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Optimization of maritime emergency base placement for inland waterway accident response: a case study of the Yangtze River

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ABSTRACT

As the construction of maritime emergency rescue systems worldwide increases, there are more maritime emergency bases along the Yangtze River, yet the mismatch between the layout of these bases and the demand for maritime emergency rescue has emerged. This paper analyzes the impact of marine transportation accident characteristics on emergency demand, uses the CRITIC assignment method to quantify the weights of accident characteristics, and classifies accident levels via the WRSR method. It introduces the equivalent accident number method's research idea and employs the DBSCAN algorithm to cluster and analyze accident blackspots on the Yangtze River mainline. Based on identified blackspots and multiple siting model characteristics, an emergency base siting model considering accident emergency demand is proposed and solved with LINGO. Taking the accident cases in the Nanjing section of the Yangtze River from 2019 to 2021 as an example, a siting scheme meeting the emergency demand of the Yangtze River trunk line is obtained. Model validation results show that at least three maritime emergency facilities need to be built in the Nanjing section to ensure comprehensive coverage of main navigable waters. As the number of emergency facilities grows, their comprehensive emergency response time decreases and multiple coverage of high-risk waters can be achieved. Decision-makers can formulate emergency facility layout plans based on the proposed siting method.

1. Introduction

Inland waterway transport is a vital component of integrated transportation networks, offering advantages such as low costs, large cargo capacity, and environmental efficiency. This mode of transport significantly contributes to regional economic exchanges and development. Notably, the Mississippi River in the United States, the Rhine River in Europe, and the Yangtze River in China exemplify the strategic role of inland waterways in supporting commerce and community connectivity. However, as inland waterway transport activities continue to intensify, there is a corresponding rise in water traffic risks, making the capacity for water emergency response increasingly crucial. Nachtmann et al. [1] proposed a feasibility index to assess

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the potential of inland waterway emergency services. Hu [2] highlighted the primary needs and theoretical requirements for search and rescue operations by examining the current water traffic conditions and emergency response capabilities in Shaanxi Province.

As one of China's major rivers, the Yangtze River plays an essential role in supporting inland navigation, and the construction of an effective emergency search and rescue system along its mainline has gained significant attention [3,4]. Currently, the Yangtze River's maritime emergency bases are primarily established around key ports, waterways, and high-traffic navigable waters, following a somewhat subjective layout process that may not fully consider the specific locations of frequent maritime traffic accidents. With the growing emphasis on maritime emergency response systems worldwide, more emergency bases have been established along the Yangtze River, which has, in turn, led to a pressing issue: the misalignment between the distribution of emergency bases and actual rescue demand [5,6].

Constructing a comprehensive, rationally distributed maritime emergency rescue system would mitigate casualties, protect the maritime environment, reduce property losses, and better support social and economic progress. Therefore, researching the siting of emergency bases on the Yangtze River mainline-scientifically planning the optimal number and locations of these bases-holds considerable significance for promoting sustainable shipping development along this critical waterway [7].

To solve the problem of mismatch between the layout of emergency bases on the Yangtze River trunk line and the demand for waterborne emergency rescue, this paper takes the Nanjing section of the Yangtze River trunk line as an example, firstly, grades waterborne traffic accidents to reflect the difference in the emergency demand for waterborne traffic accidents in the face of the emergency demand for ships, then clusters the black spots of the Yangtze River trunk line accidents by taking the grading into account to find out the black spots of the sections with a higher demand for emergency rescue. Finally, a study on the location of emergency bases along the Yangtze River trunk line is conducted to develop an emergency base location plan that meets the actual emergency response needs.

The research method proposed in this paper is based on the severity and distribution of waterborne traffic accidents to develop the location of the water emergency response base layout plan, the research results can provide a theoretical basis for the maritime management department to understand the distribution of waterborne traffic accidents on the Yangtze River trunk line and carry out the emergency response base layout and practical guidance.

The emergency response needs vary between different waters and different accidents, and to fully understand the emergency response needs of maritime transportation, it is necessary to rate the level of accidents and identify the distribution of accidents to select the site. Therefore, this section carries out a literature review of related studies from three aspects: maritime transportation accident risk evaluation, black spot identification, and emergency base siting.

Maritime traffic accident risk evaluation for maritime emergency management has an important guiding significance, only enough to understand the navigable waters of the dangerous accident characteristics, to optimize the layout of emergency facilities targeted to improve the emergency response capability.

Commonly used maritime transportation accident risk evaluation methods include Bayesian Network (BN) [8,9], Human Factor Analysis and Classification System (HFACS) [10,11], Formal Safety Assessment (FSA) [12,13], Fault Tree Analysis (FTA) [14], Cognitive Reliability Error Analysis Method (CREAM) [15,16].

In addition, to deeply analyze the degree of influence of different factors on the consequences of waterborne traffic accidents, scholars at home and abroad often adopt various assignment methods to assign corresponding weights to the influencing factors. Existing literature classifies the assignment methods into two categories, i.e., subjective assignment method and objective assignment method. The subjective assignment [17] method is based on the knowledge or experience of the decision maker to determine the size of the weights. Although the subjective assignment method has the advantage of integrating expert knowledge, due to the problem of subjective preferences of decision makers, the weights may be assigned in favor of specific criteria, which may lead to biased evaluation results. Unlike subjective assignment methods, objective assignment methods do not require any initial information or judgment from the decision maker. The objective assignment method determines the weights by evaluating the relationships of the data available in the decision matrix, thus eliminating possible errors associated with subjective evaluations and increasing the objectivity of the evaluation results.

Commonly used objective assignment methods include Criteria Importance Though Intercriteria Correlation (CRITIC) assignment method [18], Entropy Weight (EW) [19], Coefficient of Variation (CV) [20], and Principal Component Analysis (PCA) [21]. Among them, the CRITIC assignment method and EW are the most widely used objective assignment methods. Entropy weight method is a weight allocation method based on information entropy, which mainly measures the importance of indicators by analysing the degree of discrete data, and is suitable for multi-indicator evaluation systems with obvious differences in the distribution of data and a large number of evaluation objects. CRITIC method is a method of determining the weights by comprehensively taking into account the variability and correlation of indicators. Its core idea is to use the variability and interrelationship between indicators to reflect the importance of indicators and consider the redundancy of information between indicators. Indicators with low correlation and high variability are given higher weights, thus highlighting ‘important and independent’ indicators, which is more suitable for multidimensional evaluation problems with strong correlation between indicators.

With the development of risk evaluation techniques, some scholars in recent years have combined the advantages of multiple accident risk evaluation methods and proposed many new accident risk evaluation methods. Zhang et al [10] used the FSA framework to extract risk-influencing factors that could lead to major accidents and modelled the consequences of accidents in BN based on a risk matrix to evaluate the consequences and probabilities of navigational risks. Chen et al [11] proposed a framework and analysis methodology for HOFs for HFACS-Maritime accidents and combined the HOF framework with graphical analysis results to illustrate the causal relationships of the identified factors in individual cases, being able to graphically characterize accidents and provide insights into the accidents for maritime investigators. Fan et al [8] developed a tree-augmented network model using accident data to construct a BN and train the data, presenting a data-driven approach to accident analysis based on BNs. Ma et al [22] proposed a big data analytics approach utilizing data from Automatic Identification Systems (AIS) and historical accident records to assess the risk of marine traffic by identifying hotspots with significant localized correlations between ship track density, average speed, and marine accidents. Tian et al [23] proposed an Event Sequence Diagram (ESD) model based on the basic method of collision risk assessment, which quantitatively assessed the probability distribution of different collision failure modes by utilizing the historical data from the collision reports in the waters of Qinzhou Harbor from 2013-2017 as well as expert knowledge data.

Existing research mostly focuses on characterizing and analyzing the causes of maritime transportation accidents after they occur, and then proposes countermeasures and recommendations on accident prevention and vessel supervision based on expert experience, lacking targeted research on accident risk ratings that takes into account the emergency response needs of accidents.

Maritime traffic accident black spots reflect the spatial distribution characteristics of maritime traffic accidents, which can reflect the degree of risk in the waters, and an in-depth study of the distribution of maritime traffic black spots is a necessary work to improve the emergency response capability.

