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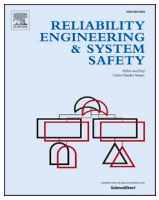

# PiracyAnalyzer: Spatial temporal patterns analysis of global piracy incidents

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ABSTRACT

Maritime piracy incidents present significant threats to maritime security, resulting in material damages and jeopardizing the safety of crews. Despite the scope of the issue, existing research has not adequately explored the diverse risks and theoretical implications involved. To fill that gap, this paper aims to develop a comprehensive framework for analyzing global piracy incidents. The framework assesses risk levels and identifies patterns from spatial, temporal, and spatio-temporal dimensions, which facilitates the development of informed anti-piracy policy decisions. Firstly, the paper introduces a novel risk assessment mechanism for piracy incidents and constructs a dataset encompassing 3,716 recorded incidents from 2010 to 2021. Secondly, this study has developed a visualization and analysis framework capable of examining piracy incidents through the identification of clusters, outliers, and hot spots. Thirdly, a number of experiments are conducted on the constructed dataset to scrutinize current spatial-temporal patterns of piracy accidents. In experiments, we analyze the current trends in piracy incidents on temporal, spatial, and spatio-temporal dimensions to provide a detailed examination of piracy incidents. The paper contributes new understandings of piracy distribution and patterns, thereby enhancing the effectiveness of anti-piracy measures.

## 1. Introduction

Seaborne trade is the backbone of global trade and remains an indispensable force for driving economic growth [1–3]. It plays a paramount role in developing the global economy and shipping industry [4,5]. Shipping accounts for over 80 % of global freight volume and faces maritime security problems when ships navigate on high seas [6–9]. The transport volume of the seaborn trade is shown in Fig. 1, which clearly indicates that it has more than doubled from 2000 to 2020 and up to 11.07 billion in 2019. However, maritime piracy poses a major threat to the stability of the global logistics chain and sustainable economic development, and also causes serious health problems for crews [10,11]. It is noteworthy that the estimated annual costs of approximately $25 billion stemming from piracy incidents underscore the severity of maritime transport's susceptibility to the effects of maritime piracy [12]. In addition, hiring Privately Contracted Armed Security Personnel (PCASP) can be a significant expense for shipping companies. Meantime, different stakeholders related to maritime transport need clear guidance on maritime piracy development trends to plan safe, affordable, and suitable shipping routes to reduce piracy risk and ensure navigational safety [13,14]. Moreover, maritime security issues caused by piracy incidents have emerged as the most pressing concern in seaborn transport [15], particularly given the fast development of autonomous ships lately. Therefore, an in-depth investigation into maritime piracy patterns is prioritized among the highly important research areas in the maritime sector.

There are mainly two definitions of maritime piracy [16]. One is from the 1982 United Nations Convention on the Law of The Sea (UNCLOS) Article 101 [17]. The attacks on high seas, which are outside the 12 nm of the territorial waters, are redeemed as piracy or robbery. It is sanctioned by international law; however, piracy around the ports and inside the 12 nm distance always occurred. To accurately analyze the pirate incidents and effectively prevent pirates attack, the International Maritime Bureau (IMB) defines maritime piracy as the apparent intent to

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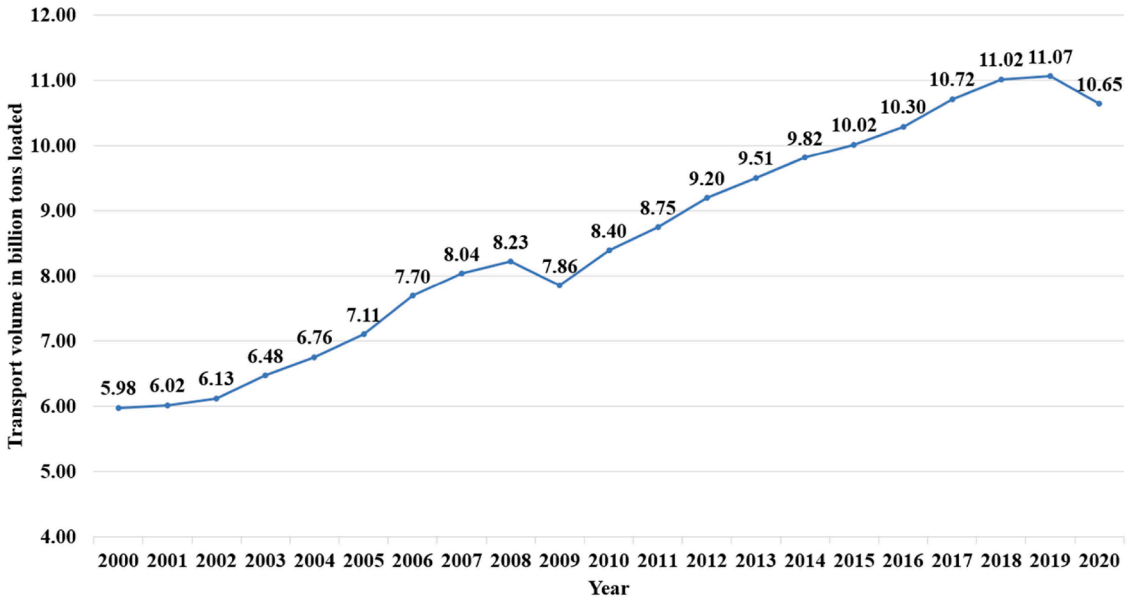


**Fig. 1.** Transport volume of seaborne trade from 2000 to 2020.

attempt to attack or board other ships with a boarding area of no distance limit [18]. This definition provides a solid foundation for maritime piracy research from global waters and for developing relevant anti-piracy measures. Maritime incidents occur without intention or organization, while pirate attacks are carefully organized and planned [19]. It is evident that piracy incidents have strong relationships with time, space, and spatial-temporal features [20]. Previous investigations generally focus on the incident frequency and economic loss, rarely on the consequences and severity of piracy incidents due to the lack of the dataset and consequence evaluation. Moreover, the related piracy research based on incident data mainly focuses on separate temporal and spatial analysis. Therefore, it is imperative to explore the spatial, temporal, and spatial-temporal patterns based on the severity of maritime piracy incidents.

To date, there is a lack of sufficient spatial-temporal analysis and quantitative risk analysis in maritime piracy incidents [21]. Moreover, the current spatial-temporal outcomes often rely on the occurrence likelihood of piracy incidents and overlook the incorporation of the impact of the severity when they occur. It is obvious that such incorporation will break through the state of the art of spatial-temporal piracy analysis mainly focusing on incident occurrence and shifting the paradigm towards a risk-driven spatial-temporal piracy analysis. Further, it lacks a comprehensive analysis from density visualization, clustering, outlier analysis, and hot spot analysis [22]. This paper sheds light on the piracy risk level and global development trends based on visualization and pattern analysis methods [23,24]. The paramount role of maritime piracy analysis is to mine the spatial-temporal features, quantify the risk level, and generate dynamic safety areas. According to the above-mentioned problems and the research status, the contributions of this paper are summarized below.

(1) Generate a new piracy incident risk level mechanism to quantify the global piracy risk.

A comprehensive global piracy incident level mechanism is generated to effectively quantify the level of piracy risk. Firstly, a new piracy dataset is developed, including 3716 coordinate points spanning from January 2010 to July 2021. It incorporates various attributes such as date, location, area, and severity of incidents. The dataset enables a detailed analysis of temporal, spatial, and spatio-temporal patterns related to piracy incidents. Secondly, the severity of piracy incidents is integrated into the analysis of piracy patterns. New visualization, clustering, and hot spot discovery methods are developed specifically for the analysis of global piracy patterns. These methods encompass density analysis, cluster analysis, outlier analysis, and hot spot analysis. By considering the severity of piracy incidents, a more comprehensive understanding of the patterns is achieved.

(1) Carry out the temporal, spatial, and spatio-temporal pattern analysis.

Extensive experiments are conducted to carry out temporal, spatial, and spatio-temporal pattern analysis using the newly established global piracy incident level scheme. The temporal dynamics of piracy incidents are examined to identify trends and patterns over time. Spatial hot spots, regions with a significantly higher frequency of piracy incidents, are detected to pinpoint areas of heightened piracy activity. Furthermore, the spatio-temporal evolution of piracy incidents is investigated to understand how the patterns change and develop over time and space.

Through these analyses, a deep understanding of the temporal, spatial, and spatio-temporal characteristics of global piracy data is obtained and used for new implications. The utilization of the global piracy incident level dataset and the application of specialized analysis techniques enable researchers to gain meaningful insights into piracy patterns and dynamics, facilitating informed decision-making for anti-piracy measures.

The structure of the remaining sections of this paper is outlined as follows. In Section 2, a review and analysis of related work is presented. Section 3 discusses the challenges and outlines the analytical tasks involved in the study. The methodology employed for the analysis is described in Section 4. In Section 5, comprehensive experiments are conducted, focusing on temporal, spatial, and spatio-temporal pattern analysis. Finally, Section 6 presents the conclusion of the study along with potential avenues for future research.

## 2. Related work

### 2.1. Research development of maritime piracy

A large and growing body of maritime piracy research has been conducted to deeply explore the different issues, including piracy concept development [25,26], historical roots [27,28], law enforcement

[29,30], coast guard cooperation [31–33], international cooperation [34,35], economy analysis [36–38], piracy risk analysis [2,39], and spatio-temporal pattern analysis [40,41]. All these studies fall into three broad categories: macro-level, micro-level, and mixed-level. The macro-level analysis mainly contains the piracy trend, historical roots, international cooperation, economic influence, and law enforcement, while the micro-level analysis involves coast guard cooperation, piracy risk analysis, and spatio-temporal pattern analysis. Meantime, international cooperation, law enforcement, and coast guard cooperation belong to the mixed-level content, which needs to be completed by multiple-party cooperation. The macro-level analysis can provide a comprehensive understanding of piracy content and development for the authorities and researchers to further apply and analyze the related content. Furthermore, the associated findings and implications are beneficial for economic development. In contrast, the micro-level content focuses on the deep analysis of local regions, the risk influential factors, and their inner relationship. The mixed-level content is about the regulation development of national coast and international partnerships to fight against pirates together.

