk assessment method based on grey relational theory. The encountering probabilities of ships in the Strait of Istanbul were calculated and mapped in the study of Altan and Otay (2018). Wang et al. (2013) and Liu et al. (2020) conducted spatial-temporal forensic analysis for ship collisions in different waterways. Zhang et al. (2016) and Hoque et al. (2019) also developed different models that can be used to map shipping risks through spatial analysis.

Since GIS is an appropriate tool for portraying accident data and analysing hot spots, it has also been used for maritime accident analysis. Compared with the research on the application of GIS in road accident analysis (Erdogan, 2009; Hu et al., 2020; Ouni and Belloumi, 2018), the research on the application of GIS in maritime accident analysis is relatively limited. Dobbins and Abkowitz (2002) used GIS technology to identify the locations of inland river ship accidents in the United States, and analysed the causes and consequences of the accidents based on the information of satellite images. Huang et al. (2013) established a GIS-based framework for the analysis of marine traffic accidents, and analysed the hot spots of marine accidents by clustering analysis and buffer analysis. Uddin et al. (2017) identified the most vulnerable locations and waterway routes for waterway accidents in the inland waterways of Bangladesh by GIS technology on the basis of accident frequencies. Mao et al. (2011) explored the application of GIS in the identification and visualization of hazardous locations along middle reach area of the Yangtze River, and analysed the relationship between the spatial patterns and severity of accidents. Uğurlu et al. (2013) applied GIS to calculate the marine accident concentrations and determine the highest risk sea areas. Mou et al. (2019) demonstrated the spatial patterns of accidents that happened in western Shenzhen port from 2003 to 2015 and proposed a framework for risk evaluation of busy waterways.

Though the above studies on GIS-based spatial analysis of maritime accidents have made beneficial exploration in the processing methods of accident data, there are still research gaps to be filled. First, most of the above studies were confined to the spatial analysis of accidents in the inland waterways or in a specific port area; the spatial analysis of maritime accidents from a global perspective were particularly rare Huang et al. (2013). Second, these studies only made a preliminary analysis of the spatial distribution of maritime accidents in terms of the number and location of maritime accidents, without taking into account the factors of ship traffic density and the severity of maritime accidents. Actually, accidents that cause serious casualties or severe maritime pollution often become the focus of attention of maritime authorities and society. Last but not least, few studies were conducted to cluster the maritime accidents on the global scale and compare the spatial patterns of maritime accidents that occurred in different sea areas, nor was the comparative study on density analysis and clustering analysis conducted in the spatial analysis of maritime accidents.

3. Objectives and contributions

The objective of this study is to propose a new framework of combining density analysis and clustering analysis to analyse the spatial patterns of maritime accidents in terms of accident frequency and severity. The contributions of this study are two-fold. First, the proposed framework could provide a rational and applicable approach to the spatial analysis of maritime accidents, which provides a clear demonstration on the efficiency of spatial analysis techniques in discovering spatial patterns in maritime accident datasets. In addition, the results of the clustering analysis can provide more abundant spatial characteristic information of maritime accidents, such as the accident severity spatial patterns, which the traditional data statistical analysis cannot achieve. Another contribution of this study is that the spatial patterns of global maritime accidents could be intuitively presented with a good accuracy, and a number of maritime-accident-prone regions and sea areas with higher accident severity, as well as the accident rates in coastal areas, could be identified, which will support effective maritime management by international and regional authorities and ultimately improves the global maritime traffic safety.

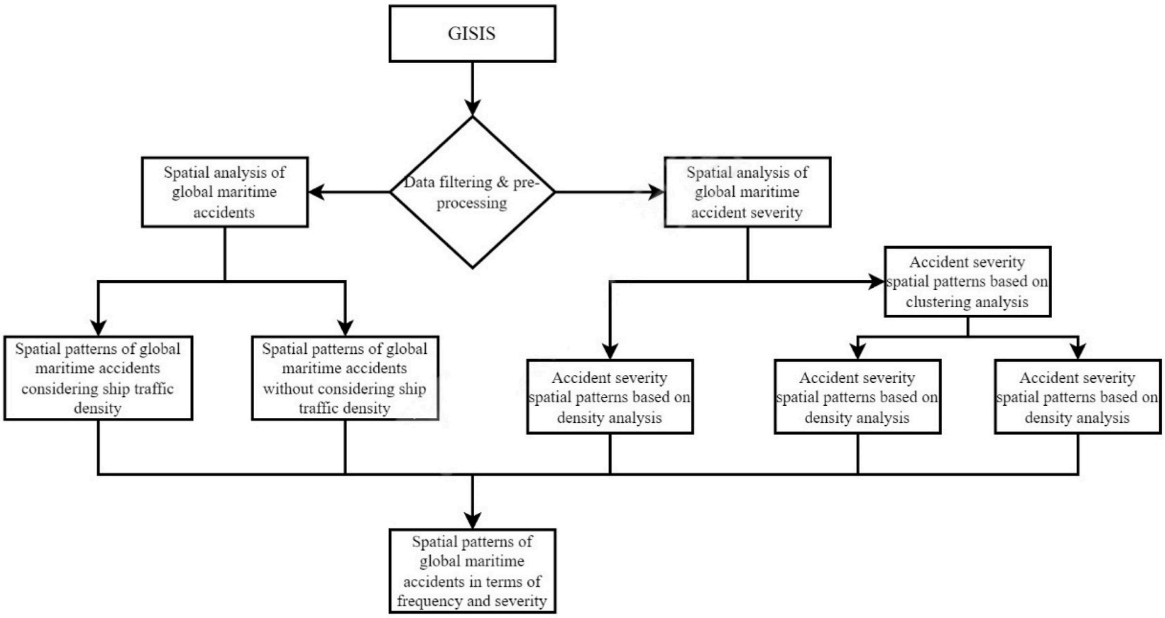


Fig. 1. The structure of the proposed framework.

4. Methodology and data

This study collects and pre-processes the global maritime accident records from GISIS, and imports them into ArcGIS for spatial pattern analysis; identifies the accident-prone sea areas in the world utilizing the point density analysis method with and without considering ship traffic density; identifies the sea areas with higher accident severity by density analysis and two clustering methods, hot spot analysis and outlier analysis respectively, and subsequently analyses and compares the results obtained. The structure of the proposed framework is illustrated in Fig. 1.

4.1. Density analysis

4.1.1. Point density analysis

The principle of point density analysis is to calculate the number of data points within a unit area range (Huang et al., 2013). The neighbourhood method is one of the most widely used density calculation methods in GIS software. A neighbourhood is defined as a circular, rectangular, or other shapes around the centre of each grid. The density of the point element is obtained by adding the number of points in the neighbourhood and then dividing it by the area of the neighbourhood. In this study, the world is divided into a number of small square cells with side length d, the density of maritime accidents of cell k is $D_k^{accident}$, and D_k^{ship} represents for the ship traffic density. Setting the neighbourhood radius as ρ, $N_k(\rho)$ is the number of accidents within the scope of a circle whose centre is the centre of cell k and whose neighbourhood radius is ρ. The accident density of cell k can be calculated by the following formula:

$$D_k^{accident} = N_k(\rho) \Big/ \left(\pi\rho^2\right) \tag{1}$$

The density of each cell can be calculated and the accident density distribution obtained. Considering the influence of ship traffic density, the density of maritime accidents per unit sea area within a certain period of time cannot fully reflect the frequency of accidents in the sea area. Therefore, it is necessary to calculate the relative accident density, which is defined as the ratio between the accident density $D_k^{accident}$ and the ship traffic density D_k^{ship}. The relative accident density $D_k^{relative}$ can be calculated as follows:

