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Maritime accidents in the Yangtze River: A time series analysis for 2011–2020

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ABSTRACT

The theoretical analysis of maritime accidents is a hot topic, but the time characteristics and dynamics of maritime accidents time series are still unclear. It is difficult to draw a clear conclusion from the cause analysis, so the accident is difficult to be predicted. To bridge this gap, this research analyzes the characteristics and evolution mechanism of maritime accidents time series from the perspective of complex network theory. The visual graph algorithm is used to model the complex network of maritime accidents data in 22 jurisdictions of the Yangtze River, map the time series into a complex network, and reveal the time characteristics and dynamics of maritime accidents time series based on the complex system theory. In the empirical analysis, degree distribution, clustering coefficient and network diameter are used to analyze the characteristics of time series. The results show that the degree distribution of maritime accidents time series network presents power-law characteristics in the macro and micro levels, which shows that the maritime accidents time series is scale-free. In addition, according to the clustering coefficient and network diameter, maritime accidents time series in the Yangtze River has the characteristics of small-world and hierarchical structure. The research of this manuscript shows that the occurrence of maritime accidents is not random events and does not follow specific patterns but presents the characteristics of complex systems, and this phenomenon is common. The analysis of maritime accidents time series by complex network theory can provide theoretical support for maritime traffic safety management.

1. Introduction

For the Marine Silk Road (MSR) of the twenty-first century to thrive and endure, maritime transportation safety is crucial (Zhao et al., 2021; Song and Fabinyi, 2022). However, shipping has long been recognized as a high dangerous business, and maritime accidents frequently result in significant loss of life, cargo, and property, as well as serious environmental contamination (Zhang et al., 2021a; Li et al., 2022). So, with the arrival of a new round of rapid development in the shipping industry, the prevention of maritime accidents and the reduction of human and property losses as a result of accidents is a matter of national importance and livelihood, as well as an essential task of maritime traffic safety management (Hänninen, 2014; Fan et al., 2020). As a result, it is critical to enhance the prevention of marine traffic accidents to safeguard human life and property (Sedova et al., 2018).

China's transport industry has been growing in recent years, but it has also brought more significant safety hazards, with frequent maritime accidents and severe social implications. Yangtze shipping plays a crucial part in the valley's economic development as a vital component of the comprehensive transport system of Yangtze valley. But compared to the development and use of inland water transport abroad, the Yangtze River shipping still lags in technology and management. At present, the maritime traffic safety situation in China is still severe, and it is necessary to carry out safety hazard investigation and risk control, improve safety emergency protection capacity, and improve the risk prevention and control system to ensure that the maritime traffic safety situation remains sound and stable (Liu et al., 2021).

Accidents, according to research, are not accidental and random but rather the inevitable result of maritime accidents that are not prevented. However, whether the occurrence of maritime accidents is purely

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random in time remains unknown. Furthermore, determining the fundamental mechanism driving the incidence of maritime accidents and how to explain this process in mathematical and statistical terms has proven challenging. The fundamental reason for this is that maritime traffic is a temporal dynamic system with complex phenomena and chaotic characteristics, which makes analytical representation methods difficult to describe (Wen et al., 2015; Sui et al., 2020, 2021). To date, time series methods in maritime traffic safety research have largely focused on the prevention of maritime accident number or statistical characteristics, such as autoregressive integrated moving average (ARIMA), vector autoregression (VAR), generalized linear models (GLM), structural equation models (SEMs), Markov and GIS-based method. But the dynamic and temporal characteristics of the time series of maritime accidents remain unclear. A comparison between VG and other methods can be seen in Table 1.

Therefore, to bridge this gap, this paper aims to gain insight into the dynamic characteristics of maritime accidents time series through complex network theory and visibility graph (VG) algorithms. The visibility graph method directly defines the data in the time series as nodes in a complex network, and the connections between the nodes are determined by the linear visual relationships between the data. Therefore, the visibility graph method can transform any time series into a network, and the statistical properties of a complex network induced by a time series can well reflect the characteristic of the time series. For example, a periodic time series can be transformed into a regular graph, a random time series into a random graph, and a fractal time series into a scale-free network.

Based on ten years of maritime accident data in the Yangtze River mainline, complex network theory is combined with accident data to reveal the patterns and dynamic features in the accident time series by analyzing the changes in network characteristics. The remainder of this paper is organized as follows. Section 2 reviews research related to maritime accidents analysis, theory, and approach to research the time series dynamic. Section 3 is the materials and method, followed by the analysis results in Section 4. Empirical analysis of maritime accident data for ten years in the Yangtze River is developed, and network topological changes for maritime accidents in different years and jurisdictions are analyzed and discussed in detail. Finally, the discussion and conclusions are summarized in Section 5 and 6 respectively.

2. Literature review

Many regulations and rules are being conducted to improve marine transportation safety and prevent maritime accidents. Nonetheless, maritime transportation safety level has not yet reached its peak, and accidents continue to be a serious concern for the maritime safety management (Fu et al., 2021). Maritime accidents can lead to injuries, loss of life and property, environmental pollution and other common and serious consequences (Hansen, et al., 2002; Wang, 2002). Analysis of maritime accidents cases in water areas is widely considered an effective approach by many researchers.

2.1. Accident causation analysis in the maritime domain

To prevent maritime transportation accidents, accident causation theory have become highly discussed topics, these methods are used to study the mechanism and influencing factors of maritime accidents. The 850 severe maritime accidents in Turkish Straits between 2001 and 2010 have been systematically analyzed by the Analytic Hierarchy Process (AHP) method. Human error was the most common cause of maritime accidents in Turkish Straits (Ugurlu et al., 2016). A fuzzy evidence model was constructed based on the fuzzy logic and evidence theory used to evaluate maritime accident risk (Yang et al., 2009). And then the fuzzy theory has been introduced to evaluate maritime risks applicable to maritime pollution risk (Balmat et al., 2011). The systems theoretic accident model and processes (STAMP) and the system-theoretic process analysis (STPA) are well-established approaches to system safety analysis (Ceylan et al., 2021, 2022). And some methodology for accident analysis based on a system perspective is presented (Zhang et al., 2021b; Patriarca et al., 2022). The regression model was widely applied in maritime accidents analysis. The regression method is a statistical inference approach used to investigate the relevant relationship between events. A negative binomial regression model has been developed based on historical maritime accident records to identify significant risk factors in Hong Kong port (Yip, 2008). And the human and organizational framework was proposed to analyze the accident cause factor from a comprehensive perspective (Chen et al., 2013). Bye and Aalberg (2018) identified the relationships between some factors and maritime accidents in Norwegian waters using a logistic regression analysis method. The regression approach has the benefit of synthesizing numerous elements of the vessel traffic system, but it requires a considerable quantity of data. Furthermore, researchers used several risk modeling methodologies to analyze maritime accident risk, especially Bayesian networks. The application of Bayesian Networks has attracted many researchers, and they found that Bayesian networks are an effective tool for maritime safety management (Sakar et al., 2021; Wu et al., 2021; Chen et al., 2022). This method has been used to analyze the risk factors of ship collision in the Gulf of Finland (Hanninen and Kujala, 2012; Hanninen, 2014). In the research of inland water traffic safety, using the Yangtze River as a case study, Zhang et al. (2014) proposed an accident data-based method to evaluate the risk of congestion on inland waterways. At the early design stage, Bolbot et al. (2021) merged the operational and functional hazard identification methodologies to thoroughly evaluate an autonomous inland waterways ship's safety. Using fault tree analysis as a method, Awal et al. (2014) published a research on contact type accidents of inland water transport in Bangladesh. Uddin et al. (2017) examined data on accidents that occurred in Bangladesh's inland waterways from 2005 to 2015 in relation to several factors, including vessel types, accident sites, accident timing, final vessel conditions following accidents, and others. The analysis revealed that the major causes of waterway accidents are collision.

