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Optimal allocation model for maritime emergency resource considering the spatial correlation between accident hotspots

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ABSTRACT

For effective maritime traffic emergency rescue (MTER) operations in the event of maritime traffic accidents (MTAs) and to improve rescue efficiency, it is necessary to analyse the MTER synergy problem and the cooperation between port states. *First*, the spatial information of accidents under the geographic information system(GIS) data structure is clarified from the global integrated shipping information system (GISIS) of the International Maritime Organization (IMO), and the density-based spatial clustering of applications with noise (DBSCAN) algorithm is used to conduct hotspot mapping analysis of MTAs to establish the clustering and classification of accident characteristics in key areas. *Second*, the classification characteristics of accident samples are extracted based on spatial information, and the correlation attributes between MTA hotspots are analysed. Furthermore by introducing complex network measurement technology, the topological model of the MTER network is established considering the correlation of accident hotspots, and combined this model with the sample data of MTAs in Southeast Asian waters from 1990 to 2022. *Third*, the MTER topological network model is quantitatively analysed under the accident space of Southeast Asia, and the degree of correlation of traffic accidents in key areas is obtained to reveal the inevitable demand for MTER between regions. The results of the analysis show that there is a network correlation between inter-regional accident hotspots, and thus the degree of correlation between accident hotspots needs to be considered for MTER in key areas. Countries in densely connected regions would set up joint rescue exercises and to be considered rescue assistance between port countries stakeholder, thus improving protection for accident emergency responses. The method of complex network topology based on spatial correlation between accident hotspots suggests a new attempt towards solving the MTER problem.

Keywords: Maritime traffic accidents, Maritime traffic emergency rescue, Emergency resource, Spatial correlation, Complex network

1. Introduction

Maritime transport occupies an important place in world trade because of its advantages such as low freight rates and high transport volumes. As the shipping industry continues to develop, maritime transport is exposed to various risks, such as sudden changes in environmental factors and inadequate observations by crew. Maritime traffic accidents (MTAs) are sudden, and once an accident occurs, it is accompanied by serious consequences, such as casualties, ship damage, or pollution as a result of oil spill (LUo and Shin,2019).On January 6, 2018 the Panamanian tanker *Sangji* collided with the Hong Kong bulk carrier *Changfeng Crystal* at the mouth of the Yangtze River approximately 160 nautical miles east of the Yangtze River, resulting in a fire that engulfed the entire vessel. After the disaster happened, Chinese merchant ships, marine police vessels and fireboats from Korean and Japanese were dispatched to conduct emergency response tasks at the scene. However, at that time, the scenario suffered serious and uncertainty, and the emergency response to such crisis still faces many challenges, such as the timely scheduling of rescue forces, collaborating to achieve maritime traffic emergency rescue (MTER) in the shortest possible time, and in-depth analysis after the emergency involved. In view of the sudden and serious consequences of such accidents, uneven spatial and temporal distributions, and other characteristics, is becoming increasingly trouble issues coordinated rescue in different regions and countries. Those show that the severity of an accident directly determines the demand for MTER resources and that more serious accidents require resource support from multiple countries stakeholder.

To protect of human life and property in the event of a MTA, and to promptly prevent the situation from deteriorating, it is necessary to carry out MTER at the earliest of crisis. We can cope with emergencies easily only by improving the capacity of emergency response to MTAs (Dominguez-Péry et al.,2023). As accidents are unpredictable, this attribute requires the relevant authorities to ensure the availability of resources in advance. To guarantee efficient rescue, it is necessary to ensure that sufficient emergency resources are available and MTER measures are implemented in a timely manner. Many scholars have conducted adequate research on the efficient and reasonable allocation of emergency resources and developed a series of methods to calculate the number of emergency resources to be allocated to different regions (Dong et al.,2021). However, with the trend of large-scale ships and the transparency of global accident data, the previous MTER considering only the occurrence of accidents in a certain region can no longer meet the requirements of current maritime safety, and emergency resources must be allocated on a scientific basis. In the actual rescue operation, the rescue organisation's emergency resources are often limited. In addition, due to the uncertainty of the type of accident, it may not be possible to determine which type of resources are required, especially when responding to several different emergencies. There could be some conflict in the use of emergency resources, leading to the failure of the emergency response (Huang et al.,2022; Li, et al.,2023). Therefore, it would be practically significance to conduct further research on emergency responses to MTAs, including the allocation of resources and the mechanism of resource use.

MTA research has gradually penetrated accident hotspot analysis, and accident occurrence has become the main basis for accident rescue. For maritime personnel, determining the requirements for MTER through accident hotspots can increase the efficiency and security of rescue processes (Wen et al.,2019). Because of the differences in the occurrences of accidents in different regions and regional differences in the intensity of accidents, once the accident exceeds the emergency response capacity of a certain region it is necessary to carry out cross-jurisdictional emergency responses to cope with the crisis. Therefore, to avoid the shortage of emergency resources in a certain rescue centre and incomplete emergency resources, in the event of an accident, it is necessary to analyse the occurrence of accidents in different regions through the analysis of accident hotspots. This is the basis of the rescue by maritime personnel. To avoid the shortage of emergency resources in one rescue centre and the incomplete variety of emergency resources, it is necessary to study the correlation between the occurrence of accidents in different regions from the perspective of accident hotspots to determine which regional rescue agencies are necessary to carry out joint rescues to achieve efficient synergy of emergency resource allocation.

The remainder of the study is organised as follows. *Section 2* introduces previous related research as well as a literature overview of related theories and adopted technologies. In *Section 3*, the data source and determination process of MTA hotspots are introduced in detail, particularly the novel model involving a complex network proposed in this study. *Section 4* presents a spatial correlation analysis of MTAs in Southeast Asia, provides network nodes and edge strengths of MTA hotspots, and uses complex network analysis techniques to propose MTER resource scheduling schemes. *Section 5* discusses the proposed model and MTER resource scheduling schemes. *Section 6* presents the results. The feasibility of this study is proven through a case study, and corresponding allocation suggestions are presented.

2. Literature review

2.1 Research on maritime traffic emergency rescue

When a MTA occurs, it is necessary to take timely MTER measures to reduce the loss of human life and property and to stop the deterioration of the situation. MTER is an indispensable means of ensuring the safety of maritime traffic. Research on MTER includes rescue systems, rescue prediction and decision-making, and rescue efficiency evaluation and optimisation. (Ma et al.,2022) used the K-means algorithm to identify the centre of the accident black spot and carried out research on the optimal allocation of rescue resources by considering the distance of the rescue centre from the accident centre, which effectively enhanced the utilisation rate of resources and funds. (Zhou et al.,2022) constructed a game model of the allocation of resources for maritime search and rescue and assessed the navigational risk of the study area. As conditions that guarantee efficient rescue, effective allocation and reasonable use of emergency resources have a great influence on the improvement of rescue efficiency (Sun et al., 2022; Zhang et al., 2021). Therefore, it is necessary to conduct research on maritime safety from the perspective of the MTER resources.

Previous studies have often focused on the allocation of emergency resources from the perspective of systems engineering theory using quantitative methods to determine the specific allocation of the number and type of resources to meet a certain demand at a certain time for the purpose of MTER (Guo et al., 2019; Ma et al., 2022). However, the occurrence of MTAs has specific spatial and temporal characteristics. Its occurrence is not isolated or predictable, and addressing the consequences of different accident scenarios (Guo, 2022; Ma et al., 2022), show that the emergency resource allocation preparation of a single or a few rescue centres can no longer satisfy the current trend of multi-party collaboration in an accident rescue operation. To ensure the efficient use of emergency resources in different regions and avoid excess or shortage of resources, it is necessary to study the MTER network and determine how emergency resource allocation in corresponding rescue regions are linked by exploring the degree of correlation between accidents in different regions.

2.2 Research on hotspots of maritime traffic accidents

For the study of MTAs, scholars at home and abroad previously applied a density clustering algorithm to spatial information from geographic information system (GIS) to identify accident hotspots. Acharya et al.(2017) conducted a geospatial analysis of MTAs along the coasts of South Korea in a GIS environment for geospatial analysis to visualise high accident and safety-deficient areas to improve safety management in vulnerable areas. Zhang et al.(2021) applied Kernel Density Estimation (KDE) and clustering analysis to explore the spatial patterns and characteristics of maritime accidents at a global scale. Wang et al.(2022) analysed the spatial pattern of maritime traffic accidents based on the frequency and severity of accidents, and identified hotspot areas of maritime traffic accidents by using density analysis and cluster analysis. Yang et al.(2022a) used KDE to identify accident prone areas in Fujian waters. Spatial autocorrelation methods were used to explore the local distribution characteristics and specific clustering of accidents, and the characteristics of vessel traffic flow were extracted from automatic identification system (AIS) data to predict the risk of accidents that had not yet occurred. Subsequently, scholars worldwide, have used accident causation theory, classical statistical analysis, and other methods intensively to conduct accident research. U gurlu et al.(2016) used hierarchical analysis (analytic hierarchy process or AHP) to systematically tabulate the data of 850 major MTAs that occurred in the Turkish Straits and concluded that the most common cause of MTAs in the Turkish Straits was human error. Bye and Aalberg(2018) carried out a statistical analysis of MTAs to determine their relationship with the factors associated with navigational accidents (groundings and collisions) that occurred in Watts, Norway. In summary, these follow-up studies on MTAs have tended to focus on one discrete region and have explored the occurrence of accidents in that discrete region rather than conducting joint studies in multiple regions to produce more in-depth results.