$$D_k^{relative} = D_k^{accident} \Big/ D_k^{ship} \tag{2}$$

Considering that accident severity is one of the important aspects of accident analysis, the accident severity is taken as the weight of each accident in this study in order to obtain more abundant density information. Then, the spatial characteristics of the severity of maritime accidents can be obtained by density analysis. If the severity of the l-th accident within the neighbourhood of cell k (detailed definition of accident severity is given in Section 4.3.1 of this study) is x_l, $l = 1, 2, \cdots, N_k(\rho)$, then the accident severity density, $D_k^{severity}$ of cell k is:

$$D_k^{severity} = \sum_{l=1}^{N_k(\rho)} \frac{x_l}{\pi\rho^2} \tag{3}$$

4.1.2. Buffer analysis

Buffer analysis (Huang et al., 2013) is used for identifying geographic features of surrounding areas. A buffer zone is first generated around existing geographic features and specific features are identified or selected based on whether they fall inside or outside the boundary of the buffer zone. In this study, the maritime accident distribution and the coastline are considered as two spatial sets, and the buffer zone is the neighbourhood of the coastline set. The buffer zone can be defined as:

$$Buffer = \{x | d(x, O) \le r\} \tag{4}$$

where, O is a given object, x represents any point in the inner boundary of the buffer zone, and $d(x, O)$ is the shortest distance between object O and point x. r is the neighbourhood radius, which is a specified distance to the coastline. If there exists a point x whose distance with object O is equal or less than r, then the object O is within the buffer zone. With the coastline as the boundary, the size of the buffer zone is determined by the neighbourhood radius r. By buffer analysis, the proportion of accidents along the coast can be determined, which is useful for coastal management.

4.2. Clustering analysis

Clustering analysis (Pilehforooshha et al., 2014) refers to the process of grouping a given set of unknown distributed data into different groups with as much similarity as possible within a group and as little similarity between groups through certain rules in an unsupervised state. In this study, the spatial distribution of the severity of maritime accidents is studied by two disaggregated spatial clustering models, outlier analysis and hot spot analysis. The term "disaggregated" here means that all calculations are based on the attributes of a single incident sample, rather than the overall attributes after spatial aggregation. Therefore, the original data samples' attributes can be retained to the maximum extent, which is conducive to the in-depth study of accident data. Compared to the traditional clustering methods which can only determine whether the samples belong to a certain category, outlier analysis and hot spot analysis can identify the outliers that do not belong to any cluster or give the confidence that the samples belong to a certain category.

4.2.1. Outlier analysis

Outlier analysis is to determine the correlation between a data point and its adjacent spatial points by calculating the Local Moran's statistic value, I (Moran, 1948), which is a statistical tool that measures the spatial dependence of the accident location. The calculation of Local Moran's statistical value, I is given as follows:

$$I_i = \frac{(n-1)(x_i - \overline{X}) \sum_{j=1, j \neq i}^{n} \left(w_{i,j} \left(x_j - \overline{X} \right) \right)}{\sum_{j=1, j \neq i}^{n} \left(x_j - \overline{X} \right)^2} \tag{5}$$

where I_i represents the Local Moran's statistical value I of data point i, n is the total number of data points, x_i and x_j are the attribute values (namely, the severity of the accident) of data points (or accident positions) i and j, $\overline{X}$ is the mean of the attribute values. $w_{i,j}$ is the spatial weight between data points i and j, which is the reciprocal of the distance between these data points. Z_{I_i} is the z-score of data point i and its absolute value indicates the distance between the original value within the standard deviation and the population mean. When the original value is below average, Z_{I_i} is negative, otherwise positive. Z_{I_i} can be calculated by the following formula:

$$Z_{I_i} = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \tag{6}$$

where,

$$E[I_i] = -\left(\sum_{j=1, j \neq i} w_{i,j} \right) \Big/ (n-1) \tag{7}$$

$$V[I_i] = E\left[I_i^2\right] - E^2[I_i] \tag{8}$$

The confidence of statistical significance is generally 95%, that is, when the p-value is less than 0.05, it can be considered as statistically significant (Lu et al., 2019). According to the law of normal distribution, the corresponding threshold of Z_{I_i} is ± 1.96 if statistical significance exists (Lu et al., 2019). Under the condition of statistical significance, if the value I is positive, the difference between the attribute values of the data point and its adjacent points is small, that is, the point is part of the high-high-value clustering or low-low-value clustering. The relationship between the attribute value of a data point and the mean value of all data points is the key to determine whether the data point belongs to high-high-value clustering or low-low-value clustering. If the value I is negative, it means that the attribute value of the data point is significantly different from that of its adjacent points, that is, the point is an outlier.

4.2.2. Hot spot analysis

The Getis-Ord statistic is used in hot spot analysis to determine whether a point belongs to the same category with its adjacent points (Getis and Ord, 1992). A high value of the Getis-Ord statistic represents a group of high index values (hot spots), while a low value represents a group of low index values (cold spots). Getis-Ord statistic G_i^* can be calculated using Eq. (9):

$$G_i^* = \left[\sum_{j=1}^{n} (w_{i,j} x_j) - \overline{X} \sum_{j=1}^{n} w_{i,j} \right] \cdot \left[\sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \overline{X}^2} \cdot \sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2}{n-1}} \right]^{-1} \tag{9}$$

In this study, G_i^* calculated by Eq. (9) is actually the z-score. Under the condition of statistical significance (*i.e.*, z-score is greater than 1.96 or less than -1.96), the higher the z-score is, the more intense the clustering of high values (hot spots) will be. The lower the z-score is, the more intense the clustering of low values (cold spot) will be (Ord and Getis, 1995).

Table 1
The number of accidents of each severity level.

Severity	Classification	Description	Number
1	Less serious accidents	Accidents which do not qualify as serious accidents and very serious accidents.	276
2	Serious accidents	Accidents involving ship damage that rending the ship unfit to proceed, injury, or pollution.	804
3	Very serious accidents	Accidents involving total loss of the ship, loss of life, or severe pollution.	1433

4.3. Data description

4.3.1. Global maritime accident data

GISIS is a global maritime information system managed by the International Maritime Organization (IMO) and consists of 30 modules, such as ballast water management, Global Maritime Distress and Safety System (GMDSS), marine casualties and incidents. The casualty module, which is only accessible to member state accounts, provides both factual data collected from various sources and detailed information extracted from accident investigation reports submitted to the IMO by member states. For the purpose of collecting information on ship casualties to populate the GISIS casualty module, ship casualties in GISIS are selected according to the following classification: "very serious casualties", "serious casualties", "less serious casualties" and "marine incidents" (IMO, 2008). In this study, maritime accidents are categorized into "very serious accidents", "serious accidents" and "less serious accidents" according to the severity of accidents, among which "less serious accidents" include "less serious casualties" and "marine incidents".

From searching GISIS from January 1, 2010 to December 31, 2019, a total of 3,484 accident records are obtained. Because complete and accurate longitude and latitude coordinates of accident locations are required for spatial analysis in GIS software, this study filters the obtained accident records by eliminating those without complete longitude and latitude coordinates. Eventually, 2,513 accidents with complete coordinates are obtained. The number of accidents of each severity level is shown in Table 1.