Table 1
Comparison between VG and other methods.

Method	Research topic				
	Statistical characteristics	Spatial characteristics	Temporal characteristics	Dynamic characteristics	Prediction
ARIMA					×
VAR					×
GLM					×
SEM					×
Markov					×
GIS-based method	×	×			
VG	×		×	×	

2.2. Analysis on spatial-temporal characteristics of maritime accident

Analysis of time characteristics of maritime accidents is another hotspot issue. From the perspective of data resources, the data sources of most studies fall into two categories: raw historical data from public resources such as GISIS (Hassel et al., 2011; Zhang et al., 2021a), second-hand data from local administration, maritime accident reports (Quddus, 2008; Chai et al., 2020; Feng et al., 2020). However, because of data collection and data matching in maritime accident reporting, studying maritime accident time series characteristics has been difficult (Psarros et al., 2010; Hassel et al., 2011; Luo and Shin, 2019). Researchers put forward a series of algorithms to resolve missing data problems. Data interpolation methods are more mature, which have been employed in maritime accident records and various data sources (Heitjan and Little, 1991; Staff et al., 2014; Cheliotis et al., 2019; Lukusa and Phoa, 2020). By comparing multiple data sources, some research attempted to estimate the reporting frequency and the actual number of shipping incidents that happened (Psarros et al., 2010; Oltedal and McArthur, 2011; Hassel et al., 2011; Bye and Aalberg, 2018). And some researchers attempt to incorporate multi-scenario underreporting rates in maritime traffic (Li et al., 2022). There are some researches aimed to deal with similar problems in road and air traffic (Galea et al., 2006; Rose, 2006; Amoros et al., 2006, 2008; Yamamoto et al., 2008; Ryan et al., 2010; Shinar et al., 2018).

In recent years, the spatial patterns of maritime accidents have been discussed. Exploring the spatial pattern of maritime accidents is vital regarding maritime risk management. GIS-based methods have been introduced to analyze maritime accidents in the Philippine waters in the past ten years, and capsizing was the most prevalent accident, followed by foundering and stranding, according to the research (Sigua and Aguilar, 2003). Dobbins and Abkowitz (2010), Dobbins and Jenkins (2011) visualized the accident locations based on GIS and satellite imagery and evaluated the maritime risk in US navigable waterways. Huang et al. (2013) developed an accident hotspot analytical method based on the global maritime accident spatial distribution between 2002 and 2011. Acharya et al. (2017) determined the high-risk areas in South Korea using geospatial techniques to visualize the distribution of maritime accidents between 2007 and 2014. Ugurlu and Yildirim (2013) constructed a maritime accident databased containing some information, including ship name, ship type, maritime accident type, and so on, based on maritime accident data between 2007 and 2011. In addition, Kernel Density Estimation, Moran's I method, network-based statistics, and K-means clustering are more often used in maritime accidents analysis (Steenberghen et al., 2004; Xie and Yan, 2008; Anderson, 2009; Prasannakumar et al., 2011; Hashimoto et al., 2016). Zhang et al. (2021a) conducted descriptive analyses using Kernel Density Estimation and K-means to obtain the overall profile of global maritime accidents based on maritime accident data from 2003 to 2018.

2.3. Research gap and contribution

According to the literature review, studies on maritime accidents have mostly concentrated on accident factor analysis, accident probability prediction, and accident risk assessment. The previous methods have exposed the inadequacies of accident analysis, include

(i) The statistical analysis method allows for mining accident characteristics from several aspects, such as accident type, accident time distribution, and spatial distribution of accident-prone areas. However, such studies only provide simple statistics on historical data, do not consider the temporal correlation characteristics between accidents, and cannot prove the inevitable link between accidents and the external environment.
(ii) Although the number of accidents can be predicted using machine learning algorithms, there is a strong reliance on historical data. And it has been difficult to answer what is the underlying mechanism governing the occurrence of maritime accidents.
(iii) A few research looked at the time series of maritime accidents from the perspective of a complex system. Furthermore, these studies only looked at the general distribution of maritime accidents at sea rather than going deeper into inland water.

The goal of this research is to close the gap. In contrast to earlier research, the current study employs ten years of maritime accident data in the Yangtze River to investigate the characteristics of maritime accidents time series using complex network theory. The contributions of the work are as follows. Firstly, a visibility graph creates a new bridge between time series and complex networks, transforming abstract numbers into a visual network topology. This approach retains some of the original data's properties in mapping time series to networks. Secondly, the complex maritime accident time series networks have scale-free and small-world features. And the characteristics of the maritime accident time series were uncovered based on Visibility Graph.

3. Materials and method

3.1. Research data collection

The maritime accident data used throughout our analyses come from the report published by the Ministry of Transport Changjiang Hangwu Management Bureau. From January 2011 to December 2020, 3285 accidents were reported. Each accident is recorded in the format as depicted in Table 2. For all accidents, information concerning the time, ship name, types of accident, jurisdiction and accident level is always displayed in the summaries, including four levels: serious accident, major accident, ordinary accident and minor accident. Table 3 presents the number of accidents distributed by type of accident and accident level. The proportion of contact/collision accidents is the largest type of accident. From the statistical results of accident level, maritime accidents have been concentrated in minor accidents.

From Fig. 1, maritime accidents generally have been declining since 2011. Fig. 2 depicts the monthly number of 3285 maritime accidents between 2011 and 2020. The incidence of maritime accidents varies with the weather seasons, and the number of maritime accidents also varies by month. The trend of much more maritime accidents in the spring and summer is substantially persistent during the ten-year analyzed period. In addition, Fig. 3 depicts the overall number of maritime accidents and the time of day they happened. The most typical times were between 2 am, and 6 am.

Table 4 presents the number of accidents distributed by type of accident and jurisdiction. The first five jurisdictions in the number of maritime accidents are Nanjing, Nantong, Zhenjiang, Taicang, and Taizhou. These jurisdictions are located in the lower reaches of the Yangtze River. The proportion of contact/collision accidents is also the largest type of accident in most jurisdictions. Because the inland shipping business is becoming increasingly busy, inland maritime accidents have repeatedly occurred in the lower reaches of the Yangtze River.

Table 2
Maritime accidents information.

Time	Ship name	Type of accident	Jurisdiction	Accident level
2011/1/1 15:30	Gan Nan De Hua 021	Contact/ Collison	Zhenjiang	Minor accident
2011/1/1 21:35	Xiang An Xiang Huo 290	Capsize/ Foundering	Chongqing	Major accident
……	……	……	……	……
2020/12/ 28 4:05	Qi Xiang 1	Grounding	Chongqing	Minor accident
2020/12/ 30 17:57	Zhe Jia Shan Huo 03928	Capsize/ Foundering	Changshu	Ordinary accident

Table 3
The number of accidents distributed by type of accident and accident level.