2.3 Correlation research and application of complex network in MTA

For research on the association analysis of MTAs, scholars initially used the apriori association rule analysis, which establishes the nodes of the accidents and the links between accidents by filtering the frequent candidate sets, visually expresses the strength and weakness of each association rule. It is mainly used to mine the correlation between the information and factors in different accidents. WENG and LI.(2019) used the apriori association rule learning method to mine the factors that are highly correlated with ship traffic accidents, identify the potential hazards of MTAs, and explore the determinants of serious and non-serious accidents. Cakir et al.(2021) used an association rule mining algorithm for tugboat accident records to derive the critical impact of ship age on serious accidents. Ozaydin et al.(2022) used Bayesian networks and association rule mining methods to analyse the Turkish occupational accident data to analyse the potential factors of accidents and predict occupational accidents. The potential factors of occupational accidents were analysed to predict the rules for them.

Complex networks, originating from Leonhard Euler's Gnesburg bridge problem (Zou et al.,2019), are large-scale networks with a complex topology and dynamical behaviour composed of a large number of nodes connected to each other by edges, where nodes denote the basic units with specific information, and edges denote the relationships or interactions between the basic units (Hussain et al.,2022; Lu et al.,2022). The complex network theory has been widely applied to many complex systems such as the internet, power networks, and transport networks(Ding et al.,2019; Hossain et al.,2017; Zhang et al.,2022). In the field of maritime safety, Deng et al(2023)constructed a network model of MTAs along the coast of China from the four risk factors of man-ship-environment-management and analysed the overall structural characteristics of MTA network based on the calculation of the characteristic parameters of complex networks. Mou et al.(2020) established a framework for assessing the resilience of maritime crude oil transport based on the theory of complex networks and explored the influence of small- and medium-sized ports in the network on the resilience of the network through the calculation of network indexes.Yang et al.(2022a) establish a maritime silk road shipping network to identify key ports, compared the correlation coefficients with several centrality measures, and obtained the port importance rankings to provide a theoretical basis for port selection.

The development of complex networks gives weight to the edges between nodes, and not only considers whether there is a connecting edge between two nodes but also the weight of the connecting edge between two nodes. The greater the weight between two nodes, the thicker the connecting edges between the network nodes, and closer the relationship between these two vertices (Yu et al.,2020; Zhou et al.,2019). In this study, by clustering the accident hotspots in different regions into one region, which is regarded as a node, connecting with nodes through nodes, and finding the relationship between nodes. An accident network is formed based on the correlation of accident hotspots. The topology model of the MTER network is established and based on this the requirements of the MTER are understood in depth by analysing the topology of the network.

2.4 Contribution of the study

To explore the correlation between accident hotspots and problems in the MTA network, this study investigates the correlation of MTER based on the spatial relationship of accidents at MTA hotspots, establishes a topological model of the MTER network, and establishes regional collaborative emergency resource allocation and dispatching measures to improve the efficiency of the MTER when a maritime traffic accident occurs. The main contributions of this study are as follows:

(1) Starting from MTA hotspots, this study established a topological model of the MTER network using complex network theory and the results of the correlation of accident hotspots to reveal the characteristics of the resource allocation and scheduling mechanism of the MTER.

(2) This study explored the network association problem based on accident hotspots by applying clustering algorithms for MTA information, clustering discrete accident hotspots to form MTA network nodes and calculating the correlation between nodes in the accident network.

(3) Based on the MTA topological network, a series of methods were used to analyse and derive the characteristics of the network attributes to achieve a quantitative analysis of the MTER topological network. The intrinsic connection of rescue requirements in different regions was explored to optimise the MTER mechanism and guide maritime agencies in making more efficient decisions for improving maritime safety.

3. Data and methodology

3.1 Maritime traffic accidents and emergency response

3.1.1 Rescue requirements for MTA

After the occurrence of an MTA, the relevant organisations and personnel must carry out the MTER response, to eliminate and reduce accident hazards, prevent the expansion or deterioration of the accident, and minimise the loss or consequences caused by the accident and rescue measures or actions taken (Zhou, 2022). MTER resources refer to all types of resources required for monitoring and warning of maritime emergencies, emergency response, and recovery, and are the material basis for the management of maritime emergencies and the prerequisite for MTER (Ma et al., 2022). The materials used for the MTER of MTAs are classified under several categories. The broad emergency resources include personnel and equipment directly used for the operation on the accident scene, called tactical resources, such as emergency crews, emergency boats, life rafts, helicopters, and skimmers, as well as non-tactical resources used to support emergency response to accidents, such as the location of the resource pool allocation and the scheduling method of the rescue materials. It is critical to conduct research on MTER resources based on accident distribution. Depending on the type of MTA, different requirements for rescue work and emergency resource allocation are required to achieve correspondence and matching (Ai et al., 2015). The MTER process is illustrated in *Figure 1*.

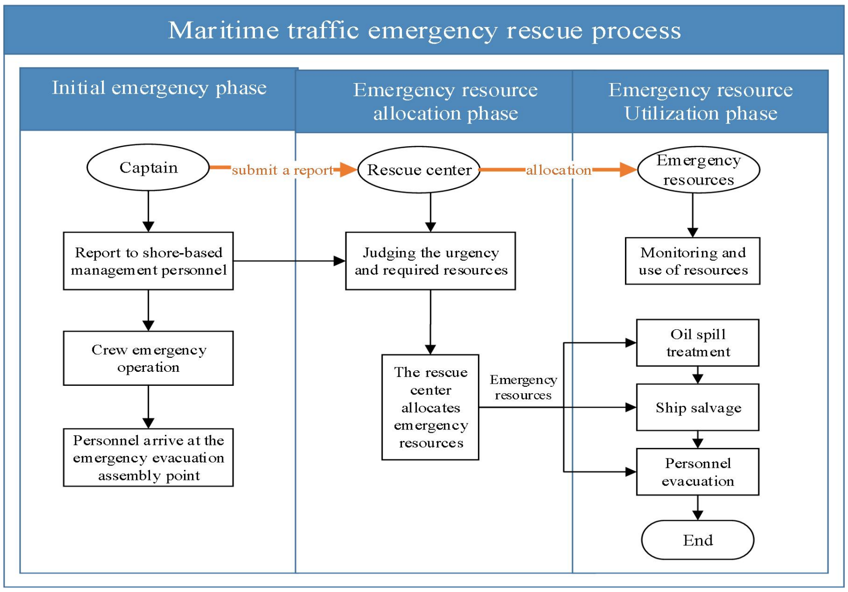

Fig.1 Maritime traffic emergency rescue flow chart

MTAs are characterised by suddenness and uncertainty, and as a result, MTER response resources have the following characteristics:

(1) Uncertainty: The uncertainty of sudden MTAs causes uncertainties in the allocation of MTER resources (Hu et al.,2022). It is impossible to accurately estimate the duration of an accident, the intensity or the size of the MTA, the scope of impact of the accident, and other factors that determine the uncertainty of the number of MTER resources, structure, mode of transport, etc.(Liu et al.,2012). When an accident is serious and emergency resources in one region alone are not sufficient to carry out an accident rescue operation, it is necessary to carry out rescue through coordination among multiple parties.

(2) Irreplaceability: Many types of MTER resources exist. Therefore, it is necessary to configure the corresponding types of emergency resources based on different accident results. It is imperative to use them in specific situations, for example, oil booms and absorbents used after oil spill accidents. Multiple types of MTER resources result in the rescue centre not being able to configure the most targeted resources for each type of MTA. This requires the assistance of an emergency resource from a rescue centre with a strong correlation.

(3) Lagging: the activation of MTER resources is based on the determination of the size, scope, and nature of the MTA after the accident; therefore, it lags behind. Emergency resources must be allocated fully in advance.

The study of MTER includes the spatial allocation of emergency resources and the mechanism of their dispatch. The dispatch of rescue forces must fully take into consideration the rescue centre, location of the accident, maritime environment, and the vessel in distress (Wang et al.,2018). Only a reasonable allocation and proper use can make the MTER process more effective.

3.1.2. Spatial allocation requirements for MTER resources

In MTA scenarios, owing to the wide range of accidents and lag in the activation of emergency resources, emergency resources must be deployed as quickly as possible to minimise the consequences caused by the accidents (Sun et al.,2013). Therefore, in terms of the spatial allocation, it is necessary to fully consider the location of the accident to reduce the time required for emergency resources to arrive at the accident site.

In addition, when the number of emergency resources is insufficient or there is competition, it is necessary to optimise the allocation of resources and complete the hierarchical collaborative allocation of emergency resources through multiparty coordination to minimise all types of losses caused by the emergencies and reduce the financial burden on the government and the operating pressure on enterprises (Wang et al.,2021).The relationship between the accident locations and maritime emergency resource scheduling is shown in *Figure 2*.

