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Towards safe navigation environment: The imminent role of spatio-temporal pattern mining in maritime piracy incidents analysis

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ABSTRACT

Since the new century, we have witnessed the fast evolution of pirate attack modes in terms of locations, time, used weapons, and targeted ships. It reveals that the current understanding of pirate attack spatio-temporal patterns is fading, requiring new technologies of big data analysis to master the hidden rules of piracy-related risk spatio-temporal patterns and rationalize the development of relevant anti-piracy measures and policies. This paper aims to develop a new framework of spatio-temporal pattern mining to realize the visualization and analysis of maritime piracy incidents from different standpoints using a new piracy incident database generated from three datasets. Time-based, space-based, and spatial-temporal pattern mining of piracy incidents are systematically investigated to dissect the influence of different risk factors and mine the characteristics of the incidents. Moreover, a novel Fast Adaptive Dynamic Time Warping (FADTW) method is proposed to uncover the hidden temporal and spatial-temporal patterns of piracy incidents. Furthermore, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is applied to extract the spatial distribution patterns and discover the high-risk areas. Finally, risk factors-based classification exploration has uncovered different spatial patterns. The findings, showing the global and local features of piracy incidents, have made significant contributions to rationalizing anti-pirate measures for safe navigation.

1. Introduction

Maritime piracy and armed robbery pose a major threat to maintaining political stability, increasing economic benefits, and promoting safety for seafarers and international trade [1]. Maritime piracy has made a significant impact on crews (hijacked or assaulted), ships (loss of cargo, missing, or incident), navigational environment (emission or pollution), shipowners (high insurance), port authorities (management difficulties), energy security (theft), reassurance (high ransom), and even substantial risks to global seaborne trade and economic prosperity [2,3]. Significantly, the fierce hijacking and high ransom demands of Somali piracy, Malacca Strait piracy, the Strait of Singapore piracy, and Gulf of Guinea piracy have gained considerable attention [4]. The high risks exposed by maritime piracy are evidenced by the severe hijacking incidents in global areas and the high random of international pirates, with an estimated US $25 billion annual costs [5]. Therefore, it is beneficial for all the aforementioned stakeholders to explore and manage piracy risks. Among the paramount steps toward pirate safety and security is to capture the characteristics of pirate attack modes.

The piracy incidents are intentional and violent that must be prevented and fought against by International Maritime Organization (IMO) guidance, regional collaboration frameworks, international navies, and anti-piracy training based on maritime security technologies and education [6]. The IMO has regulated maritime piracy through regulation, management, and technology development [7,8]. However, the United Nations Convention on the Law of the Seas (UNCLOS) only treats incidents on the high seas as acts of piracy [9,10], but piracy in other parts is often overlooked. The International Maritime Bureau (IMB) was established in 1981 to combat various maritime crimes and malpractice. The IMB Piracy Reporting center (PRC) was formed in 1992 when piracy in the shipping industry was on the rise. It defines piracy with a board concept as 'any act of boarding or attempting to board any ships with the apparent intent or capability to use force in the furtherance of the act'. Therefore, the IMB collects the piracy incidents data in global water areas to make efforts to fight pirates. The common interest among nations is to fight against piracy incidents and facilitate maritime trade. Previous spatial and temporal pattern studies in the maritime sector largely focused on maritime safety accidents [11–16], ship traffic [17–20], risk prediction [21–23], traffic flow analysis [24,25], and navigational safety [26] to explore their distribution characteristics. Compared with unintentional maritime safety accidents, maritime

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Nomenclature

Roman letters

AIS	Automatic Identification System
AML	Anti-Money Laundering
ASAM	Anti-Shipping Activity Messages
BN	Bayesian Networks
COG	Course Over Ground
CMPD	Contemporary Maritime Piracy Database
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DTW	Dynamic Time Warping
FADTW	Fast Adaptive Dynamic Time Warping
GISIS	Global Integrated Shipping Information System
GLM	Generalized Linear Models
GPS	Global Positioning System
IMO	International Maritime Organization
IMB	International Maritime Bureau
MASS	Marine Autonomous Surface Ships
NGIA	National Geospatial-Intelligence Agency
PMSC	Private Maritime Security Companies
PCASP	Privately Contracted Armed Security Personnel
PRC	Piracy Reporting center
PTSD	Post-Traumatic Stress Disorder
SOG	Speed Over Ground
UNCLOS	United Nations Convention on the Law of the Seas
WoS	Web of Science
2D	Two-dimensional

piracy has the features of strong human organization, selection, and deliberate arrangements before any incidents. Therefore, it is often argued that maritime piracy is more sensitive to time (e.g., hour, month, and monsoon), space (e.g., geographical location and navigational areas), and spatial-temporal features (e.g., year, month, areas, and the number of incidents) compared to other safety-related maritime incidents. Despite this argument, the spatial-temporal analysis of piracy incidents sits on a back-role seat in the current literature of maritime safety and security studies, possibly because of the incompleteness/unavailability of the historical data and constraints on the existing analysis methods.

Exploring the spatio-temporal patterns of maritime piracy is imperative to combat piracy attacks and guarantee maritime security. This paper aims to address the following four research questions (Qs), wanting new solutions to be found.

Q1: Lack of a comprehensive and standardized database that is characterized by all the key Risk Influencing Factors (RIFs), including but not limited to time, location, geographical areas, navigational status, attack ship types, and weapons used by attackers, the number of victims, and attack types.

Q2: Lack of an established methodology to realize the visualization and analysis of pirate attack patterns and to extract the hidden information on pirate risk probability and implicit or tacit threats.

Q3: Lack of powerful methods to measure the similarity of two-dimensional (2D) (e.g., yearly data, monthly data, and hourly data) and high-dimensional (e.g., navigational areas-year-month-the number of attacks) time series, that can deeply mine the inherent characteristics of piracy data and reveal the relationship by 2D and similarity matrix visualization results.

Q4: Lack of effective clustering and classification research of piracy incidents in terms of different RIFs.

To answer the aforementioned four questions, this paper conducts deep mining and visualization analysis of the piracy incidents dataset to uncover the patterns and implications hidden in the data. It can aid the research needs and policy-making guidance for industry, government, and academic experts. The contributions (Cs) of this paper are listed below.

(C1) Generate a novel database of maritime piracy incidents that can be used as the foundation for mining the piracy features with regard to different attributes.

A new and comprehensive piracy incident dataset is developed in this paper by deriving the data from three sources, including the Anti-Shipping Activity Messages (ASAM) in National Geospatial-Intelligence Agency (NGIA), the IMO Global Integrated Shipping Information System (GISIS), and the IMB datasets jointly.

(C2) Develop a new framework of piracy spatio-temporal pattern mining and analysis.

A spatio-temporal visualization framework is put forward to show and analyze the maritime piracy incident trend and status in the past three decades and to provide valuable insights for piracy prevention.

(C3) Create a novel time series measurement method for time-based pattern analysis.

A Fast Adaptive Dynamic Time Warping (FADTW) method is developed to conduct temporal pattern mining to reveal the incident distribution features from visualization analysis results.

(C4) Realize the advanced data-driven clustering and classification analysis in maritime piracy incidents.

An advanced data-driven method (i.e., Density-Based Spatial Clustering of Applications with Noise (DBSCAN)) is developed to dissect the influence of the geographical area and analyze the incident characteristics.

The remainder of this paper is organized as follows. The literature review of maritime piracy studies is presented to define the relevant state-of-the-art in Section 2. Section 3 describes the methodology of spatio-temporal pattern mining and deep analysis of piracy data. The time-based and space-based pattern extraction and analysis with insightful implications are presented in Section 4. A detailed discussion and description of future direction is provided in Section 5. Section 6 concludes the paper and proposes future exploration.

2. Systematic review and analysis

The state-of-the-art review is conducted to extract the research themes, which are further classified into six different categories (i.e., law, history, policy, economy, psychology, and technical) in Section 2.1. It provides the evolution and the current status of maritime piracy studies. According to the comprehensive analysis of maritime piracy, it is evident that spatial, temporal, and spatio-temporal patterns exploration at a technical level urgently needs extra attention. The organized maritime piracy attacks that emerged in the past years exposed different features compared to the classical ones in history. Therefore, the development of spatial, temporal, and spatial-temporal patterns is comprehensively described in Section 2.2 to reveal the research gap and highlight the importance of deep pattern mining. Finally, the contributions are listed and analyzed in Section 2.3 to introduce our research motivation, method and content. The identified research gaps and new contributions will aid in guiding the development of the rest of the manuscript, including the methodology and discussion of the findings about each identified gap.

2.1. Review of the studies on maritime piracy

The studies about maritime piracy and sea piracy were retrieved by the Web of Science (WoS) Core Collection in May 2022. To guarantee the high quality of research papers, we reserve journal papers with 402 results. After screening their titles, keywords, abstracts, methods, and contents, 146 journal papers, which have shown high relevance to the aim of this study, are preserved for analyzing and extracting the research themes. In this process, the selection 'maritime piracy' or 'maritime pirate' are used. Finally, 15 research themes are generated by analyzing the 146 reserved results, including various content related to or induced by maritime piracy. To better understand the progression of research themes, we have introduced the six classical categories (namely, law, history, policy, economy, psychology, and technical), which are most commonly observed in the 146 papers. These categories are used to classify the 15 research themes, resulting in valuable insights. According to the state-of-the-art literature review about maritime piracy, the 15 research themes and the corresponding six categories are listed and compared in Table 1.

It can be seen that themes 1, 3, 4, 5, and 6 belong to the law research in Table 1. The related law research contains various studies of international and criminal law, jurisdiction within and between countries, anti-piracy regional cooperation, criminal motivation, and Anti-Money Laundering (AML) regime. The findings show that the concept of piracy is changeable over time, maritime piracy activities are not random, and different countries have inconsistent abilities in anti-piracy management and control. Meantime, costly multilateral naval intervention, coast guard cooperation, Private Maritime Security Companies (PMSC), and Privately Contracted Armed Security Personnel (PCASP) are the current practice in terms of anti-piracy regional cooperation measures. Finally, AML laws and rules can effectively take away the illicit benefits to prevent pirate activities and future pirate ventures.

Piracy development has a long history, including themes 2, 5, and 9. The historical reasons behind piracy involve economic, political, and cultural issues in different regions. Scholars have investigated and shown that increasing fisherman's income and job opportunities will significantly help reduce piracy. Themes 9 and 10 are related to the economic area of piracy. The findings from the previous studies in the field reveal that a prosperous national economy and a secure way of life will reduce the occurrence of piracy incidents. Themes 6, 8, and 11 are in the areas of anti-piracy policies, and the relevant findings reveal that the currently used anti-piracy policies (e.g., international and domestic) can help reduce the occurrence of pirate attacks. Theme 7 is about psychology research behind pirate attacks, which profoundly impact the psychological well-being of seafarers, causing fear, stress, and uncertainty. This can lead to issues like anxiety, depression, and Post-Traumatic Stress Disorder (PTSD). It is crucial to provide psychological support and help seafarers recover their mental health.

Research on technical aspects of piracy incidents includes themes 7, 8, 13, 14, and 15. Maritime security is the main research content in seaborne trade, and high-risk areas need urgent attention to have a deep analysis to combat piracy. The relevant studies have demonstrated that the higher the probability of successful pirate attacks, the more likely the pirate will attack. Meantime, risk factor identification and analysis are important content in maritime piracy research. The expert questionnaires and Bayesian Networks (BN) are used to explore the influence of different factors and their combinations in high-risk areas (e.g., Gulf of Aden, Southeast Asia, and the South China Sea). Moreover, anti-piracy measures based on data fusion (e.g., Automatic Identification System (AIS), Global Positioning System (GPS), and radar data) should be better coordinated and used. The cyber threat and data fusion challenges in anti-piracy are also hotspots to aid in monitoring suspicious ships and identifying the hazards. Furthermore, statistical analysis methods are applied to explore the patterns of spatial, temporal, and spatio-temporal to demonstrate that piracy can be clustered in different perspectives.

2.2. Review of the spatio-temporal mining methods in maritime piracy

In the existing literature, there are some studies about spatio-temporal patterns. Maritime piracy is a bloody and violent sea crime. Mejia et al. [64] explored the relationship between the flag of registry, the type of vessel, and the attack probability in maritime piracy by using the merged dataset. The fundamental descriptive statistics based on a probit model and econometric analysis are listed to shed light on the fact that piracy is not random. The results have shown that flags and specific vessel types are the main RIFs. Marchione and Johnson [65] proposed time-series methods to reveal the patterns that change over time and space from both macro and micro levels based on the dataset from 1978 to 2012 in the NGIA. The kernel density estimation method is applied to present the spatial patterns, while Moran's I statistics [87] and Monte Carlo simulation are used to confirming that piracy incidents are clustered in space. The Poisson model of pirate monthly time series is calculated to show the five high-risk areas, Somalia, the Gulf of Arden, the Arabian Sea, Malaysia, and the Gulf of Guinea. Furthermore, the Knox test [88] is selected to compute the index in space-time clustering. According to the related statistical analysis, this study concludes that pirate attacks are nonrandom, dynamic, and spatially aggregated. Coggins [66] conducted descriptive statistics to show the main features of different factors and briefly illustrate the potential applications based on the IMB's PRC dataset from 2000 to 2009. The annual data and country-based data are compared to extract the five states that contribute to the highest numbers of piracy incidents, Indonesia, Malaysia, Bangladesh, Somalia, and Nigeria. Twyman-Ghoshal and Pierce [67] described the change in pirate activities and identified the form of contemporary piracy based on the Contemporary Maritime Piracy Database (CMPD) between 2001 and 2010. The descriptive analysis, histogram, line, and table are conducted to show the pirate attacks in different countries and areas. The results show that Somali piracy has a great influence on global piracy forms. The features of contemporary piracy attacks mainly focus on the places close to shore, prefer at night, find stationary vessels, have no interaction with the crew, and choose vessels with low level or armament equipment. Furthermore, this study highlighted that piracy research is limited and superficial due to the lack of dataset and deep analysis. Townsley and Oliveira [68] explored the space-time patterns in the Horn of Africa based on the IMB's piracy

Table 1
The state-of-the-art review of maritime piracy.