4.3.2. Ship traffic density

The ship traffic density is obtained from the National Water Traffic Information Service Platform of China. In this study, the world is divided into 30 × 60 grids (that is, the side length of each grid is 6° in the latitude and longitude directions) by using the uniform sampling method, and the ship traffic density in each grid is counted. As ships are always in the process of dynamic change, the ship traffic density of each grid is always changing. Considering the huge amount of data of ship traffic density in the global waters from 2010 to 2019, in this research, the daily ship traffic density of each grid is replaced by the ship traffic density of the

Table 2
Coordinate data format transforming rules.

	GISIS data format	ArcGIS data format
Transforming rules	AAA°BB.CC'	AAA + BB.CC/60
	E	+
	W	–
	S	–
	N	+
Example	119°15.83′W	−119.26

grid at 12.00 that day. Then the average ship traffic density of each grid is obtained by averaging its daily ship traffic densities from 2010 to 2019.

4.4. Data pre-processing

Before the spatial analysis of accidents using GIS software, it is necessary to locate the accidents according to their latitude and longitude coordinates. The data format of latitude and longitude coordinates of the accidents in GISIS is degrees and minutes, such as 30° 36.93′N and 122° 50.93′E. But ArcGIS only recognizes coordinate data in decimal form, such as 125.16 and −11.32. Therefore, the format of longitude and latitude coordinates of the accidents in GISIS needs to be converted first. The conversion rules are shown in Table 2.

5. Results and discussions

5.1. Accident spatial patterns

The distribution of global maritime accidents is obtained by positioning accidents in the map layer according to their longitude and latitude coordinates, as shown in Fig. 2.

According to Eq. (1), the accident density of each grid is calculated. Because the units and dimensions of different indicators are different, the indicators cannot be directly calculated or compared. In order to avoid dimensional differences between the data and for the convenience of comparison, the maximum normalization method is used to transform the obtained density values to the dimensionless form. The dimensionless value can be converted to a range of [0,1], and the greater the value, the greater the density value. The maximum normalization is given below:

$$y_i = \frac{x_i - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{10}$$

where, x_i is the initial value of the i-th indicator, while y_i is the normalized value of the i-th indicator, $1 \le i \le n$. $x_j^{\max}$ and $x_j^{\min}$ are the maximum value and minimum value of the indicators respectively, $1 \le j \le n$.

The density distribution of global maritime accidents is obtained, as shown in Fig. 3(a). The darker the sea area, the greater the accident density. As can be intuitively seen from Fig. 3(a), the coast of China, the Singapore-Malacca Strait, the east coast of Malaysia, the seas around the United Kingdom, the northern part of the Mediterranean Sea, and the west coast of Europe are the sea areas with high accident density, indicating that they are accident-prone sea areas. The result is consistent with the findings of previous studies (Huang et al., 2013) that the sea areas around the United Kingdom, the coastal area of East Asian countries (*i.e.*, China, Japan and South Korea) and the Mediterranean Sea have the largest number of accidents. Uğurlu et al. (2013) also found that high risk marine areas are the Strait of Dover, the North Europe, the Baltic Sea and the coasts of Japan and China. The above spatial distribution characteristics of global maritime accidents are mainly due to the high traffic density in the above sea areas, which are prone to maritime traffic accidents. For example, Singapore is a prime transit node on multiple routes connecting Asia, and thus has a heavy traffic flow. In addition, the large number of small vessels such as fishing boats and sailing vessels in the coastal waters of China, the west coast of Europe and the Mediterranean Sea is also an important reason for the frequent occurrence of accidents.

In order to exclude the influence of ship traffic density, the relative accident density is calculated according to Eq. (2). The results are presented in Fig. 3(b). By comparing Fig. 3(a) and (b), it can be found that the density distributions of global maritime accidents in these two graphs are different. The most obvious difference is that the Singapore-Malacca Strait and the Mediterranean Sea are no longer the sea areas of high relative accident density, while the northern part of the Gulf of Mexico and the west coast of Canada become the sea areas of high relative accident density. The above changes indicate that although many maritime accidents occurred in the Singapore and Malacca Strait and the Mediterranean Sea, but the proportion of ships involved in accidents is relatively small. In the northern part of the Gulf of Mexico and the west coast of Canada, the opposite is true. After the above

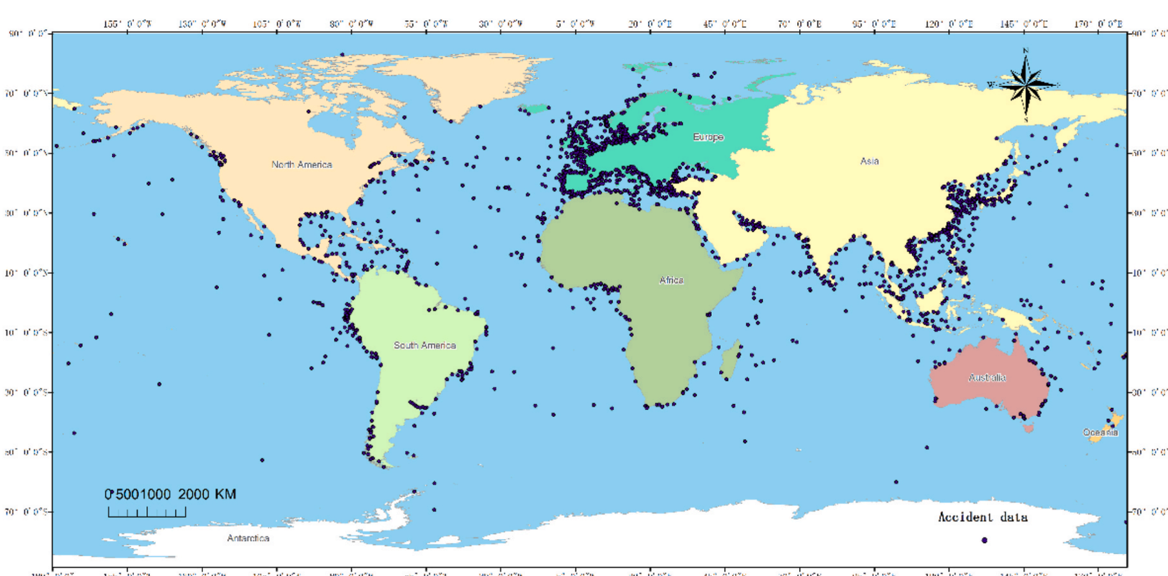
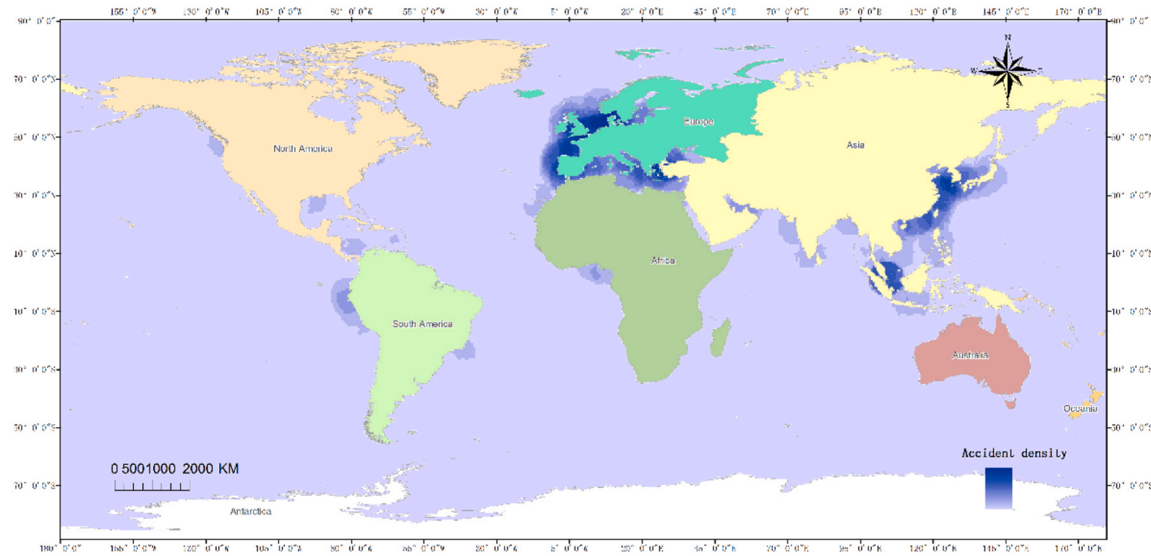
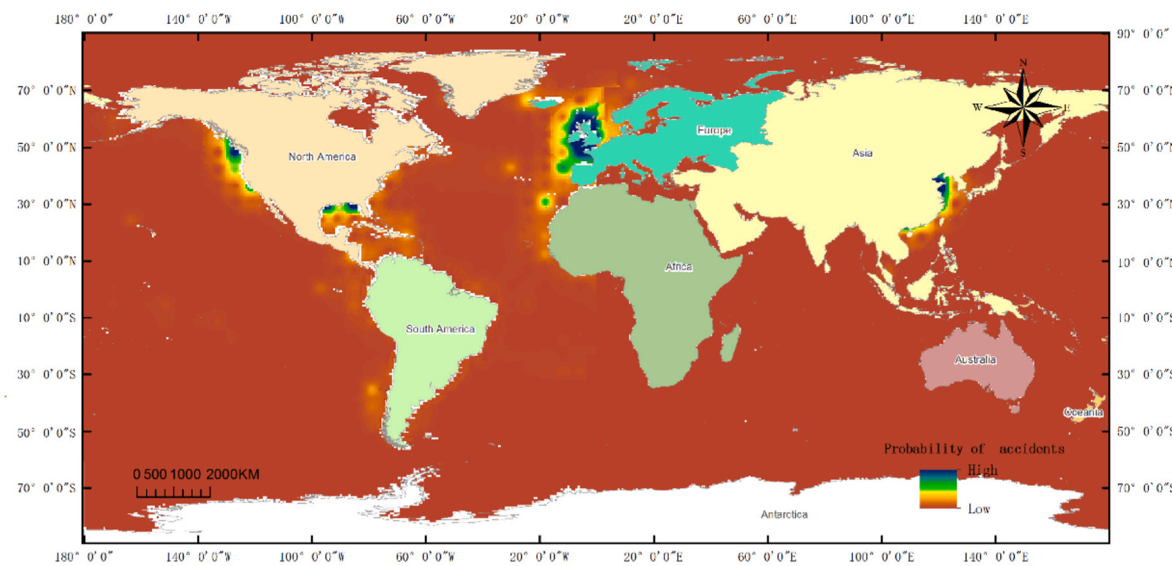