Level	Type of maritime accidents					
	Contact/Collision	Grounding	Capsize/Foundering	Fire/Exploded	Other	Total
Minor accident	2004	493	142	148	115	2902
Ordinary accident	128	10	45	10	14	207
Major accident	70	1	53	4	11	139
Serious accident	22	0	14	1	0	37
Total	2224	504	254	163	140	3285

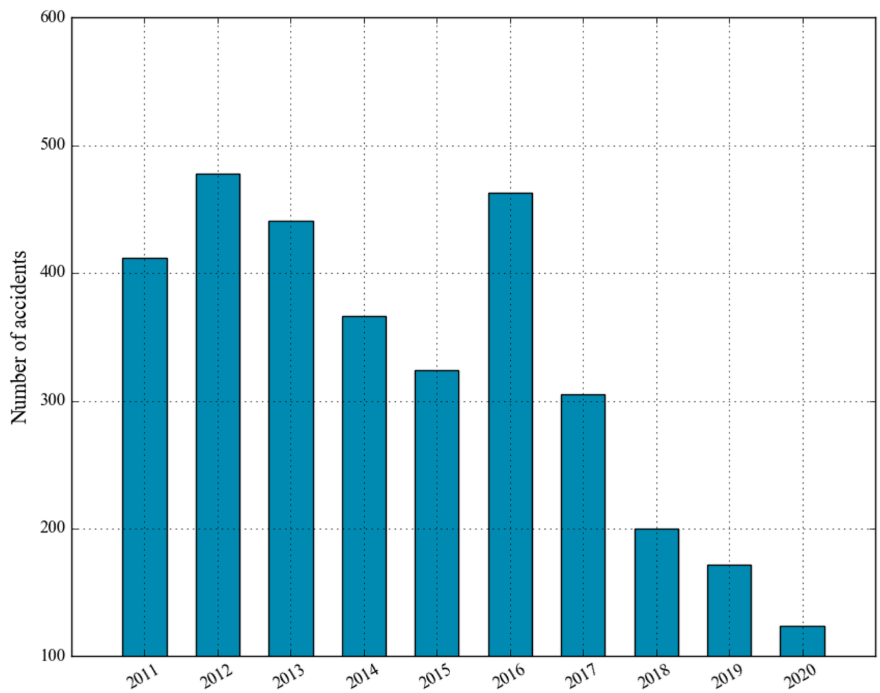

Fig. 1. Changes of maritime accidents from 2011 to 2020.

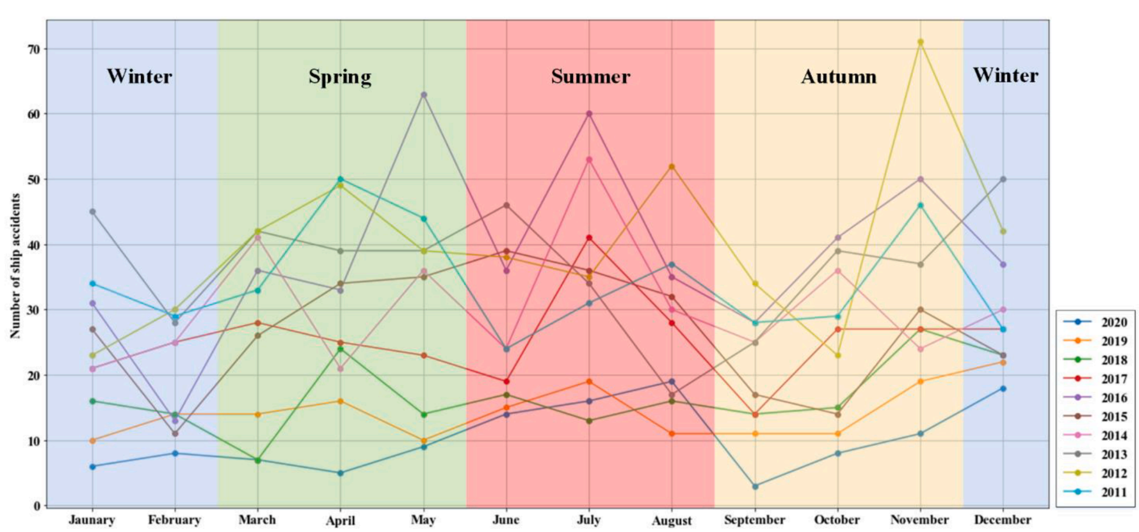

Fig. 2. Changes of maritime accidents in 2011–2020 by month.

3.2. *Visibility graph modeling*

In 2008, Spain researcher Lacasa popularized the term 'Visibility graph (VG)' to describe the characteristics of time series based on complex network theory (Lacasa et al., 2008). Based on the VG, with the continuous increase of time series data, the generation process of a complex network is similar to the dynamic generation of Barabasi-Albert scale-free network (Barabási, 2009), and the hub node in a complex network corresponds to the data with a particularly large value. The VG can transform any time series into a network, which is a fully connected

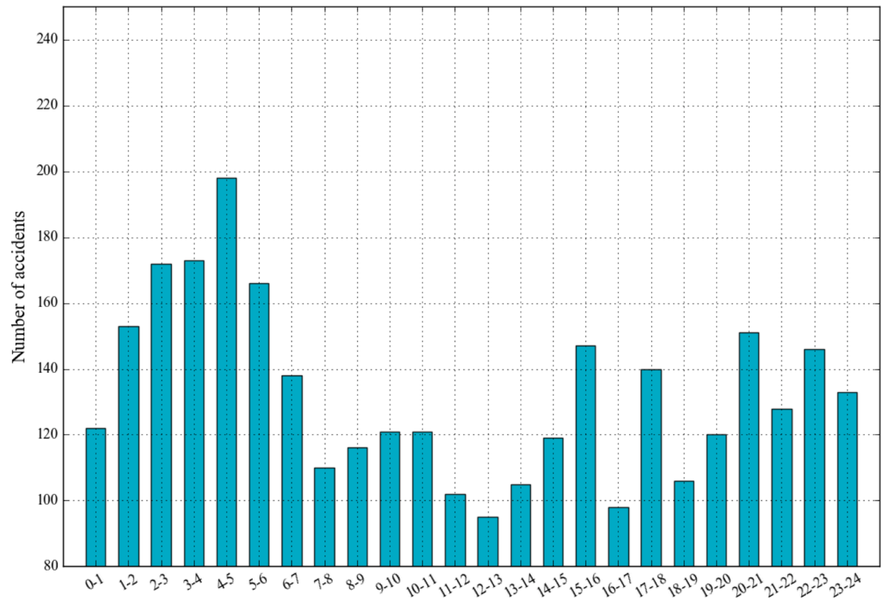

Fig. 3. Time of occurrence of maritime accidents in the Yangtze River.

Table 4
The number of accidents distributed by type of accident and jurisdiction.

Jurisdiction	Type of maritime accidents					
	Contact/Collision	Grounding	Capsize/Foundering	Fire/Exploded	Other	Total
Nanjing	298	22	12	10	8	350
Nantong	268	26	15	8	29	346
Zhenjiang	214	7	19	7	6	253
Taicang	148	2	20	7	21	198
Taizhou	155	5	14	2	15	191
Chongqing	50	88	22	18	11	189
Huangshi	122	34	9	7	7	179
Yichang	36	83	9	23	6	157
Zhangjiagang	127	3	13	6	7	156
Wuhu	83	27	18	21	6	155
Yangzhou	130	2	6	6	7	151
Wuhan	69	38	16	14	4	141
Jiujiang	86	23	7	7	3	126
Jiangyin	77	0	21	1	3	102
Yueyang	56	29	9	4	3	101
Jingzhou	39	36	5	7	2	89
Anqing	54	12	9	8	5	88
Changzhou	74	2	4	4	4	88
Changshu	54	5	18	4	3	84
Sanxia	19	6	0	1	2	28
Yibin	2	2	1	0	1	6
Luzhou	0	5	0	0	0	5

network and does not depend on the threshold. As shown in Fig. 4, periodic time series can be transformed into regular graphs, random time series can be transformed into random graphs, and fractal time series can be transformed into scale-free networks.

The visibility criteria of VG has been established: Two arbitrary data (t_a, y_a) and (t_b, y_b) will have visibility, and consequently will become two

Fig. 4. Regular network, Small-world network and Random network.

connected nodes of the associated graph, if any other data (t_i, y_i) placed between them fulfills (Lacasa et al., 2008):

$$y(t_i) < y(t_a) + \frac{t_i - t_a}{t_b - t_a}[y(t_b) - y(t_a)] \quad (1)$$

The associated graph extracted from a time series is always: (i) Connected: each node sees at least its nearest neighbors (left and right). (ii) Undirected: the way the algorithm is built up, the links have no direction defined. (iii) Invariant under affine transformations of the series data: the visibility criterion is invariant under rescaling horizontal and vertical axes and under horizontal and vertical translations.

