Safety assessment of shipping routes in the South China Sea based on the fuzzy analytic hierarchy process

Jiasheng Wang a, Manchun Li a,b, Yongxue Liu c,e, Hexia Zhang a, Wei Zou a, Liang Cheng a,b

a Department of Geographic Information Science, Nanjing University, Nanjing, Jiangsu Province 210023, PR China
b Jiangsu Provincial Key Laboratory of Geographic Information Science and Technology, Nanjing University, Nanjing, Jiangsu Province 210023, PR China
c Collaborative Innovation Center for the South China Sea Studies, Nanjing University, Nanjing, Jiangsu Province 210023, PR China

1. Introduction

The South China Sea (SCS) is a major thoroughfare for worldwide trade. More than half of the world's oil tankers and merchant ships sail through the SCS every year (Rosenberg and Chung, 2008), ranks second only to the Mediterranean Sea in terms of maritime transportation.

Though the safety of shipping in the SCS impacts the global economy, the shipping routes of the SCS are frequently threatened by both natural and manmade factors, such as complex submarine topography, extreme weather, and piracy. Previous studies of shipping safety in the SCS mainly focused on the individual ship safety and broader political policies. For this study, we applied spatial analysis to assess shipping safety along shipping routes. First, we extracted the main shipping routes from spatial analysis of the Voluntary Observing Ships data. Then, we used a qualitative review to choose influencing factors on ship safety in the SCS, for which data were available over a comparable time period. Further, annual and four seasonal criteria systems were developed. After factor normalization and mapping, the annual and seasonal navigation environment risk was evaluated along the shipping routes using the fuzzy analytic hierarchy process and geographic information science, and validated by comparison to actual incident reports. Our study shows that (1) the proposed method is a reasonable method of evaluation of navigation environment risk, at least in the SCS; (2) the majority of the shipping routes run from southwest to northeast, reflecting a linear-direction trend; (3) the risk of navigation environment in the SCS gradually decreases from the north to the south with a V-shape spatial distribution, and varies seasonally; and (4) in terms of shipping risk the four seasons are sorted in an ascending order: spring, winter, summer, and autumn.

The shipping routes of the South China Sea (SCS) are of major significance in global trade and global economy. However, the shipping routes of the SCS are frequently threatened by both natural and manmade factors, such as complex submarine topography, extreme weather, and piracy. Previous studies of safety and risk at sea for individual ships have been developed. Modeling methods for the assessment of safety and risk at sea for individual ships have been investigated (Heij et al., 2011; Hetherington et al., 2006; Lu and Tsai, 2008). Previous work focused on individual ship assessment problems. Most notably, accident statistics have been used to present collision models (Kujala et al., 2009), ship security monitoring systems have been designed through simulations (Lee et al., 2004), and human factors including supervision and ship safety culture have been investigated (Heij et al., 2011; Hetherington et al., 2006; Lu and Tsai, 2008). Modeling methods for the assessment of safety and risk at sea for individual ships have been developed (Balmat et al., 2009; Wang, 2002). Specific to the SCS, antipiracy and anti-maritime terrorism policies have been examined from the perspective of geopolitics and international relations (Huang, 2008; Rosenberg, 2009; Rosenberg and Chung, 2008).

The recent work cited above focused on individual ship assessments and broad security policies. However, the ship safety was most significantly correlated to ship routing safety, which is spatially related to geographical position and factors such as wind speed, wave height, and water depth. In this study, we set out to analyze the spatial variation of safety for SCS shipping routes. The three main components of this first spatial analysis of SCS shipping route safety are: (1) to identify the main shipping routes in use in the SCS; (2) to identify and evaluate the specific natural and manmade risks existing in the navigation environment of these shipping routes; and (3) to assess the safety of these shipping routes.
2. Data and methods

2.1. Study area location, characteristics, and environment

The South China Sea is a marginal sea of Asia bordered by the Chinese mainland and Taiwan to the north, the Philippines to the east, Vietnam to the west, and Brunei, Singapore, and Malaysia to the south (Fig. 1). The SCS connects the Pacific Ocean with the Indian Ocean between these landmasses and island chains, its waters commingling with the Pacific Ocean via the Luzon Strait and Taiwan Strait in the northeast, and with the Indian Ocean through the Malacca Strait in the southwest. The SCS has an area of 3.3 million km² excluding the gulfs of Thailand and Tonkin, and up to 3.8 million km² if these gulfs are included (Morton and Blackmore, 2001). The SCS is a huge sea basin with great slope decreasing from the margin to the center. The average depth of the water is 1212 m, and the maximum depth is 5559 m (Wang and Li, 2009). Many intrabasinal islands dot the SCS, the largest being Hainan in the northwest and Palawan in the southeast, with hundreds of smaller islands, atolls, submerged reefs and banks notably including the Pratas Islands, Paracel Islands and Spratly Islands.