Fig. 2. Distribution of global maritime accidents.



(a) Density distribution without considering ship traffic density



(b) Density distribution considering ship traffic density

Fig. 3. Density distribution of global maritime accidents.

comparison, it can be concluded that the Bohai Sea, the Yellow Sea and the waters around the United Kingdom not only have large amounts of accidents but also have high accident frequencies considering the ship traffic density.

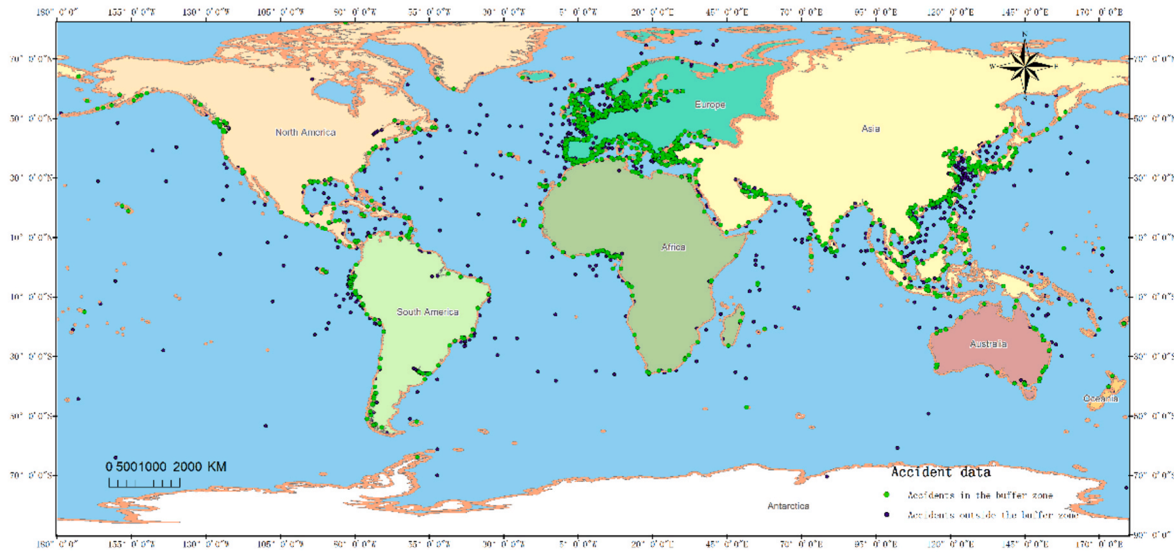
In this study, two buffer zones are set 30 nautical miles (nm) and 60 nm to the coastline respectively, as shown in Fig. 4. The accidents within 30 nm to the coastline are selected and marked with the green spots in Fig. 4(a). 1,527 accidents are found within 30 nm to the coastline, accounting for 60.8% of the total accidents. Similarly, the green spots in Fig. 4(b) represent the accidents within 60 nm to the coastline. 1,761 accidents are found within 60 nm to the coastline, accounting for 70.1% of the total accidents. The result is broadly in line with the previous research finding (Huang et al., 2013) that 51.1% of the total accidents occurred within 25 miles to the coastline and 62.2% of the total accidents occurred within 50 miles to the coastline.

The above results demonstrate that maritime accidents may not frequently occur in the open seas. However, there exists a high probability for them to happen at ports, coastal areas, or narrow waterways. Such results are rather useful for maritime safety management of coastal states.