To explore the risk and consequence impacts at macro and micro levels, this research focuses on deep and quantitative risk analysis in terms of temporal, spatial, and spatial-temporal pattern analysis. The literature review about temporal, spatial, and spatio-temporal pattern analysis is conducted and compared below.

### 2.2. Research on spatio-temporal pattern analysis of maritime piracy

Up to now, the relevant temporal, spatial, and spatio-temporal pattern analysis studies of maritime piracy were carried out by different statistical methods. A probit model was applied to investigate the distribution of piracy incidents with econometric analysis [42]. Meantime, the ship types, flag states, and the attack probability were combined to uncover that piracy attack is non-random. The two datasets were selected from the IMP and the Institute of Shipping and Logistics (ISL) of Bremen during 1996–2005 and merged into the final 2599 data records. The statistical analysis of the data revealed that the attack goal of piracy focused on specific ship types. For example, chemical tankers and product carriers with low freeboards are mainly targeting ships in Asian waters. Coggins [43] generated a new maritime piracy dataset with 3414 records from the IMB reports between 2000 and 2009. The descriptive statistics and analysis in the high-incidence incident areas showed the frequency of each year, different ship types, intensity, and violence. The statistical analysis of key variables in each year also had a clear result comparison. The detailed statistical data can provide a clear review of the incident development trend. Marchione and Johnson [40] collected data between 1978 and 2012 to uncover the pattern development from the national geospatial intelligence agency. A kernel density map was applied to mine the spatial pattern, while Moran's $I$ statistic is used to measure the significance of spatial patterns. Moreover, the monthly time series in subregions were analyzed based on the bivariate analysis and a Poison model to find the temporal patterns and seasonal characteristics. Finally, the Mantel and Knox tests are applied to analyze the general spatial-temporal patterns. Twyman-Ghoshal and Pierce [16] gather a new dataset from 2001 to 2010 in the Contemporary Maritime Piracy Database (CMPD) to extract piracy characteristics and identify piracy tactics. The detailed dataset generation, regional trends, the number of incidents, location of incidents, and time are described in detail to show the piracy development and reveal the features of high-risk areas. The vessel status, weapons, and theft distribution of Indonesia, Somalia, Nigeria, Bangladesh, India, and other areas are compared clearly based on the statistical analysis. The piracy trends and characteristics are summarized to provide a better understanding of the following research. Townsley and Oliveria [44] applied the Knox method to measure the difference in space and time information based on the distribution results generated from the dataset between 2006 and 2011. The hourly, monthly, and yearly time distribution was presented to reveal the time features, while the spatial distribution in each year was compared to show the trend development. The final results demonstrated that the piracy attacks are deliberate and opportunistic. The related findings can provide references for ship captains, crews, and the maritime sectors. Li and Yang [20] proposed a spatio-temporal pattern mining analysis based on newly developed time series similarity measurement and clustering methods to investigate the temporal, spatial, and spatio-temporal patterns in maritime piracy incidents. However, this study does not take into account risk level and analysis. Zhang et al. [45] investigated the spatial clustering of maritime accidents to identify regions with a higher concentration of incidents by using spatial analysis techniques. The study also explores the relationship between accident occurrence and environmental factors, such as water depth, navigational routes, and weather conditions. The findings of the spatial analysis highlight the hotspots and areas of high accident frequency.

While some research studies have been conducted on the spatial and temporal patterns of maritime piracy incidents, these studies often do not consider the variations among individual piracy incidents. This oversight means that the diverse nature and severity of each incident are not factored into the analysis, which is crucial for a comprehensive understanding of the risks in different areas. Furthermore, there is a lack of a standardized methodology in spatio-temporal pattern analysis that would allow for a more complete and nuanced evaluation of piracy incidents both on a global scale and at the local level. It is important to incorporating the distinct characteristics and consequences of each incident as this could significantly enhance our understanding of piracy patterns and inform more effective countermeasures.

## 3. Challenges and analytical tasks

As piracy is deemed as an act of robbery or other crime of violence, crime analysis methods can be used when mining the behavioral patterns and characteristics of piracy incidents. The challenges associated with analyzing piracy incidents are diverse and stem from the unpredictable nature of such incidents. While certain piracy events are meticulously planned and specifically targeted, others can emerge spontaneously and appear to be random. These unpredictable aspects pose significant hurdles in the analysis of piracy incidents. Taking into account the latest research and prevailing demands, the challenges involved in investigating piracy incidents can be outlined as follows.

(1) Understanding and quantifying the risk of piracy incidents.

The distribution of piracy incident hot spots exhibits variation across different regions, influenced by factors such as economics and politics. It is crucial to conduct a risk analysis of diverse piracy incidents to understand their spatial distribution patterns. Moreover, the distribution of piracy incident types differs significantly, posing challenges in visually comparing the risks associated with these incidents.

(1) Analyzing the characteristics and dynamics of piracy incidents in particular regions of the sea.

The types and patterns of piracy incidents exhibit constant changes and possess distinct characteristics within specific regions. Manual analysis of each piracy incident can be a complex and time-consuming task, particularly when certain incidents are concealed within large clusters. Visual analysis tools prove to be valuable in examining datasets and identifying cluster characteristics. These tools facilitate efficient analysis and provide insights into the data, aiding in the understanding of piracy incident dynamics.

(1) Identifying piracy hot spots within a particular region.

When analyzing the dynamics of piracy incidents, it is important to

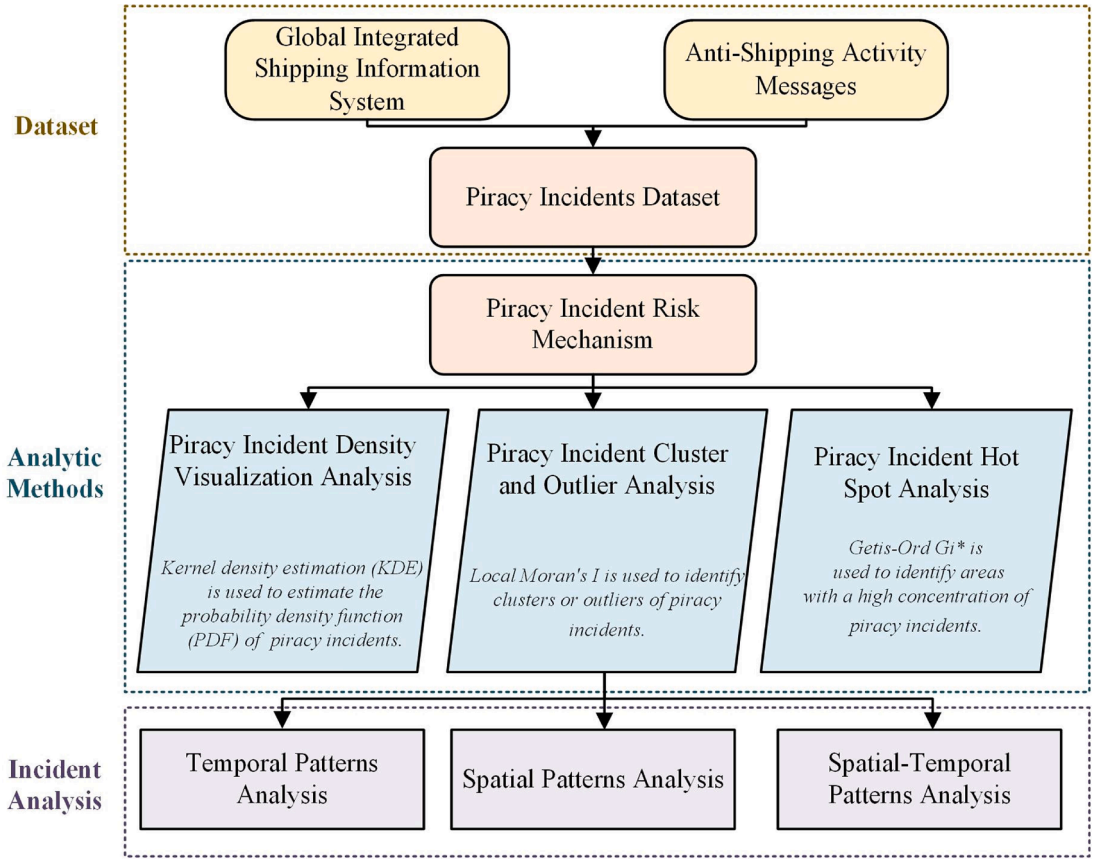


**Fig. 2.** The flowchart of the proposed PiracyAnalyzer framework.

identify hot spots, which are areas or locations where incidents occur frequently. However, it is also necessary to explore areas where incidents occur less frequently but have serious consequences. Simply relying on incident frequency alone may not be effective in uncovering these crucial areas. Therefore, a new and more effective method is needed to mine piracy incident hot spots that consider both incident frequency and consequence severity simultaneously. By integrating these two factors, a comprehensive understanding of piracy hot spots can be obtained, enabling more targeted and informed preventive measures.

## 4. Methodology

The PiracyAnalyzer framework is developed to analyze spatio-temporal global piracy data, aiming to uncover temporal dynamics and spatial hot spots. The flowchart of the proposed piracy incident analysis framework is depicted in Fig. 2. The framework begins by creating a dataset with a novel level scheme, which rates the risk levels of piracy incidents based on their descriptions. This level scheme allows for a more comprehensive assessment of the severity or significance of each piracy incident.