Because the SCS extends southward from the Tropic of Cancer, it experiences a monsoonal climate created by the influences of the Southwest Monsoon in summer and the Northeast Monsoon in winter. The Southwest Monsoon is rain bearing, but the Northeast Monsoon is stronger and characterized by a more constant dry wind that builds greater wave heights during its occurrence in autumn and winter. Typically, the wind and waves in the northeastern part of the SCS basin are more extreme than in the other basinal areas regardless of season, and in summer and autumn the SCS suffers from frequent tropical cyclones. Although most tropical cyclones are formed in the Western Pacific Ocean to the east of the Philippines, some tropical cyclones build up in the SCS near the Paracel Islands.

2.2. Data and preprocessing

The data involved in this study were organized into the following eight categories:

(1) Sea surface wind speed data. A total of 3288 phases of QuikScat daily wind speed grid data from 2000 to 2008 were collected to determine the wind speed at the height of 10 m above sea level. The data were produced by the Remote Sensing Systems (http://www.remss.com, accessed: November 24, 2012) and sponsored by the NASA Ocean Vector Winds Science Team. The grid size of the data is 900 arc second.

(2) Significant wave height data. Jason-1 Geophysical Data Record (GDR) data recorded from 2002 to 2011 were collected to acquire significant wave height. The altimeter products were produced and distributed by AVISO (http://www.aviso.oceanobs.com, accessed: October 10, 2012).

(3) Gridded bathymetric data. Bathymetric data of the SCS (grid size: 30 arc-second) was collected from the British Oceanographic Data Centre (BODC, http://www.bodc.ac.uk/data/online_delivery/gebco/, accessed: October 11, 2012).


(5) Piracy and armed robbery (PAR) data. Piracy and armed robbery incident data for events in the SCS from 2002 to 2011 were collected from the Global Integrated Shipping

(6) Marine Casualties and Incidents (MCI) data. The data were collected from the GISIS (accessed: October 10, 2012) and Hainan Maritime Safety Administration (HMSA). In the SCS, there were all together 36 serious incidents reported to the GISIS in the period 2002–2011. Another 5 incident were collected from HMSA.


(8) Auxiliary data. Shoreline and administrative areas were provided by Global Administrative Areas (http://www.gadm.org, accessed: May 10, 2012). The smaller islands, atolls, submerged reefs and banks (hereinafter referred to as reefs) were digitized manually from TIANDITU (http://www.tianditu.cn/about/index.htm, accessed: November 10, 2012).

Further processing of the datasets mentioned above included the following steps: (1) All non-spatial data (including tropical cyclone data, PAR data, and MCI data) were represented in vector format. (2) All geo-data were reprojected to the geographic coordinate system with the WGS-84 datum. (3) All raster data were resampled to a 30-arc-second grid size.

2.3. Methods

First, we extracted the main shipping routes in the SCS from VOS data. Next we identified the specific meteorological and oceanographic natural risks existing in the navigation environment, and the risks of piracy and other incidents using GIS and FAHP calculations. Finally, we assessed the safety of these shipping routes based on the integration of the spatial risk data.

2.3.1. Shipping routes extraction

Theoretically, a shipping route would be the shortest path across the water between two ports, taking no account of external factors except distance cost, and it would have a polyline shape. However, in practice, the ship captain usually chooses a safer shipping route that is still economical in consideration of the many factors that influence navigation safety. Thus, a shipping route is not fixed, and it is usually shaped as a belt along a centerline. Here, we put forward a method to extract the centerlines of the main shipping routes in the SCS.

The VOS data are an important component of the Global Climate Observing System (GCOS) and the Global Ocean Observing System (GOOS), providing weather information on air and sea (Kent et al., 2010). The ship positions of VOS data essentially reflect the distribution of ships over time and space. Hence, the VOS data of many years could be used to extract the main shipping routes. The greater the ship density of an area, the more likely the area could be considered part of a shipping route. The shipping route extraction method was divided into two steps.

