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Characterizing Fishing Behaviors and Intensity of Vessels Based on BeiDou VMS Data: A Case Study of TACs Project for *Acetes chinensis* in the Yellow Sea

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Abstract: The total allowable catch system (TACs) is a basic, widely used system for maintaining marine fishery resources. The vessel monitoring system (VMS) provides a superior method to monitor fishing activities that serve TACs project management. However, few studies have been conducted on this topic. Here, an artificial neural network was used to identify vessel position states based on BeiDou VMS data and fishing logs of vessels under the TACs project for *Acetes chinensis* in the Yellow Sea in 2021. Furthermore, fishing behaviors and intensity were explored. The results showed significant differences in the speed of vessels in different states ($p < 0.01$). Casting occurred during the day, and the azimuth of fishing nets for shrimp ranged from 60 to 90° or 240 to 270°. The length of the fishing nets of each vessel was mostly between 3500 and 4500 m. In addition, the fishing efforts of the vessels showed an obvious aggregated distribution. The main area was at 120°04′–120°16′ E, 34°42′–34°46′ N, whereas fishing intensity ranged from 120,000 to 280,000 $m^2 \cdot h/km^2$. Finally, this study provides a scientific basis for TACs project management and a VMS data mining and application expansion standard.

Keywords: vessel monitoring system; total allowable catch system; fishing intensity; *Acetes chinensis*; Yellow Sea

1. Introduction

Fishing activities can directly reduce fishery resources [1], which naturally have substantial effects on the population structure of targeted species [2] and also affect their interactions [3]. Therefore, monitoring fishing activities and behavior is a crucial step toward protecting overexploited or limited species thorough management and conversation strategies. The vessel monitoring system (VMS) is an integrated application system that utilizes a global positioning system, electronic map and chart, computer network communication, database technology, and recordings of vessel position data in large quantities [4]. Compared with traditional methods for characterizing fishing activities and behaviors to manage fishery resources, VMS data have advantages in fishing behavior analysis [5], fishing status identification [6], fishing effort calculation [7], and fishery analysis [8]. The BeiDou vessel monitoring system is based on the BeiDou Navigation Satellite System. It integrates the automatic identification system, the port of entry and exit identification system, and the fishing vessel satellite communication support system to build a comprehensive information system for the dynamic management of fishing vessels [9]. It provides services, such as real-time monitoring of vessel positions, playback of historical trajectories of fishing vessels, and management of vessel data for fishery administration departments [10].

The VMS data from the BeiDou system has an extremely high spatiotemporal resolution. Currently, more than 60,000 marine fishing vessels in China have installed the BeiDou system [11], which provides a robust guarantee for monitoring fishing activities.

The total allowable catch system (TACs) is a basic system for managing and protecting marine fishery resources in the United States, Australia, New Zealand, and other countries [12]. As an advanced management method for output control, TACs are used in combination with input control and technical measures, such as fishing effort control, gear restrictions, and area management, to form an overall system for sustainable fisheries management. It promotes global marine ecological environment governance through conservation and intensive utilization of marine resources. China is a substantial marine fishery country and has long attached great importance to conserving marine fishery resources and eco-civilization [13,14]. In 2000, the revised Fisheries Law of China (hereinafter referred to as the Fisheries Law) stipulated the implementation of TACs for the fishing industry. However, TACs have not been implemented for more than a decade since the Fisheries Law was established because of the lack of basic conditions [15]. It was not until 2017 that the Ministry of Agriculture of China launched single-species TACs pilot projects. This was a turning point in the development of marine fisheries and a substantial step towards building a global ocean governance system.

Acetes chinensis is a small planktonic shrimp of the genus Acetes in the family Sergestidae, which widely inhabits the coastal waters of the Indo-West Pacific, China, Korea, and Japan [16,17]. It is the most abundant species in marine shrimp fishing. The shrimp catch has been rising continuously since the 1950s, reaching a peak of 721,000 tons in 2006 [18], and then it began to decline sharply, falling to 367,000 tons in 2020 [19]. Therefore, it is urgent to implement a fisheries TACs project for *A. chinensis*. In 2020, a pilot project of *A. chinensis* was launched in Haizhou Bay, Yellow Sea, which expanded to the Bohai Sea in 2021. Currently, this is the most successful pilot TACs project for a single species in China. The management of fishing activities has become the key to promoting the implementation of the TACs project for *A. chinensis* and also serves as an important case study for the comprehensive implementation of TACs.