To visualize the spatial patterns of global piracy incidents, the framework employs visualization technologies such as the Kernel

**Table 1**
The definition of piracy incident indicators and their risk level.

| Indicators levels | | | Risk levels | | | |
|---|---|---|---|---|---|---|
| Level 1 | Level 2 | Level 3 | Low | Medium | High | Very high |
| Consequences | Personnel casualties | Number of minor injuries<2 | | √ | | |
| | | Number of minor injuries≥2 | | | √ | |
| | | Major injuries | | | √ | |
| | | Death | | | | √ |
| | Loss of ship's cargo/ship | Lost/stolen goods | | √ | | |
| | | Smuggling | | | √ | |
| | | Abducted/Kidnapped | | | | √ |
| | Boarding the ship | Attempted | √ | | | |
| | | Success | | √ | | |
| Capabilities | Number of pirates | 5 ≤ pirates | | √ | | |
| | | 5 < pirates <10 | | | √ | |
| | | Pirates≥10 | | | | √ |
| | Number of speedboats | Speedboats=1 | | √ | | |
| | | Speedboats≥2 | | | √ | |
| | Weapons | Cold weapon (Knife) | | √ | | |
| | | Light weapons (Guns) | | | √ | |
| | | Heavy weapons (RPG) | | | | √ |

Density Estimation (KDE) model. This enables the depiction of spatial density distributions, providing insights into the concentration and dispersion of piracy incidents across different regions. The PiracyAnalyzer framework also utilizes statistical analysis methods to identify hot spots, clusters, and outliers within global piracy incidents. It incorporates the Anselin Local Moran's Index, which examines spatial autocorrelation to identify areas with similar piracy incident levels. Additionally, the Getis-Ord Gi* statistic is employed to detect significant spatial clusters, highlighting regions where piracy incidents are significantly concentrated. By leveraging these analysis techniques, the PiracyAnalyzer framework facilitates a comprehensive exploration of spatio-temporal global piracy data, allowing for the identification of temporal dynamics and spatial hot spots in piracy incidents.

### 4.1. Piracy incident risk mechanism

Risk is often described as the combination of the likelihood of occurrence of an undesirable event and the security of the consequence if the event occurs broadly, and it is applicable in maritime piracy studies [46–49]. The consequence severity of piracy incidents is closely associated with an elevated risk of being targeted or encountering dangerous situations. As a result, it is imperative for stakeholders such as crew members, port employees, and local authorities to pay increased attention and take preventive measures against such crimes. To establish an effective system, three levels of evaluation indicators for each piracy incident have been developed, concentrating on both the capabilities and consequences of piracy acts. Additionally, a risk mechanism has been assigned to each indicator to signify the likelihood of a piracy incident. The specific details and risk levels of these indicators for piracy incidents are presented in Table 1 with respect to a risk matrix approach [51], in which all the consequence and capacity indicators are identified from the piracy incidents and the risk scores are in principle allocated to reflect the information obtained from the incident reports. For instance, when there is only an attempted attack, the associated risk is low. Depending on the injuries and/or significant economic loss (ship kidnapped) in terms of consequences and numbers of pirates and speedboats and/or use of different levels of weapons in attacks with regard to capacities, the risk levels vary from low to high, respectively. Whenever a death occurs, a ship is kidnapped, or over 10 pirates participate in an attack and/or heavy weapons are used, the risk score becomes very high.

The risk level of piracy plays a pivotal role in assessing the risk level associated with each piracy event. The implementation of this risk level mechanism is driven by two primary objectives. Different piracy incidents are evaluated based on low, medium, high, and very high risk levels, which are assigned scores of 0.25, 0.5, 1, and 2, respectively. The assignments of these risk levels are non-linear, considering the varying degrees of danger posed by different risks. For instance, pirates armed with hot weapons are much more dangerous, aiming to hijack ships, while pirates with cold weapons are primarily interested in stealing finances. To clearly distinguish between these types of incidents, a higher score is assigned to the more dangerous ones in each incident.

Firstly, the adoption of a standardized risk level mechanism enables an objective evaluation of the severity and potential risks entailed in each piracy incident. This approach facilitates informed decision-making processes and allows for the efficient allocation of resources towards the prevention and response efforts against piracy. By having a consistent risk level mechanism, stakeholders can prioritize and address piracy incidents based on their level of risk.

Secondly, the risk level mechanism takes into account the multifaceted nature of piracy incidents. It incorporates considerations of piracy capabilities and consequences, ensuring a comprehensive understanding of the severity of each incident. By encompassing various aspects, such as the capabilities of pirates and the potential consequences for victims, the risk level mechanism captures the overall severity and impact of piracy incidents more accurately.

### 4.2. Piracy incident density visualization analysis

It is crucial to understand the pattern and density of piracy incidents to develop effective strategies to combat piracy. In this paper, KDE [45] is utilized to visualize and scrutinize the density of piracy incidents. KDE is a non-parametric approach commonly employed to analyze the aggregation effects of spatial elements such as population, environment, and transportation. It was developed by Rosenblatt [50] to address the poor performance of parametric estimations. Unlike parametric estimation, KDE does not require the assumption of a density function about the dataset, instead modeling the distribution of the dataset by the input data. This flexibility allows the KDE model to be applied in various applications, including distribution estimation [51], behaviour analysis [22], traffic accidents analysis [52], etc. Furthermore, KDE is particularly advantageous for incident analysis, as it provides smooth and continuous incident statistics. The calculation process of a classical KDE model can be represented as

$$f(x,y)=\frac{1}{(\gamma)^2}\sum_{p=1}^{n}\left[\frac{3}{\pi}\cdot R_p\left(1-\left(\frac{D_p}{\gamma}\right)^2\right)^2\right] \tag{1}$$

where $\gamma$ is the default search radius, defining the area for density estimation at each location $(x,y)$. The points $p\in[1,n]$ are the input data, and $f(x,y)$ denotes the estimated density at each location. The term $D_p$ indicates the distance between point $p$ and the $(x,y)$ location. $R_p$ is an optional parameter, which represents the weight field value of point $p$. In this paper, the total risk is set as the weight field value of point $p$. The total risk at each point is determined by summing the risk scores of incidents at that point, each calculated based on predefined indicators in Table 1.

KDE only calculates points within the radius of the position $(x,y)$. The distance between a point and a location $(x,y)$ is used to determine the weight assigned to that point in the density calculation. This weight determines the contribution of the point to the overall density. By assigning lower weights to points that are farther away from the location $(x,y)$, a grid with a smooth surface can be generated. In this grid, points in close proximity to $(x,y)$ have a higher density compared to those that are located further away. The default search radius, also known as the bandwidth, is determined using an algorithm that takes into account the number of points in the data set and the dimensions of the data space. This algorithm calculates an optimal search radius that is suitable for the specific dataset being analyzed. The search radius in this paper can be expressed as

$$\gamma=0.9*min\left(SD,\sqrt{\frac{1}{\ln(2)}}*D_m\right)*n^{-0.2} \tag{2}$$

where $D_m$ symbolizes the median distance, adjusted for weight, $n$ represents the sum of the population field values. $SD$ is employed to signify the standard distance. It should be noted that the $min()$ function selects the smaller value between two options: $SD$ or $\sqrt{\frac{1}{\ln(2)}}*D_m$. There exist two methodologies for computing the standard distance, distinguished as unweighted and weighted. In this paper, the weighted distance is derived from the risk level of piracy incidents. Thus, the weighted distance can be calculated as

$$SD_\omega=\sqrt{\frac{\sum_{p=1}^{n}R_p\left(x_p-\overline{X}_\omega\right)^2}{\sum_{p=1}^{n}R_p}+\frac{\sum_{p=1}^{n}R_p\left(y_p-\overline{Y}_\omega\right)^2}{\sum_{p=1}^{n}R_p}} \tag{3}$$

where $\{x_\omega,y_\omega\}$ represents the weighted mean center.

### 4.3. Piracy incident cluster and outlier analysis

The Local Moran's I statistic, developed by Anselin in 1995 [53], is

utilized as an analytical tool for identifying clusters or outliers in spatial data. In this paper, the statistic is applied to the spatial analysis of global piracy incidents, with an objective focus on geographical clustering and pattern recognition of these occurrences.

The application of the Local Moran's I statistic allows for a granular analysis of piracy data on a per- incident basis. It decomposes global spatial patterns into local patterns, facilitating a nuanced understanding of the geographical distribution of piracy incidents. Specifically, the Local Moran's I statistic is instrumental in determining whether the location of a particular incident is statistically likely to be part of a cluster or an outlier. The function of the local Moran's I statistic can be expressed as

$$I_i = \frac{R_i - \overline{R}}{S_i^2} \sum_{j=1, j\neq i}^{n} w_{i,j}\left(R_j - \overline{R}\right) \tag{4}$$

where $R_i$ symbolizes an attribute for point $i$, i.e. total risk of point $i$. $\overline{R}$ signifies the mean of the corresponding attribute, $w_{i,j}$ delineates the spatial weight between points $i$ and $j$, which is the reciprocal of the distance between these data points. The variance $S_i^2$ can be expressed as

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n}\left(R_j - \overline{R}\right)^2}{n-1} \tag{5}$$

with $n$ denotes the total number of points. The $z_{I_i}$-score for the statistics is computed via:

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

where

$$\mathrm{E}[I_i] = -\frac{\sum_{j=1, j\neq i}^{n} w_{i,j}}{n-1} \tag{7}$$

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

Here, $\mathrm{E}[I_i]$ symbolizes the expected value of the Local Moran's I statistic, while $\mathrm{V}[I_i]$ is the variance of the statistic. The Local Moran's I statistic is calculated using a formula that takes into account the spatial relationship between each observation and its neighbors. This enables the statistic to capture the degree of spatial association between observations and identify clusters or outliers based on this association. In the piracy context, an elevated Local Moran's I value signifies that a piracy incident, in terms of its attributes such as frequency and severity, is not an isolated event but part of a broader spatial pattern or cluster. Conversely, lower values highlight areas where piracy incidents are sporadic and less influenced by spatial factors.