(1) Ship density calculation. The kernel density estimation method was used to generate the density distribution of ships based on the VOS data. The kernel density estimation is an interpolation method that calculates a magnitude per unit area from point or polyline features using a kernel function to fit a smoothly tapered surface to each point or polyline (Silverman, 1986). Value of each cell can be calculated as:

\[
\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K(\frac{1}{h} | x - x_i |), \quad i = 1, 2, \ldots, n
\]

where \(K(\cdot)\) is a kernel function, \(h\) is the range of window, \(d\) is the dimensionality. A two-dimension kernel function can be represented as:

\[
K(x, y, x_i, y_i) = \frac{3}{\pi \left(1 - \frac{1}{2} \frac{(x - x_i)^2 + (y - y_i)^2}{h^2}\right)^2}, \quad i = 1, 2, \ldots, n
\]

(2) Main shipping routes generation. We supposed that main shipping routes lay in the areas with highest ship density. First, the ship density result was reclassified into four classes according to the geometric interval method. The classes were named low density (density level = 1), normal density (density level = 2), high density (density level = 3), and very high density (density level = 4) areas respectively. The geometric interval method is a classification method in ArcGIS (ESRI [http://www.esri.com]) that creates geometric intervals by minimizing the sum of squares of the number of elements in each class. Then, the main shipping routes were digitized manually based on the high density and very-high-density areas; the low density and normal density areas had no distinguishable trends. The centerlines extracted from very-high-density areas were named level 1 shipping routes, and the centerlines extracted from high-density areas were named level 2 shipping routes.

2.3.2. Navigation environment evaluation

Evaluation of the environmental factors impacting navigation along the shipping routes required that we (1) identify the specific natural and manmade risks existing in the navigation environment of the extracted shipping routes, and the data sets available for their quantification; (2) create maps of the identified risk factors; and (3) apply spatial analysis to these mapped risks.

2.3.2.1. Evaluation criteria selection. A qualitative review of the ship navigation environment in the SCS, including the consideration of access to data conducive to spatial analysis, led us to set up an integrated quantitative criteria system containing six factors: water depth (C1), distance to shoreline or reefs (C2), annual gale frequency (C3), annual big wave frequency (C4), annual tropical cyclone frequency (C5), and annual piracy and armed robbery frequency (C6). A gale was defined as wind with speed greater than 11.7 m s\(^{-1}\), and a big wave was defined as any wave with wave height of greater than 6 m. Gales and big waves were included because they affect the navigation of ships even more commonly than do cyclones (Zeng, 2003). These six factors were grouped into three classes: terrain conditions, meteorological conditions and social conditions. Further, in order to consider seasonal variation within the navigation environment, four seasonal criteria systems were developed, in which factors of the meteorological condition were replaced by the corresponding seasonal frequency. For example, factors of the meteorological conditions in the spring season criteria system were annual spring gale frequency, annual spring big waves frequency and annual spring tropical cyclone frequency. In this paper, spring is refers to the period from March to May, summer is from June to August, autumn is from September to November, and winter is from December to February.

2.3.2.2. Criterion maps generation. In the development of criterion maps, we linked the six evaluation factors to corresponding data.
of the navigation environment using the spatial analysis methods of GIS, that is, the collected datasets were converted to raster layers in this step. Values of the raster layers were set to the range 0–100, representing the risk indices of every factor. A schematic representation of the criterion maps generation is illustrated in Fig. 2, where a parallelogram indicates data and a rectangle indicates a spatial analysis process. The processing included data conversion and normalization.

In the data conversion step, various spatial analysis methods were required to convert different source data into unstandardized criterion layers or unstandardized factor layers. The distance analysis method was used to transform shoreline and reefs into a distance grid. Distance analysis describes each cell’s relationship to a source or a set of sources based on the straight-line distance (Chang, 2012), and each cell’s value of output raster gives the distance from the cell to the closest source. Raster calculation calculates raster values cell by cell, and was used to convert the distance from the cell to the closest source. Raster calculation calculation and normalization.

where \( V \) is the original raster grid, and \( V' \) is the grids after data conversion, \( \alpha \) is a threshold to differentiate whether the original grid value is risk to ship navigation.