No	Research themes	Category	Refs	No	Research themes	Category	Refs
1	Piracy concept development; international and criminal law	Law	[27–32]	9	Marine fisheries and maritime piracy	Economy and history	[33–35]
2	Historical causes behind piracy	History	[36–39]	10	The economic model of piracy	Economy	[40–44]
3	The jurisdiction on high seas and territorial waters	Law	[45,46]	11	Insurance development and piracy	Policy	[47,48]
4	Anti-piracy regional cooperation and ways from public and private	Law and policy	[5,49–52]	12	Piracy and victim health	Psychology	[53,54]
5	Criminal motivation	Law and history	[55,56]	13	Quantitative risk analysis of pirates using BN	Technical	[57–60]
6	The relationship between money laundering and counter maritime piracy	Law and policy	[61–63]	14	Spatial, temporal, and spatio-temporal patterns exploration	Technical	[64–71]
7	Piracy analysis in high-risk areas	Technical	[2,72–80]	15	Data fusion challenges in anti-piracy	Technical	[81,82]
8	The spread and state of criminal violence	Technical and policy	[79, 83–86]				

annual reports from 2006 to 2011 and demonstrated the existence of space-time patterns to aid in preventing attacks and forecasting the high-risk areas in the future. It explores the space (e.g., yearly distribution), time (yearly and monthly distribution), and space-time patterns (near-repeats information and Knox ratio result) of pirate activities based on statistical analysis. It further illustrates that piracy is deliberate and opportunistic. Psarros et al. [69] collected the monthly reports during the period of 2000–2009 from the IMO and conducted a deep statistical analysis based on the ship type, piracy incidents severity, counter-piracy actions, attack numbers, and the trend. Meantime, Generalized Linear Models (GLM) were applied to realize the quantitative analysis of maritime piracy to estimate the probability of successful attacks. Liwång [70] investigated the features of maritime piracy off West Africa from 2010 to 2014 and revealed the results that detection techniques and protection measures should be applied to prevent more diverse, successful, and dangerous piracy in this area. AIS data is also applied to combat maritime piracy. West et al. [71] proposed a phonetic algorithm and a double metaphone algorithm to extract the navigation characteristics of merchant ships based on AIS data. The extracted route features can provide effective suggestions for ships traveling through the Gulf of Arden.

Although showing some attractiveness, the previous studies have revealed some theoretical implications that have not been well addressed in the current literature, including 1) failure in full or part of mining the complicated hidden spatio-temporal information in the incident data [64,66,69] and 2) limited analysis only focusing on selected areas/regions such as high-risk areas [65,67,68,70,71] due to the data availability. Along with the above technical analysis, a piracy dataset with 7512 attack records from 1993 to 2020 has been developed and published [89] based on the data collected from IMB and the World Bank. It is open-access and aims to combine piracy attack information with the economy of different countries. The piracy attacks, economic indicators, and country codes are integrated with reference to date based on the structured content to support anti-piracy research. However, this dataset only contains the incident date, longitude, latitude, attack type, distance from shore, vessel type, and vessel status, etc. Similar to the other two above-mentioned databases (i.e., NGIA and the IMO GISIS), it only reveals partial RIFs and hence is insufficient to support a comprehensive spatio-temporal analysis of maritime piracy. One of the realistic solutions to address incomplete/unavailable data is to merge the three most widely used piracy data sources to form a new comprehensive database.

2.3. Our contributions

In this paper, we extract the spatio-temporal patterns of pirate incidents by pioneering a new visualization framework from time series similarity-based, time-based, space-based, classification-based, and clustering-based perspectives. It aids in compiling the piracy data, extracting the piracy patterns, discerning high-risk times and areas, uncovering the hidden features, and analyzing the influence based on different factors. While most of the existing studies on temporal and spatial pattern analysis are conducted by statistical analysis and ArcGIS results, this paper proposes a novel time-series similarity analysis method, FADTW, to mine the time-based and spatio-temporal patterns. On the other hand, DBSCAN is developed to mine the spatial patterns to reveal the hidden risk information.

From an applied research perspective, it develops a new database involving all the RIFs contributing to maritime piracy. It is, therefore, for the first time to be able to explore pirate attacks in global waters (beyond the classical high-risk regions). Meantime, it also uses a similarity measure method, clustering, classification, and point density estimation jointly to capture the piracy time-series features and risk distribution. To the best of our knowledge, we are the first to analyze the comprehensive maritime piracy incidents from temporal, spatial, and spatio-temporal patterns based on the combination of time series analysis, clustering, and classification.

3. Methodology

3.1. The holistic visualization framework

This section outlines the methodology of integrating three parts: 1) layer analysis and time series similarity method in time-based pattern mining; 2) point density estimate method, classification-based method, and clustering-based method in spatial pattern mining; and 3) distribution investigation and multidimensional time series analysis for spatial-temporal pattern mining. We propose the novel FADTW method to mine the 2D and multidimensional patterns in temporal and spatial-temporal patterns. Classification-based methods are applied to investigate attack type, weapon, navigational status, and the number of attack features. A clustering-based method, DBSCAN, is further used to extract and show spatial patterns. As shown in Fig. 1, the framework includes four parts, a new maritime piracy dataset, time-based, space-based, and spatio-temporal pattern mining. Each of them responds to the solution to each of the four research questions in Section 1, respectively.

3.2. Multidimensional time series analysis method

The classical point process models mainly include the Poisson point process, Cox point process, Determinantal point process, Hawkes process, and Geometric process, which are stochastic models of irregular point patterns. These models are suitable for modeling and analyzing the point patterns and distribution in space and time. However, to fully reveal the spatio-temporal process of the pirate incidents, the attack patterns hidden in the yearly, monthly, and hourly time series have to be investigated to capture the important features in mining the relationship among years, months, and hours. Moreover, the analysis of the relationship among different high-risk areas are also strongly demanded. Therefore, compared to the point process models, the FADTW method, capable of supporting 2D and multidimensional time series analysis, is more suitable for conducting deep mining in the yearly, monthly, and hourly data distributions.

As a commonly used time series similarity measurement method, Dynamic Time Warping (DTW) will minimize the cumulative distance between two time series with overstretching and over-compression [90]. To address these problems, we propose a new FADTW method to better extract and represent the similarity between two multidimensional time series with low time and space complexity. The proposed FADTW method is inspired by two methods: fast dynamic time warping [91] and adaptive constrained dynamic time warping methods [92].

3.2.1. Two-dimensional time series analysis method

Problem Formulation. The theory of the DTW method is described as follows. Given two time series $Q=\{(t_1,q_1),\cdots,(t_i,q_i),\cdots,(t_m,q_m)\}$ and $C=\{(t_1,c_1),\cdots,(t_i,c_j),\cdots,(t_m,c_n)\}$ with lengths m and n, respectively. The Euclidean distance between the i^{th} point in series Q and the j^{th} point in series C is $d(q_i,c_j) = \sqrt{(q_i-c_j)^2}$.

The objective function is to find the optimal warping path as the similarity between two time series. The optimal warping path must meet three constraints, which are defined below [93].

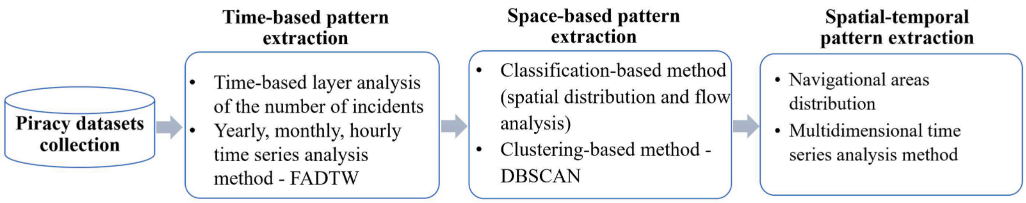


Fig. 1. The visualization framework of maritime piracy.

$$W = \{w_1, \cdots, w_t, \cdots, w_k\},$$
$$s.t. \begin{cases} \max\{m,n\} < K \le m+n-1 \\ w_1 = (1,1), w_k = (m,n) \\ w_t = (i,j), w_{t+1} = (i^{'},j^{'}) \\ i \le i^{'} \le i+1, j \le j^{'} \le j+1 \end{cases} \tag{1}$$

Problem Solving. The optimal path with the lowest warping cost in the original DTW can be calculated as follows:

$$DTW(Q,C) = \min\left\{\frac{1}{K}\sum\nolimits_{t=1}^{K} W_t\right\}$$
$$s.t. D(1,1) = d(q_1, c_1) \tag{2}$$
$$D(i,j) = d(q_i, c_j) + \min\{D(i,j-1), D(i-1,j-1), D(i-1,j)\}$$

The problem-solving of the original DTW method will lead to over-stretching and over-compression. To eliminate this drawback, a fast adaptive dynamic time warping solving method with multidimensional time series is proposed in Section 3.2.2.

3.2.2. Multidimensional time series analysis method

New Solving Method. Let $T_P = \{(p_1^1, p_2^1, \cdots, p_t^1), \cdots, (p_1^i, p_2^i, \cdots, p_t^i), \cdots, (p_1^m, p_2^m, \cdots, p_t^m)\}$ and $T_Q = \{(q_1^1, q_2^1, \cdots, q_t^1), \cdots, (q_1^j, q_2^j, \cdots, q_t^j), \cdots, (q_1^n, q_2^n, \cdots, q_t^n)\}$ are two t-dimensional time series with lengths m, respectively. The Euclidean distance between the i^{th} and j^{th} point in time series T_P and T_Q is $d(T_P^i, T_Q^j) = \sqrt{\sum_{i=1}^{m}\{(p_1^i - q_1^j)^2 + \cdots + (p_t^i - q_t^j)^2\}}, i = 1, \cdots, m; j = 1, \cdots, n.$ The solving method of the global optimal warping path is defined by the proposed FADTW method below.

$$FADTW(T_P, T_Q) = \min\left\{\frac{1}{K}\sum_{t=1}^{K} W_t\right\}$$
$$= \min \sum \min\left\{FADTW(T_P^i, T_Q^j)_1, FADTW(T_P^i, T_Q^j)_2, FADTW(T_P^i, T_Q^j)_3\right\}$$
$$s.t. FADTW(1,1) = d\left(T_P^1, T_Q^1\right)$$
$$FADTW(i,1) = FADTW(1,j) = +\infty$$
$$FADTW(T_P^i, T_Q^j)_1 = (1 + N_{i-1,j}) \times d(T_P^i, T_Q^j) + FADTW(T_P^{i-1}, T_Q^j)$$
$$FADTW(T_P^i, T_Q^j)_2 = d_{i,j} + FADTW(T_P^{i-1}, T_Q^{j-1})$$
$$FADTW(T_P^i, T_Q^j)_3 = (1 + N_{i,j-1}) \cdot d(T_P^i, T_Q^j) + FADTW(T_P^i, T_Q^{j-1})$$
$$N_{i-1,j} \le \left[\frac{m}{2^3}\right], N_{i,j-1} \le \left[\frac{n}{2^3}\right] \tag{3}$$

where $N_{i,j-1}$ and $N_{i-1,j}$ denotes the number of using times at each point in a warping route, which is an effective factor in controlling the degree of overstretching and over-compression.

The schematic diagram of two time series analysis methods is displayed in Fig. 2. It is evident that the original DTW method encounters the scenario of seven-to-one corresponding results. The proposed FADTW method can reduce this overstretching and find the global optimal warping path to express the similarity of two time series. Meanwhile, the coarsening and refinement of the proposed FADTW method are based on the Bisection method to divide the time series into small segments to find the optimal route. Finally, it can speed up the searching and solving time.

The pseudocode of the proposed FADTW algorithm is shown in Algorithm 1.

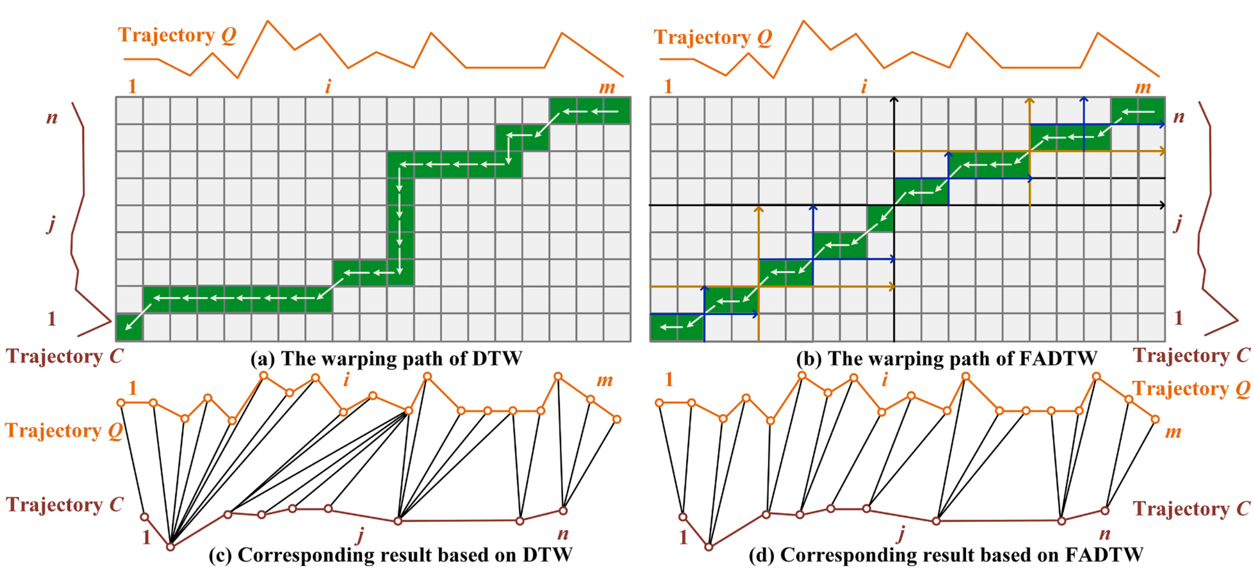


Fig. 2. The schematic diagram of two methods.

Algorithm 1
FADTW algorithm.

Input: The t-dimensional time series T_P and T_Q
Output: $FADTW(T_P, T_Q)$.
1. Initialize: $FADTW(1,1) = d_{1,1}, FADTW(i,1) = FADTW(1,j) = +\infty$
2. Time series segmentation $L_1 = [m/2^3], L_2 = [n/2^3]$
3. ***for*** $i = 1$: L_1 in each subsequence **do**
4. ***for*** $j = 1$: L_2 in each subsequence **do**
5. $F1 = d_{i,j} + N_{i-1,j} \cdot d_{i,j} + FADTW(T_P^{i-1}, T_Q^{j}), N_{i-1,j} \leq L_1$;
6. $F2 = d_{i,j} + FADTW(T_P^{i-1}, T_Q^{j-1})$;
7. $F3 = d_{i,j} + N_{i,j-1} \cdot d_{i,j} + FADTW(T_P^{i}, T_Q^{j-1}), N_{i,j-1} \leq L_2$;
8. $FADTW(T_P^{i}, T_Q^{j}) = \min(F1, F2, F3)$;
9. $W(i,j) = min\_index[(i-1,j),(i-1,j-1),(i,j-1)]$;
10. **end for**
11. **end for**

3.3. Clustering-based spatio-temporal pattern extraction

The clustering-based methods are commonly used to mine the hidden patterns. A density-based method, DBSCAN, is selected to find the high-density areas of maritime piracy incidents because of its superiority over the other clustering-based methods (e.g., [94,95]) in terms of no requirement of pre-defining the number of clustering centers. High-density incident areas refer to navigation waters with high piracy risk. To explore the spatio-temporal patterns of maritime piracy incident data, the number of clustering centers should not be defined in advance.