### 4.4. Piracy incident hot spot analysis

Hot spot analysis is a method used to calculate the Getis-Ord Gi* statistic for each data point, which relates to incidents of piracy in this paper. The statistic helps to identify clusters of high-value (hot spots) or low-value (cold spots) occurrences in a spatial context. Specifically, for a point to be considered as a hot spot, it must nothas to only have a high value itself but also be surrounded by other points with high values. The method compares the sum of values for a point and its neighbors to the sum of all the points in the dataset. If the local sum is significantly higher than the average sum, the point is assigned a high z-score, indicating that the clustering of high values is statistically significant and not random.

In the context of this piracy incident analysis, the Getis-Ord Gi* statistic is used to detect areas where piracy incidents cluster more densely than what those that would be expected if the incidents were distributed randomly across space. These clusters, or hot spots, are important because they highlight regions where piracy is more prevalent, suggesting a need for focused anti-piracy measures. To ensure the validity of our results, especially when dealing with multiple data points, we this paper applies the False Discovery Rate (FDR) correction. This adjustment accounts for the possibility of falsely identifying hot spots due to the multiple comparisons being made across the data set or the spatial dependence between data points. The Getis-Ord Gi* statistic, therefore, becomes a valuable tool for our analysis, as it quantifies and locates the concentration of piracy incidents. Mathematically, the Getis-Ord local statistic is given as

**Table 2**
Global piracy incident data used in this paper.

| Data | Type | Range | Description |
|---|---|---|---|
| Date | String | 2010/1/1–2021/7/1 | Date of the incident. |
| IMO No. | Integer | (0,000,000–9,999,999) | The International Maritime Organization Number (IMO No.) is constituted by a seven-digit numerical sequence. It is an initiative implemented with the principal objective of fortifying maritime safety and pollution prevention, while simultaneously facilitating the deterrence of maritime fraud. The system endeavors to assign a permanent, unique identifier to each vessel for recognition purposes. This identification remains immutable in spite of any transfer of the ship under different flags and is ingrained within the ship's official documentation. |
| Ship Type | String | Dry cargo ship/ Tanker/ Fishing/ Miscellaneous/ Passenger Ship/ Combination Carrier/ Barge | There are over 100 types of ships in the incident reports. To better analyze piracy incidents, we have divided these types into 6 main categories. |
| NavArea | String | [I, XXI] | The maritime geographic areas. |
| Subreg | Integer | [00, 99] | The small regions. |
| Description | String | – | Description of the incident process. |
| Total_score | Floating | (0, 10] | The score assigned to each incident is determined by its risk level, as described in Section 4.1. Total_score is calculated by adding up all individual scores of each indicator. |
| Success | String | True/False | Incidents resulting in kidnapping, casualties, and property damage are defined as successes. |
| Lat | Floating | [−90, 90] | The latitude of the incident in the WGS84 coordinate system |
| Lon | Floating | [−180, 180] | The longitude of the incident in the WGS84 coordinate system |

Web: https://msi.nga.mil/Piracy and https://gisis.imo.org/.

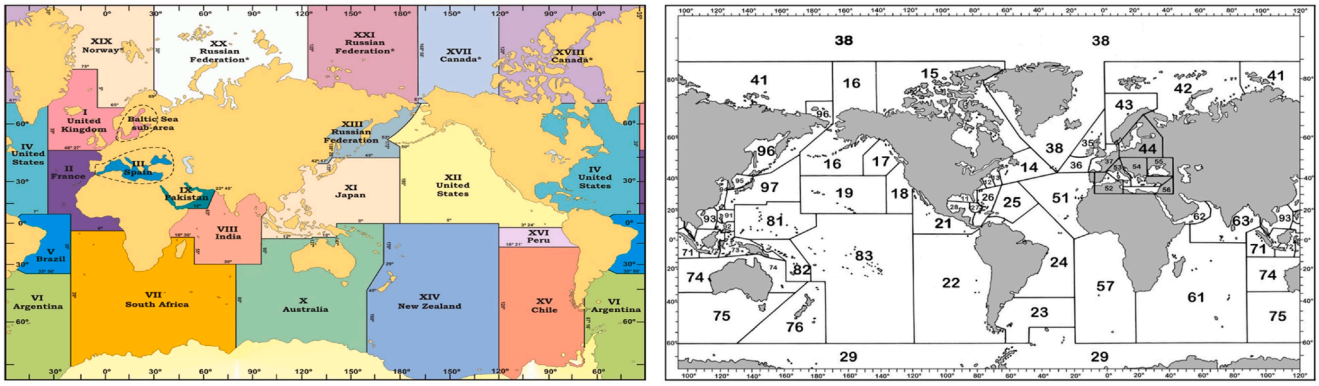


**Fig. 3.** Visualization of two global regional classifications. (a) showcases the global maritime navigational areas (NAVAREA). This is a system used for broadcasting maritime safety information. Each number and color represent a distinct navigational area. (b) presents another type of regional division called SUBREG. The numbers on this map correspond to specific subregions. Unlike NAVAREA, SUBREG divisions appear more granular, especially in certain high-density areas like Europe and Southeast Asia.

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

where $R_j$ expresses the attribute value for point $j$, i.e. total risk of point $j$.$w_{i,j}$ indicates the spatial weight between point $i$ and $j$, $n$ is equal to the total number of points, and

$$\overline{X} = \frac{\sum_{j=1}^{n}R_j}{n} \tag{10}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n}R_j^2}{n} - (\overline{R})^2} \tag{11}$$

The $G_i^*$ statistic is a $z$-score, which can be used to compute a $p$-value using a standard normal distribution. A low p-value indicates a statistically significant difference between the local sum of a point and its neighbors and the overall sum of all points, indicating the presence of a hot spot.

The FDR correction can be applied to adjust for multiple testing and spatial dependency by controlling the false discovery rate, which is the expected proportion of false discoveries among the rejected hypotheses. To apply the FDR correction, a threshold for the p-values can be set, such that only points with p-values below the threshold are deemed statistically significant.

## 5. Experimental results and analysis

In this section, numerous experiments will be conducted to demonstrate the changes in spatial-temporal patterns of global piracy incidents. Specifically, the research data will be presented first in this paper. The temporal patterns and spatial patterns analysis results of global piracy incidents are then presented in detail. Finally, extensive experiments are implemented to demonstrate the spatial-temporal patterns and results of global piracy incidents.

### 5.1. Data description

To enhance the accuracy of the study, two data sources, i.e., anti-shipping activity messages (ASAM) and global integrated shipping information system (GISIS), are used to complement each other. The ASAM and GISIS collect data through direct submissions, allowing shipping entities to actively report piracy incidents, ensuring a comprehensive and real-time assemblage of maritime security threats. The IMO number is used to synchronize the same incident recorded in the two sources. The data are collected mainly from two organizations, i.e., the U.S. National Geospatial-intelligence Agency (NGA) and IMO, as listed in Table 2. The new dataset includes piracy incident date, IMO number of ships, ship type, NavArea, Subreg, piracy description, total_score, latitude, and longitude. NavArea are the maritime geographic areas in which various governments are responsible for navigation and weather warnings, as shown in Fig. 3(a). For chart numbering purposes, the world is divided into 21 regions, each corresponding to the geographic limits of one of the 21 regions. In the National Geospatial-Intelligence Agency Catalog of Maps Charts and related products, the world is subdivided into numbered Subregions in Fig. 3(b). Fig. 4(a) displays the location of all piracy incidents that transpired between 2010 and 2021. Fig. 4(b) portrays the grid frequency

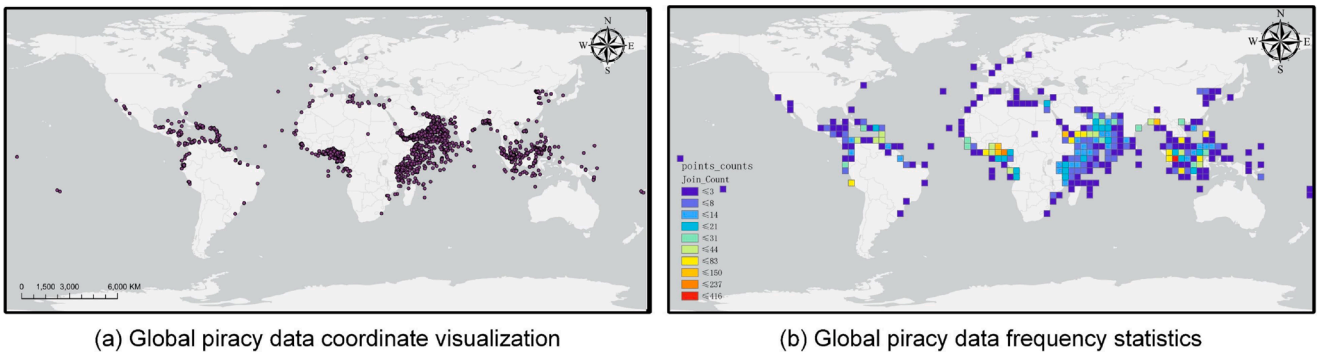


**Fig 4.** Visualization results of global piracy incidents. (a) global piracy data coordinate visualization; (b) global piracy data frequency statistics.