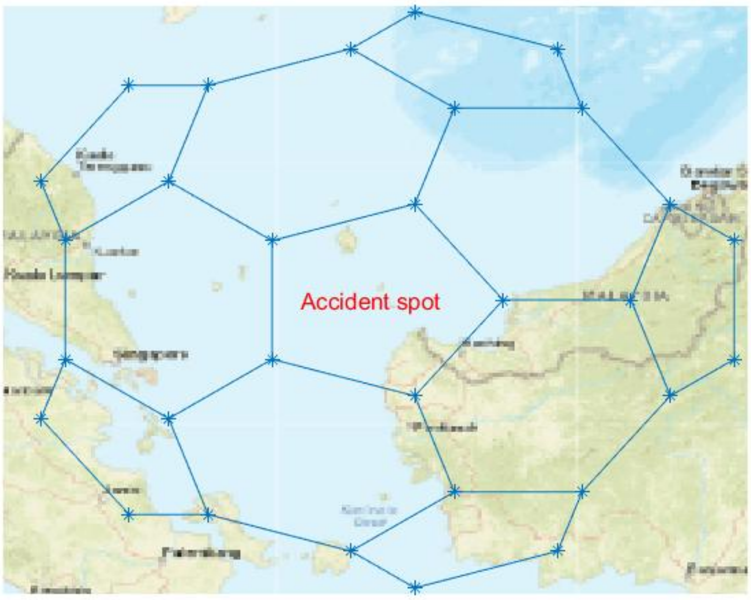

Fig. 2 Accident locations and MTER resource scheduling

3.1.3. Mechanisms for the use of MTER resources

To improve the efficiency of use and reduce the waste of emergency resources, efficient MTER places certain requirements on the mechanism of using resources (Seo et al.,2017).

The demand for MTER resources is determined according to the type and severity of the MTAs, and emergency resources are dispatched (Shahparvari et al.,2018). In addition to the allocation of different quantities of MTER resources according to accident severity, it is impossible to ensure that rescue centres in the corresponding areas are adequately prepared owing to the diversity of accident types. Therefore, it is necessary to implement rescue coordination among countries, share resources, and utilise their advantages. Many countries integrate resources, optimise their layouts, and send targeted and efficient rescue teams.

When using MTER resources, systematic processes such as sign-in, tracking, and management should be conducted. Only by having a clear understanding of the status of the resources involved in an emergency and systematically managing resources can we avoid inefficient use and achieve efficient rescue (Hu et al.,2019).

3.2 Data

MTAs often occur on a global scale, and the waters where they occur are generally far from land, such as in the territorial waters of another country, its adjacent areas, and even in the high seas. The location of these accidents is more difficult to determine. The International Maritime Organization (IMO) has continued to promote the reporting of MTAs for many years and has shared data globally. In this study, accident data from 1990 to 2022 were obtained from the global integrated shipping information system(GISIS) on the IMO website. Analysing the data structure of the database revealed multiple dimensions of information (see *Table 1*).The results of statistical analysis of accident data are shown in *Figure 3*. Although some data is not available, in general, it is still possible to conduct a follow-up analysis, especially regarding the time, location, and types of accidents. These data provide data of MTA hotspots. In this study, two accident elements, accident location and types of accidents, were selected for the next step in the accident cluster analysis and network establishment.

Table. 1 Accident data structure

Content Composition	**Parameters**	**Data structure type**
Basic information on reported accidents	Reference	Figure
	Number Of Ships Involved	Figure
	Incident Date and Time	Time
	Coordinates	LONG, LAT
	Location	Semantics,Classification
	Initial Event---type	Semantics,Classification
	Summary of Events	Semantics
	Number of Investigation Reports	Figure
	Number of Analyses	Figure
	Investigation Report Date	Date
	Analysis Date	Date
Basic information on the ship in question	Ships Involved	Semantics
	SOLAS Status	Name
	Flag States	Name
	ShipType	Semantics

Content Composition	Parameters	Data structure type
	CargoType	Semantics
	Gross Tonnage	Figure
	Dead weight	Figure
	Classification Society	Figure
Extent of damage caused by the accident	Consequences	Semantics
	Type Of Casualty - serious	Semantics,Classification
	Crew on board	Figure
	Passengers On board	Figure
	Others on board	Figure
	Dead or Missing Crew	Figure
	Dead or Missing Passengers	Figure
	Dead or Missing Others	Figure
	Seriously Injured Crew	Figure
	Seriously Injured Passengers	Figure
	Seriously Injured Others	Figure

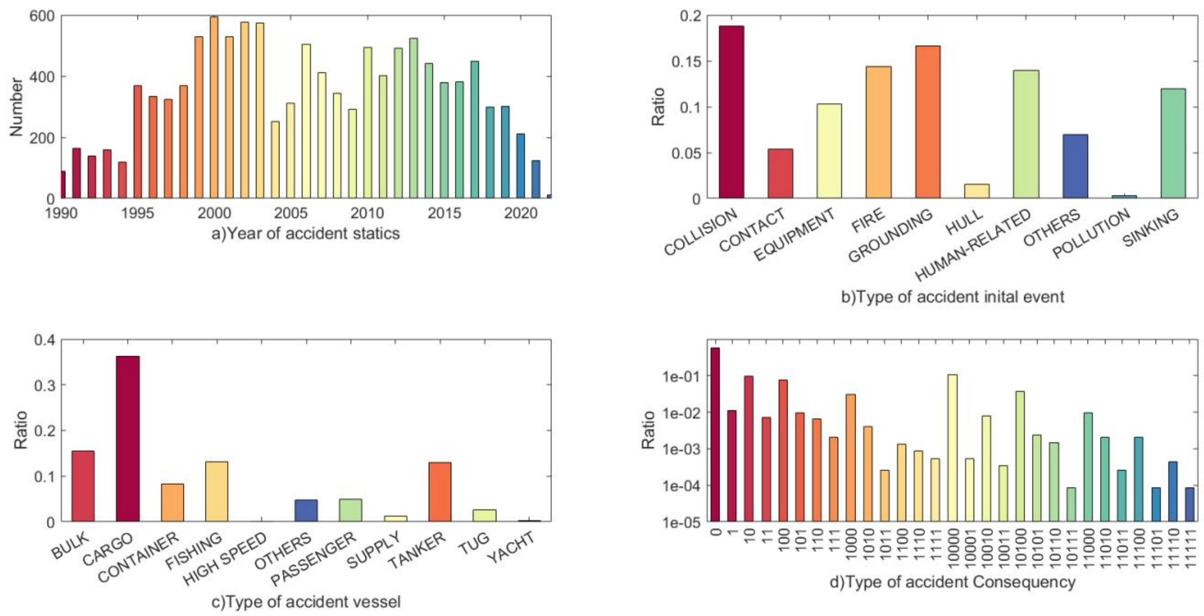

Fig.3 Statistical analysis of maritime accidents occurred during 1990 - 2022 (resource: IMO GISIS)

3.3 Methodology

3.3.1 Accident hotspot spatial relation based on 2D KDE algorithm

To study the spatial relationship of accident hotpots, a 2D kernel density estimation algorithm was chosen to establish the spatial clustering of accidents, and finally present the accident distribution on a GIS chart according to density clustering. Kernel density estimation (KDE) was used to fit the sample data using a smooth peak function, and a continuous density curve was used to describe the distribution pattern of random variables, which has the characteristics of strong robustness and weak model dependence. The 2D KDE algorithm, a non-parametric method for estimating the distribution of 2D data, can help analyse the density distribution of 2D data (Chakraborty et al.,2011).

The basic idea of the algorithm is that, for a given set of two-dimensional data points, the density distribution is estimated by placing a kernel function around each data point and summing the contributions of all kernel functions. This results in a density map on a two-dimensional plane that can be used to represent the density distribution of the data in different regions. The kernel function is usually a standardised probability density function, such as a Gaussian function.

According to KDE, the formula for the probability density estimation function of the accident at location(x, y) is

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

where $f(x, y)$ is the estimated density at the accident location (x, y); n denotes the number of accidents occurring at all locations, h denotes the bandwidth, $K(\cdot)$ denotes the kernel function, and d_i denotes the distance between the first point and the point with position (x, y).The Gaussian kernel function is given by

$$K(v) = \frac{1}{\sqrt{2\pi}} e^{-\frac{v^2}{2}} \qquad (2)$$

From Equations 1 and 2, it can be seen that the density distribution is the highest at the point closest to the centre of the calculation and gradually decreases outwards; when it is far away from a certain range, the density becomes 0.

An important parameter of the 2D kernel density algorithm is the bandwidth h which controls the degree of smoothness in the density curve estimation results. A bandwidth that is too large will result in an estimation curve that is too smooth to accurately reflect the local characteristics of the data; a bandwidth that is too small will result in an estimation curve that is too oscillating and an unstable estimation result (Kim et al.,2022). Therefore, when using this algorithm, it is necessary to select an appropriate bandwidth value to obtain reasonable density estimation results. The 2D kernel density algorithm is widely used for data visualisation, anomaly detection, and pattern recognition (Panda and Nanda,2021). This can help us discover clusters, anomalies, trends, and other information on accident distribution, thereby enhancing the comprehensive understanding of accident data.