The best *Eps* (the radius) and *MinPts* (the minimum number of points within *Eps*) can be determined by two indexes: the Silhouette Coefficient (SC) index and Davies-Bouldin (DB) Index. The SC index can measure the similarity between a cluster with other clusters, while the DB index can compare the difference between the sum of the average distance of all samples in different clusters. The larger the SC value and the smaller the DB value, the better the clustering performance. Therefore, the optimization of the SC and DB indexes is conducive to determining the two parameters. The optimal function is shown in Eq. (4).

$$f(Eps, MinPts) = \max(SC) \cap \min(DB)$$

$$SC = \sum_{t=1}^{n} s(t) = \sum_{t=1}^{n} \frac{b(t) - a(t)}{\max\{a(t), b(t)\}} = \begin{cases} 1 - \dfrac{a(t)}{b(t)}, a(t) < b(t) \\ 0 \\ \dfrac{b(t)}{a(t)} - 1, a(t) > b(t) \end{cases}$$

$$DB = \frac{1}{K} \sum_{i=1}^{K} \max\left\{ \frac{\overline{d}(C_i) + \overline{d}(C_j)}{d(\mu_i, \mu_j)} \right\} \tag{4}$$

$$a(t) = \frac{\sum_{t' \in C_i, t \neq t'} d(t, t')}{|C_i - 1|}, \quad b(t) = \min_{1 \leq j \leq K, j \neq i} \frac{\sum_{t' \in C_j} d(t, t')}{|C_j|}$$

$$\mu = \frac{1}{|C|} \sum_{1 \leq i \leq |C|} x_i, C = \{C_1, C_2, ..., C_K\}$$

$$\overline{d}(C) = \frac{1}{|C|(|C| - 1)} \sum_{1 \leq i < j \leq |C|} d(x_i, x_j)$$

where K denotes the number of groups, $a(t)$ expresses the average distance between the sample t and all the other samples in the same cluster. $b(t)$ indicates the average distance between the sample t and all the samples in other groups. $\overline{d}(C)$ indicates the average distance between samples in clusters $C = \{C_1, C_2, ..., C_K\}$, and $\mu = \{\mu_1, \mu_2, ..., \mu_K\}$ expresses the central point of the different groups k.

DBSCAN can divide all the points into core points, border points, and noise points. Then, it can discover high-density areas automatically and effectively. It does not need to set the number of clustering centers in advance and can optimize the two parameters automatically.

Given p is an arbitrary point in dataset X. The basic definition of DBSCAN is implemented in detail as follows.

Definition 1. $N_{Eps}(p)$ is the *Eps*-neighborhood of p, which is defined by

$$N_{Eps}(p) = \{q \in X, dis(p, q) \leq Eps, p \neq q\} \tag{5}$$

p is the core point when and only if $N_{Eps}(p) \geq MinPts$;

p is the border point when and only if $p \in N_{Eps}(q)$, $N_{Eps}(q) \geq MinPts$;
p is the noise point when it is not the core point and border point.

Definition 2. Directly density-reachable (DDR): p is DDR from q w.r.t. *Eps* and *MinPts* when and only if

$$p \in N_{Eps}(q), \ N_{Eps}(q) \geq MinPts \tag{6}$$

Note that DDR is essentially symmetric for all the core points.

Definition 3. Density-reachable (DR.....): p is DR..... from q when and only if there is a series of points $p_1, p_2, \cdots, p_n$, $p_1 = q$, $p_n = p$ that p_{i+1} $(1 \leq i \leq n)$ is DDR from p_i w.r.t. *Eps* and *MinPts*. Note that DR..... is not symmetric but transitive.

Definition 4. Density-connected (DC): p and q are density-connected w.r.t. *Eps* and *MinPts* when and only if $\exists o \in X$ guarantees that both p and q are simultaneously density-reachable from o w.r.t. *Eps* and *MinPts*.

Note that DC is symmetric and reflexive.

Definition 5. Cluster: A cluster C which satisfies $C \subseteq X$ w.r.t. *Eps* and *MinPts* when and only if:

(1) Maximality: if $\forall p \in C$ and q is DR..... from p, then $q \in C$;
(2) Connectivity: the relationship between p and q is DC.

The following two lemmas can help demonstrate the accuracy of cluster C

Lemma 1. *$\exists p \in X$ and p is the core point, then the set O is a cluster and$O = \{o | o \in X \cap$ the relationship from o to p is DR$\}$ w.r.t. Eps and MinPts.*

Lemma 2. *$\forall p \in C$ and p is the core point, $C \subseteq X$ is a cluster w.r.t. Eps and MinPts, then $C = O$.*

The basic architecture of the DBSCAN method is displayed in Fig. 3. The core point, border point, and noise point are shown in Fig. 3.

The procedure of DBSCAN is shown in Algorithm 2.

4. Experimental results and analysis

4.1. Data collection and dataset description

This study draws on three major data collection efforts on maritime piracy datasets by the Anti-Shipping Activity Messages (ASAM) in the NGIA, IMO GISIS, and the IMB datasets to generate a comprehensive piracy incident dataset from 1990 to 2021. The comprehensive dataset takes advantage of the three datasets, including all the piracy incident-related variables such as date, time, description, locations at sea, attack types, target ship types, navigational areas, the status of the ships when being attacked, weapons used by attackers, and the number of persons involved in an attack. Meantime, the World-Wide Navigational Warning Service (WWNWS) is jointly constructed by the IMO and International Hydrographic Organization (IHO) to divide the global NAVIgation AREAs into 21 parts (i.e., NAVAREA) and designates the corresponding coordinating countries to each part. The piracy risk areas defined with regard to the NAVAREA are analyzed in this manuscript.

In this merging process, the IMO GISIS dataset is taken as the data basis, while ship name, ship type, date, and location are used as the link

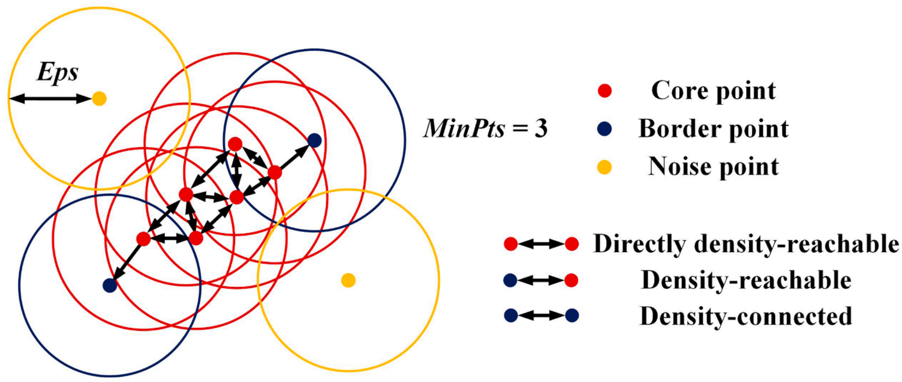


Fig. 3. The schematic diagram of the DBSCAN method.

Algorithm 2
DBSCAN algorithm.

Input: *X, Eps, MinPts*.
Output: the clustering results $C_1, \cdots, C_K$.
1. Initialize: Core point set $\Omega = \varnothing$, border point set $\Omega_b = \varnothing$, noise point set $\Omega_n = \varnothing$, directly density-reachable point set $\Omega_{DDR} = \varnothing$, density-reachable point set $\Omega_{DR} = \varnothing$, density-connected point set $\Omega_{DC} = \varnothing$.
2. **while** $\forall p \in X$ do
3. **if** $N_{Eps}(p) \geq MinPts$ then
4. $\Omega \leftarrow p$
5. **else if**
6. $\Omega_b \leftarrow p$
7. **else**
8. $\Omega_n \leftarrow p$
9. **end if**
10. repeat until all points are processed
11. **end while**
12. $\Omega_{DDR} \leftarrow$points are DDR
13. $\Omega_{DR} \leftarrow$points are DR.....
14. $\Omega_{DC} \leftarrow$points are DC
15. The optimal $(Eps, MinPts) \leftarrow \min(DB) \cap \max(SC)$
16. $C_1, \cdots, C_K \leftarrow DBSCAN(X, Eps, MinPts)$

(i.e., the bolded words in Table 2) to synchronize the incident data among the three datasets to ensure the data quality and avoid any double counting. Only the recorded incidents of complete information against all the relevant risk factors are selected to capture the risk characteristics in a comprehensive manner. The comparison of different datasets and our new dataset are listed in Table 2 to show the details. The dataset collected from ASAM has 8477 records from 1978 to 2021, the IMO GISIS dataset includes 8266 incidents from 1994 to 2021, and the IMB piracy dataset contains 7512 records from 1993 to 2020. Based on the above-mentioned data link, a comprehensive piracy incident dataset is constructed from 1990 to 2021, including 8369 records.

Three kinds of maritime piracy datasets feature different factors and records, combing together to have contemporary visualization research from different directions for mining spatio-temporal patterns. The experimental flowchart is displayed in Fig. 4. The time-based, space-based, and spatio-temporal patterns are analyzed against all the RIFs to mine features, identify findings, and reveal implications, providing useful guidance for preventing maritime piracy. Each detailed analysis in the ensuing sections follows a chain of visualized results, while insightful findings and implications are drawn from such results.

4.2. Time-based pattern extraction and analysis

4.2.1. Time-based layer analysis of the number of incidents

The layer analysis is applied to extract the features of the monthly distribution of maritime piracy incident data. The visualization result of the layer analysis is shown in Fig. 5 to uncover the five layers in the number of monthly maritime incidents from 1990 to 2021. The number of monthly piracy incidents belongs to [0,100]. Then, the layer analysis method can help quantitively compare five layers with an even distribution (i.e., $[0,20)$, $[20,40)$, $[40,60)$, $[60,80)$ and $[80,100]$) based on the number of piracy incidents. As shown in Fig. 5, the monthly distribution of maritime piracy incidents is compared visually in different colors. It is evident that the highest number of pirate attacks happened in Nov. 2010 (i.e., 90) with red color. The second highest tier occurred in Nov. 2010 (i.e., 72), Sep. 2008 (i.e., 72), Jan. 2011 (i.e., 67), Apr. 2009 (i.e., 66), and Mar. 2009 (i.e., 60), respectively. The layer analysis result reveals that maritime piracy incidents 1) face the highest risk in 2010; 2) have serious concerns in the period of 2008 to 2010; 3) decrease from the second layer to the first one from 2018 to 2019; 4) increase to the second layer again from 2020 to 2021; and 5) uncover the scope and length each layer lasts.

Across all the different involved years, the monthly layer analysis shows that the high incidence of piracy incidents is concentrated from Mar. to May and Aug. to Nov.. This has shown a harmony with the previous findings in localized/regional waters, mainly because the sea and weather conditions, as well as the trades, are in a favorable manner to attrite piracy attacks. Therefore, the ship owners and crews should pay extra attention to the attacks of strong seasonal features and deploy

Table 2
The description of different datasets.

	Dataset 1	Dataset 2	Dataset 3	New dataset
Name	ASAM	IMO GISIS	IMB	Piracy
Range	1978–2021	1994–2021	1993–2020	1990–2021
IMO number	N	Y	N	Y
Ship name	N	**Y**	**Y**	Y
Ship type	**Y**	**Y**	N	Y
Incident type	**Y**	N	**Y**	Y
Date (Year-month-day)	**Y**	**Y**	**Y**	**Y**
Time (Hour)	N	Y	N	Y
Location (longitude and latitude)	**Y**	**Y**	**Y**	**Y**
Description	Y	Y	Y	Y
NAVAERA	Y	N	N	Y
Geographical areas	N	Y	N	Y
Weapon	N	Y	N	Y
Navigation status	N	Y	Y	Y
The number of people involved in the attack	N	Y	N	Y
All	8477	8266	7512	8369

Note: 'Y' denotes that the factor is included in the corresponding dataset, and 'N' shows that the factor is not in the corresponding dataset. Datasets 1, 2, and 3 are collected from https://msi.nga.mil/Piracy, https://gisis.imo.org/Public/PAR/Search.aspx, and https://github.com/newzealandpaul/Maritime-Pirate-Attacks [89], respectively.

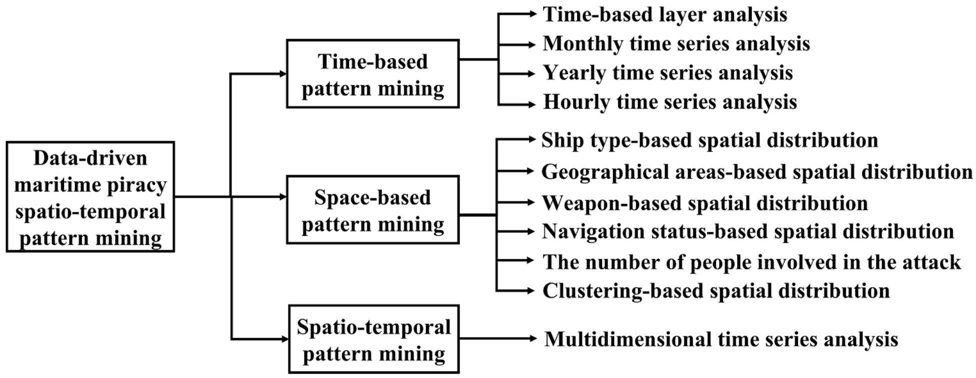


Fig. 4. The experimental flowchart.

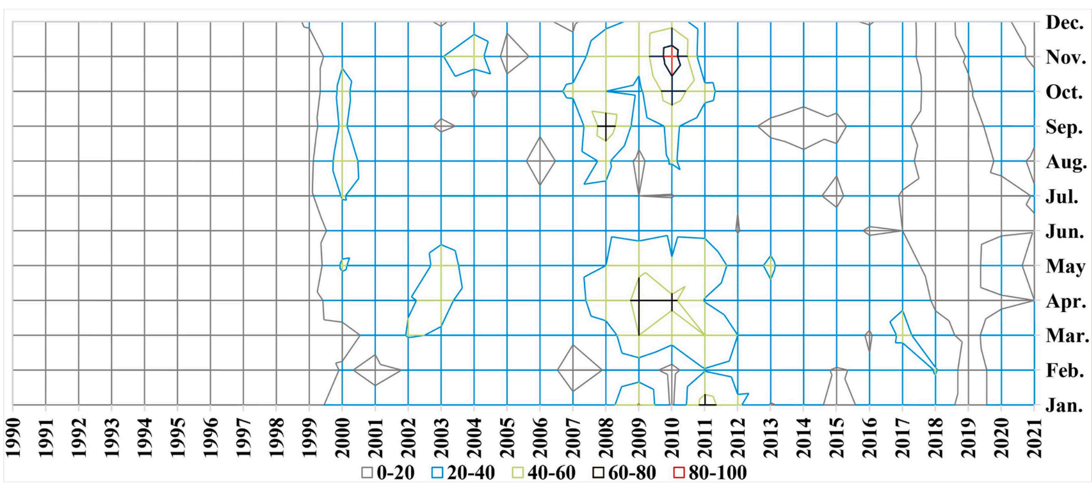


Fig. 5. The monthly layer analysis based on the number of piracy incidents.

anti-piracy measures more effectively. Meantime, it is also noteworthy that this pure time-based annual analysis results could suffer from the effect of irregular outperformance (e.g., very high number in the Indian Ocean in a few particular years). More in-depth analysis of spatio-temporal patterns is carried out in Section 4.4, while the other time-based analysis on hourly and monthly time series that can generate generic insightful findings are introduced in the ensuing sections.