Each unstandardized factor layer has its own characteristics and range, and the datum of each unstandardized factor layer has its own dimension and distribution. It is difficult to directly compare these characteristics or incorporate them together into an operational system, so these unstandardized layers need to be made dimensionless by range transformation, that is, by standardization. Because the higher grid values for each unstandardized layer meant that the indicated navigation environment was more dangerous, so we applied the maximum normalization method, expressed as Eq. (4), to transform the layers into factor layers. The generated factor layers of navigation environment risk evaluation are illustrated in Fig. 3.

\[
F = \frac{f}{\text{Max}(f)} \times 100
\]  

where \( F \) is the standardized factor layer (criterion map); \( f \) the factor unstandardized factor layer; and \( \text{Max}(f) \) the maximum value of \( f \).

2.3.2.3. Criteria weight calculation. FAHP is a method that integrates the fuzzy sets theory and analytic hierarchy process (AHP) (Naghadehi et al., 2009). There are various FAHP methods in the literature; we used the FAHP originally introduced by Chang (1996), including the following three steps of Chang’s method.

Step 1. Compare the importance of any two factors by using the triangular fuzzy numbers (TFN) in the scale of nine units proposed by Saaty (1990). A fuzzy pairwise comparison matrix (FPCM) \( \tilde{A} \) formed by the compare results was expressed as shown below.

\[
\tilde{A} = (\tilde{a}_{ij})_{n \times n} = \left[ \begin{array}{cccc}
(1, 1, 1) & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{n1}, m_{n1}, u_{n1}) \\
(1, m_{12}, u_{12}) & (1, 1, 1) & \cdots & (l_{n2}, m_{n2}, u_{n2}) \\
\vdots & \vdots & \ddots & \vdots \\
(1, m_{n1}, u_{n1}) & (1, m_{n2}, u_{n2}) & \cdots & (1, 1, 1)
\end{array} \right]
\]

where \( \tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = \tilde{a}_{ij}^{-1} = (1/u_{ij}, 1/m_{ij}, 1/l_{ij}) \) \( i, j = 1, 2, \ldots, n \).

Step 2. Sum up each row of FPCM \( \tilde{A} \) by fuzzy arithmetic operations at first as Eq. (6). Then the value of fuzzy synthetic extent with respect to the \( i \) th object was defined as Eq. (7).

\[
RS_i = \sum_{j=1}^{n} \tilde{a}_{ij} = \left( \sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij} \right), \quad i = 1, 2, \ldots, n
\]

\[
\tilde{S}_i = \frac{RS_i}{\sum_{i=1}^{n} RS_i} = (l_i, m_i, u_i), \quad i = 1, 2, \ldots, n
\]

Step 3. Compute the degree of possibility of \( \tilde{S}_i > \tilde{S}_j \) by the following equation:

\[
P(\tilde{S}_i > \tilde{S}_j) = \begin{cases} 
1 & m_i \geq m_j \\
\frac{m_i - u_i}{m_i - u_i \lor m_j - l_j} & m_i \leq m_j, \ u_i \geq l_j, \ i, j = 1, 2, \ldots, n; \ i \neq j \\
0 & \text{otherwise}
\end{cases}
\]

where \( \tilde{S}_i = (l_i, m_i, u_i) \) and \( \tilde{S}_j = (l_j, m_j, u_j) \). Then, calculate the degree of possibility of \( \tilde{S}_i \) over all the other \( (n - 1) \) fuzzy numbers by

![Fig. 2. A schematic representation of criterion maps generation method.](image)
Finally, define the priority vector $W = (w_1, w_2, \ldots, w_n)^T$ of $A$ as

$$w_i = \frac{P(\tilde{S}_i > \tilde{S}_j | j = 1, \ldots, n; i \neq j)}{\sum_{k=1}^{n} P(\tilde{S}_k > \tilde{S}_j | j = 1, \ldots, n; k \neq j)}, \quad i = 1, 2, \ldots, n$$

The integrated quantitative criteria system and corresponding weights of the six factors we analyzed are presented in Fig. 4.
2.3.2.4. Synthetic evaluation index and risk gradation. To assess the synthetic ship navigation environment risk of the SCS, a ship navigation environment risk index (SNERI) of each spatial unit (cell) was defined as the sum of the corresponding weight value of all related factors, as Eq. (11).

$$R(x, y) = \sum_{i=1}^{n} w_i F_i(x, y)$$  \hspace{1cm} (11)

where $R(x, y)$ is the cell value at location $(x, y)$ of the result raster, $F_i(x, y)$ is the cell value at location $(x, y)$ of the $i$th factor map layer, $w_i$ is the weight of the $i$th factor and $n$ is the number of factors. The SNERI values were then mapped. To simplify the process of reading and understanding the resultant SNERI map, the SNERI gained from Eq. (11) were classified into ten categories representing discrete ship navigation risk levels, to highlight the regional SNERI differences with a geometric interval method. Each category was named a level value grading from 1 to 10, a SNERI graded map was generated, and regions of Level 10 were the regions graded to be of highest risk in the study area.