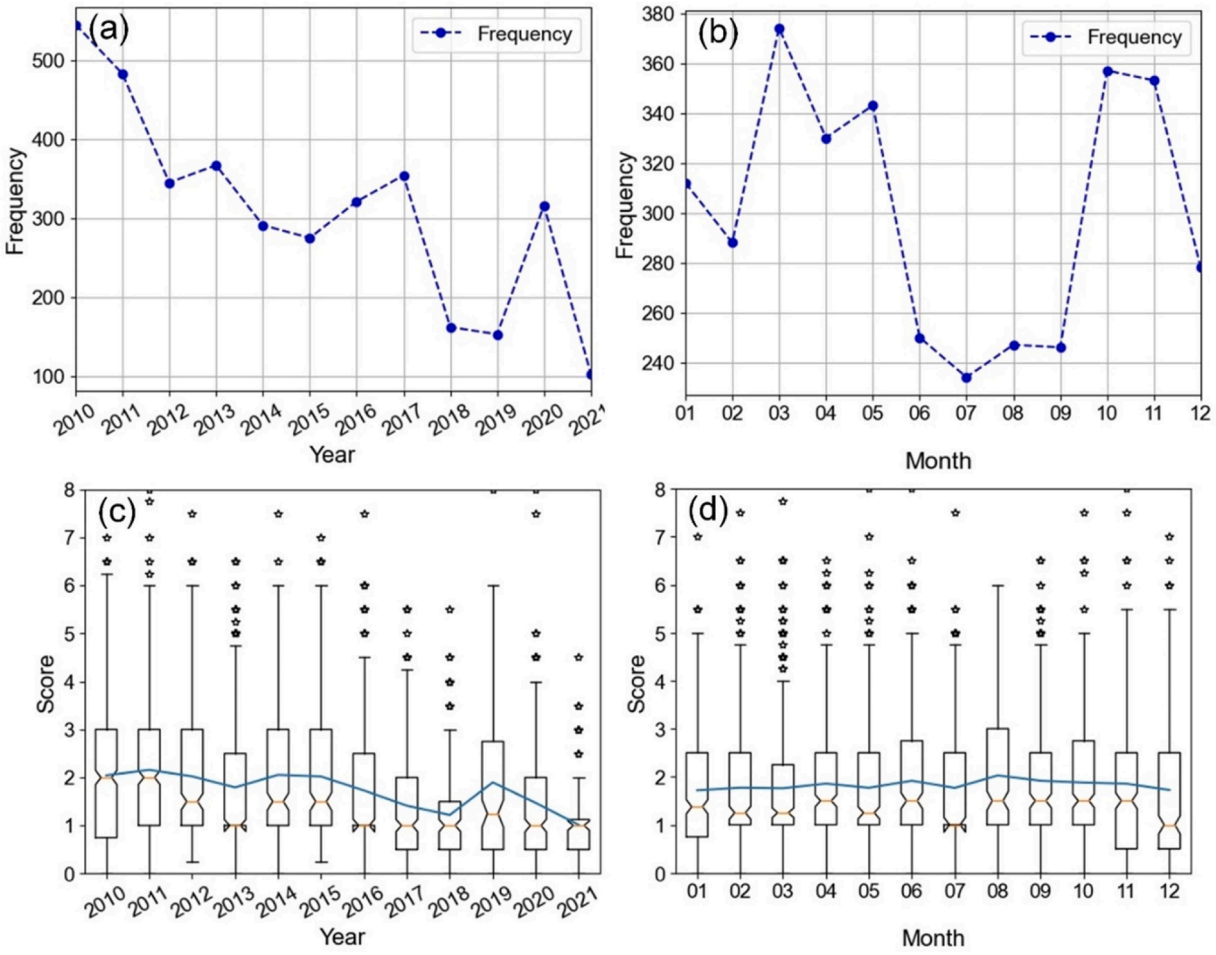


**Fig. 5.** The counts of piracy incidents by year and month from left to right, top to bottom: (a) the statistics of piracy incidents in different years; (b) the statistics of piracy incidents in different months; (c) the box plot of pirate score in different years; and (d) the box plot of pirate risk score in different months.

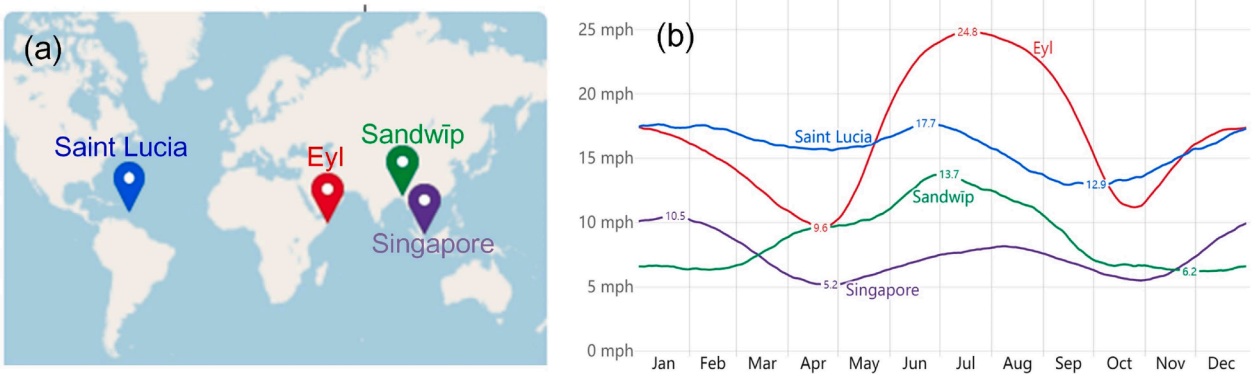


**Fig. 6.** The average wind speed in the main area of the piracy incident at 10 m. Data from weather spark (web: https://weatherspark.com/). From left to right: (a) meteorological observation stations in the vicinity of the main area of the piracy incident; (b) average wind speed in the area.

statistics values for all piracy incidents using a grid length of 500 km. The non-uniform distribution of piracy incidents is evident, with a substantial concentration of incidents occurring in certain regions. We assigned scores to each incident based on their descriptions using the formula outlined in Section 4.1, resulting in the calculation of a Total_score for each incident.

### 5.2. Temporal patterns analysis

The occurrence of piracy incidents is influenced by various factors, including geopolitics, public health events, and regional economies. Thus, the frequency of piracy incidents can exhibit significant temporal fluctuations. In this paper, the year and month statistics of piracy incidents are analyzed, as depicted in Fig. 5. It can be seen from Fig. 5(a) and (c) that both the number of piracy incidents and the incident risk score exhibit an overall decreasing trend. However, it is important to

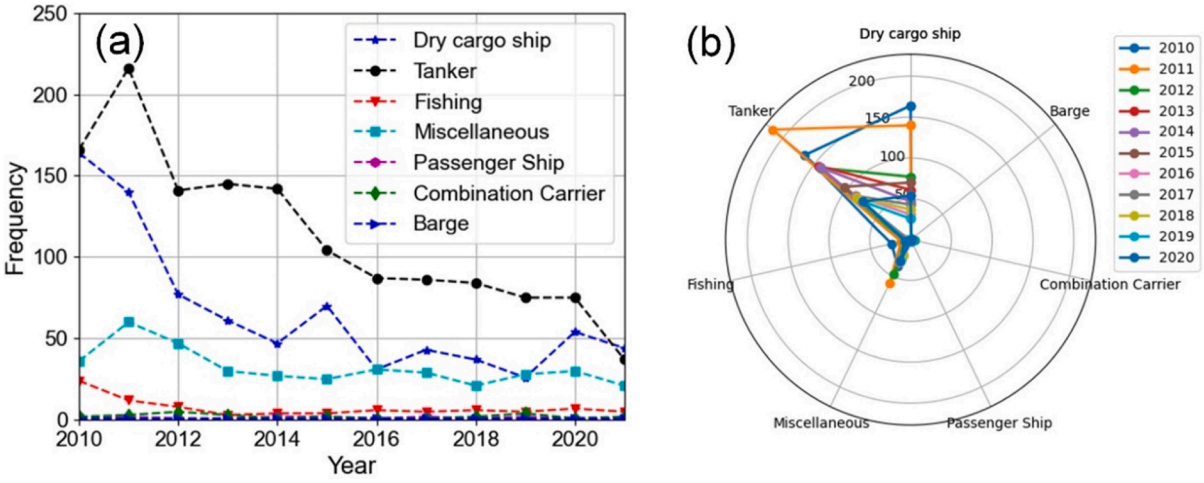


**Fig. 7.** Statistical results of different vessel types in piracy incidents.

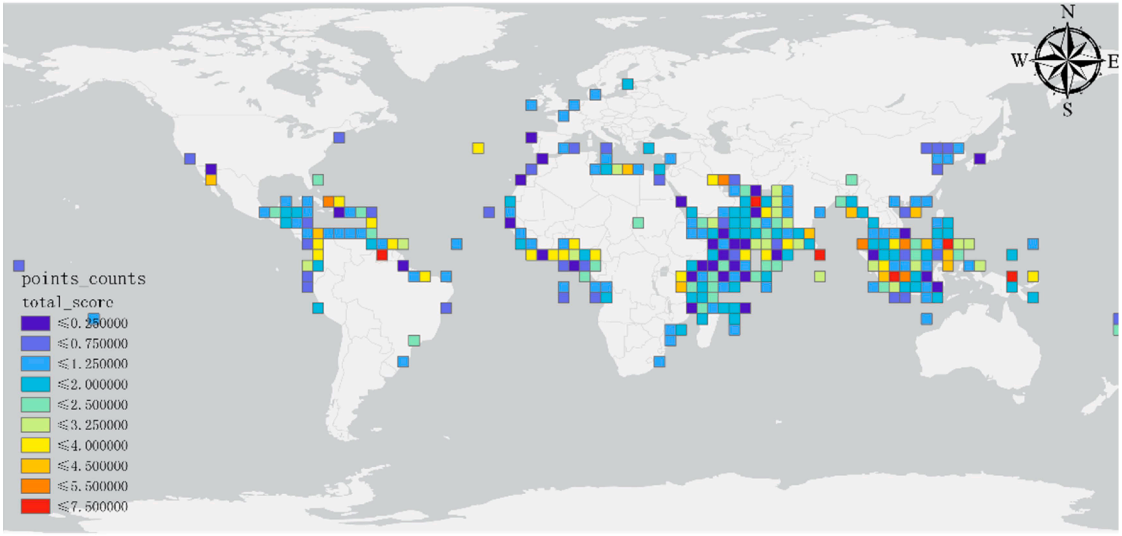


**Fig. 8.** The results of gridded piracy incident statistics with grid size=500 km. The color of the grid indicates the average score of the grid.

note that the rise in piracy activity in 2020 could be attributed to the underlying social, political, and economic issues associated with the COVID-19 pandemic. Nevertheless, there is no evidence to suggest that the pandemic will continue to impact piracy in the long term. The month statistics in Fig. 5(b) and (d) reveal that some months (such as January, February, June, July, August, September, and December) have considerably lower piracy incident numbers than others. Previous studies have indicated a reduction in piracy attacks during both summer and winter monsoons. However, as seen in Fig. 5(d), the average score of piracy incident risk does not change substantially across different months. In addition, it is observed that the plurality of piracy incident risk scores in July and December is much lower. Fig. 6 illustrates the variation of average wind speeds throughout the year in the main areas of the piracy accident. A clear inverse correlation is observed between the number of piracy incidents and wind speed. This indicates that the success rate of pirate attacks is influenced by the monsoon seasons. Furthermore, Fig. 7 illustrates the declining trend in the number of piracy incidents across all ship types. It is evident that tankers and dry bulk carriers remain the primary targets of piracy attacks.