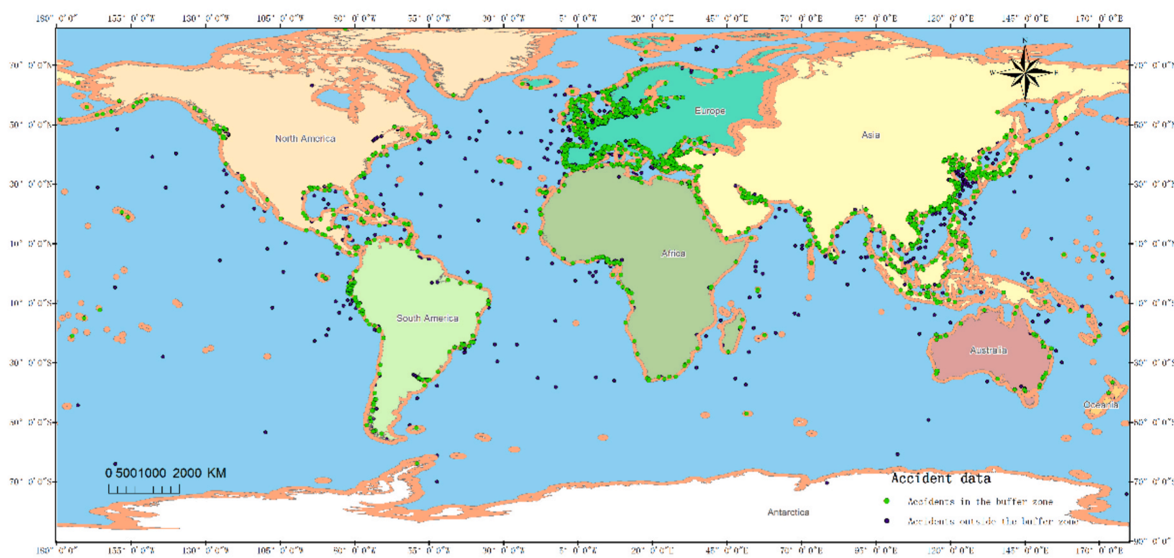
5.2. Accident severity spatial patterns

5.2.1. Accident severity spatial patterns based on density analysis

Although the frequency of maritime accidents can reflect the traffic safety level of a certain sea area, the accident severity is also an important index that cannot be ignored. A sea area that occasionally has a very serious maritime accident is usually more important than one that frequently has maritime incidents of less serious severity. As explained in Section 4.3.1, the accident severity in this study is classified into 3 levels. The spatial distribution of the severity of global maritime accidents is obtained by using the spatial classification method of GIS, as



(a) 30 nm to the coastline



(b) 60 nm to the coastline

Fig. 4. The distribution of accidents in buffer zones.

shown in Fig. 5.

Taking the accident severity as the weight, accidents with low, medium and high severity levels are weighted with 1, 2 and 3, respectively. The corresponding weighted number of accidents is calculated and the density distribution of accident severity is obtained according to Eq. (3), as shown in Fig. 6. The darker the colour of the sea area, the higher the density of accident severity.

Fig. 6 demonstrates that the sea areas of medium and high severity densities are mainly concentrated in the coastal areas of China, Japan and South Korea, the Singapore-Malacca Strait, the surrounding waters of the United Kingdom, the west coast of Europe, the Mediterranean Sea and the Black Sea, indicating that the overall consequences of the accidents in these waters are relatively serious. According to the analysis, the main reasons for the above results probably include the high ship traffic density, the dangerous navigable water area conditions and the bad weather conditions. The English Channel and the Channel of Dover around Britain are among the busiest shipping channels in the world, with 200,000 ships passing through the channels every year. China, Japan and South Korea are large trading countries having busy shipping routes and a large number of ships. The Mediterranean Sea is an important water area connecting Europe and Asia, Europe and Africa. The Turkish Straits is a key passage between Europe and Asia, and also connect the Aegean and Mediterranean to the Black Sea.

By comparing Figs. 3(a) and Fig. 6, it can be found that the density distribution centres of the two graphs are almost the same, indicating that most of the maritime accidents that occurred in these sea areas are serious or very serious. Therefore, the above sea areas should be given due attention from the maritime authorities concerned. However, slight differences also exist in the East Sea between Japan and South Korea (Sea of Japan), the Black Sea and the Mediterranean Sea. The medium and high density range in the above sea areas is larger in Fig. 6 than that in Fig. 3(a), indicating that the percentage of serious accidents and very

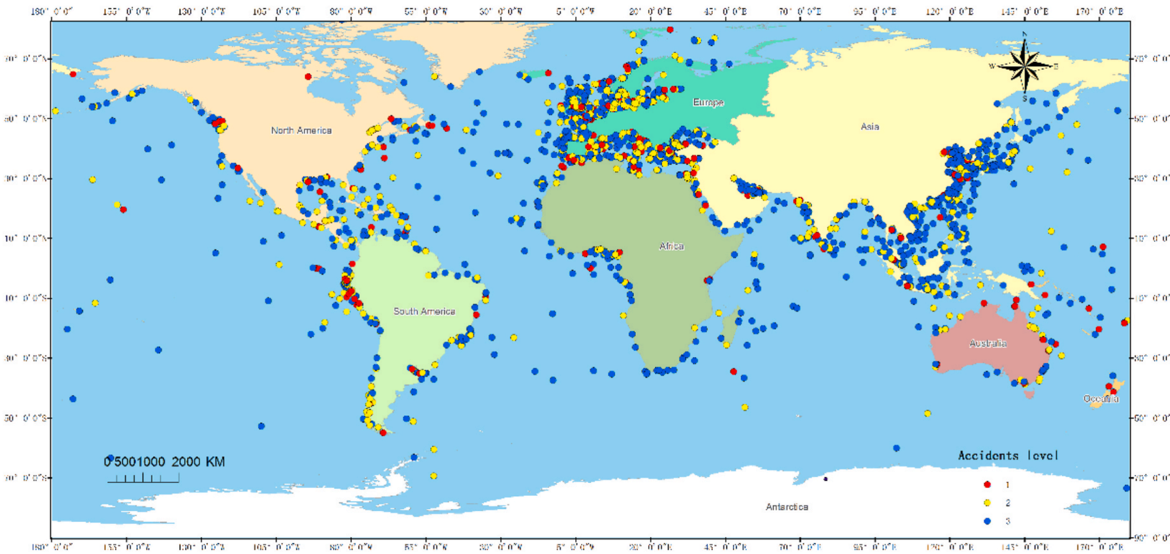


Fig. 5. The spatial distribution of global maritime accident severity.

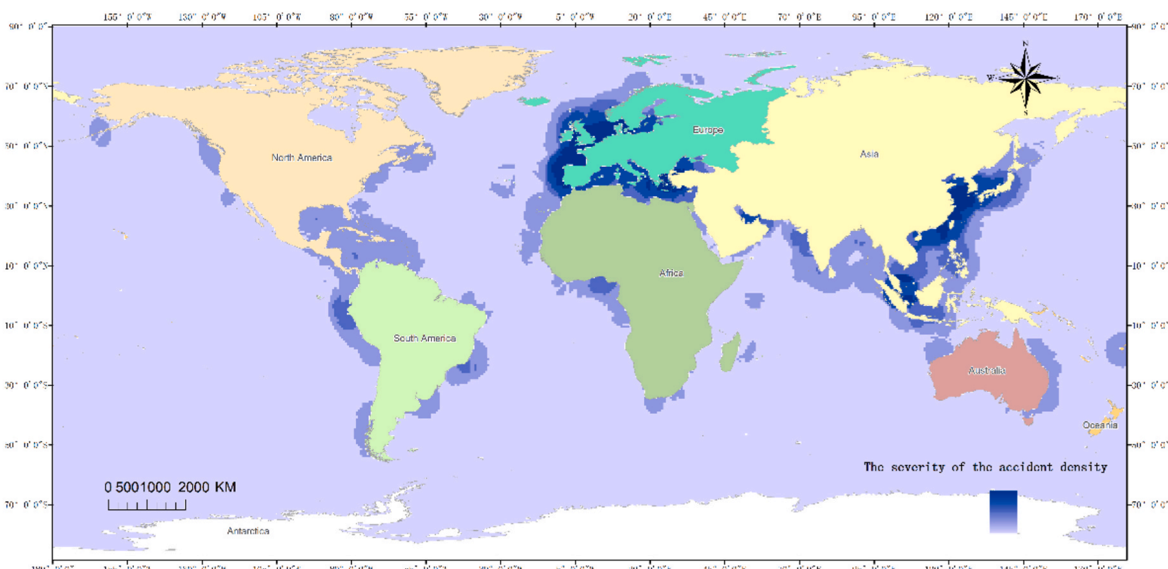


Fig. 6. Density graph of the severity of global maritime accidents.