Here we take the annual amount of maritime accidents from 2011 to 2020 as an example to illustrate the VG algorithm.

In Fig. 5, the information is shown as vertical bars sorted by time, with heights denoting the number of maritime accidents and dashed lines showing the visibility between data points. In the lower half of Fig. 5, the nodes correspond to the same sequence of time series data, and an edge links two nodes if they are visible to each other. When any two visible data are connected to build a visibility graph network, some information for the original data is lost. On the other hand, the related visible graph inherits several critical characteristics of the actual time series. Furthermore, the time series' temporal characteristics and underlying mechanisms may be analyzed using complex network theory.

3.3. Topological properties of VG

As stated previously, the visibility graph method is a fast calculation method of changing time series into complex networks, which can describe the characteristics of maritime accidents time series. Then paper abstracts some local topological properties of VG to show the direct link with neighbor nodes, including degree and cluster coefficient. And global properties have been introduced to take into account the effect on all nodes in the network, including average degree, degree distribution, cumulative degree distribution, average clustering coefficient, network diameter and average path length (Watts and Strogatz, 1998; Albert et al., 1999; Assenov et al., 2008).

The degree is an essential concept in a complex network. In a complex network, the degree of a node is the number of edges incident on that node, which is also described as node degree. In this research, a large node degree represents a ship accident after a long time of silence in the maritime traffic system. Then the average degree can be defined as follows.

$$\bar{k} = \frac{1}{N}\sum_{i=1}^{N} k_i, \quad (2)$$

where k_i is the degree of node i, $\bar{k}$ is the average degree of a complex network, N is the number of the node.

The probability of node degree k_i is denoted as $p(k)$, and the complementary cumulative distribution function is stated as follows:

$$p(k_i > X) = \sum_{i}^{n} p(k_i) \quad (3)$$

The clustering coefficient is the degree of aggregation of nodes, and the average clustering coefficient is the average value of the local clustering coefficient for all nodes in the network. The definition of clustering coefficient and average clustering coefficient are as follows.

$$C_i = \frac{E_i}{C_{k_i}^2}, \quad (4)$$

$$\bar{C} = \frac{1}{N}\sum_{i=1}^{N} C_i, \quad (5)$$

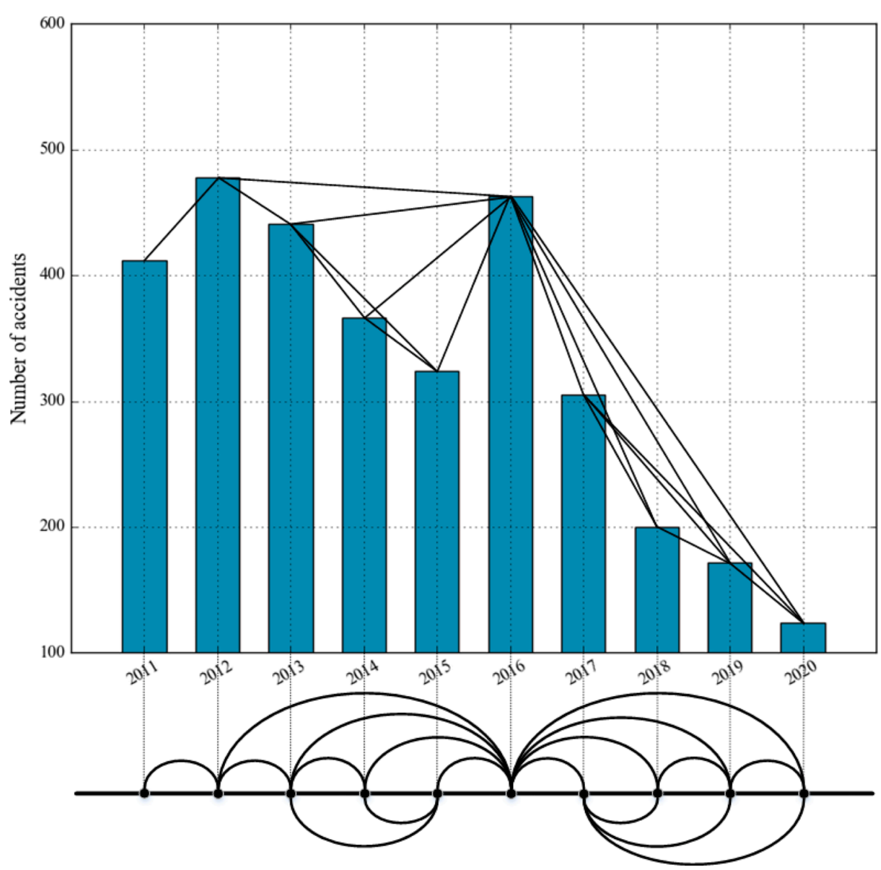

Fig. 5. An example of the VG algorithm.

where C_i is the clustering coefficient of node i, E_i is the actual number of edges node i's k_i neighbor nodes, $C_{k_i}^2$ is the number of all possible edges. $\overline{C}$ is the average network clustering coefficient.

Let d_{ij} denote the shortest distance between node i and node j. Assume that $d_{ij} = 0$ if node j cannot be reached from node i. Network diameter is given by:

$$D = \max_{1 \leqslant i < j \leqslant N} d_{ij}, \tag{6}$$

Then, the average path length L is:

$$L = \frac{1}{C_N^2} \sum_{1 \leqslant i < j \leqslant N} d_{ij} \tag{7}$$

The two properties of large clustering coefficients and small path lengths are collectively known as the 'small-world', and a network with this property is called a small-world network. In this research, 'small-world' represent the accidents often occur after long time silence.

4. Analysis results

4.1. Complex network for overall maritime accidents

The gathered maritime accidents are converted into the inter-event time series from the original occurrence time sequences to ensure that the time series is statistically significant to uncover the temporal aspects and change patterns of maritime accidents. The sequence of maritime accidents is indicated as $\{t_1, t_2, \cdots t_N\}$, where N is the number of maritime accidents in the time series. After that, the sequential inter-event times are calculated as the time differences $\Delta t = \{t_2 - t_1, t_3 - t_2, \cdots t_N - t_{N-1}\}$. Time differences time series for the maritime accidents from 2011 to 2020 is shown in Fig. 6.

In Fig. 6, the x-axis represents time, while the y-axis represents the time differences between maritime accident events. It is not difficult to see that the higher the vertical data point, the greater the time difference between two neighboring maritime accidents. This is a novel viewpoint on monitoring and evaluating the inter-event time series of maritime accidents, which differs from the previously understood time series of maritime accidents. Based on this time difference series, visibility graph have been conducted to analyze the characteristic of maritime accidents time series in the Yangtze River. In this research, all modeling and analysis were conducted in Gephi-0.9.2 on a laptop with the Windows 10 operating system.

A complex network of maritime accidents in ten years can be seen in Fig. 7. All the 3285 maritime accidents from a complex network with 3285 nodes and 11,650 edges. In its structure, the created complex network inherits the temporal features of the time series. The node degree characteristics reveal that the time series of maritime accidents display complicated and chaotic temporal dynamics. A time difference corresponding to a node with a very big degree indicates that there have been no maritime accidents for a long time. And a time difference point corresponding to a node with a low degree indicates continuous maritime accidents. Fig. 7 indicates maritime accidents over the past decade are separated by long periods of silence.