Based on reviewing the research related to accident blackspot identification, the traditional accident blackspot identification methods can be roughly categorized into the following categories: accident frequency method, the equivalent number of accidents method, accident rate method, cumulative frequency method, etc [24-27]. The accident frequency method is one of the simplest and most direct blackspot identification methods, which is widely used because of its simplicity and ease of use. However, the fact that only the number of accidents occurring is taken into account without incorporating the severity may lead to biased judgement of the actual level of risk. To overcome this shortcoming, the equivalent accident number method has been introduced, which enables the black spot identification results to reflect the level of risk in a more comprehensive way by quantifying accidents of different types and severity levels and transforming them into a uniform equivalent accident value. It is especially suitable for blackspot identification in areas with large risk differences. However, the application of the equivalent accident number method relies on reasonable weight settings, which may vary depending on different regions and accident types. The accident rate method is normalised on the basis of accident frequency and usually calculates accident rates based on road traffic flow to provide a more accurate measure of the relative risk of different road sections. The accident rate method overcomes the distortion of data due to different traffic flows and is suitable for comparative analyses of road sections with large differences in traffic flows, but it also fails to take into account the severity of accidents in a comprehensive manner. The cumulative frequency method is suitable for identifying blackspots with long-term trends, and analyses the cumulative accident risk at blackspot locations through the cumulative accident frequency curve. The method is able to show the characteristics of long-term accumulated risk, helping managers to identify black spots with significant risk in long-term observation, and is suitable for scenarios where the cumulative effect of accidents is significant. Most of the above methods are improved black spot identification Methods based on the number of accidents or accident rate, which are conceptually easy to understand and simple to operate, so they are more widely used in engineering practice. However, it is impossible to significantly improve the shortcomings of these methods because the recognition accuracy is not high and it is easy to miss the wrong judgment.

With the development of black spot recognition methods, more and more models, algorithms and theories have been used to improve the accuracy of black spot recognition methods. Zhang et al [28] proposed a two-stage black spot identification model by combining the dynamic segmentation of fairways and the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm, which can effectively identify and locate fairways with high accident rates. This study provides a very valuable reference for optimizing the allocation of waterborne emergency response resources as well as differentiated emergency management in accident-prone waters. Fan et al [29] proposed a deep neural network-based feature blackspot identification method using a machine learning approach to self-learning of multi-source data on traffic accidents and applied it to Suzhou Industrial Park to identify the distribution of blackspots of traffic accidents in the study area. Most of the above studies define traffic black spots based on the spatial discrete nature of traffic accidents, considering only the number of accidents and underestimating other factors affecting the accidents. If accident severity can be integrated into traffic blackspot studies, the distribution of traffic blackspots will be identified more accurately.

The siting of emergency bases has always been a very popular research issue. Optimizing the siting research of emergency facilities, especially in the case of limited resources, prioritizing the strengthening of the emergency response capacity of key navigation sections, and improving the utilization efficiency of emergency resources are of great significance for improving the level of emergency services of the Yangtze River mainline. The following is a literature review of the research related to the basic model of emergency base siting.

Traditional emergency base siting models mainly include the P-median Model, Location Set Covering Problem (LSCP), Maximal Covering Location Problem (MCLP), P-center Model, etc. Several classical theoretical models for site selection are summarized in Table 1 [30-34].

Table 1 Summary of classical site selection theory models

Name of The Model	Optimization Objectives	Research Question
P-median Model	Average distance minimization	Knowing the number of facilities, how to choose the optimal location of p facilities so that the full or average distance is shortest
Fixed Cost Facility Model	Minimize the total cost of facility establishment and transportation	Site selection that takes into account both the fixed costs of facility construction and the capacity (serviceability) constraints of the facility
Ensemble Coverage Model	Minimization of the number of facilities	How to minimize the number of facilities to cover all points of demand while guaranteeing a certain level of service
Maximum Coverage Model	Maximize coverage requirements	How to establish a certain number of facilities for maximizing the amount of demand covered within an acceptable service distance
P-center Model	Maximum distance min.	Knowing the demand points and potential facility points, how to choose the location of p facilities to minimize the maximum distance from the demand point to the facility nearest to it

In the issue of siting maritime emergency bases, the main concern is usually the time of arrival at the scene of an incident and the extent to which the need for rescue is met, as we want to provide as many rescue services as possible. Coverage siting models and P-median Models have been widely studied and applied in this type of emergency base siting problem. The former involves meeting the demand within a specified response distance or time criterion, while the latter aims to minimize the average response distance or time of the entire emergency response system [35].

There are two main types of coverage siting models, the LSCP model and the MCLP model. The LSCP model was the first model used to solve the coverage siting problem to find the minimum number of facilities to cover all demand points [36]. The MCLP model is also a classical and efficient approach to site selection optimization. In the case of a limited number of facilities, the model aims to maximize demand [37]. However, the LSCP model and the MCLP model share a common drawback in that when a facility is called upon to provide service, the demand points within its coverage area will no longer be covered by other facilities [38]. There are two main ways to overcome this drawback in existing studies, one is to achieve multiple coverage [39,40], and the other is to consider the busy probability [41] and reliability of facilities [42]. In contrast to the coverage siting model, the P-median Model emphasizes the distance between the point of demand and the nearest facility, intending to minimize the total distance or time for the emergency base to reach the point of demand [43].

The above literature review of related studies was conducted for the problem of emergency base siting, and these research results have important guiding significance for the study of emergency base siting on the Yangtze River trunk line. However, most of the studies are based on the site selection method proposed by the land transport system. Due to the influence of many factors, such as the characteristics of ship traffic and the maritime navigation environment, it is difficult for land-based emergency bases to play an effective role in emergency protection in the waters of the Yangtze River trunk line. Therefore, it is necessary to explore the maritime emergency resource allocation method suitable for the emergency protection system of the Yangtze River trunk line in light of the characteristics of the navigation environment of the Yangtze River trunk line waters.

The rest of the paper is organized as follows: Section 2 presents the data sources. Section 3 proposes a model for siting emergency bases on the mainline of the Yangtze River oriented to the emergency response needs of ship accidents. Subsequently, Section 4 validates and demonstrates the proposed model based on the ship accident data of the Nanjing section of the Yangtze River from 2019 to 2021. Section 5 summarizes the key findings, conclusions, and recommendations derived from the study.

2. Description of the study areas

The Nanjing section of the Yangtze River mainline, located in the lower reaches of the Yangtze River, is the busiest basin for waterborne transport on the mainline of the Yangtze River, with a much higher density of ship traffic than other sections. Accident records show that most of the water traffic accidents on the mainline of the Yangtze River occur in the downstream section. With the increase in the number of navigable ships and the development of large-scale ships in the Nanjing section of the Yangtze River mainline, the navigational environment in this water area has become more and more complicated [44], and the number of water traffic accidents has been increasing year by year, resulting in casualties, property losses, environmental damage, and other impacts. Therefore, this paper chooses the historical data of water traffic accidents in the Nanjing section of the Yangtze River trunk line as a research case, and the scope of the navigation channel of the Nanjing section is shown in Fig. 1.

Fig. 1 Schematic diagram of the scope of the navigation channel of the Nanjing section of the Yangtze River Mainline

In this paper, according to the command center duty workbench account of Jiangsu Maritime Bureau, the data of water traffic accidents occurring in the jurisdiction of Nanjing Maritime Bureau from 2019 to 2021 are statistically obtained, and there are 57 accident records in the original accident data. According to the accident characteristic index system established in the previous paper to get the basic data, the accident data samples are shown in Table 2.

Table 2 Sample basic data for accident characterization indicators

Case Number	Length of The Vessel (meters)	Gross Tonnage of Ships (tons)	Type of Vessel	Type of Accident	Accident Period	Number of People in Distress (persons)
1	140	8295	bulk carrier	collision	4:00-4:59	2
2	75	1756	general cargo ship	collision	4:00-4:59	0
3	30.3	98	liquid cargo ship	fire	22:00-22:59	6
……	……	……	……	……	……	……
56	99.98	3420	liquid cargo ship	collision	5:00-5:59	13
57	96.9	2960	bulk carrier	collision	5:00-5:59	13

3. Methodology

Fig. 2 illustrates the overall framework for applying the emergency base siting model for the Yangtze River mainline oriented to the emergency response needs of ship accidents. This framework contains three steps such as classifying the accident level, identifying the accident black spot, and setting the emergency base.