### 5.3. Spatial patterns analysis

The spatial pattern of piracy incidents provides evidence that political, economic, and social stability are significant factors influencing piracy. Fig. 8 shows the gridded statistics of piracy incidents, with the color of each grid indicating its average score. However, the average score alone does not provide an accurate indication of piracy risk. To better understand the spatial pattern of piracy incidents, KDE is applied to measure the risk of piracy, with the Ripley's K function used to select an appropriate bandwidth. Ripley's K-function is an analytical tool for distinguishing changes in spatial clustering or dispersion of feature centroids as the neighborhood size changes. In general, half of the value of maximum DiffK can be applied as the bandwidth of KDE. As seen in Fig. 9, the largest DiffK is around $3 \times 10^6$ meters. Thus, the KDE bandwidth is selected as $1.5 \times 10^6$ meters. The KDE map of global piracy incidents is displayed in Fig. 10, highlighting the areas with the highest level of piracy risk, including the Strait of Malacca, the Gulf of Aden, Equatorial Guinea, Bangladesh, Yemen, Somalia, Kenya, Tanzania, Caribbean and some Southeast Asia regions as the main areas where piracy incidents occur. In addition, to identify potential discrepancies in global piracy incidents, cluster, outlier, and hot spot analysis are employed to examine the spatial patterns. Fig. 11 illustrates the spatial clustering of piracy incidents and the types of outliers. The high–high spatial clusters can be regarded as hot spots. As seen in Fig. 11, the high-high clusters are concentrated in Malacca, Bangladesh, the Indian Ocean and Equatorial Guinea. It indicates that the risk level of

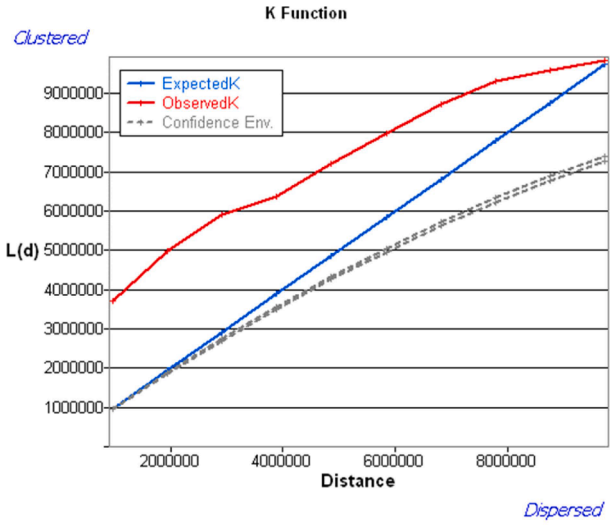


**Fig. 9.** The result of a multi-distance spatial cluster analysis pertaining to piracy incidents. Here, Ripley's K function serves as a metric to quantify spatial clustering/dispersion across a spectrum of distances. The Ripley's K-function delineates the modulation in the spatial clustering or dispersion of feature centroids as a function of varying neighborhood dimensions. The terms 'Expected K' and 'Observed K' respectively denote the anticipated and actual K values. The maximal value of DiffK, calculated as Expected K minus Observed K, signifies the distance at which the spatial processes fostering clustering are most accentuated.

piracy incidents in these regions is at a higher level in history. A similar conclusion can be drawn from Fig. 12, which shows that piracy incidents mainly occur around the 0 latitude line, with Malacca being the most concentrated region.

### 5.4. Spatial-temporal patterns analysis

In this section, the spatial and temporal patterns of piracy incidents are analyzed. According to the navarea division that has been detailedly summarized in Fig. 13. Fig. 13(a), the temporal pattern of piracy incidents demonstrates the frequency of piracy incidents per year in each navarea. It can be obtained that VIII, XI, II, IX, and IV are the areas where incidents occur frequently. The number of piracy incidents is dropping in most navareas. However, the II navarea did not show a significant change in incident frequency. As shown in Fig. 13(b), the average score of piracy incidents is also decreasing. Similarly, the total score of piracy incidents is decreasing, as shown in Fig. 13(c). In particular, the II navarea has become a high-risk area. To analyze the spatio-temporal pattern of piracy incidents in detail, the piracy incidents were analyzed using the subregion division rule. Fig. 14 shows that subreg:57 has been a high-risk incident area for the past ten years. Table 3 measures spatial autocorrelation based on both feature piracy incidents locations and feature piracy score values simultaneously. It can be seen from the data that piracy incidents tend to disperse over time. Figs. 15-16 visualize the change process of hot spots and high-high clusters. It can be concluded that the hot spots of piracy incidents are gradually decreasing. The Equatorial Guinea region has emerged as an area of significant concern due to the escalating incidents of piracy.

## 6. Discussion and implications

In terms of temporal trends, global piracy incidents are primarily experiencing a decline, accompanied by a decreasing risk of such incidents (Figs. 5 and 7). The occurrence of monsoons significantly impacts piracy accidents. Spatially, piracy incidents are concentrated in specific regions such as Malacca, Somalia, the Bay of Bengal and the Gulf of Guinea (Figs. 10–12). Both spatially and temporally, piracy incidents in key regions worldwide are showing a downward trend in piracy accidents. Notably, the Gulf of Guinea has emerged as the region with the highest frequency of piracy incidents (refer to Figs. 13–16). The global efforts to fight against piracy have yielded tangible results. However, piracy remains a complex issue that necessitates international cooperation and coordinated actions to effectively address it. To maintain progress, counter-piracy initiatives must be adaptable and responsive to the evolving nature of piracy hot spots, promptly adjusting strategies and allocating resources accordingly.

The findings and methodology presented in this paper hold significant implications for various stakeholders, including governments, shipping companies, and vessel operators. Governments can enhance their maritime security strategies by using the results of the temporal pattern analysis. By identifying the months with higher risk levels of

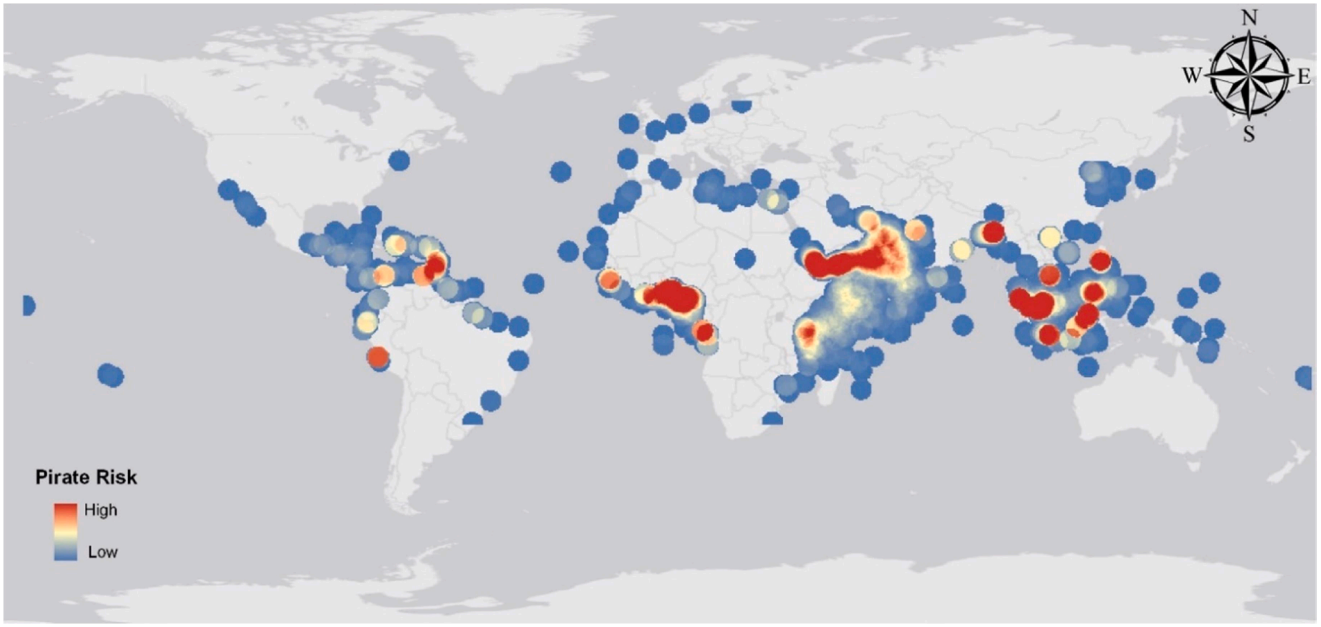


**Fig. 10.** Global KDE map of piracy incidents with bandwidth=1.5 $\times$ $10^6$. The time frame for piracy incidents is from January 1, 2010 to July 1, 2021.