3.3.2 MTA cluster analysis based on the DBSCAN approach

It is necessary to identify a new clustering algorithm to cluster accident data with multidimensional characteristics, such as accident types and consequences. The clustering description method based on the spatial density of data provides a good basis for constructing clustering algorithms. A clustering algorithm is an unsupervised learning method used to classify data into similar groups or clusters. The goal is to divide data points into groups with similar characteristics such that data points within the same group are more similar and have similar attributes or characteristics, whereas those belonging to different groups are less similar and have highly different attributes or characteristics. Density-based clustering is immune to noisy data and can flexibly define and discover clusters of arbitrary shapes (Chen et al.,2017; Ganesh et al.,2023). Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is a representative density-based clustering algorithm (Al-Mamory et al.,2019; Boonchoo et al.,2019; Li et al.,2023). After specifying the density of the accident distribution, accident data were clustered. From a spatial analysis perspective, the clustering results of MTA can be identified. The temporal and spatial differentiation results of global MTAs can be presented intuitively, and the distribution of accident hotspots can be clearly defined. Through clustering, the attributes of the nodes such as the number and overall consequences of accidents can be obtained.

In the process of clustering, samples that are closely connected or have similar densities are classified into one category to obtain a cluster category; if the density of a point is greater than a set threshold, the point is added to another category. The final results of all the clustering categories were obtained by classifying all groups of closely related samples into different categories (Luchi et al.,2019).

In the practical application of the algorithm, the core points in the dataset are found by setting the neighbourhood (Eps) and the minimum number of points(*MinPts*) called density threshold , and any core point P is selected as the starting point.By connecting the core points with direct density and connecting the edge points to the nearest core points, the required clusters are formed, clustering is realised, and noise points are identified. The computational procedure of the DBSCAN algorithm is as follows.

(1) Given the domain radius Eps and the *MinPts* in the domain radius needed to become the core object.

(2) Start from any point p, and mark it as "*visited*". Next, check if it is a core point (i.e. whether the *Eps* neighbourhood has at least *MinPts* objects); if it is not a core point, then mark it as a noise point. Otherwise, a new cluster C is created for p; create a new cluster C, and mark the cluster that puts the p of all the objects in the *Eps* neighbourhood of the cluster into the candidate set N. $N_{Eps(p)}$ refers to the area with the core point as the centre and the neighbourhood (*Eps*) as the radius, and it can be determined as follows:

$$N_{Eps}(p) = \{q \in D \mid Dist(p,q) \leq Eps\} \tag{3}$$

where Dist (p, q) is the distance value of object q from core point p, and D represents the dataset. For clustered dataset D, if NEps (p) exists and is satisfied, the definition is said to be direct from the density.

(3) Iteratively add the objects in N that do not belong to other clusters C. In this process, mark the objects marked as "*unvisited*" in N as "*visited*" and check its *Eps* neighbourhood. If they are also core objects, all the objects in the *Eps* neighbourhood are added to *N*. Continue to add objects to *C* until C cannot be extended, that is, until N is empty. At this point, cluster *C* is completely generated.

(4) Randomly select the next *unvisited* object from the remaining objects, and repeat process in step (3) until all objects have been visited.

Through the above four steps, all the clustered regions are found, and these clustered regions are used as the final cluster results, and the *Eps* can be adjusted according to the different needs of the experiments to obtain more accurate clustering results.

3.3.3 MTA network analysis based on spatial correlation

The node characteristics under the network can be obtained through the density clustering processing of the accident data in the previous section. These are the nodes in the accident network. A network with a complex structure and characteristics obtained through a high degree of abstraction is a complex MTA network. A complex network is a special network structure, which is a complex system of elements abstracted as nodes and the relationship between the elements abstracted into the edges of the network structure model. The MTA network obviously belongs to a complex network, which meets the following three characteristics:1) small-world characteristics (small world), that is the value of the characteristic path length between points in the accident space network is sometimes very small, close to the random network, but the aggregation coefficient of the network is very high, close to that of the regular network. 2) Scale-free characteristics (scale-free): The degree value of a few nodes will be very large, while most of the nodes are very small, and the degree value distribution of the nodes is in accordance with the power rate distribution law. 3) Association structure characteristics and the nodes in the complex network of the accident space tend to show clustering characteristics, that is the connection between the nodes inside the association area is very strong, whereas the connection between the nodes inside the association and the nodes outside the association is obviously weakened. The analysis of nodes and edges in an accident network includes the following main indicators:

(1) Degree of nodes

Node degree is the number of edges in a network connected to the node. The larger the value of the degree, the greater its importance.

$$A_i = \sum_{j \in N} e_{ij} \tag{4}$$

where N is the number of nodes in the network; e_{ij} is the number of connected edges between nodes and.

(2) Network diameter and average path length

Network diameter D is the maximum value of the distance between any two nodes in the network. It is expressed as follows:

$$D = \max_{i,j \in V}(d_{ij}) \tag{5}$$

The average path length L is the average distance between all pairs of nodes for which a connected path exists. The average path length reflects the number of influences passing through the incident. It is expressed as follows:

$$L = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i \neq j} d_{ij} \tag{6}$$

where N is the number of nodes in the network; d_{ij} is the node-to-node distance.

3.3.4 Topological analysis of MTA network based on the complex network approach

Scholars have used a variety of methods to conduct research on MTER, such as Bayesian networks (Qiao et al.,2022), multi-objective planning (Peng et al.,2022), and decision models (Xiong et al.,2020). Based on accident data, it is very important to choose scientific and effective methods to analyse them to provide theoretical and practical support for planning accident rescue. Based on the MTA network, the association between network nodes is limited by several factors, and the network topological relationship has a certain sensitivity. Some methods are required to explore the correlations between the hotspots of MTAs and thus analyse the requirements of maritime MTER in different regions.

As mentioned in the previous section 3.2, scale-free networks are severely heterogeneous, with a severely uneven distribution of connection status (degree) among their nodes; a small number of nodes in the network, called hub points, have an extremely large number of connections, whereas the majority of nodes have only a very small number of connections. The few hub points play a dominant role in the operation of a scale-free network. The scale-free nature of a network is an intrinsic property that describes the grossly inhomogeneous distribution of many complex systems.

The main attribute values for analysing complex networks are of the following types:

(1) Clustering coefficient

The clustering coefficient indicates the degree of node aggregation in a network. Clustering coefficient *C (i)* is the ratio of the actual number of connected edges of node *i* to the maximum possible number of connected edges. It is expressed as follows:

$$C(i) = \frac{2E(i)}{A_i(A_i - 1)} \tag{7}$$

where *i* is the number of nodes connected to node (i.e. the degree of node); A_i is the number of edges that exist between nodes adjacent to node *i*.

(2) Betweenness centrality

It is also referred to as the mediator centrality degree. The betweenness centrality *B (i)* is the ratio of the number of shortest paths through a node to the number of shortest paths between each pair of vertices in the network. The betweenness centrality degree emphasises a node's ability to regulate and transit between other nodes. The normalised expression is as follows:

$$B(i)=\frac{2}{(N-1)(N-2)}\sum_{s\neq i\neq t}\frac{\delta_{s,t}(i)}{\delta_{s,t}} \tag{8}$$

where N is the number of nodes in the network; $\delta_{\{s,t\}}$ is the number of shortest paths between nodes *s and t;* $\delta_{\{s,t\}}$ is the number of bars of the shortest path between nodes *s and t* passing through node *i*.

(3) Closeness centrality

Closeness centrality represents the inverse of the sum of the distances from a node to all other nodes, and reflects closeness to other nodes. The greater the proximity centrality of a node, the shorter the distance from the node to the other nodes; spatially, this node is also centrally located. The normalised expression for this is as follows:

$$M(i)=\left[\frac{1}{n-1}\sum\nolimits_{y}d(y,x)\right]^{-1} \tag{9}$$

where $d(y,x)$ is the node i the sum of distances to all other nodes.

(4) Edge strength

After determining the accident clustering nodes, the centre of the accident clustering nodes can be determined, and the edge strength can then be calculated. As this study explores the degree of interconnection between accidents, not only the number of accidents but also their severity and the degree of spatial distance should be considered. Based on the original accident data, the severity of the consequences of the accident is classified, the clustering centre obtains the coordinate point, the distance between nodes is calculated, and the edge strength is determined by integrating the clustering range and number of accidents. The association strength between accident clustering nodes 1 and 2 is denoted by W_{12} and it can be expressed as follows:

$$W_{12}=k\frac{N(P,S)}{d_{12}} \tag{10}$$

where d_{12} is the distance between accident *Node 1* and accident *Node 2*, N is the sum of the number of accidents at the two nodes under the consideration for the accident range under determination for accident intensity, and k is the adjustment factor. Based on accident attributes, in this study the correlation network between accident clustering nodes is constructed and analysed and the structure and degree of accident correlation is evaluated.

3.4 Modelling

The research framework of the model used in this study is shown in *Figure 4*. The accident data were processed using the two-dimensional kernel density and DBSCAN methods, to realise the complete visualisation of global MTAs and determine accident hotspots. Based on the determination of accident hotspots, different clustering areas are regarded as network nodes, and the correlation between accident clustering nodes is regarded as the edge of the network. According to the spatial distribution results of accidents obtained by clustering, the correlation between accident hotspots is presented in the form of a network, and through in-depth exploration of accident information, a MTER network topological model of the is established to obtain the requirements of joint allocation of MTER forces in related areas.