The annual and seasonal SNERI layers and the corresponding graded layers were completed according to the weights and the navigation environment evaluation method described above.

2.3.3. validation of SNERI graded results

The validation method of SNERI graded results was based on the MCI data with attributes of incident time, location, initial event, summary of events, etc. The causation of an incidents could be extracted out from the summary of events. Firstly, we eliminated the incidents without location information or incidents with causation not relevant to navigation environment (such as collision, missing person, management and machine error). According to location information, the MCI data were transformed to a spatial point layer. The chosen incidents were also divided into four seasons to verify the seasonal evaluation results. Then, the SNERI graded maps were overlaid with MCI point layer and the risk level of the incidents was figured out. Because the SNERI values represented the possibility prone to incidents, we took the proportion of MCI points plot in areas with risk level equal or greater than 5 as

![Fig. 4. Criteria system and corresponding weights in navigation environment risk evaluation.](image)

![Fig. 5. Spatial distribution of annual SNERI and the MCI: (a) continuous results, and (b) graded results.](image)
validation criteria. If the proportion was greater than 80%, we believed that the SNERI result was effective.

For seasonal SNERI results, it was necessary to verify the consistency of the causation of incidents and the main influence factor in the SNERI maps. The method was illustrated as below: (1) Sample the values from each factor map according to the MCI points; (2) Multiply each sample value with the weight of the corresponding factor; (3) Select the factor with max weighted value as the main influence factor; (4) Decide whether the main influence factor and the causation had consistency.

2.3.4. Shipping routes safety assessment

The final shipping route safety assessment included calculation and mapping of the spatial distribution of the navigation environment risk of shipping routes. For this study, we used a piecewise assignment method as described below.

First, the SNERI risk gradation results were converted into vector polygon layers with the attribute of navigation environment risk level. Then, these vector polygon layers were overlaid by the shipping routes layer and the spatial identity method was used to generate the navigation risk of shipping routes. Spatial identity is a vector overlay analysis method that computes a geometric intersection of the input features and identity features, and assigns to the input features or portions thereof that overlap identity features the attributes of those identity features. For this study, we set the vector polygons layer as the identity feature and the shipping routes layer as the input feature, so each shipping route was

![Fig. 6. Spatial distribution of seasonal SNERI graded results and the MCI: (a) spring, (b) summer, (c) autumn, and (d) winter.](image)

<table>
<thead>
<tr>
<th>Accident ID</th>
<th>Causation</th>
<th>Risk level (1–10)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Annual</td>
</tr>
<tr>
<td>1</td>
<td>Terrain</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>Terrain</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>Weather</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>Weather</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>Weather</td>
<td>6</td>
</tr>
<tr>
<td>6</td>
<td>Weather</td>
<td>5</td>
</tr>
<tr>
<td>7</td>
<td>Weather</td>
<td>7</td>
</tr>
<tr>
<td>8</td>
<td>Weather</td>
<td>7</td>
</tr>
<tr>
<td>9</td>
<td>Weather</td>
<td>6</td>
</tr>
<tr>
<td>10</td>
<td>Weather</td>
<td>9</td>
</tr>
<tr>
<td>11</td>
<td>Weather</td>
<td>7</td>
</tr>
<tr>
<td>12</td>
<td>Weather</td>
<td>6</td>
</tr>
<tr>
<td>Risk level ≥ 5 (%)</td>
<td></td>
<td>91.7</td>
</tr>
</tbody>
</table>
piecewise and each piece had a different navigation environment risk level. Finally, the length of each shipping route was summarized by risk level, and the thematic maps of shipping route safety were completed according to the navigation environment risk.