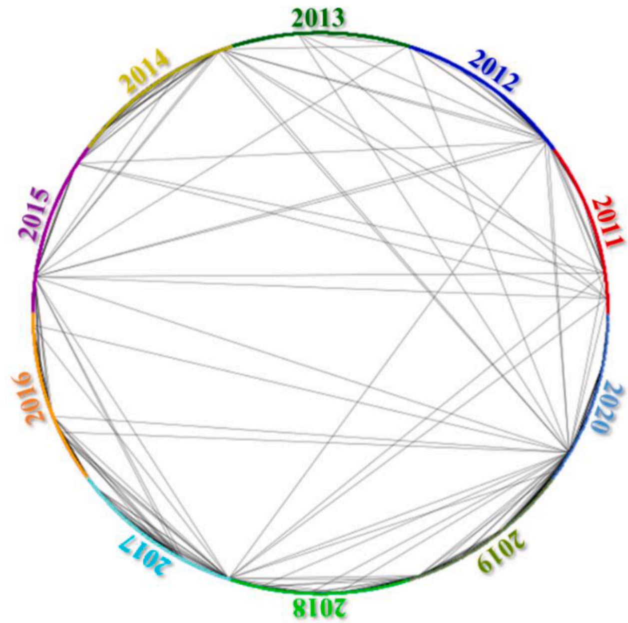

Fig. 7. Complex network of maritime accidents in ten years.

As shown in Fig. 8, the degree distribution and cumulative probability distribution of node degree over the whole network have been examined. And the cumulative distribution of node degree has been visualized in a log-log plot to discover the law of degree distribution in the network. There is an approximate power-law distribution of the node degree distribution in VG network. As a result of the node distribution analysis, the time difference series of maritime accidents transforms into a scale-free network. According to the characteristic of a scale-free network, there are few hubs with a high degree in the maritime accidents time difference series network. In contrast, the majority

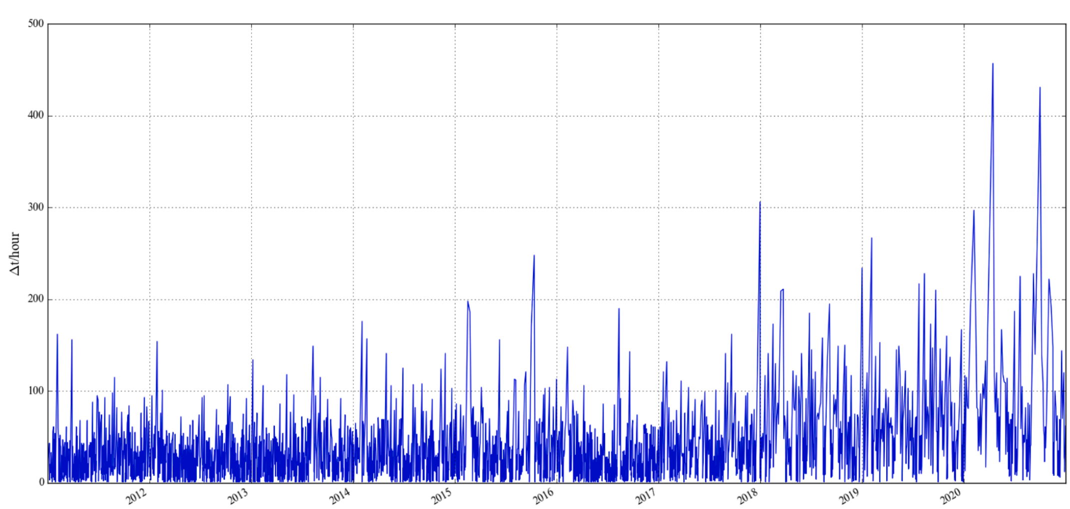

Fig. 6. Time differences series for the maritime accidents from 2011 to 2020.

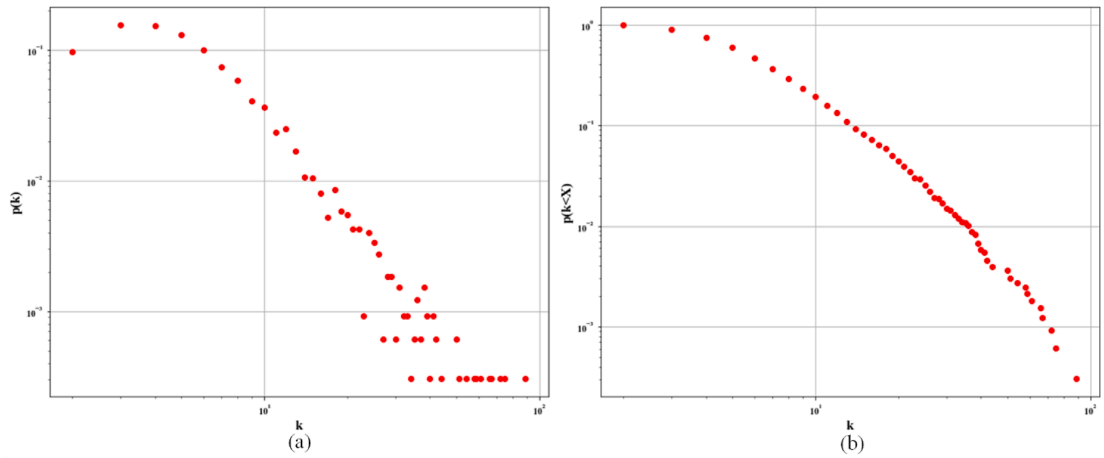

Fig. 8. Degree distribution and cumulative probability distribution of node degree for whole maritime accidents.

of nodes have a low degree. Because the occurrence of maritime accidents is intermittent, maritime accidents may occur continuously for a while and then enter a safe period. Table 5 displays network characteristics such as the number of nodes, the number of edges, the average time difference, the average network degree, the average clustering coefficient, the network width, and the average path length. The characteristic of a complex network for the yearly accident will be analyzed in Section 4.2.

4.2. Topological changes for maritime accidents in various years

Since the topology of these 10 networks differs, distinct time series from 2011 to 2020 exhibit different features. The node degree distributions of the 10-year networks also followed a power-law distribution, as seen in Figs. 9 and 10. And it is approximated by a power-law distribution $p(k) \propto k^{\lambda}$, and the exponents of each power-law distribution were derived and presented in Table 6. In general, the exponent is positively associated with the number of maritime accidents.

Complex networks for maritime accidents by year from 2011 to 2020 have been constructed, maritime accidents with large time differences mostly occurred in February, March, September and October, which can be observed in Fig. 9. The node degree distribution of the entire accident has a steeper slope and thicker tail than that of each year because the exponent of the total accidents is marginally larger than the exponent of the node degree distribution in the network of each year. Furthermore, the fact that the exponents of 2012, 2013, and 2014 are similar suggests that these three years were more homogenous than others. Similarly, the exponents of 2018 and 2019 are close together. The occurrences of accidents may be impacted by a more complicated mix of elements, such as human and environmental factors, which may explain why the degree distribution of marine accidents network is diverse each year.

The statistics of the ten networks are calculated and shown in Table 6. Because of the disturbance of the environment, management, and other factors, different networks show different characteristics. The average of the clustering coefficients is higher than 0.7, indicating that the networks are highly clustered. The largest network diameter in all ten networks is 8, indicating that each network's diameter is small, even though the maximum number of maritime accidents is 478. Furthermore, the maximum average of the network's shortest path lengths is 3.0656, smaller than the network diameters. The research on these parameters is shown that the time series of maritime accidents in Yangtze River have 'small-world' characteristics (Watts and Strogatz, 1998). The small-world networks based on maritime accidents time series are characterized with self-organization and self-similarity features. All the networks have higher clustering coefficients yet smaller characteristic path lengths.

Table 5
Properties of complex network for the whole maritime accidents in ten years.