The data processing in this study mainly includes four steps:

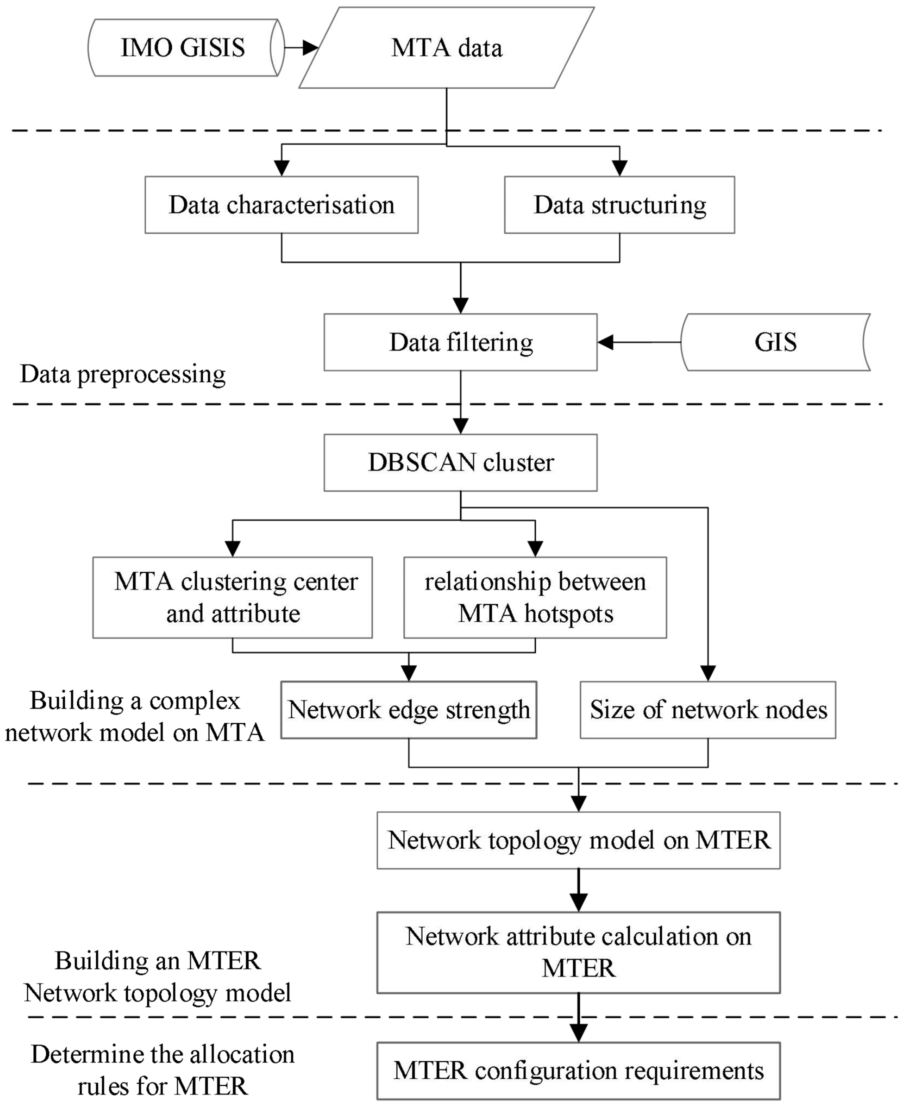

Fig. 4 Framework of the modelling study

(i) Pre-processing the data through data structuring and characterisation and using 2D kernel density algorithms and density-based clustering methods with noise to carry out spatial analysis of MTAs and identify hotspot areas.

(ii) Based on the confirmation of accident hotspots, algorithms are used to extract the clustering centre information of each cluster point separately, including the overall spatial location of the accident and the statistical characteristics of the accident.

(iii) Determining the measurement direction of the network node correlation and calculating the characteristic parameters such as network node strength and edge strength of the network.

(iv) Determining the network topology relationship of the accident multi-dimensional attributes and evaluate the network hierarchy.

4. Results

Taking Southeast Asia as examples, this study establishes the region defined by [90 °E, 150 °E] and [20 °S, 50 °N] as its research scope. A total of 1228 samples were collected from the spatial and temporal dimensions of MTAs over the last 30 years from the IMO GISIS and analysed according to the calculation process of the previous algorithm.

4.1 Accident hotspot map and MTA network

4.1.1 Spatial analysis of MTA hotspots

Combined with the scheduling model in the previous section 3, the calculations were processed separately. After analysing the acquired MTA samples by applying the 2D kernel density algorithm, the results showed that the accident distribution was uneven on the map. To make the data analysis more sensitive, the data densities of 0.5 and 2 are selected here. As shown in *Figure 5*, the 5(a) shows a data density radius of 0.5 degrees, whereas the 5(b) shows a radius of 2.0 degrees.

The data show that the Southeast Asia region contains three accident hotspots, namely, the Yangtze River Delta region, the Pearl River Delta region, and the Malacca Strait region; these results are consistent with the results of previous studies, and the distribution of MTAs is dense in the area of the land-ocean interface, and in the oceanic region it is looser. This again confirms that MTAs account for 80% of accidents occurring in 20% of the waters. This also provides the basis for a relatively centralised allocation of maritime emergency resources (Zhang et al.,2021).

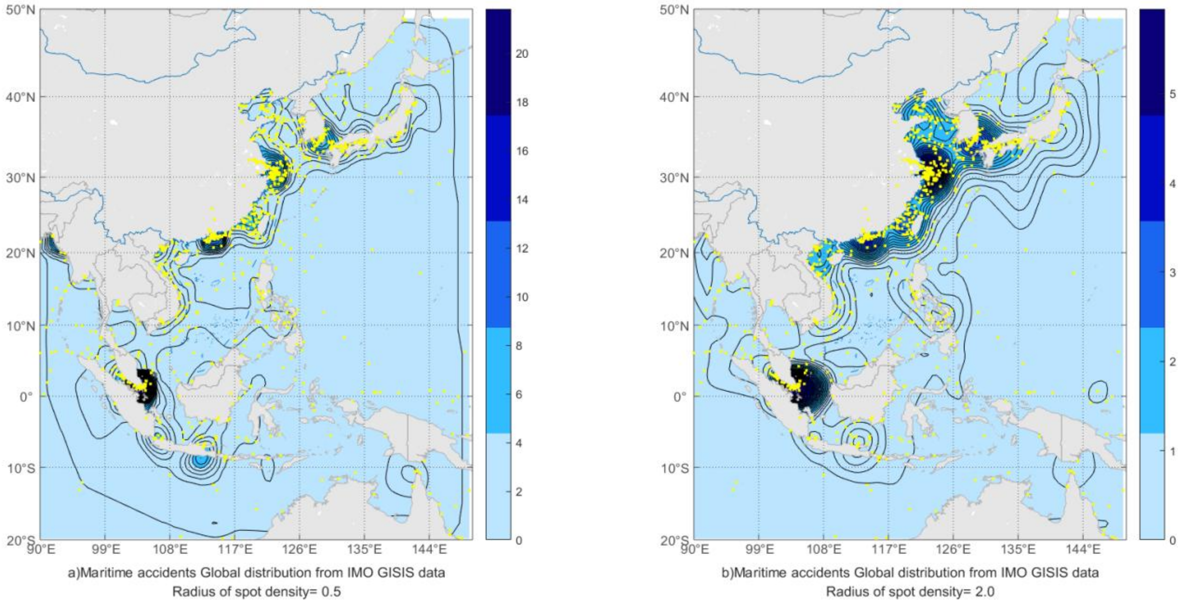

Fig. 5 MTA clustering hotspots for Southeast Asia

4.1.2 Spatial relation of MTAs

Combined with the model in the previous section 3, the calculations were processed separately, and accident severity was used as the classification criterion to obtain the results of very serious accidnts clustering and serious accidnts clustering. According to the spatial clustering model established by the DBSCAN algorithm, *Eps=0.5*, the accident points were substituted into the algorithm to calculate, and the core points connected by density were gathered into a cluster. A plurality of clusters closely related to each other were formed through the density correlation of different spaces, thus realising the clustering of MTAs. Based on the results of accident clustering in Southeast Asia, the clustering region was condensed into network nodes, and owing to the different number of accidents covered by each clustering region and the different range of accidents. Each accident clustering node has its own size and colour, as shown in *Figure 6.* The node colour represents the number of accidents in the clustered region, and the rectangular area represents the regional scope covered by the clustered region, thus completing the node construction of the MTA network.

This is an example of clustering of very serious accidents. The data are divided into 22 accident clustering nodes, Nodes 1-19 accidents are shown in *Table 2*. The other nodes have no statistical values owing to the single sample data and are therefore not listed in this table.