Table 2

<table>
<thead>
<tr>
<th>Incident ID</th>
<th>Causation</th>
<th>Main influence factor in SNERI maps</th>
<th>Consistence</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Spring</td>
<td>Summer</td>
</tr>
<tr>
<td>1</td>
<td>Terrain</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>2</td>
<td>Terrain</td>
<td>N/A</td>
<td>Water depth</td>
</tr>
<tr>
<td>3</td>
<td>Weather</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>4</td>
<td>Weather</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>5</td>
<td>Weather</td>
<td>N/A</td>
<td>Tropical cyclone</td>
</tr>
<tr>
<td>6</td>
<td>Weather</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>7</td>
<td>Weather</td>
<td>N/A</td>
<td>Tropical cyclone</td>
</tr>
<tr>
<td>8</td>
<td>Weather</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>9</td>
<td>Weather</td>
<td>Water depth</td>
<td>N/A</td>
</tr>
<tr>
<td>10</td>
<td>Weather</td>
<td>N/A</td>
<td>Tropical cyclone</td>
</tr>
<tr>
<td>11</td>
<td>Weather</td>
<td>Tropical cyclone</td>
<td>N/A</td>
</tr>
<tr>
<td>12</td>
<td>Weather</td>
<td>Big wave</td>
<td>N/A</td>
</tr>
</tbody>
</table>

^ Yes.

^ No.
3. Results and discussion

3.1. Validation results

Based on spatial analysis and FAHP method, annual and seasonal SNERI maps and graded maps were generated. The MCI data was used to verify the evaluation results. After eliminating invalid incidents, 12 incidents were left. From the view of varieties of season, one incident occurred in spring, one incident in summer, eight incidents in autumn, and two incidents in winter. The overlaid results of incidents and SNERI graded maps are shown in Figs. 5 and 6. According to the figures, the risk level of each incident was counted in both annual and seasonal SNERI maps (Table 1). In Table 1, we also calculated the proportion of incidents plot in area with risk level equal to or greater than 5.

As shown in Table 1, the proportion of incidents at areas with risk level equal to or greater than 5 were above 80% in all the SNERI maps. This indicated that the annual and seasonal evaluation results are valid relatively and could be used to approximate the navigation environment risk of the SCS. Except for the validation of risk level, the causation of the incidents needed to be considered in order to link with the factors. Table 2 listed the verification results of the consistence of the main influence factor and the causation of incidents. It shows that the seasonal SNERI maps had a good consistency. In brief, both annual and seasonal SNERI results were effective.

However, the number of the MCI incidents was limited. GISIS database only gathers those accidents with serious causalities or above. There were still many accidents underreporting. The possible reasons for the underreporting issue include oversight and deliberate withholding, local reporting procedures not known to the crew or ship owner, etc. This paper focused on the risk evaluation of navigation environment from macro perspectives, so the accidents caused by micro-factors such as ship collisions were ignored in this study. According to Qu et al. (2012), ship collisions accounted for more than 50% out of all types of accidents. In addition, the SNERI value indicated the potential risk of shipping. So the underreporting issue had less influence to the validation results, although it might affect the data quality. It is anticipated to collect more underreporting accident records to improve the data quality of the validation in the future.

3.2. Spatial distribution of annual SNERI in the SCS

As illustrated in Fig. 5, there are two apparent distribution characteristics of different navigation risk levels in annual SNERI graded results. (1) Regions around islands are high risk aggregation areas. The regions are discrete and aggregate as the distribution of islands with risk levels larger than 7. The Paracel Islands, Spratly Islands and Natuna Islands are central to the three main high risk cluster regions. The factors most influencing the high risk of the islands are the terrain conditions (water depth and distance to reef) around islands. (2) The SNERI follows a V-shaped spatial distribution. The angular point of the V-shape extends to an area adjacent to the Malacca Strait. Risk levels increase gradually from south to north in the SCS, with the highest risk region occurring mainly in the northeast of the SCS, especially west of the Luzon Strait, having risk levels higher than level 8. The second highest risk region is located in the west of the Spratly Islands and most of the northern part of the SCS adjacent to the highest risk region. The lowest risk levels occur in the northwest and southeast of the SCS. The factors most influencing the spatial distribution are the meteorological conditions (annual gale frequency, annual big wave frequency, annual tropical cyclone frequency). The factor most influencing the high risk of angular point of the V-shape is annual piracy and armed robbery frequency.