Table 3
The number of accidents of each severity level within buffer zones.

Distance to the coastline	Severity level 1 (Less serious accidents)	Severity level 2 (Serious accidents)	Severity level 3 (Very serious accidents)	The total number
30 nm	171	503	853	1,527
60 nm	198	563	1,000	1,761

serious accidents is higher in these sea areas than that in other sea areas. Therefore, specific attention should be paid to these sea areas to ensure maritime safety.

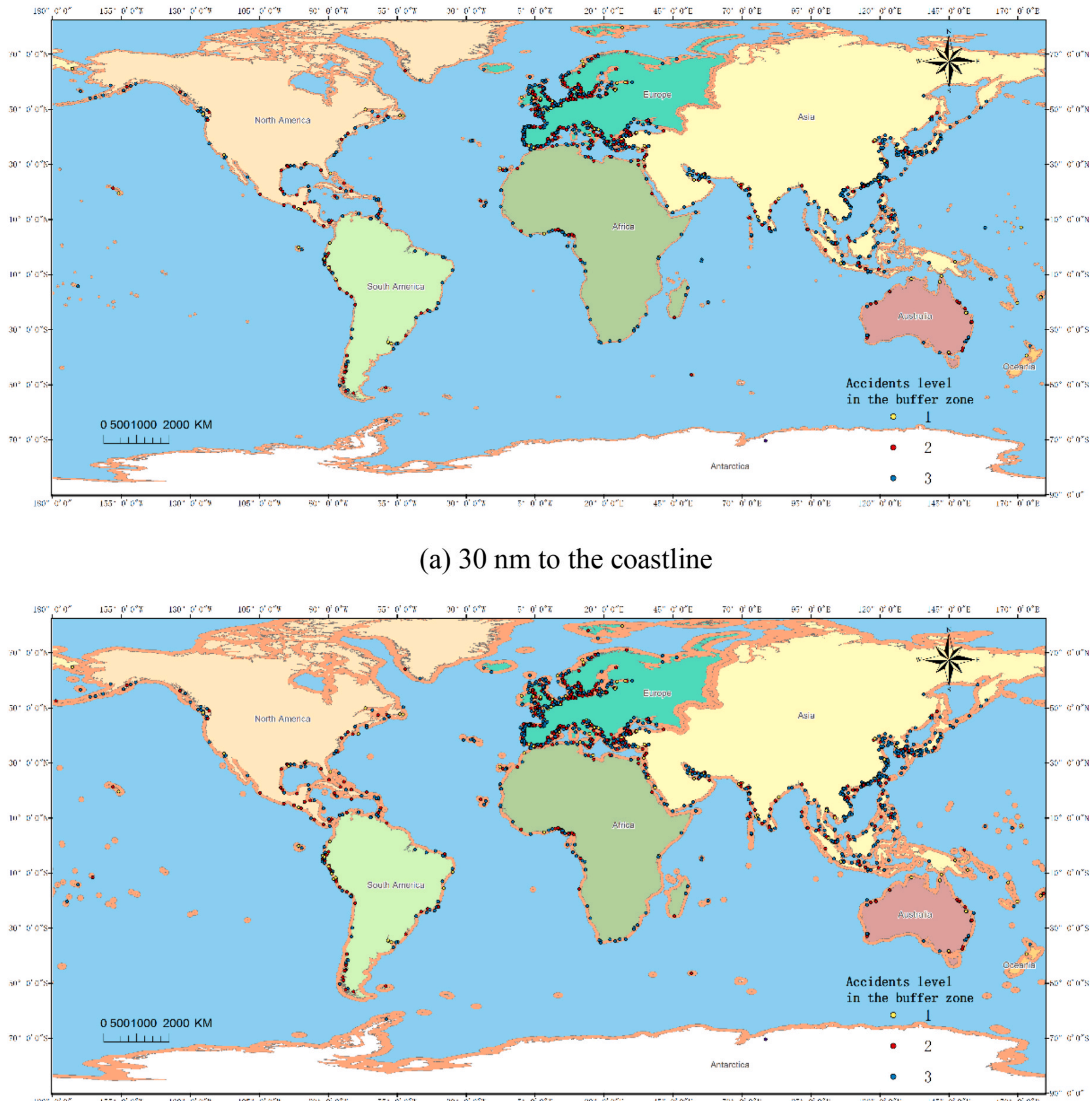
The number of accidents of each severity level within the buffer zones is also calculated, as shown in Table 3. The spatial distribution of accidents of each severity level in the buffer zones is then determined using Eq. (1) and the results are presented in Fig. 7. It can be seen that 853 very serious accidents and 503 serious accidents are found within 30 nm to the coastline, accounting for 59.5% and 62.6% of the total accidents of the corresponding severity levels. Similarly, 1,000 very serious accidents and 563 serious accidents are found within 60 nm to the coastline, accounting for 69.8% and 70% of the total accidents of the corresponding severity levels. The above results indicate that more than half of serious accidents and very serious accidents occurred within the sea areas less than 30 nm to the coastline. Therefore, safety management of sea areas within 30 nm to the coastline should have priority for risk reduction.

5.2.2. Accident severity spatial patterns based on clustering analysis

In order to further analyse the spatial distribution patterns of maritime accident severity, hot spot analysis and outlier analysis are conducted respectively in this section.

(1) Hot spot analysis

Hot spot analysis focuses on the aggregated form of samples according to the high and low target eigenvalues, and the results can show more regional distribution characteristics. In this study, hot spot analysis is conducted on the data of accident severity according to Eq. (9)



(a) 30 nm to the coastline

(b) 60 nm to the coastline

Fig. 7. The spatial distribution of accidents of each severity level within the buffer zones.

and the results are shown in Fig. 8. The red dots are called “hot spots”, which represent high-severity accidents. The blue spots, known as “cold spots”, represent low-severity accidents. The yellow dots are the ones that are not distinctive. For “hot spots” and “cold spots”, the shade of the colour represents different confidence levels. The darker the colour the sea area, the higher confidence level the point belongs to the corresponding category.

It can be seen from Fig. 8 that, under the 95% confidence level, there is a clustering trend for the maritime accidents in the South China Sea, the waters around Japan, South Korea and Vietnam, the Singapore-Malacca Strait and the Bay of Biscay, on the feature of high severity. In other words, the above sea areas belong to high severity accident zones, namely the “hot spots”. In contrast, the North Sea, the Baltic Sea, the seas around Italy, and the coast of Ecuador and Peru show a distinct low-severity clustering pattern. This difference is probably related to the types of ships in the above sea areas. There are many merchant ships and fishing vessels in the South China Sea, the surrounding waters of Japan and South Korea, and the Singapore-Malacca Strait, thus the probability of occurrence of accidents causing casualties or ship sinking is relatively high. The North Sea, the Baltic Sea and the waters around Italy, where there are many sailboats and yachts, have a relatively low probability of occurrence of accidents of high severity.