Step (i): Starting from historical data on waterborne traffic accidents, select representative indicators of accident characteristics by analyzing the impact of waterborne traffic accident characteristics on emergency response needs, and standardize the indicator data to establish an accident level evaluation matrix. The CRITIC assignment method was used to quantify the accident feature weights, and the accident cases were comprehensively evaluated based on the WRSR method. The criteria for classifying waterborne traffic accidents have been established to reflect the differences in emergency response needs for waterborne traffic accidents.

Step (ii): The Equivalent Number of Accidents Method and DBSCAN algorithm are combined to study the impact of the severity of water traffic accidents on the distribution of black spots, and then when the quantitatively processed accident cases with the limited algorithmic parameters are inputted into the DBSCAN algorithm, the profile coefficients under different parameters are compared through several experiments, and a set of experimental parameters with better clustering effect is taken to carry out the accidental clustering and identify the accidental black spots in the waterway.

Step (iii): Improve the classical siting model according to the influencing factors and basic principles of the Yangtze River trunk line emergency base siting, construct a multi-objective optimization model for the Yangtze River trunk line emergency base, and transform the multi-objective optimization model into the Mixed-Integer Linear Programming (MILP) model for solving by the weighting method to formulate a solution that The MILP model was solved to develop an emergency base siting plan that meets the emergency needs of the Yangtze River trunk line.

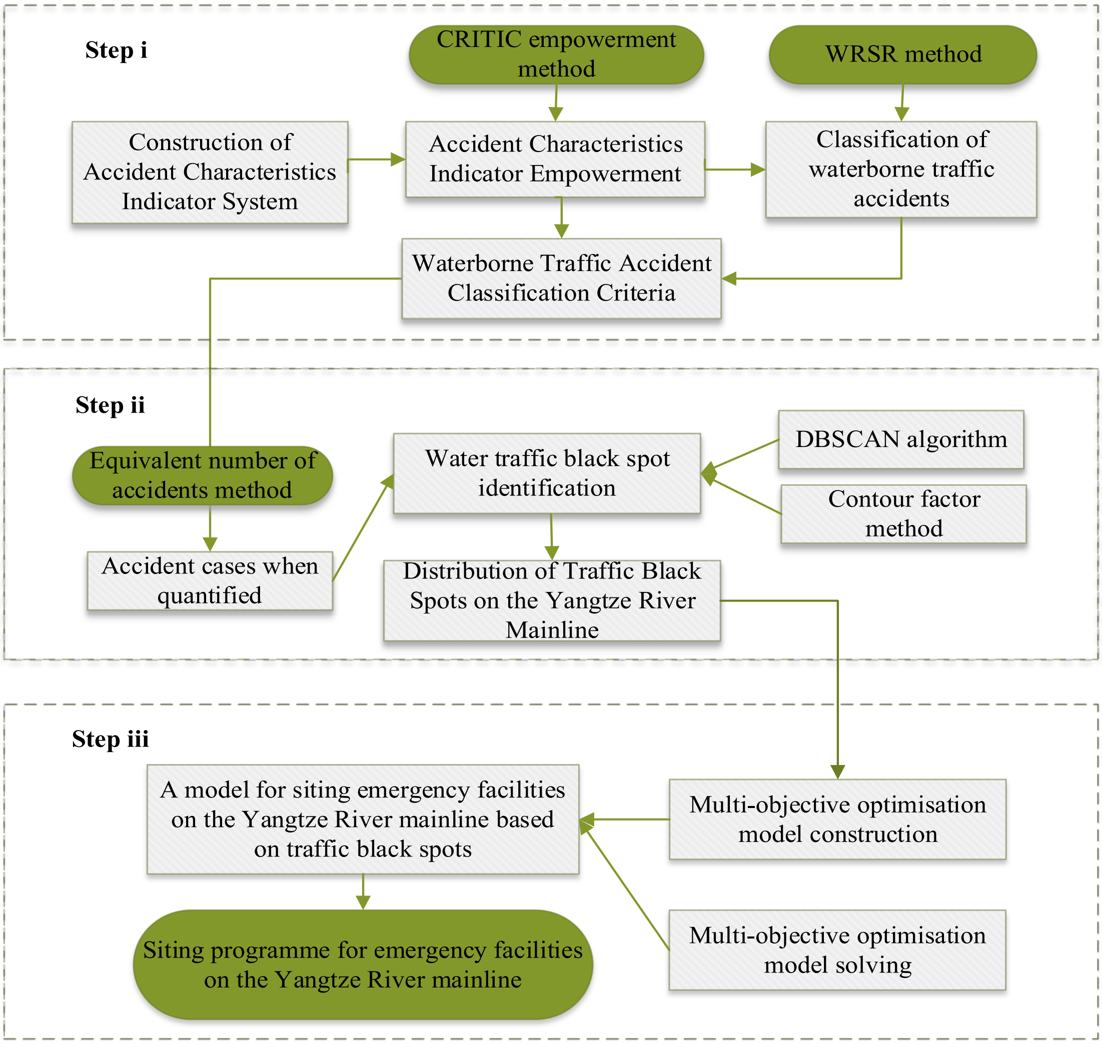

Fig. 2 The flowchart of optimization of maritime emergency base placement for inland waterway accident response

3.1 WRSR-based accident classification

WRSR is a method for comprehensive evaluation and ranking of multiple indicators, mainly derived from the extension and improvement of Rank Sum Ratio, (RSR) method. The WRSR method does not rely on specific distributional assumptions, is applicable to a wide range of data types and the calculation process is relatively simple and easy to understand and operate [45].

3.1.1 Characteristic indicator system construction

1) Selection of indicators

In this paper, the difficulty of water emergency search and rescue and the distribution characteristics of water traffic accidents are the two main aspects of selecting the accident classification evaluation indexes, and the evaluation indexes are divided into ship attribute indexes and accident attribute indexes. Ship attribute indicators include ship type, ship length [7,46], and ship gross tonnage. Among them, ship type reflects the differences in emergency response needs arising from different types of ships, and ship types with a higher frequency of accidents should be targeted to strengthen emergency prevention and control measures. Vessel length and gross tonnage reflect the impact of vessel size on emergency response needs. Usually, the larger the scale of the vessel, the more difficult it is to maneuver, the larger the area of water affected, and the more difficult it is for the search and rescue vessel to rescue the vessel, and its incident level should be relatively high. The main accident attribute indicators are the time of day of the accident, the type of accident, and the number of people in distress. The impact of accident time on emergency response demand is mainly reflected in the impact of visibility on waterborne emergency search and rescue work. The number of people in distress in water traffic accidents can reflect the severity of the accident to a certain extent, the more people in distress, the more serious the accident and the higher the emergency response demand.

2) Indicator data processing

The indicator system of water traffic accident characteristics includes both quantitative data such as ship length, tonnage, and number of people in distress, and qualitative data such as ship type, type of accident, and time of accident. Since qualitative indicators cannot be mathematically calculated, they cannot be directly used for accident assessment. To reasonably quantify the indicators, this paper establishes four levels of assessment criteria from low to high according to the degree of influence of accident characteristics on emergency needs. The quantitative data can be obtained from water transport accident case statistics and are all divided into four levels. The qualitative indicators take the accident proportion as the evaluation standard, with a value range of 0~1, and are evenly divided into four grades according to their size. In addition, to obtain reliable evaluation results of accident classification, this paper standardizes the indicators and adopts the Min-max normalization function to standardize the indicator values in the original accident statistics. The evaluation grading of each indicator is shown in Table 3.