3.3. Seasonal differences in shipping risk in the SCS

The seasonal differences in SNERI maps were mainly caused by meteorological factors. The seasonal SNERI maps showed different risk spatial distribution in four seasons as illustrated in Fig. 6.

(1) In spring, the higher SNERI areas mainly lie in the northeastern SCS and the west of Spratly Islands. But as a whole the risk level is lower than other seasons (Fig. 6a). The spatial distribution were caused by the monsoon climate. Spring is a transition season from winter monsoon to summer monsoon. At the same time, the tropical cyclone frequency is lower than other seasons.

(2) In summer, the higher SNERI areas mainly lie in the northeastern SCS and the Gulf of Tonkin (Fig. 6b). Summer is the southwest monsoon season of SCS, and also a season with a lot of tropical cyclones in northeastern SCS. So it is dangerous to navigation in the northeastern SCS.

(3) In autumn, the higher SNERI areas lie in the northern SCS. Also, the average SNERI in autumn was higher than the value in other seasons (Fig. 6c). Autumn is a transition season from southwest monsoon to northeast monsoon. It is also a season with high tropical cyclone frequency. It is very dangerous to navigation in the northern SCS. There had been many causalities and incidents happened in autumn according to the MCI data.

Table 3
The summarization of annual and seasonal shipping routes risk levels.

<table>
<thead>
<tr>
<th>Risk level</th>
<th>Result type</th>
<th>Year (nm)</th>
<th>Spring (nm)</th>
<th>Summer (nm)</th>
<th>Autumn (nm)</th>
<th>Winter (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>298.78</td>
<td>941.34</td>
<td>98.83</td>
<td>505.21</td>
<td>900.02</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>1209.09</td>
<td>2197.22</td>
<td>647.95</td>
<td>1933.71</td>
<td>990.03</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>2181.31</td>
<td>1566.83</td>
<td>2553.38</td>
<td>1017.50</td>
<td>935.25</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>646.64</td>
<td>3923.79</td>
<td>1370.27</td>
<td>552.81</td>
<td>1644.03</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>640.84</td>
<td>3647.67</td>
<td>1732.92</td>
<td>693.42</td>
<td>3022.65</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2810.59*</td>
<td>493.89</td>
<td>1362.80</td>
<td>1534.32</td>
<td>2551.84</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>3377.30</td>
<td>1.03</td>
<td>1234.41</td>
<td>1774.34</td>
<td>1774.34</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>1536.64</td>
<td>0.00</td>
<td>3037.71</td>
<td>2653.77</td>
<td>862.08</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>67.64</td>
<td>0.00</td>
<td>742.41</td>
<td>1033.64</td>
<td>71.41</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1.03</td>
<td>0.00</td>
<td>1.48</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>

* Bold numbers indicate the number are two largest number in all the risk levels.
(4) In winter, the higher SNERI areas lie mainly in the central SCS (Fig. 6d). Winter is the northeast monsoon season. And it is also a lower tropical cyclone frequency season. These weather conditions resulted in the spatial distribution of winter SNERI.

3.4. Spatial distribution of shipping routes of the SCS

Seventeen main shipping routes were extracted from VOS data in the SCS. The results of the extraction are illustrated in Fig. 7, including spatial distribution of VOS points (Fig. 7a), ship density

Fig. 8. Spatial distribution of: (a) annual shipping routes risk assessment, (b) spring shipping routes risk assessment, (c) summer shipping routes risk assessment, (d) autumn shipping routes risk assessment, and (e) winter shipping routes risk assessment.
map (Fig. 7b), graded results of the ship density map (Fig. 7c) and spatial distribution map of main shipping routes (Fig. 7d). It can be seen from Fig. 7d that most shipping routes have a northeast trend, and accesses of the shipping routes mainly include the Luzon Strait and Taiwan Strait in the northeast, Mindoro Strait and Balabac Strait in the east, and Malacca Strait in the south. The extraction results are composed of four level 1 routes and 15 level 2 routes.

The four level 1 routes include: (1) the route in the west of the SCS from Singapore along the west of the Spratly Islands and the east of the Paracel Islands to Hong Kong and Guangzhou; (2) the route in the east of the SCS from Bintulu along the coast of Malaysia, Brunei, and the Philippines to the Luzon Strait; (3) One route from the Luzon Strait to the Mindoro Strait; and (4) one route from Guangzhou and Hong Kong to the Taiwan Strait.