4.2.2. *Similarity analysis of monthly time series*

Although the monthly layer analysis has revealed the distribution features in the number of maritime pirates, the similarity that is hidden in the number of incidents still needs to be further explored to show the features in monthly and yearly distribution. It is worth noting that year, month, and hour are important indexes in the record of incidents due to pirate attacks that are humanly organized and hence sensitive to time. The monthly time series is presented in Fig. 6, showing that the months

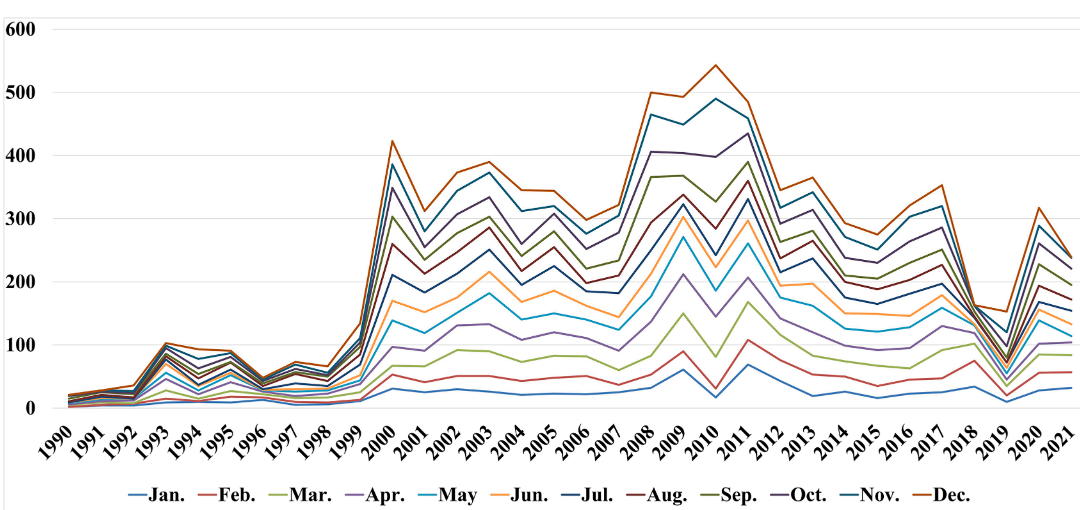


Fig. 6. Monthly distribution of maritime piracy incidents.

have the same trends from 2000 to 2009 and 2012 to 2017. To have a deep analysis of the monthly, yearly, and hourly time series, the FADTW is proposed to calculate the distance and measure the similarity to uncover the intrinsic features.

The similarities among monthly time series based on the proposed FADTW method are calculated and displayed in Fig. 7. The 2D heatmap visualization based on the FADTW method can show the relationship between different months. The larger the distance value, the smaller the similarity. Therefore, it is worth noting that the most similar months focus on the dark cran squares in Fig. 7.

To have a clear understanding of similarity, the top 20 similarities are further listed in Table 3. From the results in Fig. 7 and Table 3, it is evident that the top two similarity clusters are (1) Jun., Jul., Aug., and Sep.; (2) Mar., Apr., and May. The hidden similarity analysis reveals the monthly patterns.

It is interesting to note that attacks are highly related to the same weather and monsoon. This finding can provide recommendations for ship owners to focus on coordinating ship scheduling and trade plans, for crews to strengthen the lookout and rationalize the resources for anti-piracy measures, and for policymakers to make security recommendations with regard to the dynamic high-risk areas in different months.

4.2.3. Statistical analysis of yearly time series

The yearly time series based on hourly data (from 0:00 to 23:59) is also an important index in exploring the influence of incident time each year. Therefore, the statistical analysis of yearly time series based on hourly data is compared to mine the time patterns in different years. 0 h indicates the time period 00:00–00:59, and 23 h expresses 23:00 to 23:59. The statistical analysis result (i.e., the detailed percentage of each hour) of the yearly time series is shown in Fig. 8, which reveals the higher incident rate occurred between 00:00 and 05:59 from the visualization results.

It is observed that the time range from 23 h to 5 h witnesses a high number of pirate incidents, with 19.04% of incidents occurring from 00:00 to 00:59 am. It was often attributed to the fact that the low light conditions and reduced visibility made it easier for pirates to approach and board ships unnoticed. The findings provide useful insights on the most dangerous hours for pirate attacks, and accordingly, more anti-piracy measures such as an outreach rope net could be implemented.

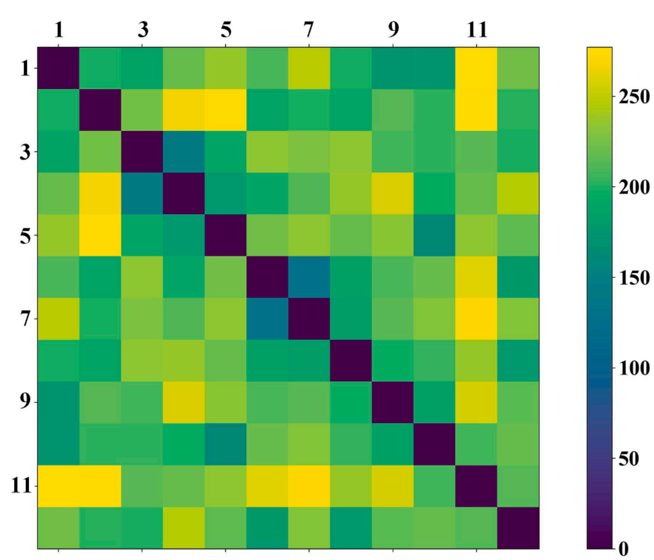


Fig. 7. The visualization result of the similarity among the monthly time series analysis.

Table 3
The top 20 similarity values by the results of the monthly time series.

Similarity value	Month	Month	Similarity value	Month	Month
133.7	Jun.	Jul.	185.0	Sep.	Oct.
143.8	Mar.	Apr.	185.5	Jan.	Mar.
157.5	May	Oct.	186.5	Feb.	Aug.
173.1	Jan.	Sep.	187.1	Feb.	Jun.
175.2	Jan.	Oct.	190.5	Mar.	May
177.1	Apr.	May	191.7	Apr.	Jun.
177.3	Aug.	Dec.	196.8	Apr.	Oct.
178.0	Jun.	Dec.	197.9	Aug.	Sep.
181.8	Jul.	Aug.	198.2	Jan.	Feb.
184.5	Jun.	Aug.	198.4	Jan.	Aug.

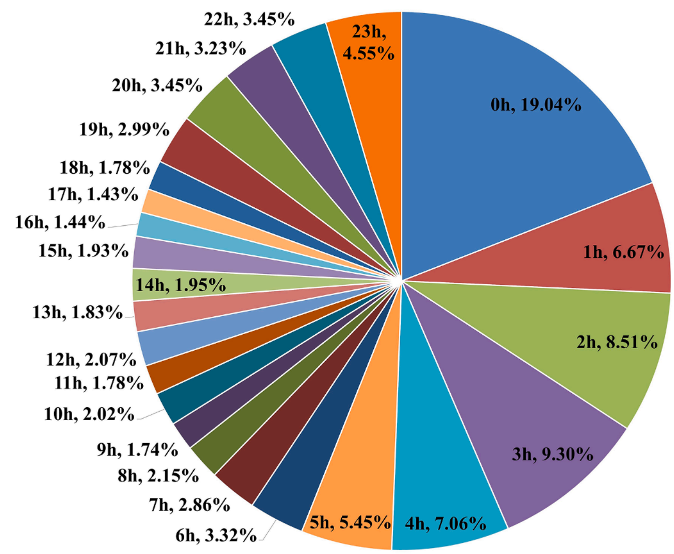


Fig. 8. Annual distribution of maritime piracy incidents based on cumulative hourly data.

4.2.4. Similarity analysis of hourly time series

The hourly data is associated with the incident records from 1994 to 2021 and is presented in Fig. 9. An interesting observation from the finding is that the difference in terms of piracy incidents between 0 h and other hours of darkness (e.g., 1 h) has been becoming smaller since 2004. Among the various contributory factors to the reduction of maritime pirate incidents, maritime piracy regulations and measures play an important role in anti-piracy. Since 2004, a few regulations and associated countermeasures have been developed and implemented with positive effects. It probably explains the reduced gap between different hours in the dark, as many of the regulations and measures (see Table 4) address the hourly effect of pirate incidents in their developments. However, the effect of these regulations on the reduced gap needs to be further investigated.

Obviously, it fails to directly show the trends like the ones obtained from monthly data. To have a clearer view of the hourly time series in yearly time series, the FADTW is used to calculate the distance and measure the intrinsic similarity. The top 20 similarity values of the hourly time series analysis are listed in Table 5, and it is obvious that the high incident period is from 0:00 to 5:59. The top three similar annual trends of the hourly time series are 21 h (21:00–21:59) and 23 h (23:00–23:59), 15 h (15:00–15:59) and 21 h (21:00–21:59), 6 h (6:00–6:59) and 12 h (12:00–12:59). Meantime, the top three chains are $21 \rightarrow 23$; $15 \rightarrow 21, 20$, and $6 \rightarrow 12, 10, 14$. The events that happened during these hours from 1994 to 2021 have high similarities, meaning the same anti-piracy actions should be taken in each of the three time periods. Take 21:00–21:59 as an example, its annual trend is similar to one of 23:00–23:59, 15:00–15:59, 9:00–9:59, 18:00–18:59, 14:00–14:59, and

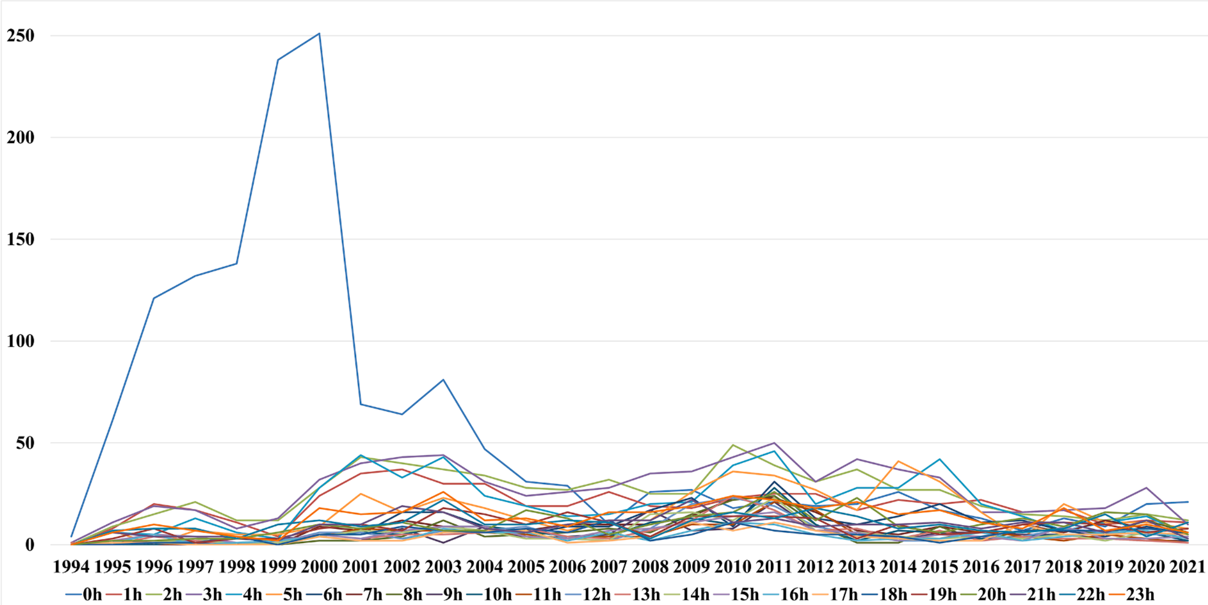


Fig. 9. Hourly time series of maritime piracy incidents based on the annual piracy incidents.

Table 4
Some anti-piracy regulations and measures after 2004.

The United Nations Convention on the Law of the Sea	Since 2004, there have been several efforts to strengthen the implementation of the Convention, including the adoption of the 2005 SUA Protocol, which criminalizes acts of piracy and armed robbery against ships
IMO	In 2005, the IMO issued guidance on the use of privately contracted armed security personnel on board ships, which has become an important measure for protecting against piracy.
Regional agreements	There have been several regional agreements established to address the issue of piracy. For example, in 2008, the East African Community (EAC) and the Intergovernmental Authority on Development (IGAD) established a regional mechanism for maritime security in the Western Indian Ocean, known as the Mombasa Declaration. Similarly, in 2009, the Gulf of Aden and the Red Sea countries signed the Djibouti Code of Conduct, which established a framework for cooperation in the fight against piracy.
Military interventions	Since 2004, there have been several military interventions aimed at combating piracy, particularly off the coast of Somalia. In 2008, the European Union launched its first naval mission, Operation Atalanta, to protect ships from piracy in the Gulf of Aden. Other countries, such as the United States, China, and India, have also deployed naval vessels to the region.
Industry measures	The shipping industry has taken several measures to protect against piracy, including the use of onboard security measures, such as barbed wire, water hoses, and acoustic devices. Additionally, some shipping companies have implemented armed guards on board their vessels.

11:00 to 11:59. This finding can provide the data fitting guidance for incident analysis. Meanwhile, this implication can also support time-based management and patrol scheduling for policymakers and crews.

Compared to the previous time-based piracy analysis, the results reveal new findings, including 1) the similar features in different hours; 2) the three clusters in 24 h; and 3) the hidden patterns in different clusters. All of these findings provide valuable implications for crews to pay more attention in the period of 0:00 to 5:59 and take the same anti-piracy measures in similar time chains.

Table 5
The top 20 similarity values of hourly time series.

Similarity value	Hour	Hour	Similarity value	Hour	Hour
100.0	21	23	109.0	14	21
102.9	15	21	109.9	7	17
103.0	6	12	109.4	0	5
104.4	4	5	110.4	11	21
105.1	9	19	112.0	10	22
105.2	6	10	112.1	10	20
105.8	9	21	112.1	19	23
106.2	18	21	113.7	7	16
108.3	15	20	114.1	12	22
108.5	12	20	115.1	6	14

4.3. *Space-based pattern extraction and analysis*

Maritime piracy is sensitive to locations because it is organized, not random, and happens in international waters of higher attack success. Therefore, classification-based spatial distribution should be further explored based on different factors to extract the patterns and identify different risk factors.

4.3.1. *Ship type-based spatial distribution*

Ship type-based spatial distribution is conducive to understanding the attack situation of different ship types in different geographical areas and providing a reference for future navigation. The first part is analyzed based on the original ship type in the maritime piracy dataset. The number of different types of ships attacked is shown in Fig. 10. There are 40 types of ships in the maritime piracy dataset. To have a clear spatial distribution of different ship types, a threshold of 100 attacks (indicated by a dotted line) is set to visualize the result and identify the predominant types of targeted vessels. The threshold of 100 is established based on the distribution of attack frequencies of various ship types.