Table 3 Standardised classification of accident characteristic indicators

Evaluation Indicators	Rating Levels			
	First Level	Second Level	Third Level	Fourth Level
Vessel length	[0,0.25)	[0.25,0.50)	[0.50,0.75)	[0.75,1.00]
Gross Tonnage of Ships	[0,0.25)	[0.25,0.50)	[0.50,0.75)	[0.75,1.00]
Type of Vessel	[0,0.25)	[0.25,0.50)	[0.50,0.75)	[0.75,1.00]
Type of Incident	[0,0.25)	[0.25,0.50)	[0.50,0.75)	[0.75,1.00]
Accident Period	[0,0.25)	[0.25,0.50)	[0.50,0.75)	[0.75,1.00]
Number of People In Distress	[0,0.25)	[0.25,0.50)	[0.50,0.75)	[0.75,1.00]

3.1.2 CRITIC-based assignment of accident characterization metrics

The basic idea of the CRITIC assignment method is to comprehensively calculate the amount of information carried by the indicators based on the comparative strength and conflictiveness of the evaluation indicators and to assign weights to the indicators based on the magnitude of the amount of information. The comparative strength of evaluation indicators is usually measured by the standard deviation, and the larger the standard deviation, the more information the indicator carries and the larger the weight. This method ensures that higher weights are assigned to indicators with higher contrast strengths or standard deviations. The conflict of the evaluation indicators is reflected by the Pearson correlation coefficient, if the stronger correlation between the indicators means the weaker the conflict of the indicators. Therefore, to reduce the influence of repetitive factors on the classification of waterborne traffic accidents, it should be ensured that the indicators with strong correlations have smaller weights. In summary, the CRITIC assignment method can assign higher weights to the indicators with higher contrast strength and a higher degree of conflict with other indicators.

Based on the constructed accident grading evaluation matrix, this paper applies the calculation process of the CRITIC assignment method as follows:

1) Calculate the standard deviation of each indicator as shown in Eq. (1):

$$\sigma_j = \sqrt{\sum_{i=1}^{m}\left(a_{ij} - \bar{a}_j\right)^2 /(m-1)} \tag{1}$$

where i is the index of water traffic accident cases and j is the index of evaluation indicators. σ_j is the standard deviation of the j^{th} indicator, a_{ij} is the standardized value of the j^{th} indicator for the i^{th} case, and $\bar{a}_j$ is the mean value of the j^{th} indicator.

2) Calculation of the coefficient of conflict between indicators.

The correlation coefficient r_{tj} between indicators t and j is calculated as shown in Eq. (2), and the coefficient of the degree of conflict between the j^{th} indicator and other indicators R_j is calculated as shown in Eq. (3):

$$r_{tj} = \frac{\sum_{i=1}^{m} (a_{ti} - \bar{a}_t)(a_{ji} - \bar{a}_j)}{\sqrt{\sum_{i=1}^{m} (a_{ti} - \bar{a}_t)^2} \cdot \sqrt{\sum_{i=1}^{m} (a_{ji} - \bar{a}_j)^2}} \tag{2}$$

$$R_j = \sum_{t=1}^{n} (1 - r_{tj}) \tag{3}$$

where a_{ti} is the standardized value of the t^{th}indicator for the i^{th} case, and $\bar{a}_t$ is the mean value of the t^{th} indicator.

3) Calculate the amount of information for each indicator and determine the weights.

The information content of the j^{th} indicator can be expressed as C_i, as shown in Eq. (4), and the weighting formula is shown in Eq. (5):

$$C_j = \sigma_j \times R_j \tag{4}$$

$$\omega_j = C_j / \sum_{j=1}^{n} C_j \tag{5}$$

where ω_j is the weight of the j^{th} indicator.

3.1.3 Accident classification based on the weighted rank-sum ratio approach

The main idea of the Rank-Sum Ratio Method is to get the dimensionless statistic *RSR* value according to the rank transformation calculation in an $m \times n$ matrix, and then use the *RSR* value to rank the advantages and disadvantages of the evaluation objects, and finally, according to the number of groups of the evaluation objects, to carry out the graded processing (the number of groups is large) or to carry out the *RSR* square root azimuthal transformation value credible interval processing (the number of groups is small). The *RSR* value is the average or weighted average of the row (or column) rank totals in the evaluation data, which has the characteristics of a continuous variable in the interval of 0 to 1. It is a comprehensive index of non-parametric measurement, reflecting the comprehensive information of the evaluation object. Assuming that there are *m* evaluation objects and *n* evaluation indicators in a comprehensive evaluation system containing multiple indicators, according to which an $m \times n$ matrix is established, the formula for calculating the *RSR* value is shown in Eq. (6):

$$RSR_i = \frac{\sum_{j=1}^{m} R_{ij}}{m \cdot n} \tag{6}$$

where R_{ij} is the rank of the element in the j^{th} column of the i^{th} row. The value of the rank-sum ratio method can cover the information of all indicators and reflect the comprehensive degree of all indicators, and the larger the value of RSR_i indicates the higher level of comprehensive evaluation. The steps for applying the weighted rank-sum ratio method are as follows:

1) Adopt the non-integer rank sum ratio method to rank the waterborne traffic accident classification evaluation matrix.

Before ranking, it is stipulated that low-optimal indicators need to be ranked from large to small, and high-optimal indicators need to be ranked from small to large. Based on the evaluation matrix of waterborne traffic accident classification established in the previous section. For m accident cases, according to the size of the indicator value is sorted, the maximum value is given m rank, the minimum value is given 1 rank, and the approximate linear interpolation method is used to compile the rank for the remaining evaluation indicator values, as shown in Eq. (7):

$$R_{ij} = 1 + (m-1)\frac{a_{ij} - a_{jmin}}{a_{jmax} - a_{jmin}} \tag{7}$$

where R_{ij} is the rank of the j^{th} indicator of the i^{th} accident case, a_{jmin} is the minimum value of the j^{th} indicator value, and a_{jmax} is the maximum value of the j^{th} indicator value. According to Eq. (7), the rank matrix $Z \in \mathbb{R}^{m\times n}$ can be calculated.

2) Calculate the WRSR value of each accident case

In this paper, the CRITIC assignment method is used to give different indicator weights to each accident characteristic indicator, and the WRSR value of each accident case can be calculated according to Eq. (8), which reflects the severity of waterborne traffic accidents:

$$WRSR_i = \sum_{j=1}^{n} \omega_j R_{ij}/m \tag{8}$$

where ω_j is the weight of the j^{th} evaluation indicator and $\mathrm{WRSR_i}$ is the WRSR value of the i^{th} accident case.

3) Determine the weighted rank-sum ratio distribution for each accident case

The distribution of weighted rank-sum ratios is the downward cumulative frequency of WRSR values expressed in terms of *Probit* values. First, the WRSR frequency distribution table in order of smallest to largest, listing the frequency of each group f Calculate the cumulative frequency of each group ($\sum f$), calculate the cumulative frequency ($p = \bar{R}/m \times 100\%$), and convert the cumulative frequency to the corresponding *Probit* value.

4) Calculate the regression equation.

Setting the WRSR value as the dependent variable and its corresponding *Probit* value as the independent variable, the regression equation is calculated according to Eq. (9), and error analysis is performed to ensure that the regression equation is statistically significant:

$$WRSR = a + b \cdot Probit \tag{9}$$

where a and b are estimated parameters.

Combined with the regression Eq., the fitted value of WRSR can be deduced, and according to the results of accident grading evaluation (WRSR value), the water traffic accident cases can be graded and sorted, and the accident cases with higher water emergency response needs can be identified. Finally, after the weighted rank and ratio method of grading and ranking, the grading standard of water traffic accidents can be obtained, and each accident case can be ranked and graded.

3.2 Identification of accident blackspots on the Yangtze River mainline considering accident classification

3.2.1 Current quantification of incident cases

The emergency response needs of different accidents are very different, and it may not work in practice if all accidents are treated equally in the process of identifying black spots of water accidents. To reflect the influence of accident severity on the distribution of black spots, the idea of the Equivalent Number of Accidents Method is introduced in this paper.

Equivalent number of accidents method is a black spot identification method based on mathematical statistics. Equivalent number of accidents method can unify different types of accident data into the same standard, so that accident data that originally cannot be directly compared can be comprehensively evaluated on the same scale, which is convenient for the comparison and analysis of various types of accidents. Generally speaking, the method takes the number of casualties and property losses as the evaluation indexes of accident consequences, and calculates the equivalent number of accidents by assigning certain weights to the indexes, and if it is determined that the equivalent number of accidents in a certain section of the waterway area is greater than the threshold value of the blackspot, then the section will be judged as the accident blackspot. In this paper, the accident cases are quantified when they are classified according to the results of the classification of the accident cases, and the specific calculation formula is shown in Eq. (10):

$$ETAN = TAN * G_{WRSR} \tag{10}$$

where TAN - represents the number of accidents for a given case; G_{WRSR} - represents the water traffic accident rating obtained from the comprehensive evaluation of the case by the weighted rank-sum ratio method; $ETAN$ represents the equivalent number of accidents for the case.