Fishing behavior characteristics include information about the states of vessels, such as speed, heading, and spatiotemporal distribution. Characterizing fishing behavior and intensity is important for managing fishing activities in the TACs project. Machine learning methods are increasingly used to automate identification and classification and improve the accuracy of identification tasks [20]. Artificial neural network models with multi-layer network perceptrons are the most widely applied classifiers for processing VMS data to identify fishing vessels [21,22]. However, there is almost no VMS data mining and machine learning application in fishing behaviors and intensity analysis of fishing vessels under the TACs project. In particular, the authenticity, timeliness, and usefulness of fishing logs cannot be fully ensured [15]. BeiDou VMS data and machine learning provide a new technical approach for implementing the fisheries TACs project [10].

In this study, an artificial neural network was used to automatically extract vessels' fishing behavior and intensity based on VMS data and fishing logs of vessels during the TACs project of *A. chinensis* in the Yellow Sea in 2021. This is expected to become the standard for VMS data mining and its application in managing TACs projects for other marine species.

2. Materials and Methods

2.1. Fishing Activity and Nets

In 2021, a total of 32 vessels were licensed to fish for *A. chinensis* under the TACs project in Haizhou Bay, Yellow Sea. From 15 June to 15 July, the fishing catches were on the designated shore at Yanwei Port. The fishing net used was the *A. chinensis* stow net (a multi-anchor and single-piece stow net), which is a type of stow net. A single piece is 60 m in length and 18 m in height (Figure 1). A single vessel can carry no more than 25 pieces of the net.

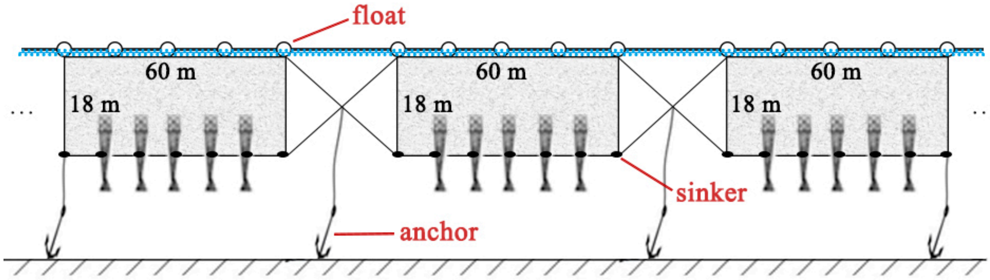

Figure 1. Schematic diagram of *A. chinensis* stow nets.

Fishers generally engage in fishing operations during the day. Each voyage is divided into five stages: departure from port, fishing, suspending, exploring, and returning to port [23]. Fishing stages can also be subdivided into three operational statuses in chronological order: casting, waiting, and hauling (Table 1). When the catch income from the fishing area cannot cover the cost and profit, the vessels move to other areas to explore or end the fishing and return to the port. Li et al. [23] and Wang et al. [24] summarized the fishing activities for *A. chinensis* in the Yellow Sea, and fishers have a high degree of similarity in fishing operation habits, which are mainly reflected in the vessels' speed and the operation time. In this study, all fishing vessels for *A. chinensis* were divided into sample fishing vessels (their fishing logs recorded by observers) and non-sample fishing vessels. The sample fishing vessels were representative of all fishing vessels regarding operating habits.

Table 1. Description of the five stages within the voyage of the vessels fishing for *Acetes chinensis*.