The spatial distribution result is displayed in Fig. 11. Bulker carriers are the most attacked, followed by container ships, general cargo ships, tankers, and chemical tankers. Although the number of attacks against different types is affected by the number of ships by type, there is a significant difference between the two ranking lists (attack numbers by

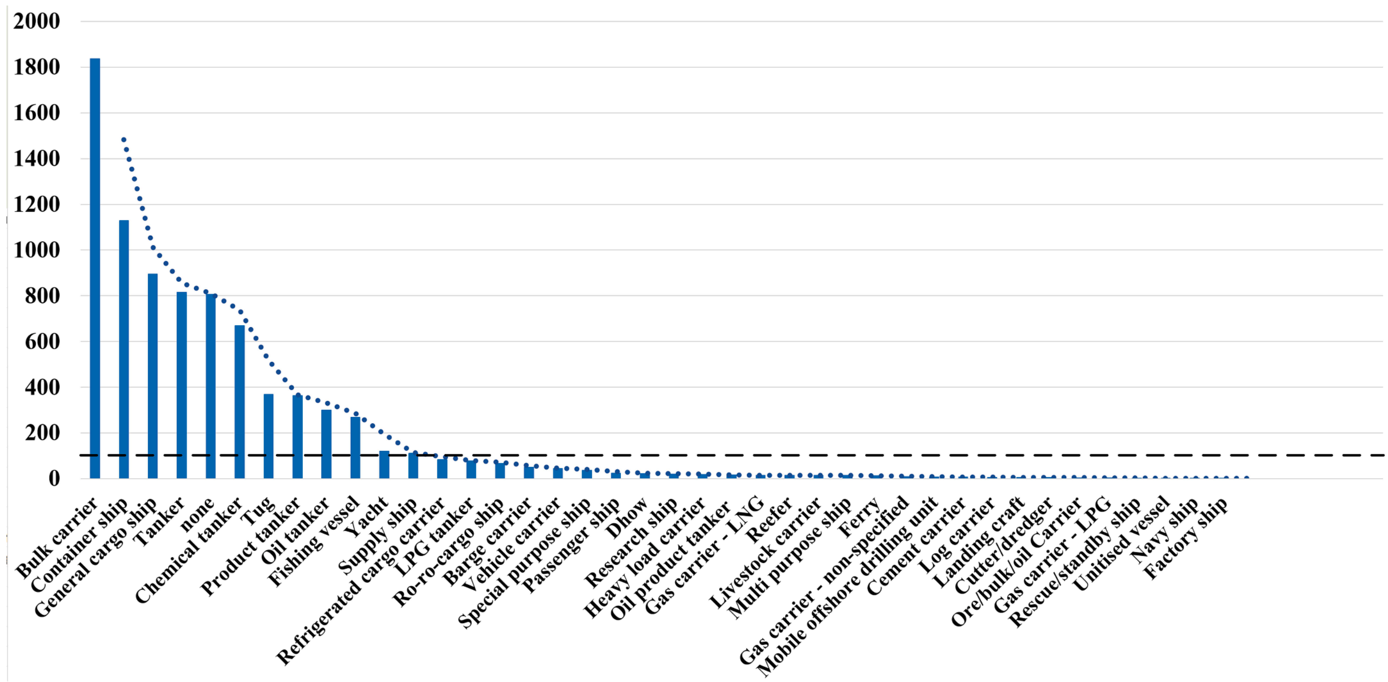
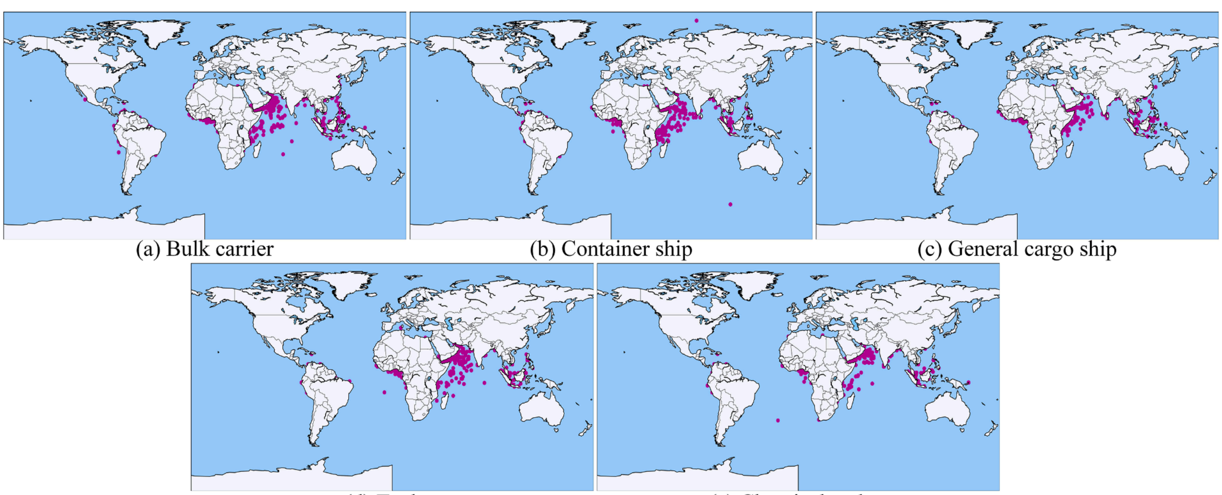


Fig. 10. The statistical result based on ship types.



(a) Bulk carrier (b) Container ship (c) General cargo ship

(d) Tanker (e) Chemical tanker

Fig. 11. The spatial distribution results by ship types.

ship type and ship number by ship type), showing the significance of this analysis. According to the Statista 2022 [96], the number of ships in the world merchant fleet as of 1 Jan. 2022 by ship type is 17,784 (Ro-Ro/general cargo ships), 12,941 (bulk carriers), 8258 (crude oil tankers), 6122 (chemical tankers), 5574 (container ships), 5369 (passenger ships), and 2180 (LNG tankers), respectively. The ratio between attack numbers and ship numbers is calculated to show the relative attraction of different major types of ships to pirates at different locations. They are 5.41% (Ro-Ro/general cargo ships), 14.20% (bulk carriers), 3.69% (crude oil tankers), 10.93% (chemical tankers), 20.25% (container ships), 0.45% (passenger ships), and 0.69% (LNG tankers), respectively. It reveals that the order of attack probability is container ships first, followed by bulk carriers, chemical tankers, Ro-Ro/general cargo ships, crude oil tankers, LNG tankers, and passenger ships.

From the comparison results, the spatial patterns of 11 ship types are projected on the world map. In terms of navigational area distribution, the attack targets in Southeast Asia, the Arabian Sea, East Africa, and the Gulf of Guinea mainly focus on bulker carriers, container ships, cargo ships, and different types of tankers. Passenger ships and LNG tankers are less attractive among the major ship types. The visualization result can effectively help identify risk factors (ship type and area) in incident cause analysis. This finding could be a wake-up call for the sailing of different types of ships. The anti-piracy measures and arming need to be strengthened in bulk carriers and container ships, especially when navigating in Southeast Asia, the Arabian Sea, East Africa, and the Gulf of Guinea.

4.3.2. Geographical areas-based spatial distribution

The geographical areas are a significant index to explore the navigation risk. To provide intuitive and effective information, the spatial distribution based on the geographical areas is shown in Fig. 12. The piracy attack happens in international areas, followed by port areas and

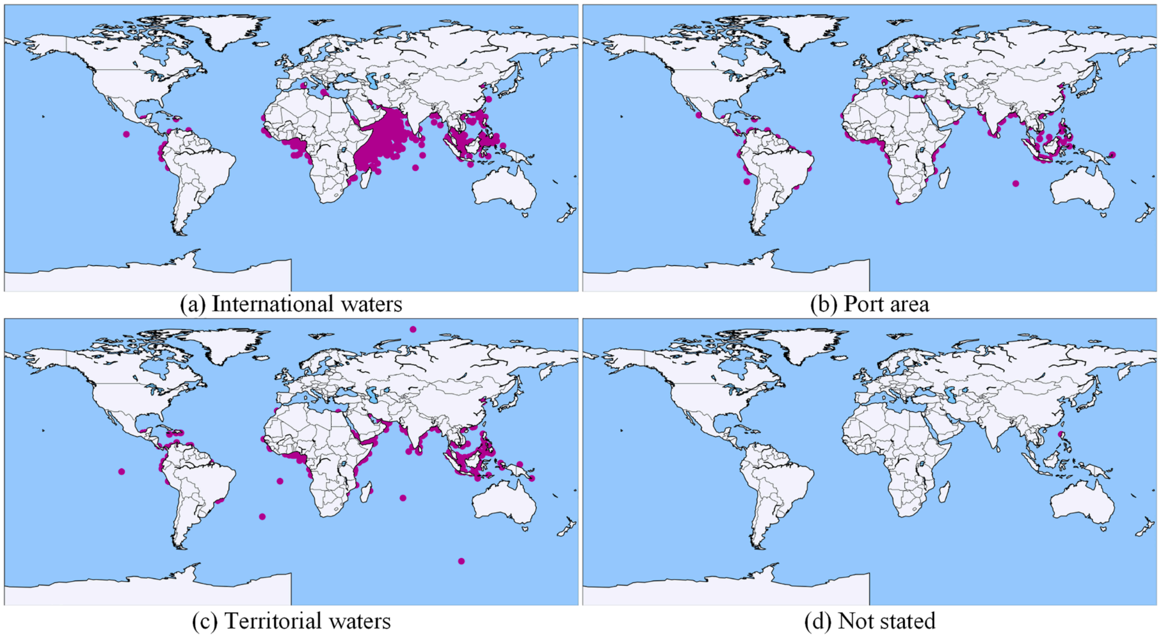


Fig. 12. The spatial distribution result based on the different geographical areas.

territorial waters. It is crucial as piracy activity has shown a strong correlation with the coastal states' political stability and economic situations. Analysis of the attacks that occurred in port areas or territorial waters can effectively aid in monitoring the associated port state's status to safeguard the passing ships. The serious attacks in the Somali waters in 2010 are typical demonstrations of the significance of this analysis. Property rights are not defined in international areas, so this is an important reason why piracy prevention is difficult and different from other forms of crime prevention. The attacks in international waters are mainly distributed in Southeast Asia, the Arabian Sea (including the Gulf of Arden and Somalia), East Africa, and the Gulf of Guinea, largely due to their strategic gateway roles in international shipping and geographical characteristics such as the narrow channels in Malacca Strait in Southeast Aisa. The spatial patterns of geographical areas are among the most important influential factors for rational risk management. These findings provide a strong warning signal on how to improve the safety resource allocation when navigating through different international waters. Furthermore, an immediate implication of this finding is to benchmark the geographical governance and jurisdiction of regional anti-piracy laws and stimulate the sharing of the best practices on anti-piracy measures among the waters of similarity.

4.3.3. *Weapon-based spatial distribution*

The weapon employed in an attack is crucial in establishing its success and pinpointing the cause of the incident. Therefore, the weapon-based spatial distribution is analyzed and displayed in Fig. 13. The main three kinds of weapons used in modern piracy are rocket-propelled grenades, guns, and knives. The attacks with rocket-propelled grenades mainly occurred in the Arabian Sea (including the Gulf of Arden and Somalia), East Africa, and the Gulf of Guinea. Guns are common in Southeast Asia, followed by the Arabian Sea (including the Gulf of Arden and Somalia), East Africa, and the Gulf of Guinea. It explains why piracy in Somalia, the Gulf of Arden, and East Africa often leads to much more serious consequences. It is, therefore, helpful for ship owners to make route planning, underwriters to adjust premiums, and crews to increase anti-piracy training skills when facing various weapon threats in different waters.

4.3.4. *The navigational status–based visualization and analysis*

The spatial distribution of navigational status is analyzed and compared in Fig. 14. The 12 types of status are steaming, anchored, berthed, underway, drifting, stationary, towed, fishing, grounded, bunkering, and moored. As shown in Fig. 14, the anchored (i.e.,

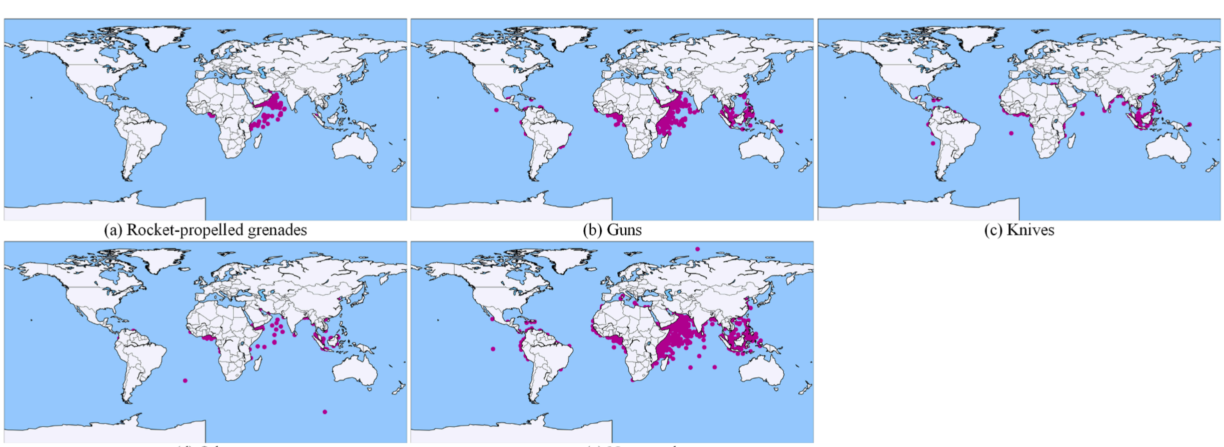


Fig. 13. The distribution results based on the weapons used by attackers.

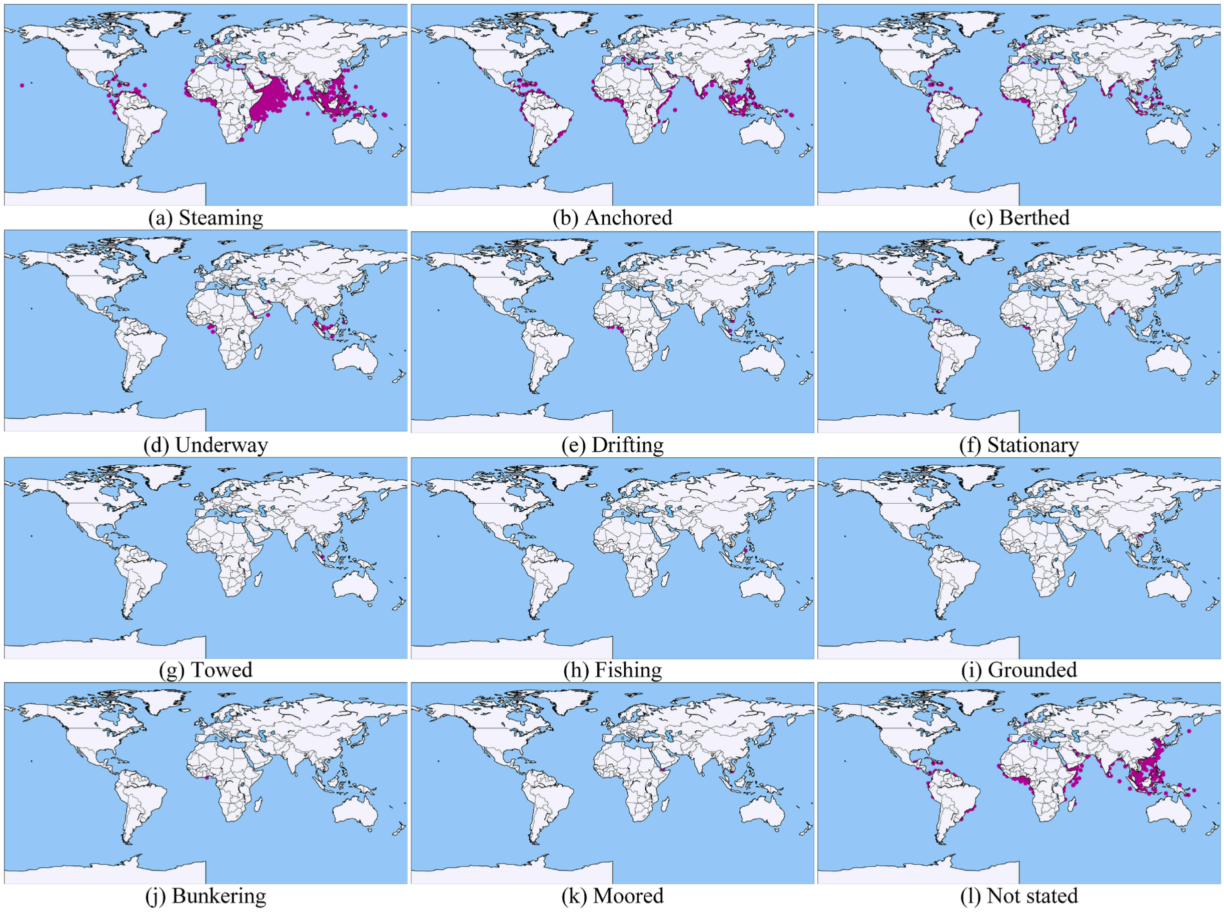


Fig. 14. The distribution based on the navigational status of ships when attacked.