The Equivalent Number of Accidents Method can better reflect the severity of accident cases, reduce misjudgment and omission, and is commonly used for preliminary black spot identification. However, the black spot area obtained by this method has a large range, and in the next step, this paper will combine with the DBSCAN algorithm to further accurately identify the accident black spots on the water.

3.2.2 Identification of accidental black spots

To accurately identify the spatial distribution of black dots, this section combines the DBSCAN algorithm and the Contour Coefficient Method to improve the accuracy of black dot identification, and the following section mainly introduces the basic principles of the DBSCAN algorithm and the Contour Coefficient Method and their applications in this paper.

1) The basic principle of DBSCAN algorithm

The main idea of the DBSCAN algorithm is to use some metrics to measure the importance and accessibility of an incident point [47]. Among them, two important concepts are neighborhood radius (ε) and density threshold (*MinPts*). Assuming that there is an accident case as point *p*, the range with point p as the center of the circle and ε as the radius is defined as the neighborhood of point p. $MinPts$ is an important qualification that determines whether an accident case cluster is established or not, and when the number of cases satisfying the condition exceeds *MinPts*, a case cluster can be formed. The algorithm initially uses a particular case as the core point based on the set ε and *MinPts*, and then continuously extends to the range of density reachable until it forms a maximized accident case cluster that contains both core and boundary points.

Among the various clustering algorithms, the DBSCAN algorithm has some advantages in dealing with the black point identification problem. Firstly, the algorithm does not need to set the number of black spot classes in advance. Since the number of accident blackspots cannot be determined in advance, this advantage is more in line with the actual situation of blackspot identification. On the other hand, some accidents in the output may not belong to any blackspot, because accident cases in waters with fewer accidents should not be recognized as accident blackspots. In addition, the DBSCAN algorithm can identify blackspot regions of arbitrary shapes. Therefore, in this paper, the DBSCAN algorithm is used for the accurate identification of accident black spots on water.

2) The basic principle of contour coefficient method

The contour coefficient is a kind of internal evaluation index to measure the clustering effect of the model, which can be understood as an index describing the clarity of the contour of each cluster after clustering, and its evaluation criteria include two factors of cohesion and separation, and the calculation formula is shown in Eq. (11):

$$S(i)=\frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \tag{11}$$

$$a(i)=\sum_{j\neq i}^{n} d(i,j)/(n-1) \tag{12}$$

where i is the index of water traffic accident cases; $a(i)$ represents the degree of cohesion, which is the average value of the distance between accident case i and other accident cases within the same accident blackspot class, which is calculated as shown in Eq. (12), reflecting the denseness of the distribution of accident cases in a blackspot; $b(i)$-represents the separation degree, which is the minimum average of the distances between accident case i and other accident cases within the same accident blackspot class, which is calculated in a similar way as $a(i)$, but requires traversing other non-similar blackspots and taking the minimum value, j denotes other cases in the same black point class as accident case I, $d_{(i,j)}$- denotes the distance between accident case i and j, so the smaller $a(i)$ indicates the closer the accident cases in that black spot class are.

3) Application of the DBSCAN algorithm and contour coefficient method in this paper

The clustering results of the DBSCAN algorithm are sensitive to the values of ε and *MinPts*, which must be specified by the decision maker, however, there is no clear criterion to determine the optimal parameter values. If the value of ε is too small, it will lead to some neighboring accident cases cannot be clustered; if the value of ε is too large, it will lead to multiple case clusters being classified into one category, and the accuracy of the blackspot segments will be significantly reduced. Similarly, the value of *MinPts* will also affect the clustering results, too small a value may misclassify noise points as black points, and too large a value will classify multiple neighboring black points into one category. Therefore, in existing studies, the determination of parameter values often requires complex and time-consuming calculations or expert domain knowledge. In this paper, we limit the range of ε and *MinPts* values by taking into account the actual situation of waterborne emergency management on the mainline of the Yangtze River in China and use the contour coefficient method to evaluate the clustering effect under different parameters to select the appropriate parameter values. The larger value of the contour coefficient indicates that the clustering effect of black spots is better, and finally, a set of experimental parameters with the largest contour coefficient is selected to be substituted into the algorithm to identify the accidental black spots of the Yangtze River mainline.

3.3 Study on the siting of emergency bases on the Yangtze River mainline based on accident black spots

Classical site selection models help to locate emergency facilities based on different optimisation objectives. Each model has its own advantages and helps to select emergency bases along the Yangtze River. However, no single model can fully satisfy the basic siting principles. In this section, the classical model will be improved to construct a multi-objective optimisation model for the selection of emergency bases along the Yangtze River trunk line by combining the principles of comprehensive coverage, focused reinforcement, rapid response and cost constraints.

3.3.1 Multi-objective optimization model construction

There are two main optimization objectives in the accident blackspot-based emergency base siting model for the Yangtze River mainline, which are the minimization of the emergency relief distance and the minimization of the number of emergency bases to be constructed. The minimization of the emergency relief distance reflects the rapid response principle of siting the emergency base on the Yangtze River mainline, and its objective function is shown in Eq. (13). At the same time, the use of contingency demand weights in this objective function to reflect the differences in contingency demand in different segments reflects the principle of focused reinforcement. Minimizing the number of emergency bases to be built reflects the principle of cost limitation, with the objective function shown in Eq. (14):

$$min\colon f_1 = \sum_i \sum_j h_i d_{ij} y_{ij} \tag{13}$$

$$min\colon f_2 = \sum_j x_j \tag{14}$$

According to the site selection principles and influencing factors of the emergency base layout of the Yangtze River trunk line, this paper proposes the following constraints in the process of model construction:

1) To guarantee that the demand points are fully covered by the emergency base, it is required that the number of times each demand point is covered should be greater than 1. The constraint equation is shown in Eq. (15):

$$\sum_j y_{ij} \geq 1 \forall i \in I_n \tag{15}$$

2) To ensure that each demand point can receive effective emergency relief services, the distance between the emergency base and each demand point it covers is required to be less than the maximum emergency relief distance, and the constraint equation is shown in Eq. (16):

$$d_{ij}^{*} y_{ij} \leq d_0 \forall i \in I, j \in J \tag{16}$$

3) Require that no emergency aid service will be provided to the demand point y_{ij} when the facility point j is not selected, with the constraint equation shown in Eq. (17):

$$y_{ij} \leq x_j \forall i \in I, j \in J \tag{17}$$

4) The formula for calculating the weights of emergency needs is shown in Eq. (18):

$$h_i = \frac{S_i / L_i}{\sum_i S_i / L_i} \forall i \in I \tag{18}$$

For ease of understanding, the relevant parameters of the model are defined below:

I - the set of demand points, denoted by subscript i;

J - the set of candidate facility points, denoted by subscript j;

h_i - contingency demand weight for demand point i;

f_1- total weighted distance from the selected facility point to the demand point;

f_2- the number of water emergency bases to be built;

S_i - the number of equivalent accidents at demand point i;

L_i - the length of the segment at demand point i;

d_{ij} - distance between demand point i and candidate facility point j;

d_0 - maximum emergency aid distance of the water emergency base;

x_j- decision variable, 1 when the j^{th} candidate facility site is selected and 0 otherwise;

y_{ij} - decision variable, 1 when the j^{th} candidate facility point is assigned to demand point i, 0 otherwise.

In the process of model construction, the following assumptions are made in this paper:

1) In this chapter, the central waters of the blackspot segments are used as the demand points, and the number of equivalent accidents per kilometer of the blackspot segments is used as the contingency demand weights as a means of reflecting the differences in contingency demand between segments.

2) The length of the waterway on the mainline of the Yangtze River is much greater than the width of the waterway, and the width of the waterway has less influence on the rescue range of the emergency base. Therefore, it is assumed that the candidate locations of the emergency bases on the Yangtze River mainline are points distributed on the Yangtze River mainline.

3) This paper adopts the average speed of rescue vessels to calculate the rescue range of emergency bases, assuming that factors such as natural conditions and traffic environment have less influence on the average speed of rescue vessels.