Level 2 routes surround level 1 routes and connect the important ports of surrounding countries, such as Guangzhou, Hong Kong, Kaohsiung, Manila, Seri Begawan, Bintulu, Singapore and Ho Chi Minh.

From the trend of the SCS shipping routes, it can be seen that these routes service China, Japan and Korea in the north, cross over the Malacca Strait to the Indian Ocean in the southwest, and reach Australia in the south.

3.5. Shipping routes safety spatial distribution

Results of the shipping routes safety assessment are illustrated in Fig. 8, including the annual safety assessment thematic map (Fig. 8a) and four seasonal assessment thematic maps (Fig. 8b–e). The length of different risk levels in each assessment result is summarized in Table 3. The main characteristics of shipping routes safety spatial distribution in the SCS are apparent in Fig. 8 and Table 3.

(1) Most shipping routes do not pass through the highest risk areas. The length values of shipping routes in risk level 10 are all less than 1.5 km, and the values in risk level 9 are less than 100 km except for the summer and autumn risk evaluation results. Level 1 routes have shorter length of high risk level (>5) than level 2 routes.

(2) Spring is the safest season, and winter is the most dangerous season to navigate in the SCS. A review of Table 1 reveals that the two largest risk values for each season are: levels 4 and 5 in spring; levels 8 and 3 in summer; levels 8 and 7 in autumn; and levels 6 and 5 in winter. Also note that the values of risk level above 7 are zero in spring. Therefore, the four seasons sorted according to the quantitative seasonal risk level evaluation in an ascending order would be spring, winter, summer and autumn.

4. Conclusions

By combining the methods of FAHP and GIS, this study used the factors of terrain conditions, meteorological conditions and social conditions as indices. First, the shipping routes were extracted according to the VOS data. Then an evaluation model was established to quantitatively calculate the annual and seasonal SNERI values in the SCS. At last, the shipping routes annual and seasonal SNERI spatial distributions were calculated out by overlaying them with the SNERI maps.

The following conclusions are drawn from these evaluation maps.

(1) The proposed method for the evaluation of shipping route safety using GIS and FAHP is reasonable, at least as applied to the South China Sea shipping routes and validated by MCI data.

(2) The shipping routes in the SCS as determined by spatial analysis of VOS data have a dominant northeast trend. The main accesses of the shipping routes include Luzon Strait, Taiwan Strait, Mindoro Strait, Balabac Strait and Malacca Strait. There are four level 1 routes and 15 level 2 routes. The western level 1 route connects Singapore, Hong Kong and Guangzhou. The eastern level 1 route connects Bintulu and the Luzon Strait. Other shipping routes connect the important ports of the surrounding countries.

(3) The navigation environment risk in the SCS gradually decreases from the north to the south with a V-shape spatial distribution. From an annual basis evaluation, the main dangerous areas lie in the northeast, and the safest areas lie in the southwest and southeast. From a seasonal basis evaluation, the main dangerous areas lie in the north and middle SCS in spring and autumn, lie in the middle SCS in summer, and lie in the northeast SCS in winter. The spatial distribution of navigation environment risk was mainly influenced by the monsoonal climate and tropical cyclones in the SCS. Furthermore, areas around islands have a higher risk when considered both annually and seasonally.

(4) The overall safety of shipping routes throughout the SCS has apparent seasonal variation. The SCS shipping routes are the most dangerous in autumn and the safest in spring, and summer is more dangerous than winter.

(5) Though we have confidence in the results and import of this spatial analysis, errors are inevitable in the assessment. Sources of error include that the datasets of this study were collected from different sources and across different temporal spans in part; that the spatial resolution, temporal resolution and data performance of the datasets have significant difference; and that some factors were converted through interpolation. Moreover, dispute of the Spratly Islands among five countries and six parties (Brunei, China, Malaysia, the Philippines, Chinese Taipei, and Vietnam) could influence the navigation safety in the SCS.

Acknowledgements

This work was supported by the National High Technology Research and Development Program of China (863 Program, No. 2012AA12A406), the National Natural Sciences Foundation of China (Nos. 40701117, 41171325, and J1103408), the Program for New Century Excellent Talents in University (NCET-12-0264), and the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD). The authors are also grateful for the valuable suggestions by the anonymous reviewers. Any errors or shortcoming in the paper are the responsibility of the authors.

References