43.42%), seaming (i.e., 34.59%), and berthed ships (i.e., 8.68%) need more attention to prevent pirate attacks by enhanced patrols on board. The piracy incident data flow analysis result is displayed in Fig. 15, which represents the relationship between attack types and navigational status. From the dynamic data flow results, boarded and boarding events mainly occur in anchored (accounts for 85.37%), steaming (accounts for 85.30%), and berthed ships (accounts for 90.81%). Hijacked events (accounts for 73.19%) mainly happen in steaming ships. The attempted events are mainly in steaming and anchored ships, accounting for 55%. The findings can provide important implications for crews to increase anti-piracy attention during ships of different statuses. The anti-piracy training and patrols on board should be enhanced to combat pirates at the right time and place.

4.3.5. Spatial distribution of the number of people involved in an attack

The number of people involved in the attack is an important index to assess the consequences of pirate attacks. The spatial distribution of the number of persons involved in the attack is shown in Fig. 16 based on three criteria: more than 10, 5–10, and 1–4 people. The regions with the largest number of people involved in pirate attacks are the Arabian Sea (including the Gulf of Arden and Somalia), East Africa, and the Gulf of Guinea. It is worth noting that the number of people involved in the attack is only one of the factors in assessing the consequences. Therefore, the relationship between the weapons used in the attack and the number of persons involved in the attack needs to be further analyzed holistically to mine the important findings and implications.

The relationship among ship types, geographical areas, attack weapons, and the number of persons involved in the attack is displayed based on the piracy incident flow data in Fig. 17. It is evident that pirate gangs with 1–4 people mainly use knives and guns to attack bulk ships (525), tankers (246), and container ships (239). Knives and guns are also employed in the pirate groups of 5–10 persons to raid bulk carriers (450), container ships (255), tankers (206), and general cargo ships (168). Pirates robbers with more than ten people mainly attack bulk carriers (62), container ships (62), general cargo ships (42), and tankers (33). This finding provides shipowners with insights on how to effectively develop anti-piracy measures for different kinds of ships in different routes. These implications also help authorities and crews better understand the pirate attack modes, learn the best policies, and improve anti-piracy training.

4.3.6. The spatial analysis based on DBSCAN

Following the above spatial analysis, a more in-depth incident density analysis is conducted in this section. The best values of *Eps* and *MinPts* are determined from Eq. (4), and the optimal parameters are *Eps*=5.5 and *MinPts*=8. The spatial patterns are mined based on the DBSCAN method, and the visualization result is shown in Fig. 18. Ten clusters are received to reveal the features of piracy data distribution. The dark green cluster (i.e., C-1) is the low-density area and is not taken into account to uncover the feature distribution. The ten different clusters with the number of attack points are listed in Table 6. The top three patterns focus on Southeast Asia (red points), East Africa and the Arabian Sea (yellow points), and West Africa (green points). These findings provide a solid foundation for scholars to conduct deep research in high-density areas, for authorities to pay more attention to these areas, for shipowners to consider routes, and for crews to be vigilant in these waters. Future studies could develop new real-time risk prediction models targeting specific hotspots identified from this analysis to realize the results of joint RIFs on pirate attacks in high-risk areas.

To further visualize the location with the highest density of piracy

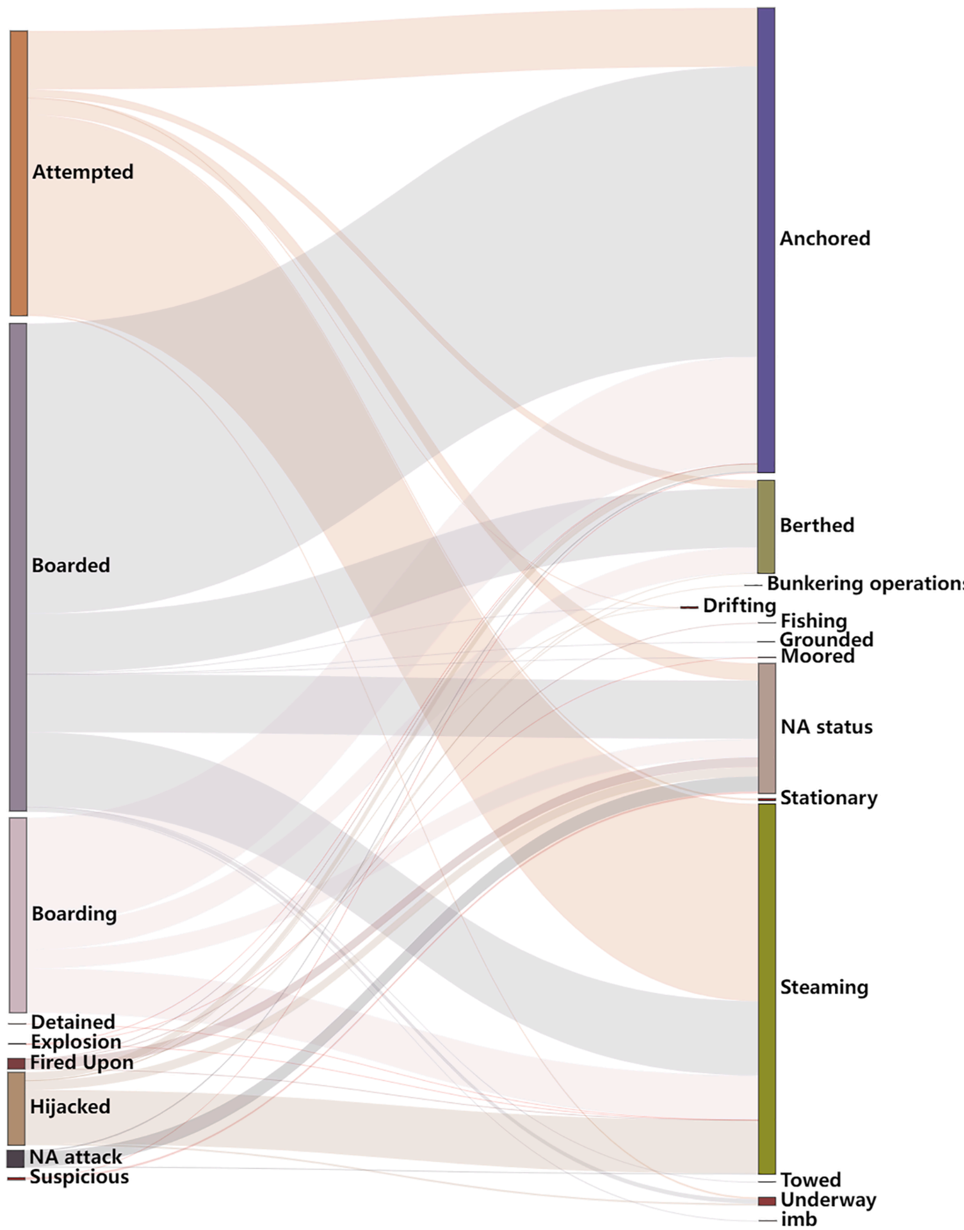


Fig. 15. The piracy incident flow analysis between attack type and navigational status.

incidents, the heatmap based on the point density estimation result is displayed in Fig. 19. It is clear that high-risk areas in the historical piracy data are presented in red and yellow colors. The main risk areas are Southeast Asia, the Red Sea, the Gulf of Arden, the Arabian Sea, the Gulf of Guinea, and the Caribbean Sea. The crews should pay special attention and enhance the patrols on board when navigating these areas. Different from previous studies in the field, this heatmap is for the first time to project the pirate attack density of different hotspots on the same map, showing a universal solution to pirate incident heatmap in the world using the so far most comprehensive incident database. It therefore makes significant contributions to ensuring safety and security at sea. In the future, a more detailed analysis of the attack consequences could be integrated to update this frequency density map towards a risk-based density one.

4.3.7. The incident features in five high-risk areas

Based on the above-mentioned spatial pattern analysis results, the monthly distribution and features are deeply analyzed in five high incident areas: Southeast Asia, East Africa and the Indian Ocean, West Africa, the Gulf of Aden and the Arabian Sea, and the Caribbean Sea.

The distribution results of piracy incidents in the top five high accident areas are shown in Fig. 20. For Southeast Asia in Fig. 20(a), the proportion of incident rates ranged from 6 to 11% and especially in ranking as Apr. (11%), May (9%), Oct. (9%), Nov. (9%), Jun. to Sep. (8%), Dec. (8%), Jan. (8%), Mar. (8%), and Feb. (6%). There are two rainy and dry seasons in Southeast Asia. The first rainy season is from Jul. to Sep., with southeasterly winds, and the minor dry season is Oct.-Nov., with no wind. The second rainy season is during the period of Dec. to Feb., and the wind is from the northeast. Obviously, rainy days in winter have a significant impact on piracy activities in Southeast Asia. Mar. to Jun. is the dry season with no wind. It is observed that although the effect of seasons and winds/waves on piracy in the Southeast Asia region has mild variation, the dry season with no wind in April and May still reveals a higher ratio. It is therefore evident that the monsoon season (e.g., winds and high waves) influences the maritime pirate attacks in Southeast Asia to some extent.

As shown in Fig. 20(b), the incident rate proportion is graded as six levels in East Africa and the Indian Ocean, (1) Oct. (12%), (2) Mar. and

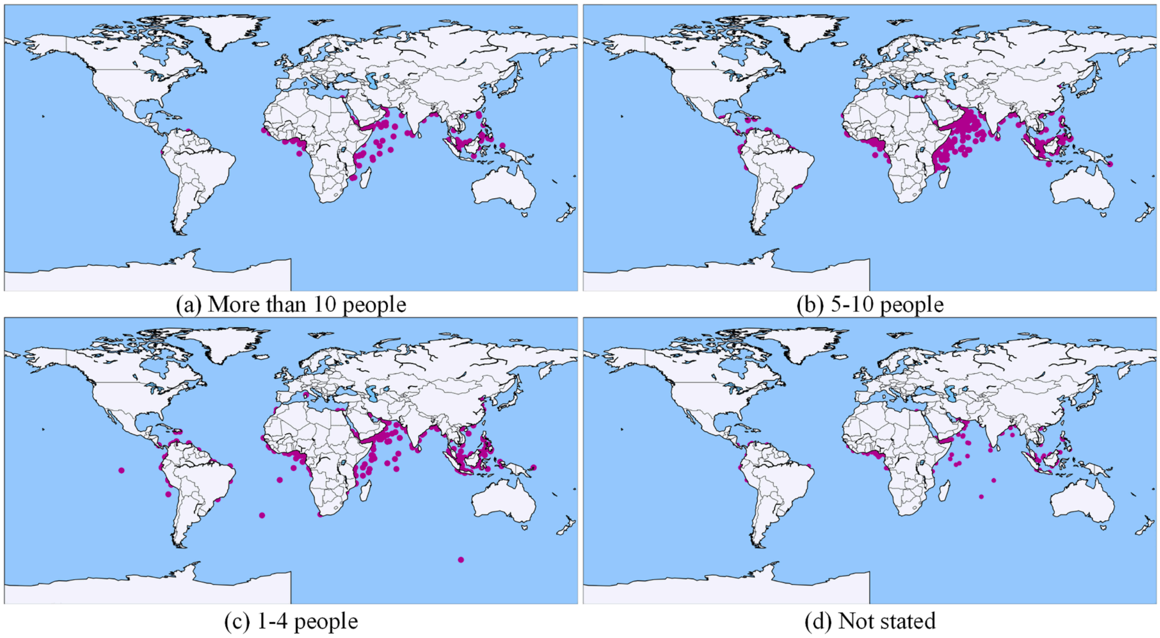


Fig. 16. The distribution result based on the number of persons involved in the attack.

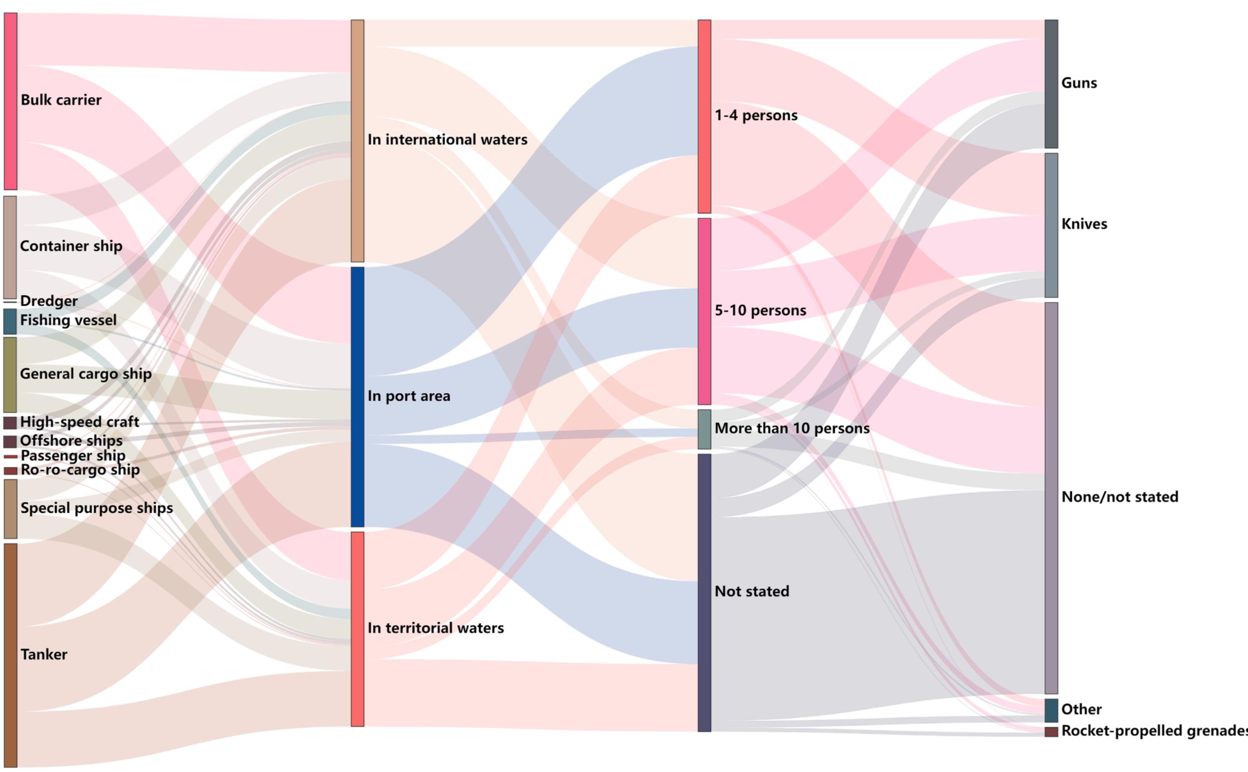


Fig. 17. The flow analysis among ship types, geographical areas, the number of persons involved in the attack, and attack weapons.