3.3.2 Multi-objective optimization model solution

The site selection model proposed in this paper is a multi-objective optimization model, therefore, the multi-objective optimization problem needs to be handled before proceeding with the model solution. There are two main treatments: the first, converting a multi-objective optimization problem into a single-objective optimization problem by weighting or sequential processing, is more sensitive to the importance of the optimization objectives, and the solution results are more focused on the optimization objectives with higher importance; in the second one, the concept of Pareto optimal solution is introduced in the model solution to obtain a set of mutually non-dominated solution schemes.

The adoption of the weighting method can effectively differentiate the importance of the optimization objectives, and the emergency management department can assign different weights to different optimization objectives according to the actual needs, and the site selection scheme will be more flexible and applicable. Therefore, in this paper, the weighting method is used to transform the objective functions (13) and (14) into the objective function shown in Eq. (19) in the process of model solving:

$$min: Z = \omega_1 f_1 + \omega_2 f_2 \tag{19}$$

Z-Objective of optimization after transformation using weighting method; ω_1,ω_2- the weights of the objective function f_1 and f_2.

After the weighting method, the multi-objective optimization model will be transformed into a MILP model for solving. Based on the established mathematical model, this paper uses LINGO to solve the model.

4. Case study

4.1 Classification of incidents

4.1.1 Calculation of indicator weights

The evaluation indicators are standardized according to the indicator data processing process, and the indicator data can be specifically graded according to the indicator evaluation criteria. According to the results of the standardized processing of indicators in each case, the corresponding accident grading evaluation matrix A can be established:

$$A = \begin{bmatrix} 1.00 & 0.65 & \cdots & 0.07 \\ 0.91 & 0.27 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1.00 & 0.40 & \cdots & 0.46 \end{bmatrix} \tag{20}$$

Based on the establishment of the accident grading evaluation matrix A, combined with the CRITIC assignment method can be calculated to get the weight of each indicator, the calculation results are shown in Table 4. The variability of the indicators is measured using the standard deviation, which reflects the degree of dispersion of the data of each indicator, and the higher the standard deviation, the higher the weight. The standard deviation of the type of accident indicator is 0.476, which is significantly higher than that of several other indicators, implying that its data are more volatile and relatively more heavily weighted.

Finally, according to the results of the CRITIC weighting method, the weight of the accident type indicator is 28.35 percent, which is much higher than that of the other indicators, indicating that the accident type indicator has a greater impact on the evaluation of emergency response needs on the water. This may be because the distribution of the types of ship accidents in the waterways of the Nanjing section of the Yangtze River mainline is relatively concentrated, mostly collision and touching accidents, which require targeted enhancement of waterborne emergency prevention and control measures. The two indicators, ship length, and ship gross tonnage, were assigned lower weights, probably because these indicators reflect the impact of ship size on waterborne emergency response needs, and there is some duplication in the information they carry. In summary, after the CRITIC assignment method to evaluate the indicators, the importance of each indicator is clearly distinguished.

Table 4 Evaluation indicator weights

Evaluation Indicators	Indicator Variability	Conflicting Indicators	Informativeness	Weights
Type of Vessel	0.223	4.620	1.030	14.13%
Vessel Length	0.223	3.536	0.788	10.81%
Gross Tonnage of Ships	0.207	3.759	0.780	10.70%
Accident Period	0.321	4.432	1.422	19.51%
Type of Accident	0.476	4.337	2.065	28.35%
Number of People In Distress	0.260	4.615	1.202	16.50%

4.1.2 Classification of accidents

According to the application process of the WRSR, the evaluation indicators are first ranked using Eq. (7), and then the WRSR value of each accident case is calculated by substituting the weights of the indicators with Eq. (8), which in turn can correspond to the WRSR ranking of each case. Table 5 illustrates some of the ranked data and the calculation results of WRSR values.

Table 5 Sample results of weighted rank-sum ratio calculations for selected cases

Case Number	Length of Vessel (rank)	Gross Tonnage of Ships (rank)	Type of Vessel (rank)	Type of Accident (rank)	Accident Period (rank)	Number of People in Distress (rank)	*WRSR*	*WRSR* (rank)
1	57.0	37.5	14.4	22.2	57.0	5.0	0.613	15
2	51.9	16.3	3.7	22.2	57.0	1.0	0.529	22
3	29.0	1.7	1.0	15.0	5.5	13.0	0.193	51
……	……	……	……	……	……	……	……	……
56	29.0	24.4	6.4	57.0	57.0.	27.0	0.687	6
57	57.0	23.4	5.7	57.0	57.0	27.0	0.753	3

According to the WRSR value of each accident case, it is sorted and grouped from the largest to the smallest, and the frequency, rank range, average rank, and cumulative frequency of each group are calculated, and then the *Probit* value of each group of cases is obtained by checking the table, and the example of part of the results is shown in Table 6.

Table 6 Sample weighted rank-sum ratio distribution table

WRSR	Frequency	Cumulative Frequency	Average Rank	Cumulative Frequency	*Probit*
0.162	1	1	1	1.8%	2.893
0.164	1	2	2	3.5%	3.189
0.167	1	3	3	5.3%	3.380
……	……	……	……	……	……
0.828	1	56	56	98.2%	7.107
0.829	1	57	57	99.6%	7.621

In the following, the *Probit* value of each group of accident cases was used as the independent variable and the WRSR value was used as the dependent variable to establish a linear regression equation, and the regression equation was tested, and the regression equation was obtained according to the results of the model test as shown in Eq. (9). As shown in Table 7, the F-test reveals that the significant p-value of this equation is less than 0.005, which indicates that it has some statistical significance.

Table 7 Regression model test results

	Unstandardized Coefficient	Standard Error	Standardized Coefficient	p	F
Constant	-0.507	0.028	—	0	F (1,55) =1198.136, p=0
Probit	0.188	0.005	0.978	0	

Based on the regression equation shown in Eq. (9), the fitted value of the weighted rank-sum ratio can be deduced to classify the accident cases, and the results are shown in Table 8.

Table 8 Accident classification thresholds

Accident Level	Grade	Percentile Thresholds（%）	*Probit* Threshold	*WRSR* Threshold (fitted values)	Number of Cases (cases)
First level	Low contingency requirements	[0.00, 6.68)	[0.000, 4.000)	[0.000, 0.150)	3
Second level	Lower contingency requirements	[6.68, 50.00)	[4.000, 5.000)	[0.150, 0.432)	25
Third level	General emergency requirements	[50.00, 93.32)	[5.000, 7.000)	[0.432, 0.713)	25
Fourth level	Higher emergency response needs	[93.32, 100.00]	[7.000, 7.621]	[0.713, 0.924]	4

As can be seen from Table 8, the accident cases were classified into four levels, and there were three accident cases with a comprehensive evaluation of "low emergency response needs", indicating that the probability of occurrence of these types of accidents is relatively small and the impact on the environment is relatively minor; there were four cases of accidents with a comprehensive evaluation of "high emergency response needs". The number of accidents of this type is relatively small, but when they occur, they may have a bad impact on the water transport environment and cause great loss of life and property, so it is necessary to focus on strengthening emergency prevention and control measures for this type of accident; there were 25 cases in both Second level and Third level, which do not have the highest accident ratings, but if the distribution of accidents is concentrated in a particular body of water, it may result in a significant increase in emergency response needs in that body of water.

4.2 Identification of black spots of water accidents on the mainline of the Yangtze River

The data for this section of the study were taken from the water traffic accident cases in Section 2 and the results of the accident rating evaluation corresponding to each case, and a sample of the data for the accident cases are shown in Table 9. Firstly, the accident cases are converted into the equivalent number of accidents according to Eq. (11). The accident cases used in this paper are counted according to the accidental ships, for example, if two ships have collision accidents, the ship information is counted according to the two accidents respectively. Therefore, the number of accidents in each case is recorded as 1, and the total number of equivalent accidents is calculated to be 144.