Property	Value
The number of node/N	3285
The number of edge/E	11,650
The average of time difference/Δt	27.1626 h
The average of degree/$\overline{k}$	7.095
The average of clustering coefficient/$\overline{C}$	0.783
The network diameter/D	10
The average path length/L	5.0297

4.3. Characteristic of accidents time series in different jurisdictions

The inter-event time series of marine incidents is based, as previously said, on the combined data of all concerned jurisdictions over the course of ten years. The overall and annual network characteristics are produced by combining maritime incidents that occur in different jurisdictions. Each jurisdiction's inter-event time distribution was also examined to estimate the micro level of the temporal dynamic phenomena of maritime accidents because the temporal dynamics of the overall and annual data can be shown through complex networks. The existence of the complex network's features at the level of specific jurisdictions, in particular, needs to be confirmed. In this section, the maritime accidents time series in 22 jurisdictions have been analyzed. Complex networks for the first 5 jurisdictions in the number of maritime accidents is shown in Fig. 11. The results show that the fluctuation of the accidents time difference in Nantong and Taicang are substantial. It means that the time series patterns in different jurisdictions are different. And the accident time series pattern at different times showed different characteristics. For example, in Nanjing and Taizhou, the accidents time series pattern has been changed from homogeneous (2011–2014) form to heterogeneous (2015–2020). This shows that the safety level is improving.

Degree distribution and cumulative probability distribution of node degree in 22 jurisdictions can be seen in Fig. 12. The degree distribution of maritime accidents in different jurisdictions is also power-law distribution, which has heavy-tailed forms (Gomes et al., 2000). It shows that the behind mechanism of maritime accidents time series pattern is the accident occurred intensively, and then long periods of silence. So at the macro and micro levels, the maritime accidents time series are not random, and all have a universal property of scale-free.

Properties of complex networks for maritime accidents in 22 jurisdictions are shown in Table 7. As shown in Table 7. The average of the clustering coefficients indicates that the networks are also highly

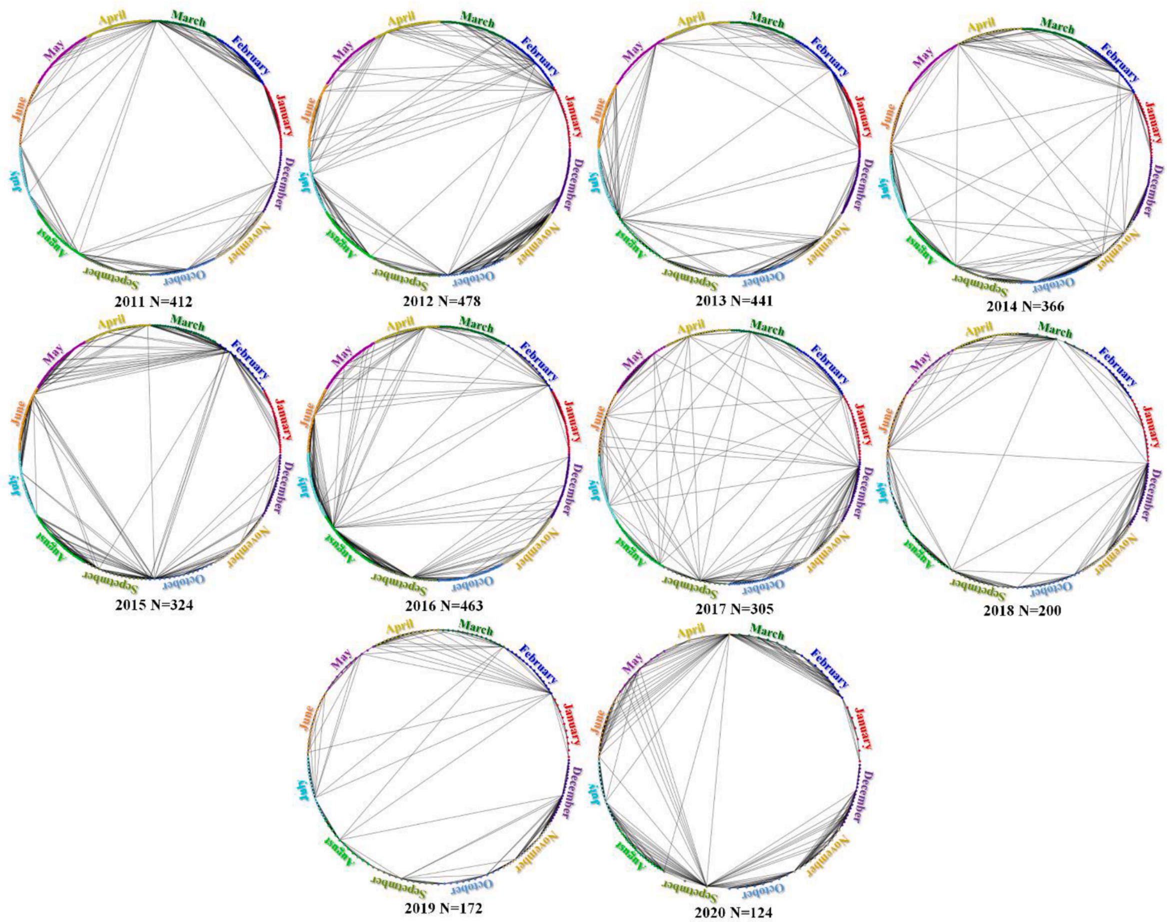

Fig. 9. Complex networks for maritime accidents from 2011 to 2020.

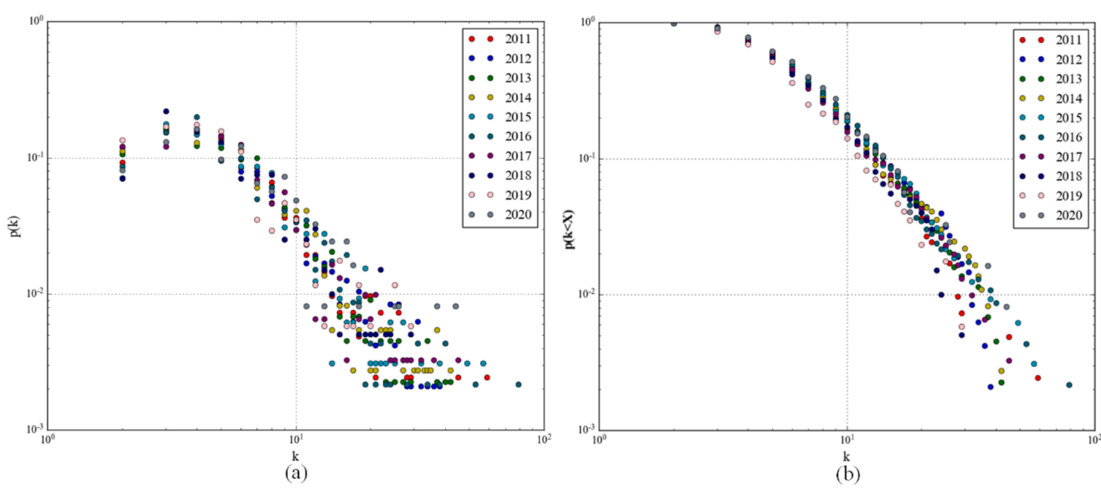

Fig. 10. Degree distribution and cumulative probability distribution of node degree for the yearly maritime accidents.

clustered in 22 jurisdictions. The network diameter of the eventful jurisdictions of accidents is higher than in other areas. It indicates the time series in the eventful jurisdictions of accidents have 'small-world' characteristics. Additionally, their slope indicates a more chaotic dynamic with a lower exponent, but higher values for the exponent of the degree distribution suggest a system that is relatively stable and predictable, with the exponent increasing these qualities. And they are basically in the lower reaches of the Yangtze River. But in Luzhou and Yibin, the complex network with less self-organization and self-similarity characteristics, the number of accidents is very small because they are located in the upper reaches of the Yangtze River. This phenomenon can be seen in Fig. 13.