Stages	Status	Detailed Information
Departure from port	Sailing	The captain sails at high speed to gain more fishing time.
Fishing operation	Casting	The *A. chinensis* stow nets are connected with anchors and are cast in sequence.
	Waiting	After casting, the vessel is fixed with an iron anchor. *A. chinensis* are carried by currents into the nets used for fishing.
	Hauling	The catch is transported back to the port by speedboat, and the vessel continues to operate at the fishing ground.
Suspending	Suspending	Vessels generally stop operating at night. That is similar to the state of waiting for the catch.
Exploring	Sailing	Sailing occurs at high speed to achieve more fishing time.
Returning to port	Sailing	In case of bad weather or the end of fishing activities, the vessels sail at high speed to return to port.

2.2. Data Preprocessing and Analysing

In this study, the VMS data for all vessels were downloaded from the BeiDou civilian branch service provider (Figure 2) and mainly included positioning time, latitude, longitude, speed, and heading information. The temporal and spatial resolutions were 3 min and 10 m, respectively. Three sample vessels equipped with scientific fishery observers recorded fishing logs and information such as the net deployment; the casting and hauling time; and the corresponding latitude, longitude, and water depth. Current data for Haizhou Bay from June to July were obtained from the Ocean Science Data Center of the Institute of Oceanography, Chinese Academy of Sciences (http://msdc.qdio.ac.cn/, accessed on 15 January 2022). The data processing workflow is shown in Figure 3.

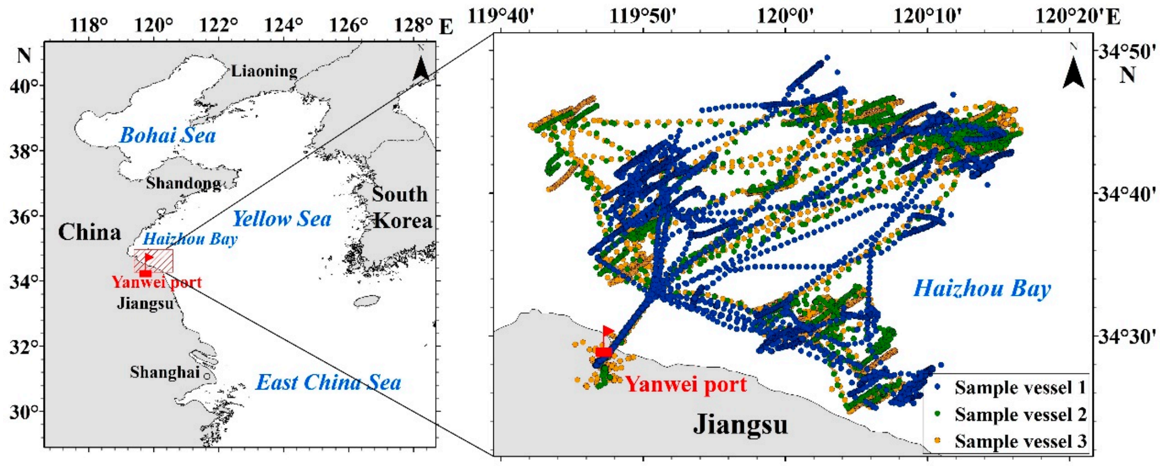

Figure 2. Spatial distribution of the vessel monitoring system (VMS) data of three sample vessels.