Table 9 Sample accident case data

Case Number	Latitude and Longitude (°)	Accident Level
1	32.179°N, 119.000°E	Third level
2	32.177°N, 119.011°E	Third level
3	32.243°N, 119.145°E	Second level
……	……	……
56	32.186°N, 118.764°E	Third level
57	31.970°N, 118.643°E	Fourth level

Two important parameters of the DBSCAN algorithm need to be pre-set, where *MinPts* is the density threshold that limits the minimum number of cases to be included in a neighborhood. Since the number of equivalent accidents for accident cases with accident class 4 is 4 after an equalization process, if *MinPts*≤4, this means that every accident case with accident class 4 is considered a black spot. To avoid accidental chance, *MinPts* =5 can be set, i.e. there are at least 5 equivalent accidents in the neighborhood. On this basis, the value of neighborhood radius (ε) can be taken by several tests to compare the clustering results of accident cases to choose the appropriate parameter values and the values of the test parameters are shown in Table 10.

Table 10 Test parameter values

Parameters	Test Group a	Test Group b	Test Group c	Test Group d	Test Group e	Test Group f
z	0.01	0.02	0.03	0.04	0.05	0.06
MinPts	5	5	5	5	5	5

4.2.1 Analysis of clustering effect with different algorithm parameters

The clustering effect of the model under the six sets of parameters was evaluated by combining the contour coefficient method. When ε takes the value of 0.03, the contour coefficient value is the largest, which indicates that the density of accident cases within the accident blackspot class is the highest under this parameter, while the distance of accident cases between accident blackspots is the largest. After comprehensive consideration, the clustering effect is better when the parameter is set to ε = 0.03 and *MinPts* = 5. The clustering effect of accidental black spots under different algorithm parameters is shown in Fig. 3.

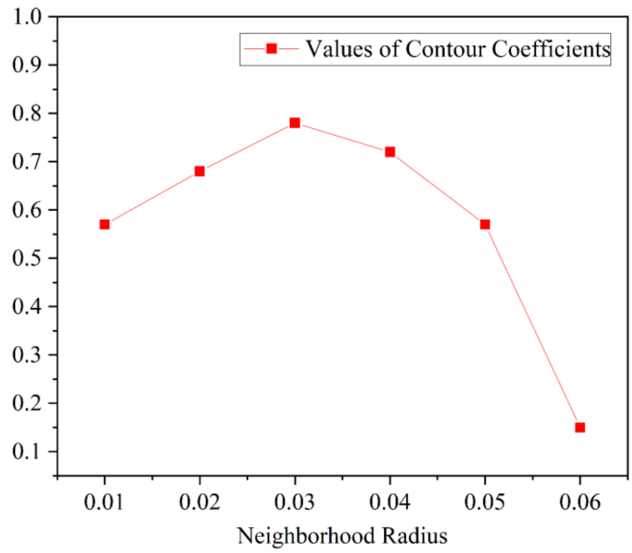

Fig. 3 Clustering effect of accident black spots with different parameter values

4.2.2 Analysis of the results of the identification of black spots in water accidents

The above equivalent accident dataset and the set algorithm parameters (ε = 0.03, *MinPts* = 5) are inputted into the DBSCAN algorithm to obtain the black spot clustering results of the accidents on the Nanjing section of the Yangtze River mainline, as shown in Fig. 4. Four cases were marked with black forks representing noise points, the other cases were clustered together to get 12 black points for water accidents, and different colored dot markings represented a class of accident black points. Each accidental black spot class was marked sequentially from the upstream to the downstream of the Nanjing section of the Yangtze River mainline, and the coordinates of the cluster center, the extent of the water area, and its equivalent number of accidents were calculated, and the results are shown in Table 11. According to the clustering results of accident black spots on the Nanjing section of the Yangtze River mainline, the total length of the black spot section is 13.971 n miles, accounting for about 26.4 percent of the total length of the Nanjing section of the Yangtze River mainline; the number of equivalent accidents in the black spot section is 123, accounting for 85.4 percent of the total number of equivalent accidents. This suggests that the majority of water traffic accidents during the period 2019-2021 occurred within 26.4% of the channel area in the NJ section, reflecting the fact that the Black Spot section is at greater risk than the other sections and that special attention should be paid to strengthening water traffic safety management.

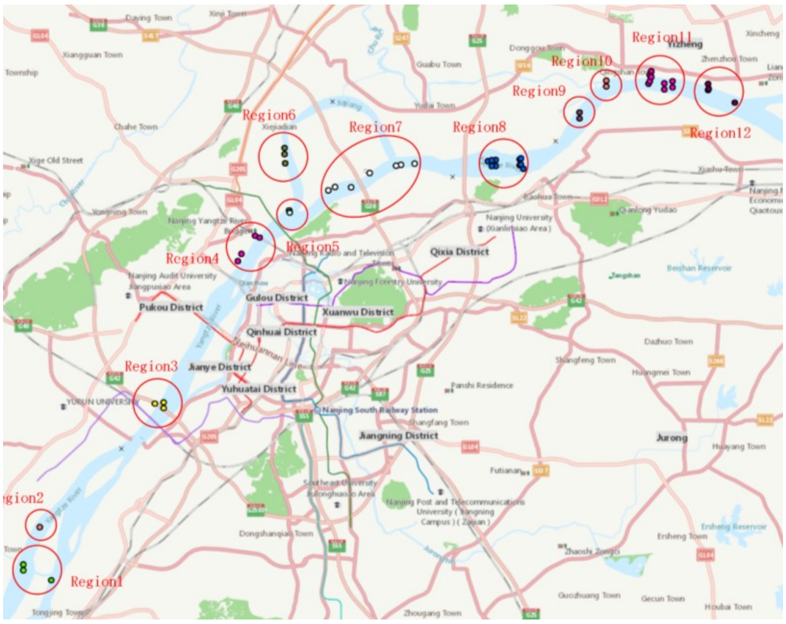

Fig. 4 Clustering results of accidental black spots in Nanjing section of the Yangtze River mainline

Table 11 Accidental black spots in the Nanjing section of the Yangtze River trunk line and their equivalent number of accidents

Accident Black Spot Category	Cluster Center Coordinates	Length of Segments (n mile)	Equivalent Number of Accidents (cases)
1	31.832°N, 118.504°E	1.583	8
2	31.869°N, 118.520°E	0.127	6
3	31.971°N, 118.643°E	0.52	9
4	32.102°N, 118.722°E	1.630	8
5	32.137°N, 118.770°E	0.128	6
6	32.187°N, 118.765°E	0.570	8
7	32.170°N, 118.849°E	4.592	17
8	32.179°N, 118.977°E	1.849	15
9	32.217°N, 119.061°E	0.123	5
10	32.243°N, 119.087°E	0.125	6
11	32.243°N, 119.145°E	1.200	27
12	32.241°N, 119.189°E	1.513	8
Total		13.971	123

In summary, by identifying the accident black spots, we can accurately find the navigation safety hazards in the Nanjing section of the Yangtze River trunk line, where there are multiple accident-prone waters. Combined with the water traffic accident level evaluation based on multi-attribute features, it can help decision-makers to have a clearer understanding of the level of emergency response demand in each navigation section, and the emergency management department can target the allocation of water emergency response resources, especially in the case of shortage of resources, and be able to reduce the waste of resources as much as possible.

4.3 Siting of the Yangtze River mainline emergency response base

4.3.1 Model parameterization

In this paper, the coordinates of the center of the accident black spot are adopted as the coordinates of the demand point, and the emergency demand weight of the demand point is calculated according to the length of the section and the number of equivalent accidents of the accident black spot, and the emergency demand weight of each demand point can be calculated by substituting the corresponding data in Table 11 into Eq. (18), and the results are shown in Table 12.

Table 12 Contingency requirement weights for demand points

Demand Point Number	Demand Point Coordinates	Number of Accidents Per N Mile Equivalent (cases)	Demand Point Weighting
Y1	31.832°N, 118.504°E	2.729	0.019
Y2	31.869°N, 118.520°E	25.424	0.179
Y3	31.971°N, 118.643°E	9.336	0.066
Y4	32.102°N, 118.722°E	2.650	0.019
Y5	32.137°N, 118.770°E	25.316	0.178
Y6	32.187°N, 118.765°E	7.449	0.052
Y7	32.170°N, 118.849°E	1.999	0.014
Y8	32.179°N, 118.977°E	4.381	0.031
Y9	32.217°N, 119.061°E	22.026	0.155
Y10	32.243°N, 119.087°E	25.974	0.183
Y11	32.243°N, 119.145°E	12.140	0.085
Y12	32.241°N, 119.189°E	2.855	0.020

The channel mileage of the Nanjing section of the Yangtze River mainline is about 53.995 n miles (100 km) long, and this chapter divides the Nanjing section into 20 sections along the Yangtze River mainline, starting from the channel mileage of 207.883 n mile from the mouth of Wusong, and then setting up one candidate facility point along the downstream direction for every 2.700 n miles (5 km), and ending at the channel mileage of 159.287 n miles from the mouth of Wusong, with the specific distribution as shown in Table 13.