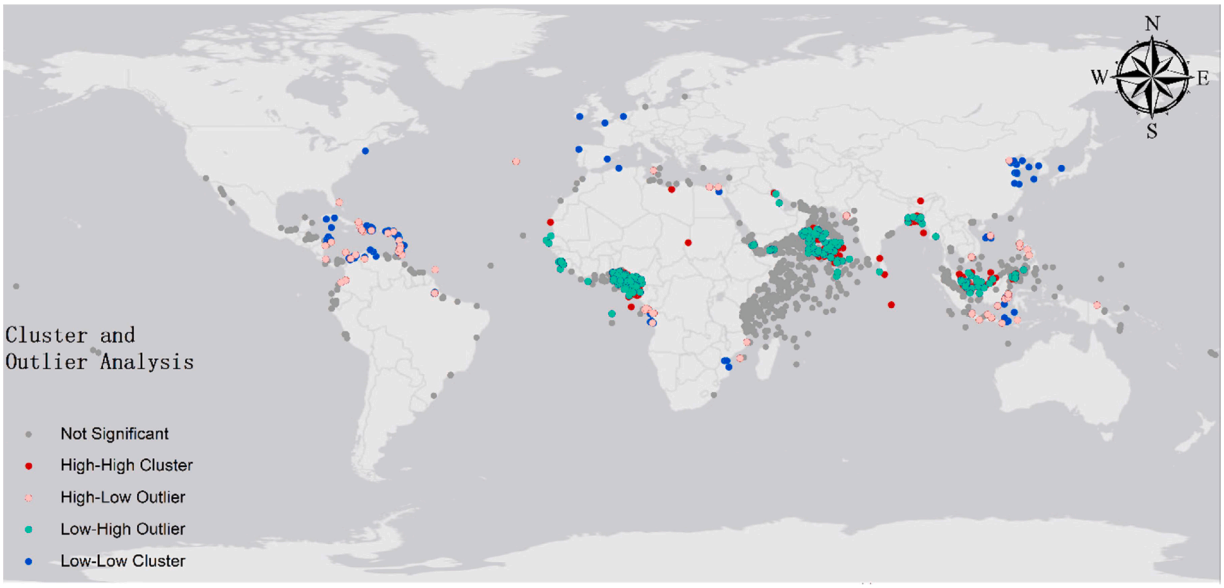


**Fig. 11.** The results of the cluster and outlier analysis. In this context, the high-high cluster delineates regions where high values are circumscribed by other high values. Conversely, the low-low cluster characterizes regions where low values are encircled by other low values. The high-low cluster defines regions where elevated values are encompassed by lower values, while the low-high cluster demarcates areas where lower values are encased by higher values.

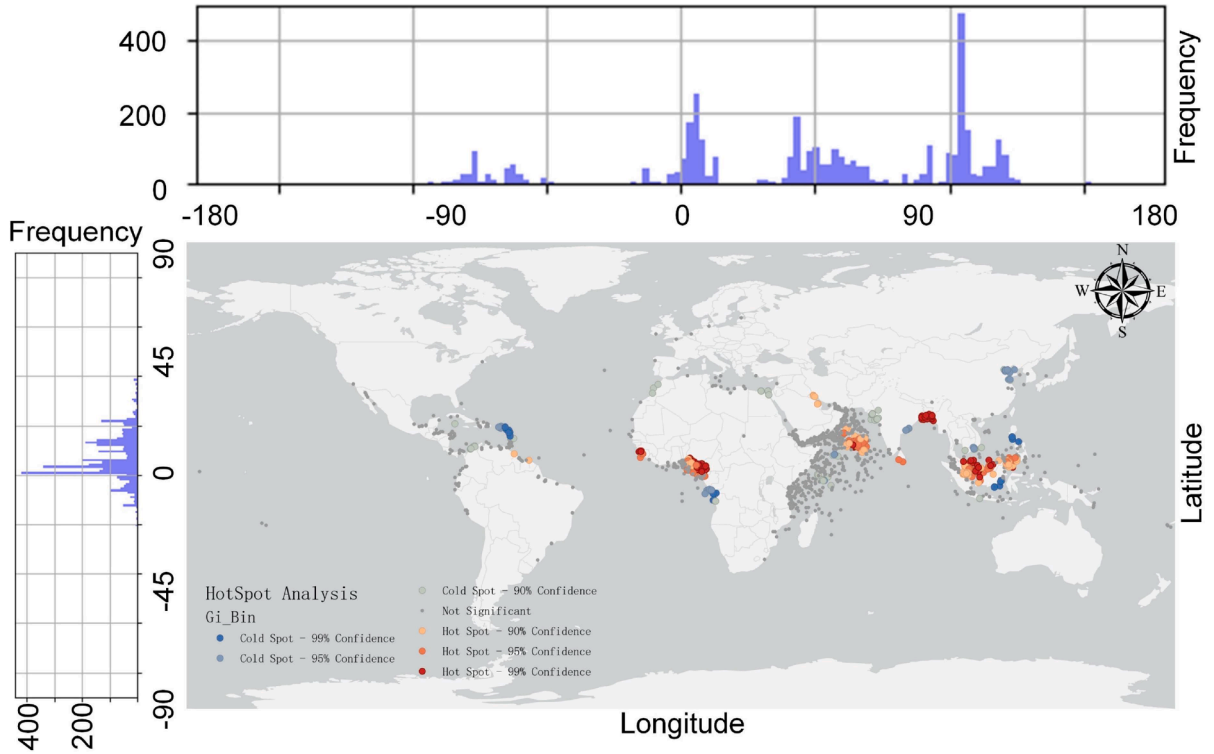


**Fig. 12.** Hot spot analysis results. A hot spot refers to a geographical region characterized by a numerically superior incidence rate and risk factor for piracy episodes, or alternatively, a region wherein vessels endure an elevated risk of victimization surpassing the mean probability.

piracy incidents, governments can allocate resources and implement targeted measures during these periods to safeguard vessels and crew members. Shipping companies can leverage the insights gained from the spatial pattern analysis to inform their route planning and risk assessment processes. This enables them to proactively avoid or mitigate piracy-prone regions. By providing a comprehensive analysis of the spatio-temporal patterns of piracy incidents, vessel operators can make more informed decisions regarding their anti-piracy strategies and measures. They can allocate resources and implement enhanced security measures during high-risk periods, thereby better protecting their crew, cargo, and vessels from potential pirate attacks.

## 7. Conclusions and future perspectives

In the globalized shipping market, the enormous losses caused by piracy incidents have become unbearable. To analyze the spatial,

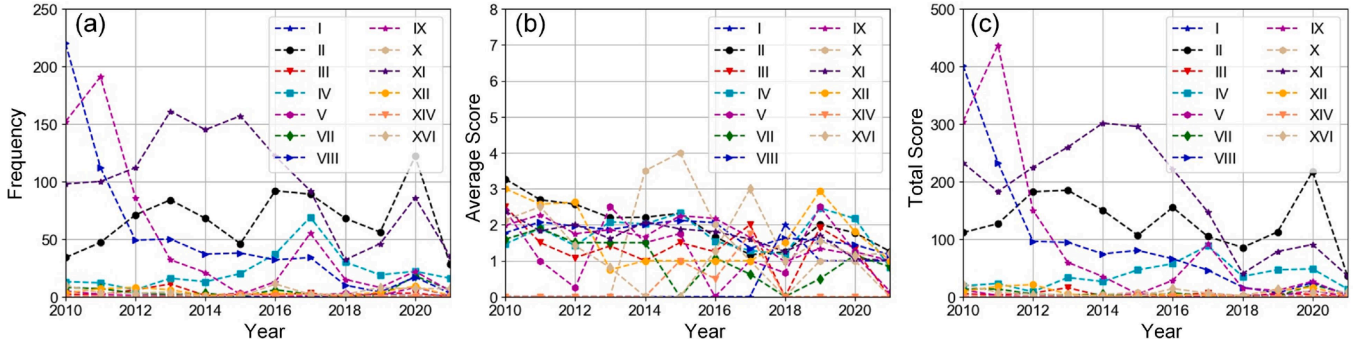


**Fig. 13.** The temporal pattern of piracy incidents in the top 10 navarea areas temporal pattern of piracy incidents. From right to left: (a) frequency of piracy incidents per year in each navarea; (b) average score of piracy incidents per year in each navarea; (c) total score of piracy incidents per year in each navarea.

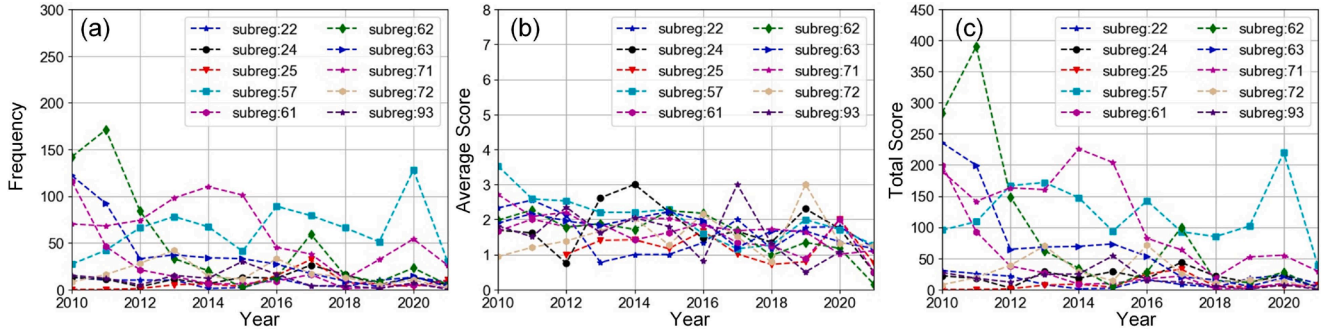


**Fig. 14.** The top 10 subreg areas temporal pattern of piracy incidents in the top 10 subreg areas. From right to left: (a) frequency of piracy incidents per year in each subreg; (b) average score of piracy incidents per year in each subreg; (c) total score of piracy incidents per year in each subreg.