Nov. (11%); (3) Apr. and May (9%); (4) Sep. (8%); (5) Jan., Feb., Jul., and Dec. (7%); (6) Jun. and Aug. (6%). The incident rates vary much more significantly compared to the Southeast Asia region. It reveals that the monsoon season (seasonal wind speed and wave height) has shown a significant impact on piracy in East Africa and the Indian Ocean from an analysis of historical piracy events. It is also well reflected by the fact that the sea and weather conditions in monsoon seasons in these two areas are much tougher than in the Southeast Asia region in general.

The monthly distribution of piracy attacks in West Africa is ranged from 7% (Jun., Jul., and Sep.) to 10% (Jan. and Mar.) from Fig. 20(c). Incident rates vary not much from month to month. The northeast monsoon is from Oct. to May, and it turns to the southwest monsoon from Jul. to Aug.. West Africa also displays alternating southwest and northeast monsoons. The four months of summer are the southwest monsoon, which is caused by trans-equatorial airflow. The rest of the time is wet and rainy. Compared to the other high-risk areas, there is less evidence to show the coordination between monsoon seasons and pirate attacks in the region.

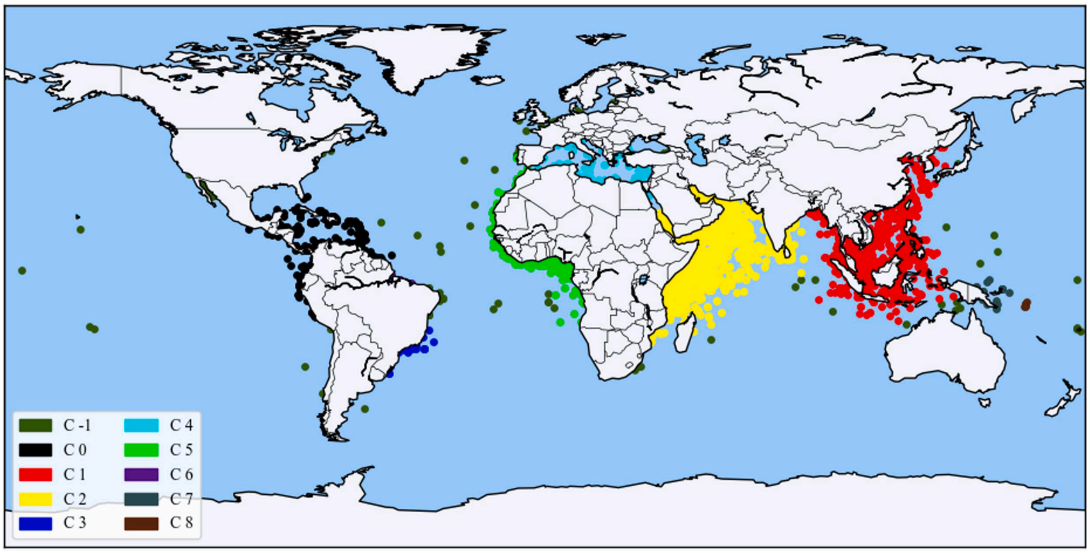


Fig. 18. Visualizatin of the clustering result based on DBSCAN.

Table 6
The number of each cluster based on DBSCAN.

Cluster	Number	Cluster	Number
C-1	88	C4	92
C0	801	C5	1452
C1	3484	C6	37
C2	2398	C7	21
C3	94	C8	10

The proportion of accident rates is ranked as Apr. and May (11%), Jan. and Mar. (10%), Jun., Oct., and Nov. (8%), Feb., Aug., Sep., and Dec. (7%), and Jul. (6%) in the Gulf of Aden and the Arabian Sea from Fig. 20(d). Extensive convection, strong evaporation, and monsoon influences among the Red Sea, Gulf of Aden, and the Arabian Sea make the water structure very complex. Surface water has high salinity. The water temperature is between 25 and 32 °C. From Nov. to Mar. of the following year, the northeast monsoon often blows with little precipitation, which helps from the dry season. The southwest monsoon strikes from Apr. to Oct., with abundant precipitation, which is the rainy season. The analysis reveals that water temperature (exposure to sun light) and monsoon season (wind speed and wave height) significantly affect pirate attacks in the region.

From Fig. 20(e), the monthly piracy incident rates in the Caribean Sea are detailed as (1) Jan., Mar., and Jul. (11%); (2) Apr. and Nov. (9%); (3) Jun., Aug, and Sep. (8%); (4) May and Oct. (10%); (5) Feb. (6%); and (6) Dec. (5%), involving the biggest difference in terms of attack rates (e.g., 6% difference between 11% (Jan., Mar., and Jul.) and 5% in Dec.). The temperature in the Caribbean Sea range from 25 to 27 °C year-round, with small temperature differences. However, Sep. to Dec. is the period involving tropical storms and hurricanes. Therefore, monsoon season and climate change have a significant influence in this area.

The above analysis focuses on the natural environment's impact on the incident rates in the five high-risk areas. In the future, more impact analysis from political, historical, cultural, and legal perspectives could be conducted based on the identified five high-risk areas in this section. More interestingly, the joint impact from multiple perspectives could provide new insights for anti-piracy measure development. According to such an analysis, the trade-off effect of an anti-piracy measure on different perspectives can be thoroughly analyzed holistically, and then the measure can be confirmed rational from a strategic viewpoint. To address this new research challenge which is beyond the scope of this work, advanced hybrid models based on uncertainty methods (e.g., BN)

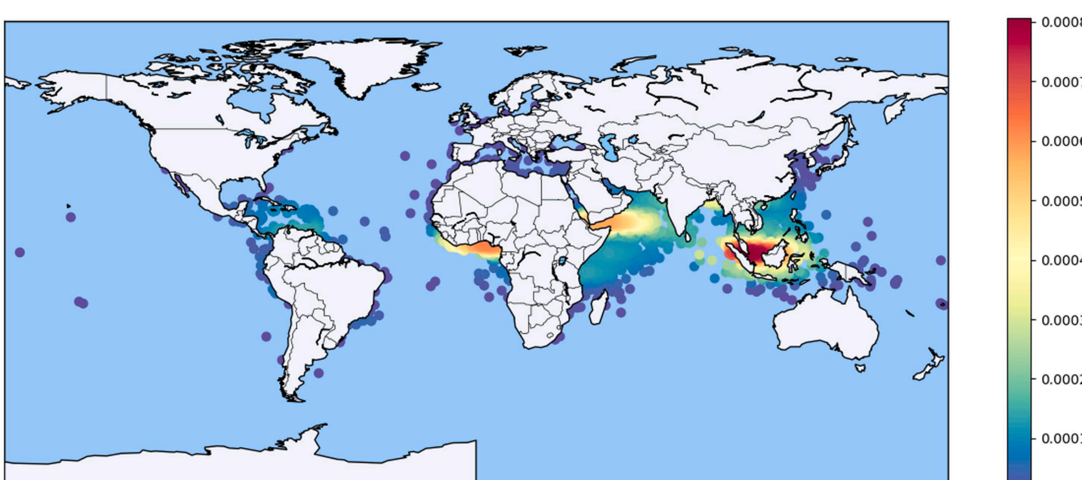
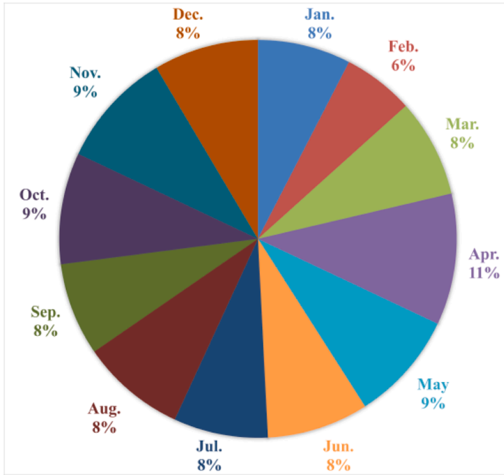
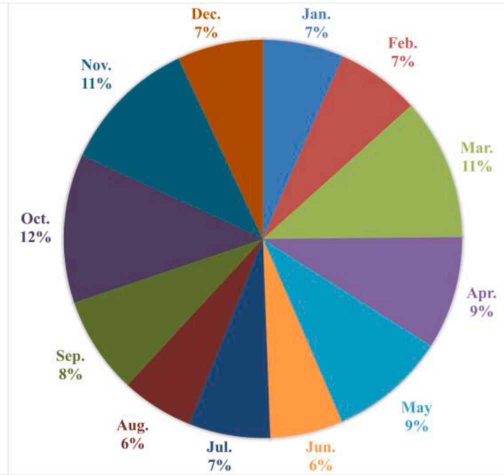


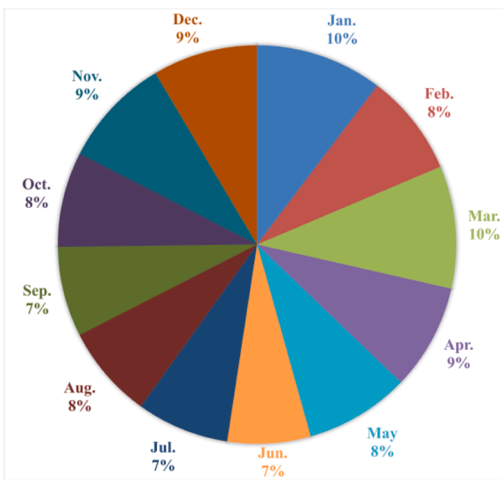
Fig. 19. The point density estimation result.



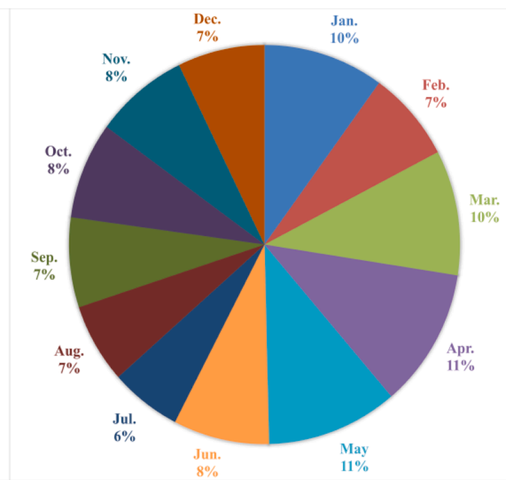
(a) Southeast Asian



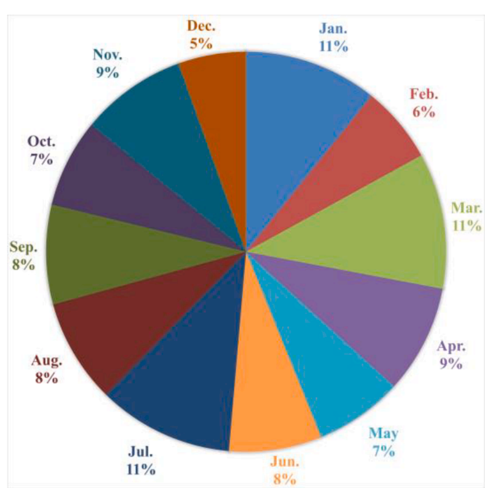
(b) East Africa and the Indian Ocean



(c) West Africa



(d) The Red Sea, the Gulf of Aden, and the Arabian Sea



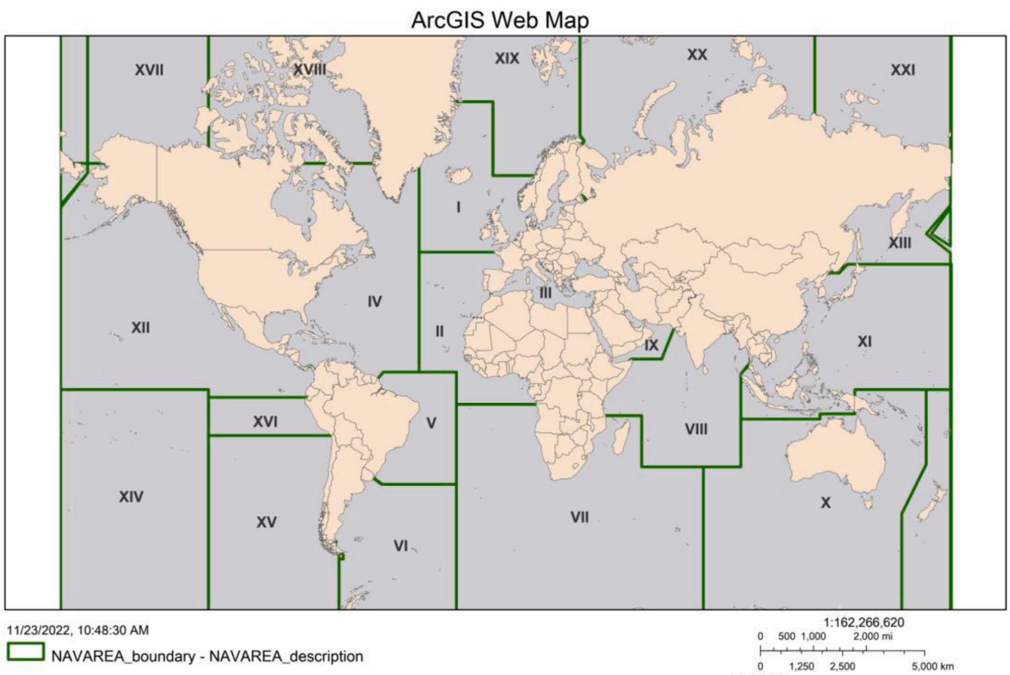
(e) Caribean Sea

Fig. 20. The distribution of piracy incidents in the top five high incident areas by month.