Table 2 Characteristics of accidents at hotspots (cases with serious consequences accidents)

Location of accident clustering centers (°E-°N)		**clustering label**	**Average number of persons involved**	**Overall number of persons involved**	**Number of accidents**	**Range radius (km)**
119.3926	26.2605	1	18	3229	178	495.2
122.4729	36.7293	2	17	815	47	213.7
101.5970	2.5356	3	11	103	9	56.7
130.3343	34.3609	4	13	904	71	267.4
103.9816	1.3454	5	12	452	38	59.6
107.0438	19.0480	6	8	246	30	174.9
139.7346	35.3086	7	9	105	12	57.9
120.8495	14.2119	8	40	357	9	62.1
106.3843	-5.8940	9	18	176	10	39.0
124.1167	10.1633	10	4	20	5	28.9
107.0178	10.4620	11	6	46	8	37.0
136.9235	34.2592	12	15	58	4	54.1
112.6048	-7.0190	13	9	65	7	34.0
91.7695	22.2439	14	12	87	7	5.0
109.2339	14.0280	15	3	31	9	46.6
109.3683	11.1978	16	5	31	6	60.8
114.3002	-6.0588	17	79	315	4	35.0
118.3420	38.8609	18	22	131	6	9.7
123.5389	34.0223	19	16	64	4	30.6

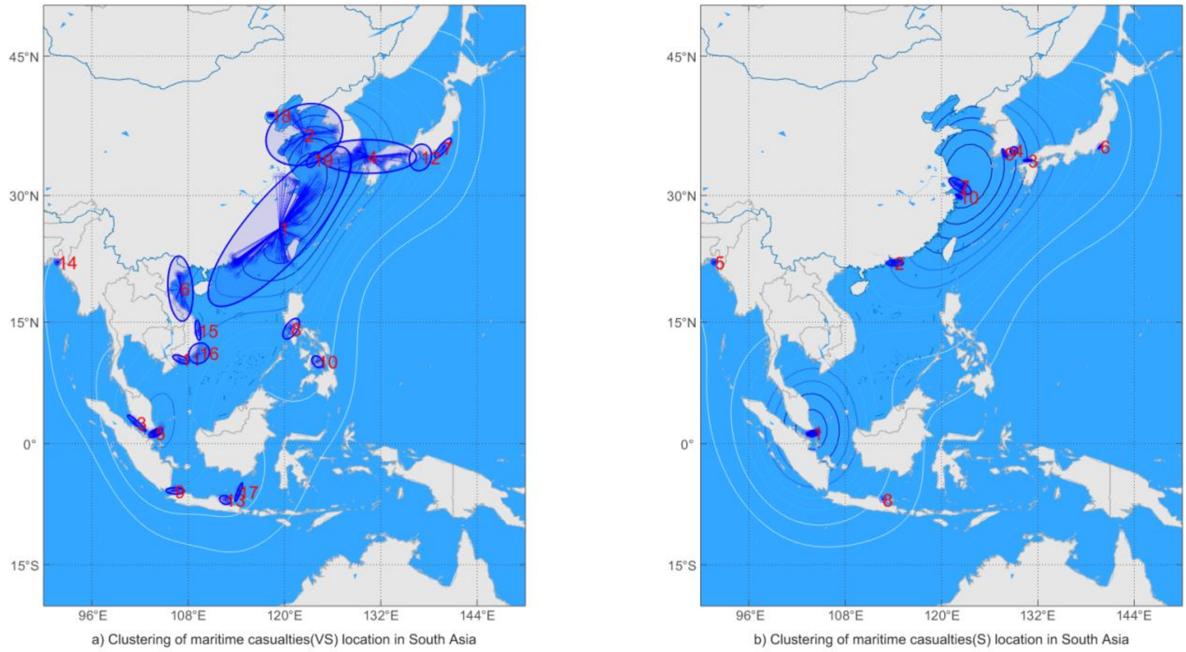

Fig. 6 Network nodes under the clustering of MTA in Southeast Asia

It can be found in the table 2 and figures 6:

(1) The network relationship can be constructed by connecting the nodes of accident clustering, and there are close or loose correlation relationships between the different clustering areas in addition to distance correlation. Through the complex network research method, the nodes are identified and the edge strength is quantitatively calculated to explore the correlation between different accident clustering regions.

(2) Considering the number, location, and coverage of accidents, each node is assigned a different size and each edge is assigned a different strength, which is determined by the sum of the distances between the nodes and the number of accidents at the connected nodes.

(3) Based on the spatio-temporal clustering results of the accidents that were clustered using the DBSCAN algorithm, model data are extracted to establish MTA network.

4.2 MTA network and network topology of MTER

4.2.1 Network connecting edges of MTA

Based on the MTA network establishment method analysed in Section 4.1, an example of a complex network established by clustering results with *eps=0.5*, is shown in *Figure 7*.

According to the global MTA clustering results, each accident points was regarded as one of the 22 nodes, and each node had attributes such as accident number and scope. As shown in

Figure 7(a), the accident points covered many countries and regions such as China, Japan, Korea, South Asia, and Indonesia. Then, the edge strength was calculated according to the position of the accident point and the distance between the accident points as the input value of the associated network, where the edge strength is calculated using Equation (10); the input value is shown in *Figure 7(b)*. Based on the 2D data heat map, We evaluated all methods used previously.

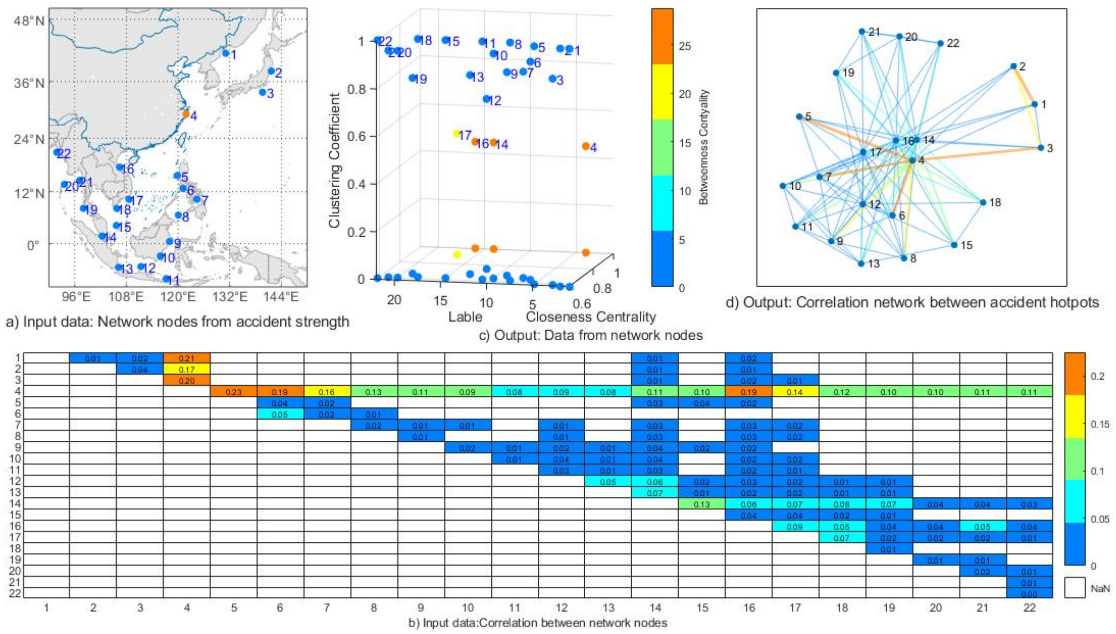

Fig. 7 Process and outcomes of MTA network in Southeast Asia

4.2.2 Network nodes and degree of association in MTA network

Among the values of network attributes, the clustering coefficient represents the degree of aggregation of the network at a certain node, Betweenness Centrality indicates the size of the node's regulating and connecting role in the network. Closeness Centrality represents the closeness of a node to other nodes, and the larger the closeness centrality, the closer the node's role is to the centre of the network (Lu et al.,2022). In this study, these three coefficients have been selected to statistically analyse the network.

Calculations were performed using Equations (7)–(9) to obtain the analysis results for each node, and *Table 3* shows the experimental results of the nodes. The experimental results are shown in *Figure 7(c)*, which shows that *Node 4* is closer to the centre of the network and has the greatest degree of association with other nodes, in terms of the clustering coefficients. The denser the accident point area, such as Indonesia, the larger the clustering coefficient owing to the higher number of clustered areas. The degree of betweenness centrality and closeness centrality is also higher for *Nodes 16* and *17* because Vietnam is located off-centre in the Southeast Asia and occupies a larger connectivity role in the network.

Table 3 Statistical values of nodes of MTA network in Southeast Asia

Nodes	Clustering coefficient	Betweenness Centrality	Closeness Centrality
1	1.00	0.00	0.57
2	1.00	0.00	0.57
3	0.87	0.50	0.58
4	0.45	28.75	1.00
5	1.00	0.00	0.58
6	0.92	0.50	0.64
7	0.87	0.99	0.66
8	1.00	0.00	0.62
9	0.85	1.24	0.68
10	0.94	0.29	0.64
11	1.00	0.00	0.62
12	0.71	4.54	0.75
13	0.84	1.50	0.68
14	0.45	28.75	1.00
15	1.00	0.00	0.62
16	0.45	28.75	1.00
17	0.51	18.25	0.91
18	1.00	0.00	0.62
19	0.82	1.60	0.66
20	0.95	0.17	0.60
21	0.95	0.17	0.60
22	1.00	0.00	0.58

4.2.3 Modularity Analysis in MTER Network

To further derive the laws of the MTER network, the network was modularised, and based on the degree of the nodes, the network was finally divided into three modules: the core circle centred on *Node* 4, as well as the secondary and edge circles except *Nodes 1-7*, as shown in *Figure 7(d)*. The results of this study could serve as a basis for an in-depth study of the intrinsic laws of the MTER network topology model.

4.2.4 MTER Network Topology characteristics

A mathematical analysis of the network was performed based on the network analysis results of the accident data. To effectively study the emergency allocation from the perspective of the correlation of accident hotspots, a MTER network topology model is presented on the map, as shown in *Figure 8*. Through the network analysis of the accident data, the topological relationship between MTA networks can be established. The weighted degree of this topological network model is 10.455 and the average weighted degree s 12.054.