(2) Outlier analysis

As a comparison, outlier analysis is carried out according to Eqs. (5)–(8) and the clustering results are shown in Fig. 9. The selected feature field is accident severity. In Fig. 9, the black dots represent the high severity accident class (High - High Cluster); the blue dots represent the low severity accident classes (Low - Low Cluster); the yellow dots represent the High - Low Outlier, that is, the class of a small number of high severity accidents contained in the space occupied by low severity accidents; the white dots represent the Low - High Outlier, that is, the class of a small number of low severity accidents contained in the space

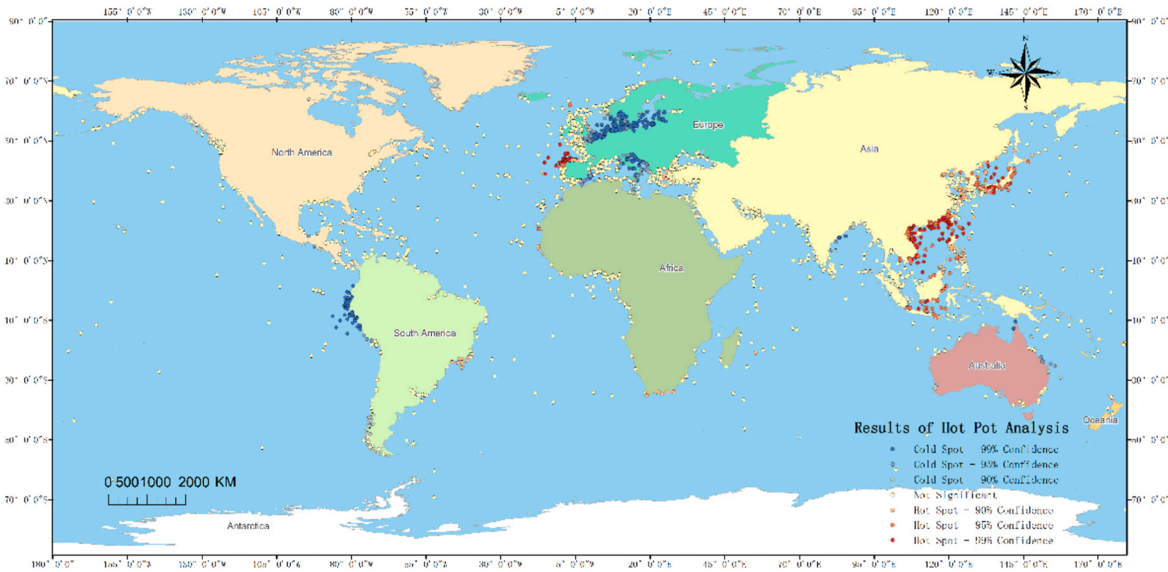


Fig. 8. Results of hot spot analysis on the severity of global maritime traffic accidents.

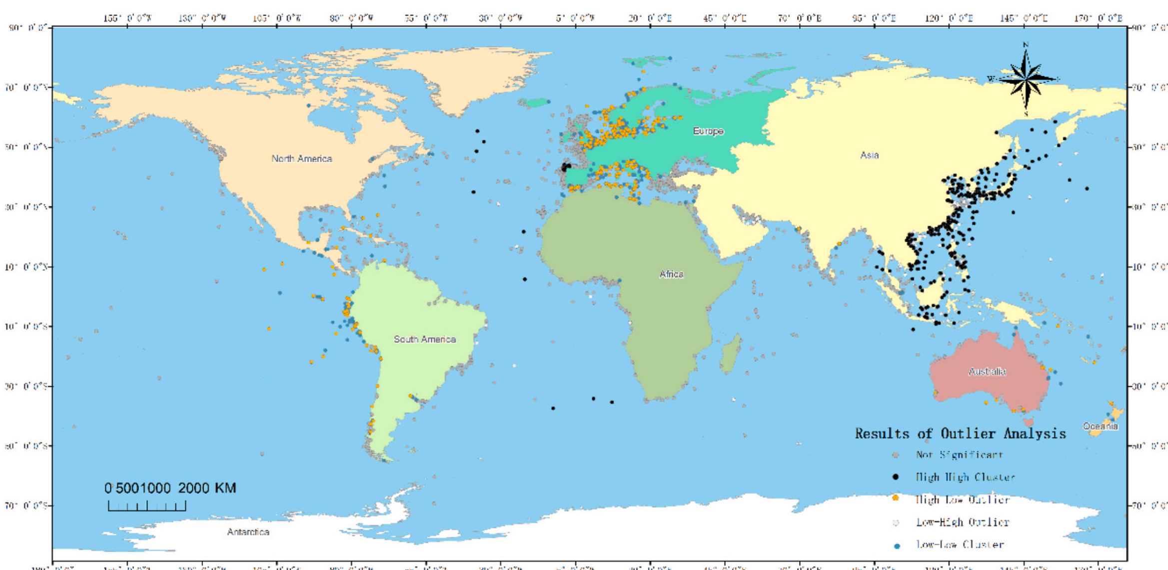


Fig. 9. Results of outlier analysis on the severity of global maritime accidents.

occupied by high severity accidents; grey points represent accidents without obvious clustering characteristics.

As can be seen from Fig. 9, in the seas around China, Japan and South Korea, the coast of Vietnam, the Philippines islands and the northwest waters of Spain, maritime accidents show a trend of clustering distribution in terms of high accident severity. In contrast, maritime accidents in the North Sea, the Baltic Sea and the Mediterranean Sea, which also cause casualties and ship sinking, are geographically scattered and thus show the characteristics of a high-low outlier. This difference is likely to be related to the factors such as a high proportion of sailing boats and yachts, and the strong maritime salvage ability in such sea areas.

5.2.3. Comparison of density analysis and clustering analysis

In order to analyse the advantages and disadvantages of density analysis and clustering analysis and to identify the applicability of the two methods under different scenarios, the two methods are compared from two perspectives: the consistency of the results obtained by the two methods and the computational efficiency of the two methods. In terms of computational efficiency, the average calculation time of each method for a single analysis was obtained by massive repeated calculations of the calculation time required by density analysis and clustering analysis for simulating data volumes of different complexities. The average calculation time required by density analysis and clustering analysis (hot spot analysis and outlier analysis) under different data complexities is shown in Fig. 10. It can be seen that under different complexities, the time required by hot spot analysis is similar to that of density analysis, while the time required by outlier analysis is not only larger than density analysis, but also significantly greater than hot spot analysis, which is conducted using a clustering algorithm. The difference of calculation times between outlier analysis and hot spot analysis may be related to the fact that outlier analysis has one more step to calculate the z value than hot spot analysis.

In terms of the consistency of analysis results, cosine similarity is used to calculate the similarity between the results obtained by density analysis and the ones by hot spot analysis. The formula of cosine similarity is given in Eq. (11). The cosine value of the angle between two

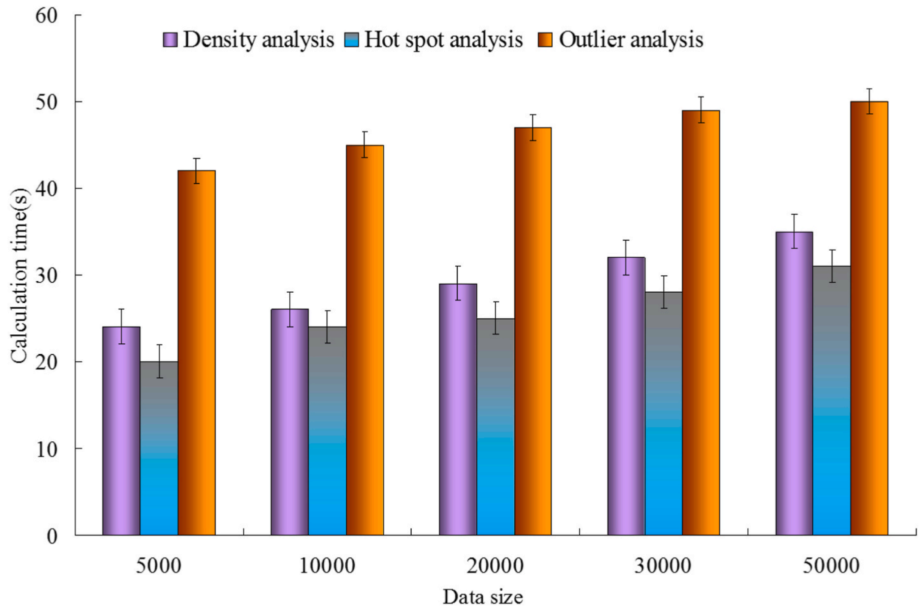


Fig. 10. The average calculation time required by density analysis, hot spot analysis and outlier analysis under different data complexities.