5. Discussion

It is well known that theoretical analysis of maritime accidents has often been recommended. However, the dynamic and temporal characteristics of the time series of maritime accidents remain unclear and

Table 6
Properties of complex network for the yearly maritime accidents.

Year	N	E	Δt	$\overline{k}$	$\overline{C}$	D	L	λ
2011	412	1362	21.664	6.628	0.784	8	3.9649	2.9191
2012	478	1652	18.912	6.927	0.777	8	4.1215	3.0444
2013	441	1534	20.358	6.973	0.792	8	4.0955	3.0593
2014	366	1265	24.327	6.923	0.781	7	3.6572	3.0656
2015	324	1153	27.608	7.139	0.779	7	3.5394	2.9872
2016	463	1647	19.468	7.130	0.785	8	3.8096	3.0229
2017	305	1021	29.173	6.717	0.783	7	3.5698	3.0121
2018	200	634	44.282	6.372	0.767	7	3.5093	2.8148
2019	172	505	51.255	5.906	0.777	6	3.3693	2.8122
2020	124	499	71.338	5.301	0.784	6	2.9452	2.7158
Total	3285	11,650	27.162	7.095	0.783	10	5.0297	3.5495

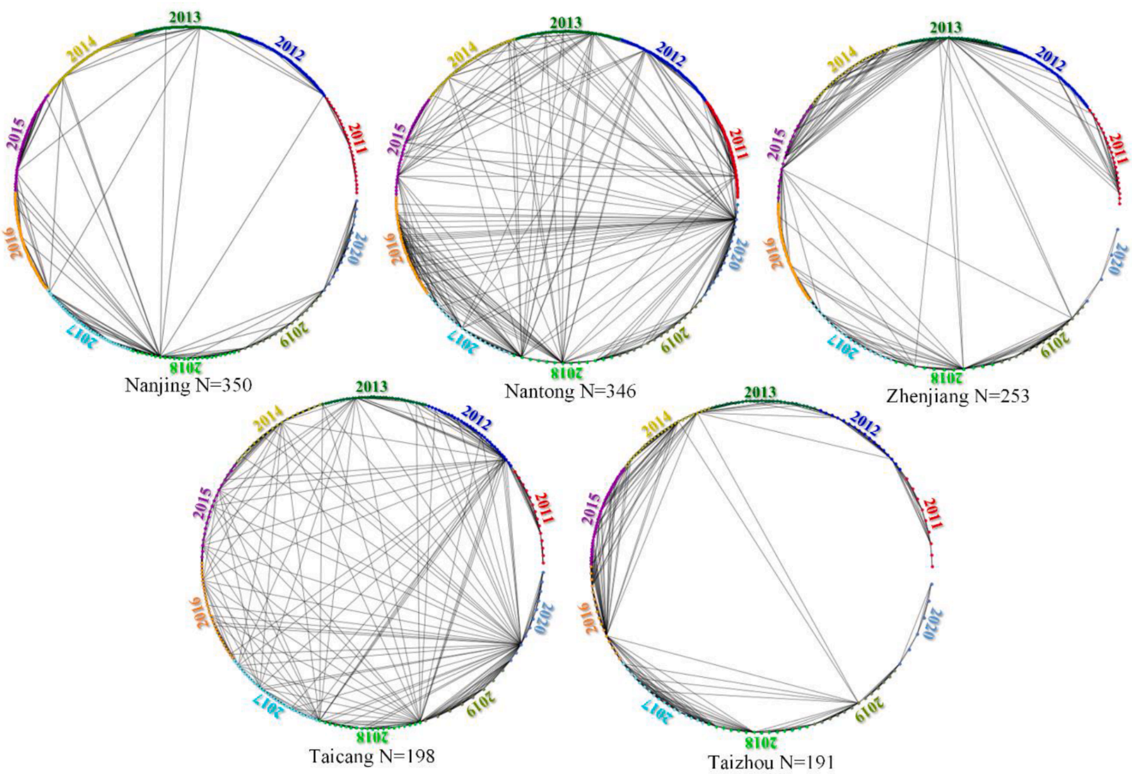

Fig. 11. Complex networks for the first 5 jurisdictions in the number of maritime accidents.

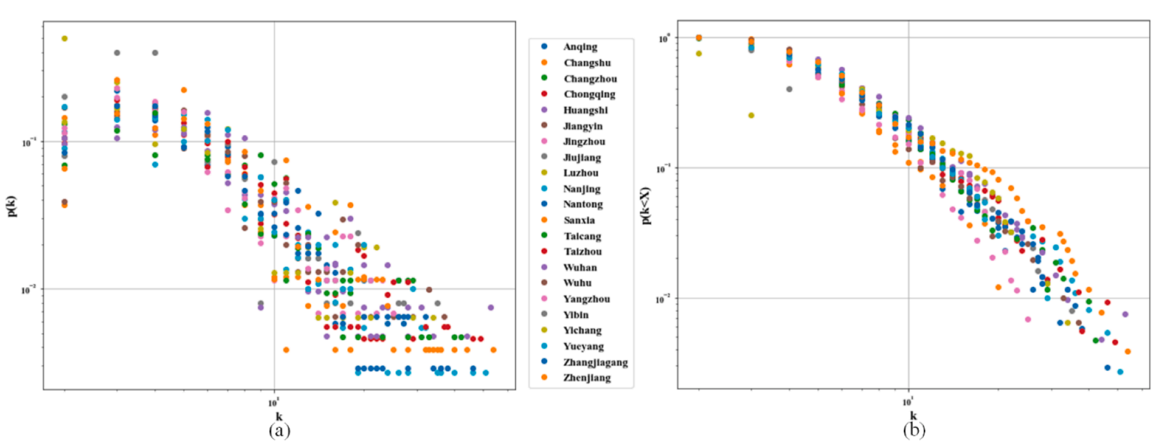

Fig. 12. Degree distribution and cumulative probability distribution of node degree in 22 jurisdictions.

Table 7
Properties of complex networks for maritime accidents of 22 jurisdictions.

Jurisdictions	N	E	Δt	$\overline{k}$	$\overline{C}$	D	L	λ
Nanjing	350	1288	235.122	6.981	0.782	8	3.984	3.1095
Nantong	346	1145	252.0696	6.638	0.785	7	3.74	2.4591
Zhenjiang	253	1009	336.0849	7.792	0.78	7	3.525	3.0474
Taicang	198	736	395.1408	6.911	0.795	7	3.601	3.0457
Taizhou	191	636	467.6167	7.067	0.797	7	3.498	3.0034
Chongqing	189	765	402.1376	7.018	0.783	7	3.225	2.9395
Huangshi	179	743	419.0048	7.144	0.791	6	3.267	3.0724
Yichang	157	553	561.3141	7.090	0.789	6	3.145	3.0456
Zhangjiagang	156	537	559.1613	6.929	0.787	5	3.084	2.8349
Wuhu	155	531	566.9156	6.896	0.799	6	3.145	2.9345
Yangzhou	151	414	595.4315	5.671	0.778	6	3.094	2.7724
Wuhan	141	512	650.5075	7.642	0.785	6	2.862	2.9453
Jiujiang	126	429	678.872	6.864	0.799	6	3.077	2.9583
Jiangyin	102	302	853.5743	5.98	0.774	5	2.993	2.8493
Yueyang	101	329	856.11	6.58	0.763	6	3.077	2.9583
Jingzhou	89	275	957.6477	6.25	0.781	6	2.848	2.7924
Anqing	88	270	998.8621	6.207	0.791	5	2.983	2.8423
Changzhou	88	297	982.3793	6.828	0.781	6	2.762	2.6934
Changshu	84	225	1053.12	5.422	0.767	5	2.973	2.7452
Sanxia	28	77	3129.667	5.704	0.773	4	2.134	2.6034
Yibin	6	8	6775.2	3.2	0.767	2	1.2	2.6253
Luzhou	5	4	4577	2	0.778	2	1.333	2.6945