The data in the figure 8 shows that:

(1) In an undirected graph, the degree indicates the number of edges directly connected to a node, while the weighted degree describes the sum of the weights of edges directly connected to a node, that is, the sum of the strengths of the connections; the larger the value, the stronger the degree of connection between the node and other nodes. This indicates that there is a significant increase in the degree of association between accidents after considering edge strengths, and that accident assistance requires a rational allocation of strengths and weaknesses; therefore, the increase in accident attributes contributes to the analysis of accident assistance.

(2) The network graph density is 0.498, and the network diameter is 2, which indicates that each accident clustering node has strong correlation attribute with the other, and that the nodes are easily reachable from each other; therefore, a joint rescue mechanism is needed.

(3) The connecting edges with strengths in the top were retained in the final topological map. China, Japan, and South Korea formed a strong correlation network centred in China, whereas Indonesia formed a weak correlation network centred in the Straits of Malacca. Meanwhile, the China-Vietnam region is also more closely connected because of its geographical proximity. This suggests that the Southeast Asian region has formed a closely linked network of accidents, and that the coordination of emergency resources among key countries in the global region is necessary for an effective response to accidents and rescue.

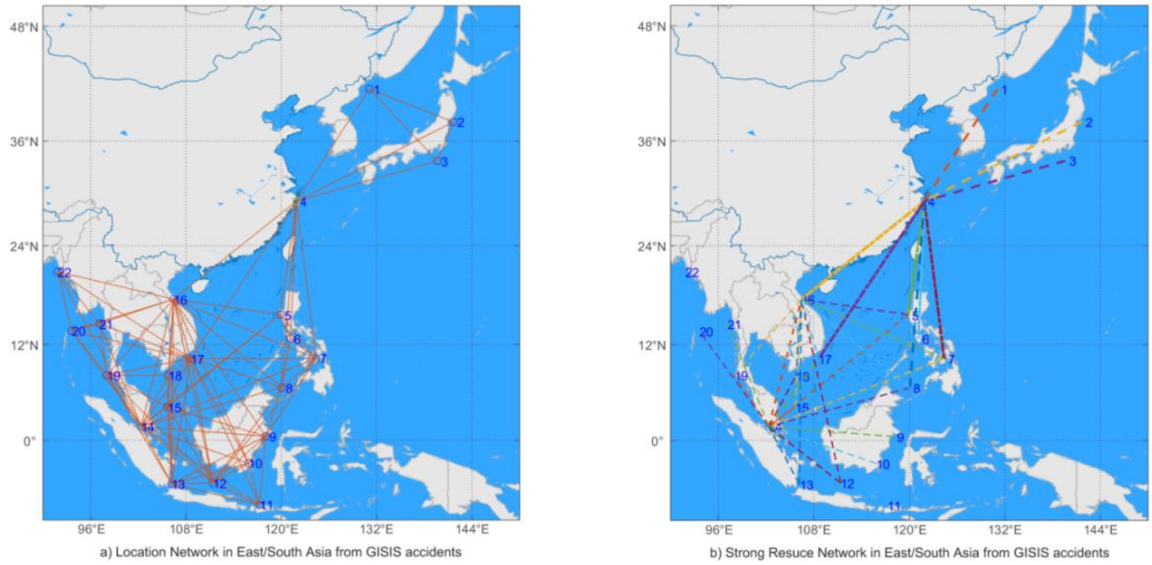

Fig. 8 MTER network topology model in Southeast Asia

4.2.5 Sensitivity analysis in network topology

To consider the computational results obtained under the conditions of varying parameters, a sensitivity analysis was required to demonstrate how variations in the parameters of the clustering algorithm affect the proposed network topology model. Because the accident clustering results are the basis for establishing this model, and *Eps*, as the basis for clustering region division, has a significant influence on the accident clustering results, the parameter for this analysis was selected as the *Eps* value, and a new MTER topology network was established by changing *Eps*. In the experimental process, it can be observed that when *Eps* changes from 0.5 to 2, the experimental results remain unchanged, all of which are consistent with the clustering results when *Eps=0.5*, whereas when *Eps=2*, the experimental results are significantly different from the results obtained earlier.

In this analysis, the accidents were divided into very serious accidents and serious accidents for the purpose of analysis, and networks were established. Very serious accidents account for a large proportion of all accidents worldwide; therefore, they are the key research objects. The results of the topological networks for MTER are shown in *Figures 9 and 10*. In very serious accidents, according to the clustering results of the Southeast Asian region, the accident points are clustered into 20 nodes, and then, according to the formula the value of the strength of the connecting edge between the 20 nodes is calculated. The calculation results show that the centre of the network is still the Pearl River Delta region of China and the Malacca Strait sea area, whereas the aggregation coefficients of the nodes are larger in the Indonesian and Japan-Korea regions because of the large number of islands and the complexity of the coastline.

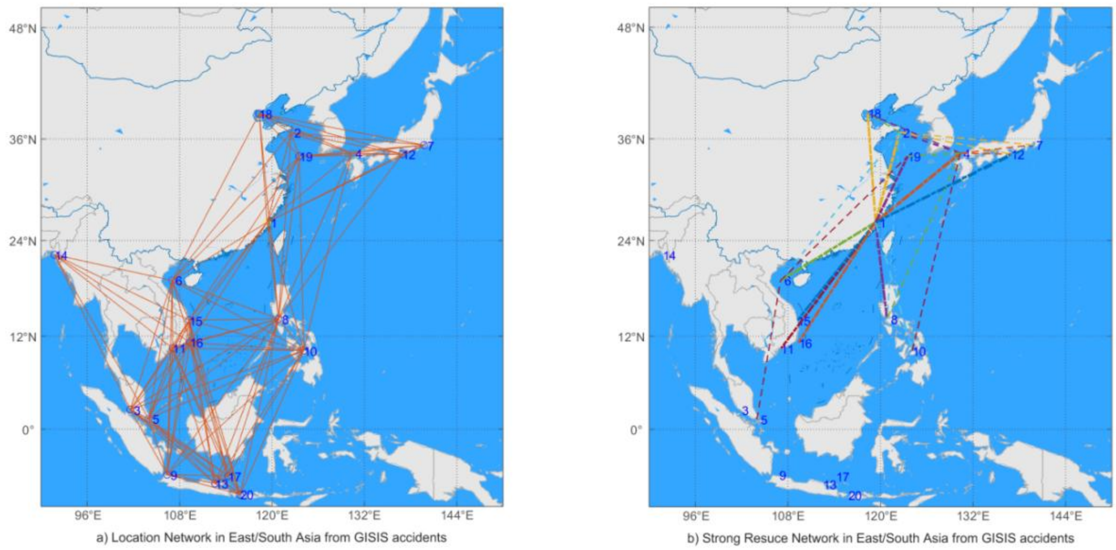

Fig. 9 MTER network topology model in Southeast Asia (Source: MTA with very serious consequences)

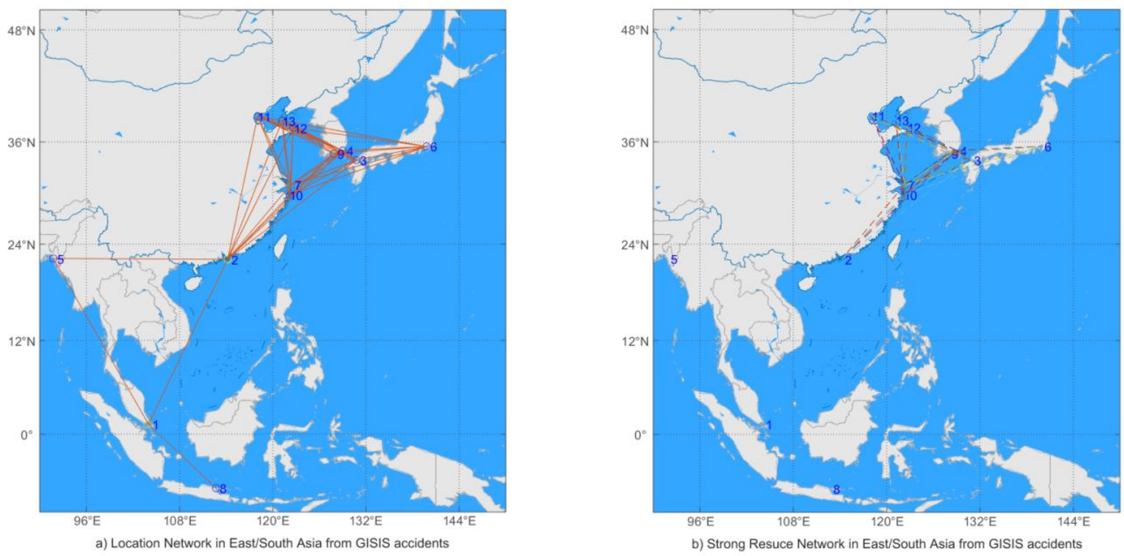

Fig. 10 MTER network topology model in Southeast Asia (Source: MTA with generally serious consequences)

For serious accidents, the clustering resulted in a total of 13 network nodes, with Node 1 having the largest mediated centrality and proximity to the centre, suggesting that the Malacca Strait, as an important transport hub connecting the Pacific and Indian Oceans, carries many transport vessels, and the proportion of accidents resulting in serious consequences is also higher in comparison to the Pearl River Delta region in China.