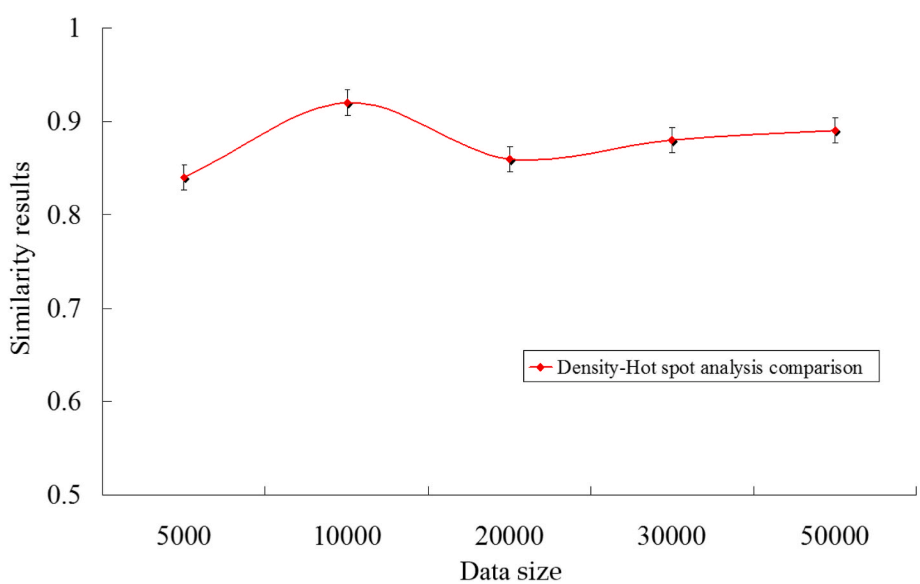


Fig. 11. Results of cosine similarity analysis of density analysis and clustering analysis.

vectors in a vector space is used to measure the difference between two individuals in cosine similarity analysis. The closer the cosine is to 1, the more similar the two vectors are, and the closer the cosine gets to 0, the less similar the two vectors are. The result of the cosine similarity analysis is shown in Fig. 11. As shown in the figure, the cosine between the results obtained by density analysis and the ones by hot spot analysis is greater than 0.8, which indicates that the results of the two methods have good consistency.

$$\cos(\theta) = \frac{\sum_{i=1}^{n} (x_i \times y_i)}{\sqrt{\sum_{i=1}^{n} (x_i)^2} \times \sqrt{\sum_{i=1}^{n} (y_i)^2}} \tag{11}$$

The above comparison results indicate that the analysis results of density analysis and clustering analysis have a good consistency, but the two methods have their own advantages and disadvantages. Generally speaking, the advantage of density analysis is that it is easy to understand and general information about the spatial distribution of maritime accidents can be obtained without complex algorithms, while the disadvantage is that the analysis results can only reflect the distribution of accidents under a severity level and cannot accurately present the proportion and distribution of accidents of various severity levels in specific sea areas. The results of clustering analysis, however, can provide more abundant spatial characteristic information of maritime accidents. Based on the location of accident points, clustering analysis can identify the outliers of maritime accident severity and the reliability of the clustering results of accident points from point to point. The above characteristics of the two methods lead to different levels of applicability in different scenarios. Density analysis can help maritime authorities to have an intuitive and rapid understanding of the spatial characteristics of the distribution of maritime accidents, while clustering analysis can provide refined information support for maritime authorities with high demand.

6. Conclusions

Two spatial analysis methods, density analysis and clustering analysis, are used in this study to conduct the spatial analysis of worldwide maritime accidents from 2010 to 2019 based on the GISIS database. The findings are concluded as follows:

(1) Hot spots of maritime accidents are identified. The results indicate that the coast of China, the Singapore-Malacca Strait, the east coast of Malaysia, the seas around the United Kingdom, the northern part of the Mediterranean Sea, and the west coast of Europe are accident-prone sea areas. However, considering the ship traffic density, the Singapore-Malacca Strait and the Mediterranean Sea are no longer the sea areas of high relative accident density, while the northern part of the Gulf of Mexico and the west coast of Canada become the sea areas of high relative accident density.
(2) As to the spatial distribution of accident severity, the results of density analysis and clustering analysis both demonstrate that the coastal waters surrounding China, Japan, South Korea, Vietnam and the Philippines, the Singapore-Malacca Strait and the Bay of Biscay form high severity accident clustering. The North Sea, the Baltic Sea and the Mediterranean Sea form low severity accident clustering in the clustering analysis, but show medium and high density of accident severity in the density analysis.
(3) The results of buffer analysis indicate that more than 60% accidents occurred within the sea areas less than 30 nm from the coastline, among which the proportion of serious accidents and very serious accidents is almost 60% for the total number of accidents of the corresponding severity level.
(4) The comparison of the results of density analysis and clustering analysis demonstrates that the spatial distribution patterns of maritime accident severity obtained by the two methods are generally consistent. However, clustering analysis can provide more abundant spatial characteristic information, while density analysis is superior in terms of simplicity and computational efficiency.

In terms of the limitations of this study, the following aspects are worth being conducted in the future. First, further work on the data collection should be done to ensure the completeness of maritime accident data for analysis. Commercial databases, such as the Lloyd's List Intelligence, may be used to complement the accident data collection. Second, in-depth research on the causes of various maritime accidents in different sea areas should be conducted combining multi-source data so as to improve maritime safety management more specifically. Last but not least, future studies may also find it worthwhile to combine different spatial analysis techniques such as Kernel Density Estimation, K-means clustering and DBSCAN in the spatial analysis of maritime accidents, with the aim to further improve the accuracy of spatial information analysis and extract more abundant maritime accident information.

Disclaimer

The authors are solely responsible for all the views and analysis in this paper. This paper is the opinion of the authors and does not represent the belief and policy of their employers.

CRediT authorship contribution statement

Huanxin Wang: Conceived and designed the experiments, Performed the experiments, Data pre-processing, Formal analysis, Revised the manuscript. **Zhengjiang Liu:** Conceived and designed the experiments, Contributed materials/, Formal analysis, Revised the manuscript. **Zhichen Liu:** Conceived and designed the experiments, Performed the experiments, Data pre-processing, Formal analysis, Revised the manuscript. **Xinjian Wang:** Conceived and designed the experiments, Performed the experiments, Data pre-processing, Formal analysis, Revised the manuscript. **Jin Wang:** Conceived and designed the experiments, Formal analysis, Revised the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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