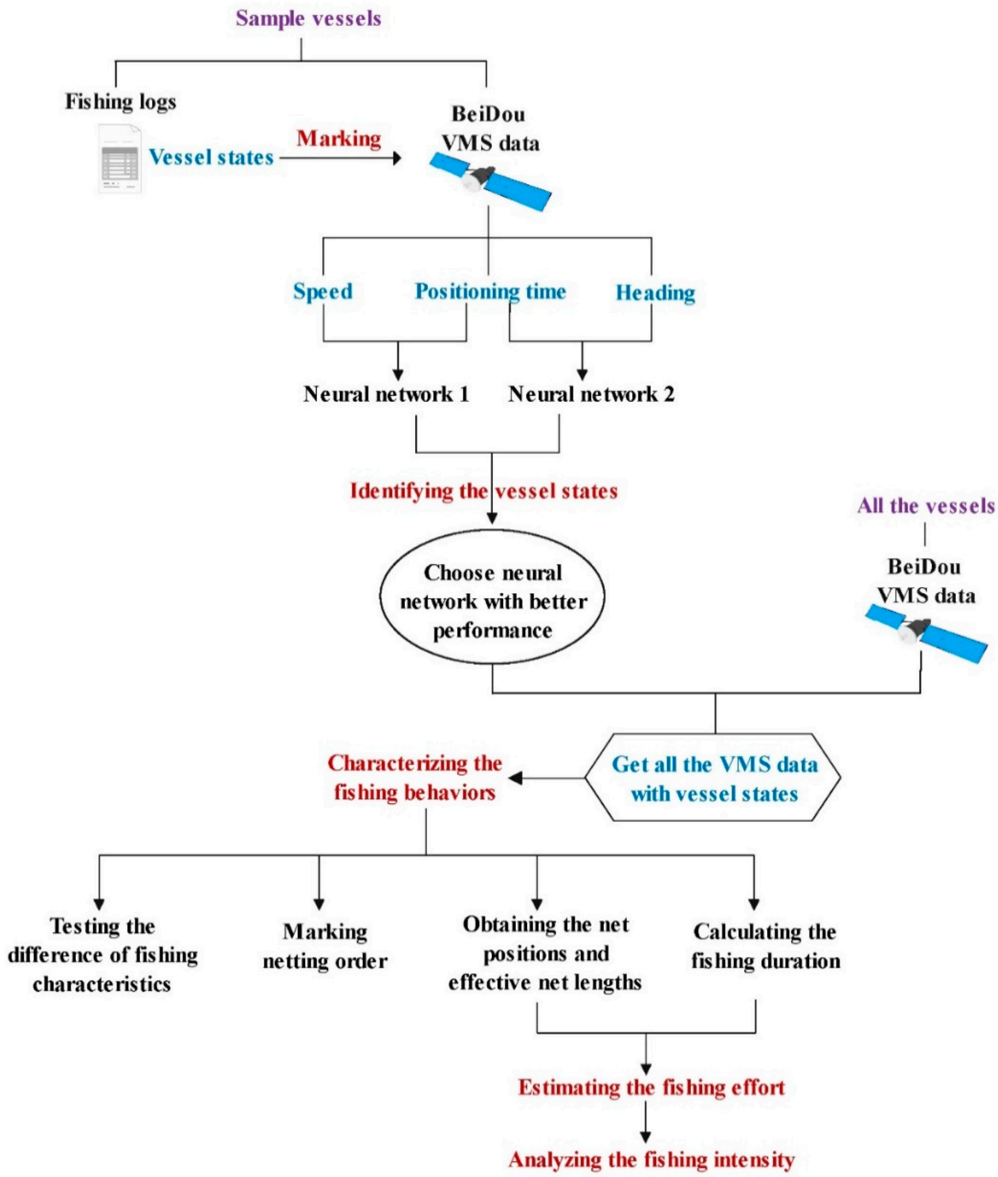

Figure 3. Data processing workflow of this study.

2.2.1. VMS Data Preprocessing

To reduce the amount of data and maintain the original VMS data characteristics, the speed, heading, latitude, longitude, and positioning time data of 32 fishing vessels during the TACs project were extracted by averaging three pieces of VMS data in chronological order. Meanwhile, the VMS data with speeds less than 0.2 knots were excluded to ensure that the vessels were in the state of casting, hauling, or sailing. Finally, 28,956 VMS data points were obtained. The VMS data were processed using the 2020 version of Microsoft Excel.

2.2.2. Back-Propagation Neural Network Modelling

A back-propagation (BP) neural network is a multilayer feedforward network characterized by signal forward propagation and error backward propagation. If the expectations are not met, back-propagation is performed, and the weights and thresholds of the network are adjusted according to the prediction error. The network training stops when the output error value reaches the minimum or preset range. Finally, the error and classification results are outputted [25]. Generally, when each node adopts a sigmoid function, the hidden layer is sufficient to realize any decision classification problem, and compared to the number of hidden layers, the number of neural network iterations (i.e., the number of back-propagations to the weights) is more important to the correct rate [26].