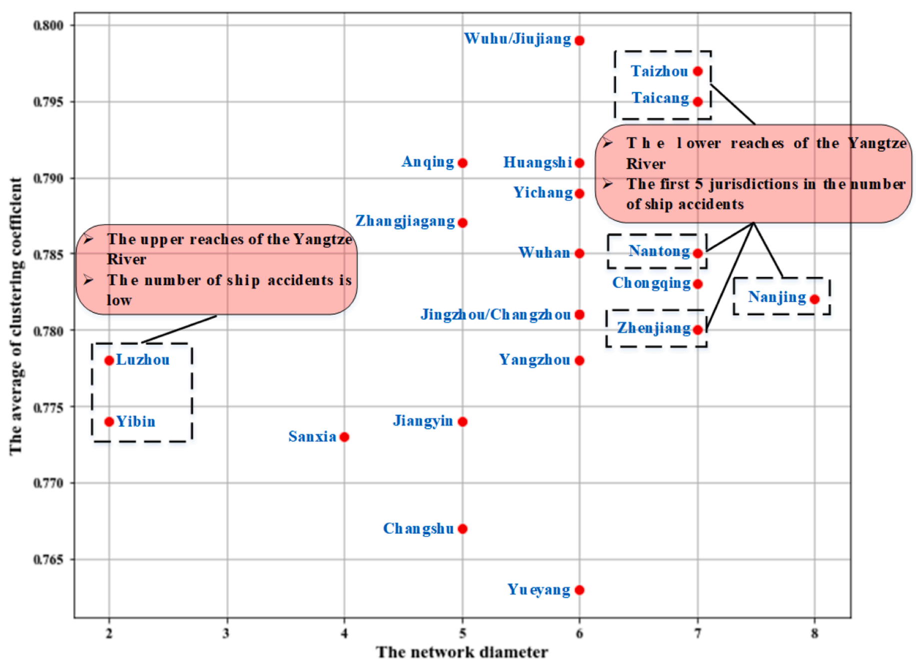

Fig. 13. Relationship between the network diameter and the average of clustering coefficient.

cannot easily be uncovered by analytical representations. Complex network theory has been applied to examine the characteristics of the maritime accidents time series and the mechanisms underlying the maritime accidents in the Yangtze River to address this gap. Mapping time series into a complex network with VG algorithm, temporal characters, and dynamics of inter-event time series of maritime accidents has been revealed through the analysis and discussion of maritime accident data. All degree distributions of the time series networks, followed by power law, demonstrate that the inter-event time series of maritime accidents in the Yangtze River are scale-free. Practical insights into maritime accidents and safety management are also proposed with the analysis of the time series via complex network theory. The complex network theory provides three main discussions for maritime accident management: (i) A rethinking of the maritime accidents time series pattern; (ii) Maritime safety performance based on the network properties; (iii) An enrichment of the maritime accident prediction and safety barrier generation.

(i) A rethinking of the maritime accidents time series pattern

Learning from maritime accidents is to interpret and assess their risk implications and to transform ship accident data into risk-informed interventions, safety improvements, and increased awareness. Conventional wisdoms are mainly divided into two aspects. Some researchers believe that maritime accidents are without any pattern and are completely random time series. Others believe that maritime accidents are regular and follow a certain periodicity. However, this research has led to some new conclusions. As the previous experimental results pointed out, the maritime accidents time series has a heavy-tailed distribution, indicating that maritime accidents have scale-free and small-world characteristics. Some of these sudden accidents may lead to a sharp drop in local traffic safety management in a short time. Therefore, traffic managers need to clearly understand the complex dynamics and non-linear characteristics of maritime accident time series so that they can develop preventive measures for maritime accidents based on the chaos in the historical information.

(ii) Maritime safety performance based on the network properties

From the view of the complex network, the topological properties of the network can be used to evaluate the robustness and vulnerability of the system and to monitor and identify critical nodes. Therefore, by subjecting historical maritime accidents data to complex network analysis, the characteristics of maritime accidents time series can be mined and some network topological properties can be introduced into maritime traffic safety assessments and used to evaluate the current safety situation. In Figs. 10 and 12, the node degree and degree distributions show that the maritime accidents time series shows a heavy-tailed distribution in different years and in different jurisdictions, which indicates that the accident time series is not random but has a scale-free character. In addition, according to the clustering coefficients and network diameters, it can be seen that the maritime accidents time series network has small-world characteristics and appears to be geographically distributed, with the lower reaches showing distinctly different network characteristics from the upper reaches of the Yangtze River.

(iii) Maritime accident prediction and safety barrier generation

The maritime supervision personnel cannot completely control the growth routes of the marine accident management system due to the system's structure. As a result, a complexity science viewpoint motivates the exploration of adaptive, incremental ways to forecast the abrupt swings and chaos in marine accident time series, which may be useful for addressing uncertainties and shifting conditions in metro construction. However, the inability to predict maritime accidents and proactively build up safety barriers for them is hampered by the absence of data on marine accidents. To address this issue, real-time monitoring of the water area using IT infrastructures and support entails gathering and prioritizing data on maritime accidents, analyzing and evaluating their intricate systemic implications, and converting this data into risk-informed interventions, safety enhancements, and awareness.

6. Conclusions

To enhance the visualization of traffic accident time series and their characterization, a visibility graph has been introduced to indicate the dynamics of the time difference of maritime accidents time series in the Yangtze River. The characteristics of maritime accidents time series are analyzed from the perspective of complex networks, and statistical analysis is given on the characteristic properties of these networks. The degree distribution, clustering coefficients, and network diameters of the complex networks constructed from maritime accidents time series in different states show certain patterns of variation, providing a visual perspective for studying traffic safety.

The maritime accidents time series is a complex system—this research analyses maritime accidents time series from macro and micro aspects. On the one hand, different accident time series networks appear to have different structures, generating chaos in the time series that are not entirely random or follow a specific pattern. On the other hand, the accident time series network is a scale-free network, where nodes with a large degree represent long periods without accidents, followed by outbreaks of accidents.

The method used in this research enables the analysis of the dynamical characteristics of the time series between maritime accidents from a new perspective. It uses it as a reference for improving maritime traffic safety. Although the visibility graph can analyze the fluctuation and chaotic characteristics in the time series of maritime accidents, it does not predict the occurrence of accidents. Therefore, safety monitoring should be enhanced in practical traffic management and minimized risks based on data analysis.

Nonetheless, there are several drawbacks to this study. This study used all maritime accident data in the Yangtze River and did not consider specific vessel types or accident types. In the subsequent research, factors such as different types of vessels and different types of accidents will be deemed to explore the accident time series characteristics further. In addition, the data used in this research are all inland river accident data, and it remains to be further verified whether open water maritime accidents follow the pattern found in this research. Therefore, there is a need to collect maritime accidents data from the sea and to verify whether these data also have the characteristics of a long-tailed distribution.

CRediT authorship contribution statement

Zhongyi Sui: Conceptualization, Methodology, Writing – original draft, Visualization, Data curation, Formal analysis. **Yuanqiao Wen:** Methodology, Conceptualization, Writing – review & editing, Formal analysis, Funding acquisition, Project administration. **Yamin Huang:** Writing – review & editing, Formal analysis. **Rongxin Song:** Methodology, Writing – review & editing. **Miquel Angel Piera:** Supervision, Writing – review & editing.

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.

Data availability

The authors do not have permission to share data.

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