Table 13 Distribution of candidate facility sites

Candidate Facility Site Number	Coordinates of Candidate Facility Sites	Miles of Waterways (n miles)
X1	31.809°N, 118.521°E	207.883
X2	31.857°N, 118.537°E	205.184
X3	31.908°N, 118.554°E	202.484
X4	31.935°N, 118.591°E	199.784
X5	31.965°N, 118.635°E	197.084
X6	31.998°N, 118.663°E	194.384
X7	32.038°N, 118.681°E	191.685
X8	32.076°N, 118.705°E	188.985
X9	32.113°N, 118.738°E	186.285
X10	32.138°N, 118.782°E	183.585
X11	32.160°N, 118.828°E	180.886
X12	32.180°N, 118.875°E	178.186
X13	32.178°N, 118.929°E	175.486
X14	32.175°N, 118.983°E	172.786
X15	32.196°N, 119.037°E	170.086
X16	32.229°N, 119.068°E	167.387
X17	32.247°N, 119.112°E	164.687
X18	32.244°N, 119.164°E	161.987
X19	32.229°N, 119.213°E	159.287

The rescue distance of the water emergency base is calculated according to the average speed of the rescue ship multiplied by the maximum response time. In this paper, the average speed of the rescue ship is taken as 16.198 kn; according to the requirements of China, the emergency response time of the important inland waterway section is no more than 45 min. The relief distance of the emergency base was calculated to be 12.149 n miles. In addition, the distance between the facility point and the demand point was calculated using the Semi-Positive Vector Formula (Haversine formula). Due to changes in the course of the channel, the actual channel mileage between the facility point and the demand point is greater than the spherical distance, and some errors may exist. Generally speaking, the greater the change in the course of the waterway and the longer the distance, the greater the error. For the Nanjing section, the channel course is relatively straight and the relief distance of the emergency base is 12.149 n miles, so the error is small and negligible. However, for the navigable waters where the channel direction is more complicated, a more accurate distance measurement method is needed.

To explore the link between the number of water emergency bases and the distance of emergency aid, this chapter takes multiple groups of objective function weights for testing, the weight test grouping is brought into the Eq. (19) for testing, and the weight grouping is shown in Table 14.

Table 14 Grouping of weighting tests

Test Group	ω_1	ω_2
1	0.9	0.1
2	0.7	0.3
3	0.5	0.5
4	0.3	0.7
5	0.1	0.9

4.3.2 Site selection model solution

The optimization model under different weight combinations is solved according to Table 14, and the results are shown in Table 15. Where Z is the corresponding objective function value, f_1 is the total weighted distance from the selected facility point to the demand point, and f_2 is the construction quantity of the water emergency base.

Table 15 Weighting test groupings and their objective function values

Test Group	Z	f_1	f_2	Site Selection Programme
1	2.54396	2.15996	6	X2, X5, X10, X14, X16, X18
2	3.21812	2.45446	5	X2, X5, X10, X16, X18
3	3.55074	4.10147	3	X2, X10, X16
4	3.33044	4.10147	3	X2, X10, X16
5	3.11014	4.10147	3	X2, X10, X16

Taking test group 1 as an example, the solution of the objective function Z has achieved the minimum value, indicating that the site selection scheme of test group 1 is the optimal solution in multiple tests. According to the results of the model solution, the value of the objective function f_1 is 2.15996, which represents the total weighted distance from the facility point to the demand point; the value of the objective function f_2 is 6, which represents the number of construction of the emergency response base, and the selected facility points are X2, X5, X10, X14, X16, and X18, and the final siting results and the coverage of the facility points are shown in Table 16.

According to the final site selection results of test group 1, every demand point received coverage from the emergency base, realizing the site selection principle of full coverage. Among them, demand points Y7, Y8, Y9, Y10, and Y11 all got 3 times coverage, and demand points Y1, Y2, Y3, Y4, Y5, Y6 and Y12 all got 2 times coverage, reflecting the principle of focused reinforcement. It can be seen that the siting model proposed in this section can effectively solve the problem of emergency base siting in the Nanjing section of the Yangtze River trunk line and improve the water emergency response capability.

Table 16 Final site selection results for test group 1

Selected Facility Points	Miles of Waterways (n miles)	Points of Need Covered
X2	205.184	Y1, Y2, Y3
X5	197.084	Y1, Y2, Y3, Y4
X10	183.585	Y4, Y5, Y6, Y7
X14	172.786	Y5, Y6, Y7, Y8, Y9, Y10, Y11
X16	167.387	Y7, Y8, Y9, Y10, Y11, Y12
X18	161.987	Y8, Y9, Y10, Y11, Y12

Comparing test groups 1, 2, and 3, it can be found that the number of waterborne emergency bases gradually decreases with the decrease and increase of the number of waterborne emergency bases, and the rescue distance between the waterborne emergency bases and the demand points gradually increases, which indicates that the decrease of the number of emergency bases construction leads to the increase of the emergency response time and the decrease of the emergency response capacity. Comparing test groups 3, 4, and 5, it can be found that when the number of emergency bases decreases to 3, the siting scheme no longer changes, indicating that at least 3 emergency bases are needed to ensure that the Nanjing section of the Yangtze River mainline is fully covered, and if the number of emergency bases is less than 3, some sections of the shipping line cannot be effectively provided with emergency rescue services. In conclusion, in the process of the construction of emergency bases on the Yangtze River mainline, decision-makers can refer to the site selection scheme obtained from the accident black spot-based emergency base selection model for layout planning, and gradually increase the number of emergency bases with the input of emergency resources to improve the emergency response capacity of the Yangtze River mainline.

5. Conclusions

This paper proposes a model for siting emergency bases on the mainline of the Yangtze River that considers the emergency demand of accidents and optimizes the siting layout of water emergency bases based on the emergency demand reflected in the characteristics of water traffic accidents on the mainline of the Yangtze River. This paper focuses on the connection between accident characteristics and emergency response demand and combines the CRITIC assignment method and the WRSR to classify the accident cases based on the accident cases of the Nanjing section of the Yangtze River from 2019 to 2021. Then the Equivalent Number of Accidents Method and DBSCAN algorithm are combined to identify the black spots of water accidents in the Nanjing section of the Yangtze River, and based on the identified black spots, according to the principles of the Yangtze River Emergency Response Base siting and combined with the classical siting model, the emergency response base siting scheme for the waters is obtained. The model is solved by LINGO. According to the results of the model validation, at least three water emergency bases need to be constructed in the Nanjing section of the Yangtze River mainline to guarantee the comprehensive coverage of the main navigable waters. With the increase in the number of emergency bases, their comprehensive emergency response time gradually decreases and multiple coverage of high-risk waters can be achieved. The optimal siting scheme in the test group is 6 waterborne emergency bases, which has the shortest total weighted distance between waterborne emergency bases and demand points, and 5 demand points are covered 3 times, and 7 demand points are covered 2 times. In addition, based on the analysis of the impact of the number of emergency bases and the emergency response capacity, the decision makers can formulate the layout plan of the emergency bases based on the site selection method proposed in this paper, and gradually improve the level of the emergency service of the Yangtze River mainline with the increase in the number of emergency bases.

In order to improve the emergency service level of the Yangtze River mainline, this paper carries out some researches on water traffic accident classification, traffic black spot identification, and emergency base siting. The research results can provide some theoretical support for the construction of the emergency search and rescue system on the Yangtze River mainline. However, limited by personal practical experience and insufficient datasets, the study did not consider the effects of conditions such as traffic density, navigational constraints and hydrodynamics on the demand for accident response. In addition, this paper has the limitation of transforming the multi-objective optimisation problem into a single-objective optimisation problem when solving the siting model, and introduces the Pareto-optimal solution to solve similar inland waterway siting problems in future studies.

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