**Table 3**
The global Moran's Index and the P values of global piracy incidents in 2010, 2015, 2020, and 2021. The Moran's I examines whether the spatial distribution is dispersed (Moran's $I < 0$), random (Moran's $I = 0$), or clustered (Moran's $I > 0$).

| Year | Moran's I | Expected index | Variance | z-score | p-value |
|---|---|---|---|---|---|
| 2021 | 0.256409 | −0.009804 | 0.075940 | 0.966039 | 0.334025 |
| 2020 | 0.372190 | −0.003175 | 0.044539 | 1.778612 | 0.075303 |
| 2015 | 0.380777 | −0.003650 | 0.022157 | 2.582591 | 0.009806 |
| 2010 | 0.085959 | −0.001838 | 0.000611 | 3.552682 | 0.000381 |

temporal, and spatio-temporal evolution patterns of piracy incidents, this paper proposes a framework for the visualization and analysis of piracy incidents. Specifically, this paper rates a large number of historical piracy incidents. In addition, a series of visualization methods are proposed for the analysis of spatio-temporal patterns of piracy incidents. Finally, extensive experiments are implemented to analyze the hot spots and spatio-temporal patterns of piracy incidents on historical piracy incidents.

The paper contributes to both research and practical applications in several ways. Firstly, the results of the temporal pattern analysis reveal distinct differences in the risk levels of piracy incidents across different months, with dry bulk carriers and oil tankers being the primary targets of piracy attacks. Secondly, the spatial pattern analysis indicates that piracy incidents are concentrated along the 0 latitude line, particularly in regions such regions as Malacca and Equatorial Guinea. Thirdly, piracy incidents in Somalia exhibit relatively dispersed patterns. The spatio-temporal pattern mining demonstrates a global decrease in the number of piracy incidents along with a corresponding decline in associated risk levels. However, the piracy incidents in Equatorial Guinea do not exhibit a significant decreasing trend. In conclusion, piracy in international waters is in decline and remains a reasonably localized issue. International naval forces have made ongoing efforts to combat piracy, but these measures are argued to sometimes only provide partial protection and have not eradicated piracy entirely. It is therefore a long-term goal to combat piracy from different perspectives.

The limitation of current research relies on one separate secondary piracy dataset, the current research is its reliance on self-reported data sets, which may not capture the full scope of piracy incidents due to incomplete information against a few selected parameters of their own interests. This reliance on self-reporting secondary dataset could introduce biases and gaps in the data, potentially affecting the comprehensiveness and accuracy of the analysis. Future studies could aim to address these limitations by incorporating more robust and complete primary data sources directly from pirate reports to enhance the understanding of piracy incidents and their underlying causes. The investigation of spatial-temporal patterns of piracy incidents is a new dynamic topic suiting the fast evolution of the field. Future research directions could incorporate more of the impact of political, economic, historical, cultural, and public health events on piracy incidents research. In addition, it will be interesting to find out the main reasons for the emergence of pirates in particular regions. The current study focused on the refinement of piracy incident risk level.

## Author statement

Authors would like to declare that the paper is from original research that has not been published previously nor submitted to other journals. All the authors listed have approved the enclosed manuscript.

## CRediT authorship contribution statement

**Maohan Liang:** Writing – original draft, Visualization, Validation, Methodology, Data curation. **Huanhuan Li:** Writing – review & editing, Writing – original draft, Methodology. **Ryan Wen Liu:** Methodology,

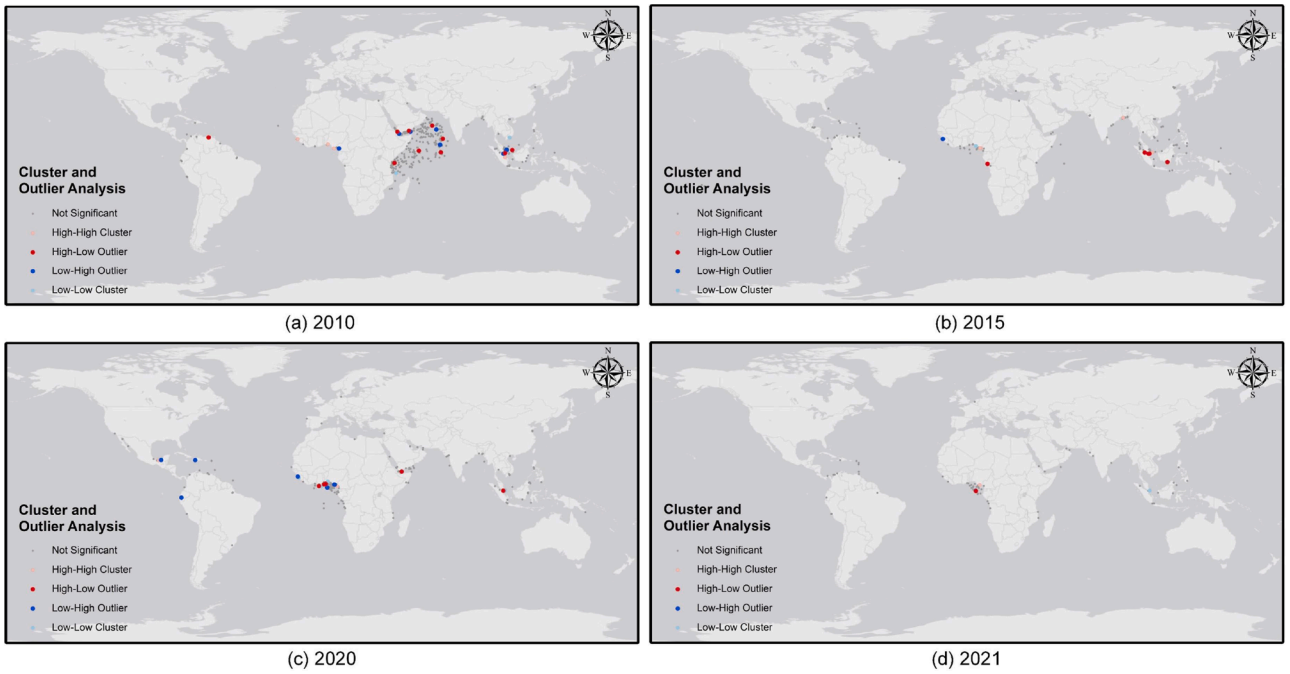


**Fig. 15.** The cluster and outlier analysis results for piracy incidents in 2010, 2015, 2020 and 2021.

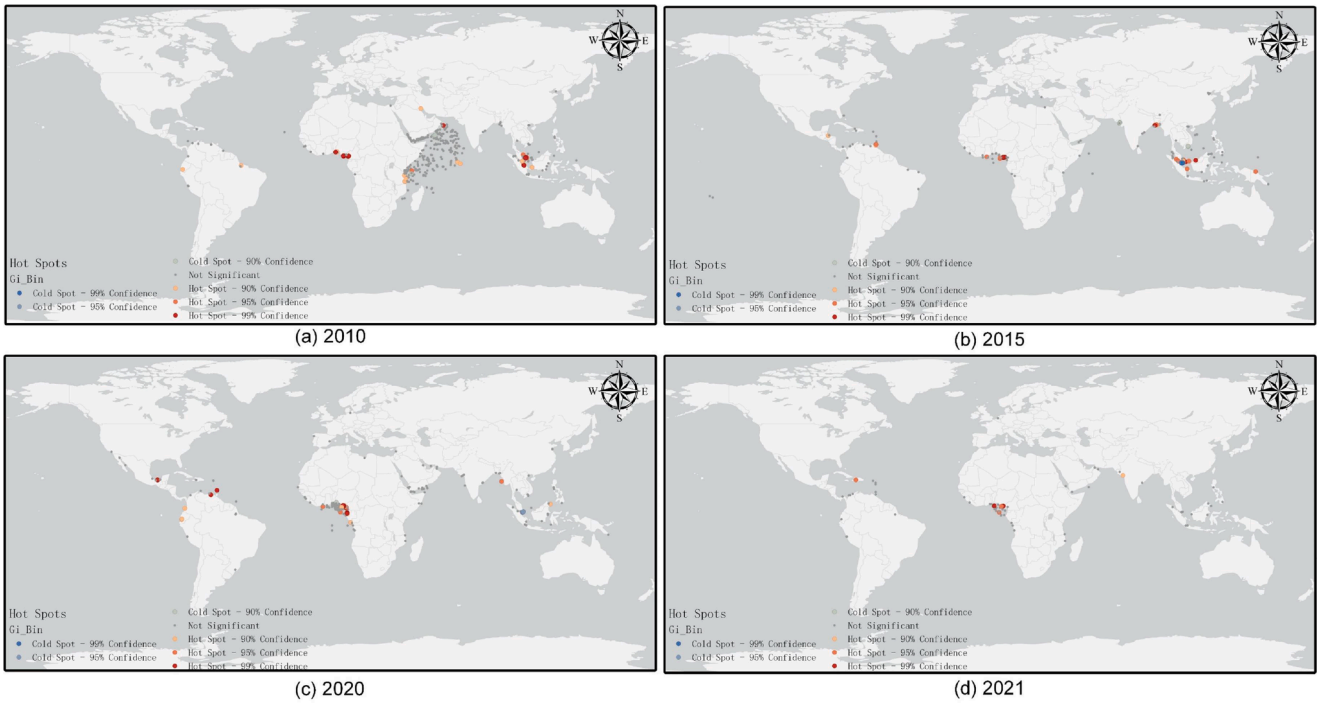


**Fig. 16.** The hot spot analysis results for piracy incidents in 2010, 2015, 2020, and 2021.

Investigation, Funding acquisition. **Jasmine Siu Lee Lam:** Writing – review & editing, Validation, Supervision, Funding acquisition. **Zaili Yang:** Writing – review & editing, Writing – original draft, Supervision, Formal analysis.

## Declaration of Competing Interest

This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal's policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare.

## Data availability

Data will be made available on request.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ress.2023.109877.

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