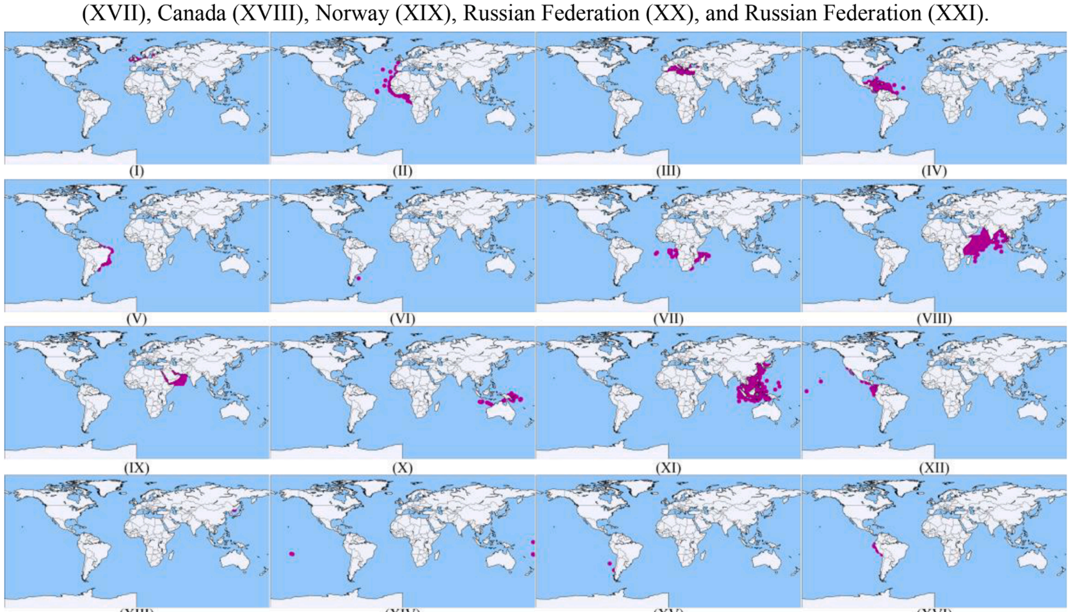
and decision science (e.g., game theory) are highly demanded.

4.4. Spatio-temporal pattern extraction

The boundary division of global navigation warning areas (NAVAREA_boundary) based on the ArcGIS web map is shown in Fig. 21(a). To display the distribution of piracy incidents in each navigational area, the results are visualized in the NAVAREA and displayed in Fig. 21(b). It is evident that maritime piracy incidents mainly occurred in the first 16 areas, and the last 5 areas in the Arctic waters are excluded as there is little evidence of pirate attacks in these regions. From Fig. 21, more specific high-risk sea areas are identified in West Africa (area II), the Mediterranean Sea (area III), the Caribbean Sea (area IV), South Africa (S) (area V), the Gulf of Guinea (area VII), East Africa, the Arabian Sea, and Indian Sea (area VIII), the Gulf of Aden (area IX), and Southeast Asia (area XI). High dimensional spatio-temporal pattern analysis in different areas can reveal hidden information. These findings provide safety implications for international organizations, authorities, shipowners,



(a) The boundary division of global navigation warning areas (NAVAREA_boundary) based on ArcGIS web map, while the corresponding coordinating country and the NAVAREA are listed in detail: United Kingdom (I), France (II), Spain (III), USA (IV), Brazil (V), Argentina (VI), South Africa (VII), India (VIII), Pakistan (IX), Australia (X), Japan (XI), USA (XII), Russian Federation (XIII), New Zealand (XIV), Chile (XV), Peru (XVI), Canada (XVII), Canada (XVIII), Norway (XIX), Russian Federation (XX), and Russian Federation (XXI).



(b) Visualization of the piracy attacks in each NAVAREA.

Fig. 21. The results in the different navigational areas.

crews, and private armed service companies in combatting piracy, as the defined areas, are closely related to the established shipping routes.

The piracy data statistical result in different navigational areas is shown in Fig. 22. From the perspectives of statistical analysis, the top four high-risk areas are Southeast Asia (area XI), East Africa, the Arabian Sea, and Indian Sea (area VIII), West Africa (area II), and the Gulf of Aden (area IX) based on the number of piracy attacks. These findings can provide data-driven support to authorities and academia to carry out incident cause analysis in high-risk areas to prevent and combat piracy.

To further mine the similarities among navigation areas, year, month, and the number of attacks, the FADTW is applied to carry out a multidimensional time series analysis. The navigational areas-year-month-the number of attacks time series is calculated and visualized to show the similarity and differences among all the areas. Taking area VII as the research target, it has high spatio-temporal similarity with areas VI, V, VIII, IV, III, I, II, and X. The results show that areas VIII and XII have spatio-temporal similarities with area XI. Therefore, Southeast Asia (area XI), East Africa, the Arabian Sea, and the Indian Ocean (area VIII), the Gulf of Aden (area IX), the Gulf of Guinea (area II), the Mediterranean Sea (area III), and the Caribbean Sea (area IV) should be the research hotspots in academia and industry, and are also the areas to improve the pirate prevention attention. Among the significant implications of the results is to showcase how international organizations can justify and promote international cooperation to combat piracy for authorities to synchronize the issuing of warnings and alerts in these high-risk areas, particularly taking into account the legislation concerns.

Compared to the traditional statistical analysis methods, multidimensional time series analysis based on the FADTW method can not only discover more high-risk areas, but also measure the inherent similarity in different regions. Meantime, the areas with high similarity can consider sharing anti-piracy measures and policies, such as East Africa, the Arabian Sea, and the Indian Ocean (area VIII), South America (A) (area XII), and Southeast Asia (area XI).

5. Discussion and future directions

5.1. Discussion

Spatio-temporal pattern mining refers to the process of discovering meaningful patterns in data that are both spatially and temporally dependent. This study presents a comprehensive spatio-temporal pattern mining approach for analyzing and identifying intricate characteristics in maritime piracy incidents. The proposed method includes a new FADTW-based time series similarity method, ship type-based classification, and DBSCAN-based clustering techniques. It is divided into three components: time-based pattern extraction, space-based pattern extraction, and spatio-temporal pattern extraction. This methodology is utilized to identify and analyze patterns in space (i.e., location, ship type, weapon, the number of people involved in the attack, high-risk areas distribution), time (i.e., hour, month, year), and space-time (i.e., the inner relationship between area, time, and the number of incidents) of piracy incidents. The findings and implications help understand the behavior of pirates and develop effective strategies for preventing and responding to piracy attacks.

According to the findings in Section 4, the comparison of spatial-temporal pattern mining and statistical analysis mining methods in maritime piracy is presented in Table 7, uncovering their similarities and differences. Spatial-temporal mining provides much deeper insights into the patterns and dynamics of piracy attacks in comparison to statistical analysis methods. Specifically, it offers the following advantages:

(1) It can extract both spatial and temporal features, and reveal spatio-temporal patterns that contain valuable hidden information, such as the inner relationships between area, time, and the number of incidents;
(2) It can identify spatio-temporal patterns and trends in piracy attacks, enabling a better understanding of how these attacks evolve over time and space;
(3) It is capable of exploring intrinsic similarities in hourly, monthly, and yearly time series, providing a more comprehensive understanding of the underlying patterns of pirate attacks on time;
(4) It can depict the dynamic flow in different RIFs relating to pirate attacks;
(5) It can provide a thorough understanding of the root causes of piracy attacks.

One limitation of the proposed spatio-temporal pattern mining methodology for maritime piracy is that it does not take into account weather factors (e.g., wind, current, and temperature). These RIFs can be further collected to conduct a more comprehensive risk analysis in the future.

The aforementioned advantages can provide valuable insights for the following stakeholders in the maritime industry:

(1) Maritime safety research communities: In-depth spatial-temporal analysis can help reveal the geographical and temporal trends of

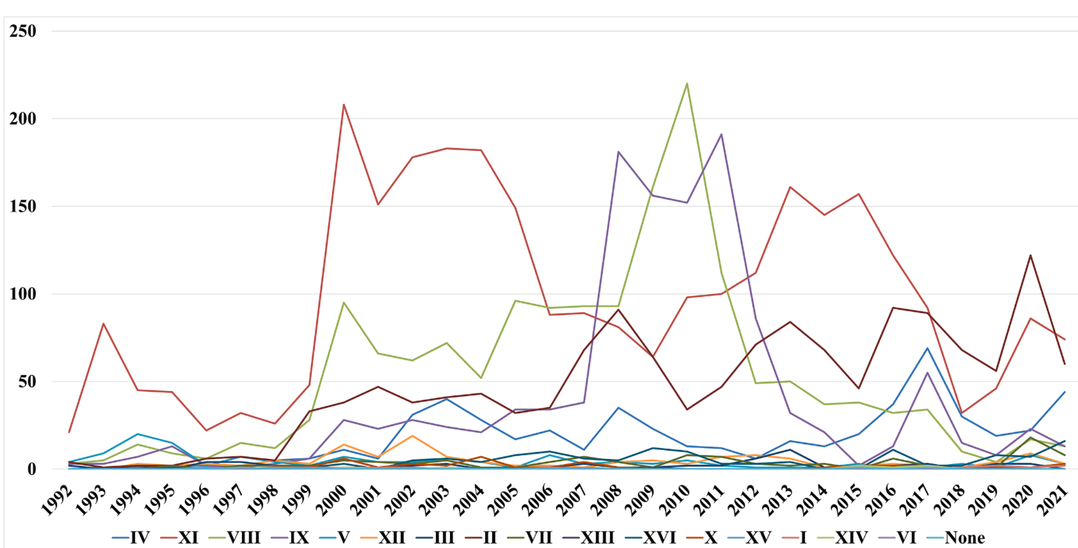


Fig. 22. The piracy data statistical result in different navigational areas.

Table 7
The comparison of spatial-temporal pattern mining and statistical analysis mining in maritime piracy.

Method	Spatial-temporal pattern mining	Statistical analysis
Similarities	(1) Identify high-risk areas, attack patterns, and factors associated with maritime piracy attacks; (2) Incorporate multiple factors, such as vessel characteristics, incident distribution, and time of day, to better understand the dynamics of piracy attacks; (3) Be limited by data availability.	
Differences	(1) Focus on the spatial features (i.e., location, ship type, weapon, the number of people involved in the attack, high-risk areas distribution), temporal features (i.e., hour, month, year), and spatial-temporal features (i.e., the inner relationship between area, time, and the number of incidents) of piracy incidents; (2) Suitable for identifying the spatio-temporal patterns and trends in piracy attacks; (3) Ability to explore the intrinsic similarities in hourly, monthly, and yearly time series; (4) Ability to show the dynamic flow in different RIFs; (5) Provision of a full understanding of the underlying causes of piracy attacks.	(1) Focus on identifying significant factors associated with piracy attacks; (2) Suitable for identifying the key factors associated with piracy attacks; (3) Failure to mine the spatio-temporal features; (4) Failure to provide a full understanding of the underlying causes of piracy attacks.

pirate attacks, thus improving the management and planning of maritime security.

(2) Ship owners and shipping companies: Understanding the patterns and trends of pirate attacks in different regions and time frames can help better plan routes and adjust transportation arrangements, thereby reducing losses and risks.
(3) Governmental bodies and maritime regulatory agencies: Spatial-temporal analysis can provide a better understanding of the nature and distribution of pirate attack events, thus allowing for more targeted policies and measures.
(4) Marine insurance institutions: In-depth spatial-temporal analysis can help better assess and manage maritime risks, providing clients with more comprehensive and effective insurance services.
(5) Maritime logistics companies: Spatial-temporal analysis can provide a better understanding of the risks and security factors in different regions, thereby enabling better planning and management of maritime transportation activities, improving efficiency, and reducing risks.

Therefore, different stakeholders can gain insights into the behavior of pirates and develop targeted strategies for preventing and responding to attacks, ultimately helping to reduce the impact of piracy on the shipping industry and the global economy.

5.2. Future directions

Maritime piracy attacks are a multifaceted phenomenon that involves various economic, social, political, and legal factors. Analysis of maritime piracy attacks requires a powerful approach to examine these factors in a comprehensive and systematic manner. Despite the effort of this paper, there are still some aspects to be addressed in future, including:

Economic factors: Piracy attacks can be driven by economic factors, such as poverty, unemployment, and a lack of economic opportunities. An analysis of the economic conditions in the regions where piracy attacks occur could shed light on the underlying causes of the problem.

Social factors: Piracy attacks can also be influenced by social factors, such as cultural attitudes toward piracy and the social status of pirates in their communities. An examination of these factors could help to understand why piracy persists in some areas and not in others.

Political factors: Political instability and corruption in some countries can create an environment that is conducive to piracy. The study of the political factors on how they contribute to piracy could provide insights into the development of effective political solutions.

Legal factors: The lack of an effective legal framework to combat piracy and prosecute pirates remains a significant challenge. The future study of the legal aspects of piracy, including international conventions, domestic laws, and judicial systems, could inform policy recommendations.

Along with the well-recognized factor investigation, further research on maritime piracy attacks could also focus on the following emerging or newly identified factors:

The impact of technology on piracy: Advances in technology, such as satellite tracking and drones, have the potential to help prevent piracy attacks.

The role of the international community: A comprehensive analysis of the effectiveness of international efforts to combat piracy, including naval patrols, international cooperation, and legal frameworks, could inform future strategies.

The impact of piracy on local communities: A study of the social and economic impact of piracy on local communities could inform policies to mitigate the negative effects of piracy and reduce the incentives for piracy.

The role of private security companies: Private security companies have become increasingly involved in providing security for ships in piracy-prone areas. An analysis of the effectiveness of these companies and their impact on piracy could provide valuable insights.

6. Conclusion

This paper develops a holistic framework for piracy incident spatio-temporal pattern mining to conduct temporal, spatial, and spatial-temporal pattern analysis based on a novel time series analysis method (i.e., FADTW), point density estimation, classification, and clustering (i.e., DBSCAN) methods. The comprehensive maritime piracy dataset is first established by merging the raw data from three main piracy incident databases, and it provides a solid foundation for spatial, temporal, and spatio-temporal pattern analysis. The proposed FADTW method aids in extracting valuable and accurate features hidden in the time series to help piracy pattern mining. Monthly, yearly, and hourly time series are carried out to analyze the similarity and extract the time-based patterns. Furthermore, the data-driven classification analysis in maritime piracy incidents is further implemented to identify the influence of ship type, attack type, geographical areas, weapon, navigational status, and the number of people involved in the attack. Multidimensional time series analysis is conducted to explore the spatio-temporal relationship among different navigational areas based on yearly, monthly, and hourly distribution and the number of incidents.

The spatial and temporal patterns extracted from the maritime piracy dataset can provide effective information for different sectors to guarantee maritime security. All the anti-piracy implications and references to guide policy developments have also been proposed with the new findings from each of the aforementioned analyses. They undoubtedly provide useful insights on RIF identification, the risk cause analysis of pirate attacks, and future risk prediction and prevention. Furthermore, the findings are also helpful for pirate risk quantification and hence can be used to support the development of cost-effective anti-piracy measures.

Along with the analysis of the challenges and limitations embedded in the discussion, this study could benefit from a few extensions in future, including 1) further specification of the non-stated information in the novel dataset; 2) the relevant post-accident investigation that requires a large amount of manpower and financial resources; 3) the incorporation of the results in risk analysis models to realize reliable risk prediction; 4) incident cause analysis and risk assessment based on complete data; and 5) the development of advanced hybrid models based on uncertainty methods (e.g., BN) and decision science (e.g., game theory).

CRediT authorship contribution statement

Huanhuan Li: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Project administration, Data curation, Software, Visualization, Writing – original draft, Writing – review & editing. **Zaili Yang:** Validation, Investigation, Resources, Supervision, Project administration, Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Zaili Yang reports financial support was provided by European Research Council.

Data availability

Data will be made available on request.

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