The results of the above analyses prove that the model in this study can produce corresponding results for different accident input situations, which is universal and applicable, and that the clustering algorithm used in this study has a certain degree of sensitivity to the establishment of the network topology model because the results of the accident clustering largely determine the basic shape of the rescue topology network. The conclusions of the topological model of the MTER network established through several experiments were consistent.

4.3 MTER response under the network topology mode

According to the results of the study on the topological model of the MTER network established in the previous section, we know the following:

(1) The China-Japan-Korea region formed a strong relief coordination network centred in China, while the Indonesian region formed a weak relief coordination network centred in the Malacca Strait. At the same time, China and Vietnam are more closely related because of their geographical proximity. This suggests that a rescue coordination network has been formed in the Southeast Asian region and that coordination of emergency resources among key countries in the global region is necessary for an effective response to accidents and rescue.

(2) The MTER network exhibits complex small-world and scale-free characteristics. Nodes in a network exhibit strong heterogeneity. The nodes in the network have a short average distance from each other, and their local cluster characteristics make the network coupling closer and promote a degree of interconnection between the nodes in the local area.

After the occurrence of an MTA, the relevant departments receive MTER instructions according to the emergency plan and requires a series of operations, such as the scheduling of emergency supplies, allocation of rescue personnel, and decision-making by emergency programmers. Existing maritime authorities have set certain standards and requirements for the rescue process of MTAs, and the deployment of MTER supplies and the selection of rescue equipment play an irreplaceable and crucial role in the emergency response process as the basic guarantee for the success of rescue operations.

(3) With regard to the allocation of emergency resources, it is necessary to ensure the familiarity of professional rescue teams and MTER equipment in advance and further enhance the synergy of rescue and protection for major disasters and accidents through the cultivation of high-quality professional MTER teams, the establishment of a sound system for MTER equipment, and a system for reserving and redeploying professional rescue teams and rescue equipment in places where accidents frequently occur.

(4) With regard to the mechanism for the use of MTER resources, optimise the operational power of command and decision-making coordination by improving the process of quickly and efficiently formulating and selecting an optimal plan for the coordinating rescue programmers. Construct a data information management platform, thus playing a basic role in MTER and ensuring scientific and efficient rescue operations; establish a perfect platform for monitoring data sharing and information management of major disasters and accidents and clarify the timeliness and accuracy of data sharing by all parties; and organise rescue personnel training drills regularly to improve the ability to coordinate the actions of various rescue organisations.

(5) To improve the MTER capability in different areas of the seas, it is necessary to conduct joint exercises during the MTER process. The exercise is mainly aimed at all types of serious accidents in the Haihe River, coordinating and dispatching multi-party rescue forces, ensuring the adequacy of emergency resources, and implementing life, environment, and property rescue, aiming to improve the practical skills and emergency response coordination and linkage ability of maritime search and rescue centres, social search and rescue forces, and water rescuers, enhancing the anti-pollution emergency response ability of water workers, and promoting sustained and stable water traffic safety norms in various jurisdictions(Li and Yang,2022b).

(6) Different decision-making schemes should be developed according to the location of the accident and the different flag countries. The results of this study indicate that China, Japan, and South Korea should establish a joint MTER mechanism, rationally allocate rescue forces, and minimise the losses caused by accidents. At present, under the unified coordination and guidance of the China Maritime Search and Rescue Center, China, Japan, and South Korea have conducted several joint maritime search and rescue exercises to simulate different roles, such as search and rescue centres, ships in distress, and shipping companies. They have jointly carried out search and rescue emergency operations to test the emergency command and handling ability of participants in dealing with foreign-related emergencies, effectively

improving the emergency communication and handling ability of multinational ferries and ships with multinational maritime search and rescue centres.

5. Discussion

5.1 Advantages of this methodology

Based on MTA data, the DBSCAN algorithm was used for clustering, and the complex network correlation formula was used for the analysis of further networks. The visual representation of the MTER topological network was realised on a map. This is because of the existence of the MTER topological network that reveals our understanding of MTA emergency response, and as accident research becomes increasingly in-depth, the allocation of accident emergency resources should not only be based on the location of accidents, but also behind the many discrete accident points. There is a more profound accident network correlation relation, which determines that the emergency resources must be correlated and allocated as well.

The findings of this study indicate several advantages:

(1) In response to the research problem of MTER synergy, a series of clustering and network analysis algorithms were used from accident hotspots to conclude that there is a correlation between accidents and to provide a reference for the rational allocation of MTER resources.

(2) Taking the accident distribution heat map and accident clustering classification map as the starting points for the study, a MTER network topology model was established.

(3) The rescue network topology model was visualised on a map, and the actual emergency allocation scheme and efficient use mechanism were derived from the research results to provide a reference for accident rescue.

5.2 Limitations of this methodology

(1) This algorithm has several limitations. The determination of the nodes in the MTER topological network depends largely on the accident clustering results. There is a certain degree of sensitivity in Eps, but the degree is general, and the clustering results of accidents change only when changes in Eps are sufficiently high.

(2) The number of accidents and the geographic locations of the accident points were used as a quantitative basis for establishing the topological network, and the accuracy of the network

requires further improvement. In the next step, more dimensions should be considered for inclusion in the network based on accident samples to draw richer conclusions.

5.3 MTER allocation Strategy

The frequent occurrence of MTAs has caused enormous loss of life and property, and MTER in the case of MTAs is crucial for saving the lives of people on board wrecked ships. A accident is an emergency at sea and its occurrence is characterised by instantaneity, catastrophe, and uncertainty. Injury factors have a significant influence on people in distress, and the environment and attention have a significant influence on rescue work. The difficulties of the MTER are mainly the development of on-site rescue, search and rescue of people in the water, casualty medical treatment at sea, and coordination of the command of shore and sea organisations (Hu et al.,2007). To this end, a three-dimensional joint search-and-rescue mechanism should be established for the sea and air, three-dimensional rescue technology and equipment should be developed for the sea and air, professional rescue forces should be stockpiled, and regular drills and training should be conducted.

The reasonable and effective allocation of MTER resources is a key means of effectively responding to water emergencies. In the process of safeguarding safety in navigable waters, all relevant stakeholders should establish a safety management system for MTER based on the "personnel, ships (equipment, facilities), environment, management, and other aspects" involved in the safety system project and constantly adjust and improve it dynamically.

The MTER of ships in MTAs is divided into maritime rescue and shore-based rescue, according to the disposal location. Owing to shore-based rescue being closer to the human leisure environment (including harbours, residential areas, seaside recreational areas, fishing grounds, etc.) and causing greater harm, it is best to adopt maritime rescue, unless the leakage plugging has been completed, or due to the limitations of maritime rescue, inability to complete the rescue task; only under such circumstance should the accident ship be towed to the neighbouring port to carry out shore-based rescue.

After the accident, in addition to mastering the specific circumstances of the accident, it is also necessary to make an accurate prediction of the further development trend of the situation and draw the administrative department of the jurisdiction to mobilise relevant linkage forces to be present for collaborative disposal: (1) linkage departments: emergency response, maritime, maritime search and rescue centre, public security, fire, environmental protection, meteorology, medical, publicity, ports, and related business units; (2) technical experts:

maritime rescue, meteorology, environmental protection, hydrography, ship construction, and hazardous chemicals; (3) Rescue equipment: guardian ship, tugboat, barge, maritime rescue helicopters, nitrogen equipment and clean-up ship, clean-up equipment, adsorbent materials and decontamination chemicals.

It is better to be prepared than wait until one arrives at the scene and then make adjustments according to the situation. While mobilising chemical protective clothing, detection, plugging, decontamination, and other equipment, we should pay attention to actively collect and master field information, assemble forces and consider night lighting, communication, plugging, and personal protective equipment in advance of emergencies.

6. Conclusion

Based on MTA data from the International Maritime Organization, this study made a breakthrough in the research on the MTER network. Accidents in Southeast Asia were selected as the research object, the accident clustering area was obtained using the DBSCAN method, accident hotspots were clarified, and the accident hotspot correlation was calculated. Combined with complex network theory, the corresponding MTER network topology model was established using indicators of the strength of the connecting edges and the centrality of intermediaries. Through analysis of the MTER network topology model, the mechanism of collaborative allocation and use of emergency resources was determined to respond to diversified emergency needs in different areas of the sea.

Research shows that the MTER network topology model in Southeast Asia has a large clustering coefficient, a high average node, and a short average network path, which indicates that rescue in this region is closely related. According to the results of the correlation analysis, it is necessary to study the rescue topology network, particularly the strong rescue network with China as the core and the weak rescue network with the Malacca Strait as the core. According to the analysis of the MTER network topology model, a hierarchical and stepped emergency response should be established, and the emergency mechanism should be strengthened to conduct maritime emergency drills and improve rescue efficiency.

This study fully considered accident hotspot distribution characteristics to establish the spatial layout and arrangement of emergency resources for effective disaster prevention, providing a basis and reference. The next step is to adopt more cutting-edge technical methods to achieve the quantitative allocation of emergency relief resources in collaborating countries. In terms of the emergency relief model, integrating or effectively allocating the resources of the collaborating countries will be one of the challenges that must be addressed to establish a cooperative mechanism for MTER.

Acknowledgements

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