By combining the position, speed, and heading data from the VMS with the fishing time, longitude, and latitude data from the fishing logs of the three sample vessels, the VMS data with casting, hauling, or sailing states were extracted. Each state's 300 VMS data points were randomly selected as the training and test set samples. Two groups of network topology structures were established based on the speed/positioning time (neural network 1) and heading/positioning time (neural network 2), including the number of nodes in the input, hidden, and output layers. There were two nodes in the input layer: speed and positioning time or heading and positioning time. There were three nodes in the output layer: casting, hauling, and sailing. According to Equation (1), proposed by Yuan [27], the number of hidden layer nodes was set at 3 to 12. When there were 10 nodes, the identification accuracy was the highest, and the training speed was fast.

$$J = \sqrt{n + m} + a \tag{1}$$

where J is the number of hidden layer nodes, n is the number of input neurons, m is the number of output neurons, and a is a constant between 1 and 10. In this study, the neural network was based on the delta method to adjust the weights to increase the momentum term and the self-adaptive learning rate to address the problems of the BP neural network, such as ease of falling into the local optimal solution, low learning efficiency, and slow convergence speed.

In MATLAB R2016a, 300 VMS data points of each state were normalized, and all numerical values were controlled between -1 and 1. The corresponding Boolean variables were also established. The classification target values corresponded to 1, while the rest were zero. Therefore, the casting, hauling, and sailing states were [1,0,0], [0,1,0], and [0,0,1], respectively. The transmission functions of the nodes were logsig and purelin. The training function adopted trainingdx, which is the gradient descent self-adaptive learning rate training function. Training and test samples were randomly allocated (80% and 20%, respectively). The maximum number of network training iterations was set to 1000, and the learning rate was 0.02. In addition, the maximum error was 0.001, and the maximum failure verification was six times. Finally, a trained neural network with better performance at identifying the position states was used to identify the position states of all vessels.

2.2.3. Fishing Behaviors Characterization

(1) Testing differences in fishing characteristics.

A one-way ANOVA with repetitions was conducted on the different fishing characteristics of different vessel states identified by the neural network model to test whether there were significant differences in different vessel states. The vessel state was considered as a factor, whereas fishing characteristics were a dependent variable. This part was tested using IBM SPSS Statistics 22.

(2) Marking netting order

The VMS data with casting and hauling states were obtained. A single fishing vessel can only be one state at a time, and casting and hauling of different nets were alternately carried out. Therefore, the adjacent VMS data in order of time with the same state were classified as the same netting order. Subsequently, the VMS data with casting and hauling states were marked with netting order.

(3) Obtaining the net positions, azimuths, and effective net lengths

Because the anchors fix the *A. chinensis* stow nets in the ocean current, the point set of the casting state represents the fishing positions of the vessels. The mean center toolbox was used to process the VMS data with the casting state to obtain the net positions. In addition, all the beginning and ending points of the point sets with the hauling state at each fishing time were extracted and connected into lines. Then, the azimuths and actual distribution distances of all nets were calculated by adding the geometric attributes. Finally, the effective lengths of fishing nets were obtained from the ratio of the maximum effective net length to the corresponding actual distribution distance.

(4) Calculation of fishing duration

The intermediate points of the VMS data in the casting and hauling states were considered the beginning and ending points of fishing. Therefore, the positioning time of these two points was regarded as the beginning and ending time of fishing for each net. The fishing duration of the nets was calculated using Equation (2).

$$T_k = E_k - B_k \tag{2}$$

where E_k and B_k are the ending and beginning times of the kth net, respectively, and T_k is the fishing duration (h) of the kth net.

(5) Estimating fishing effort

Fishing effort is an important parameter in fishery resource management and evaluation. The calculation process is shown in Equation (3).

$$E = L \times h \times T \tag{3}$$

where E is the amount of fishing effort ($m^2 \cdot h$) put into the catch, L is the effective net length (m), h is the water depth (m), and T is the fishing duration (h). Because the net height used for *A. chinensis* fishing is higher than the fishing sea depth, it is more reasonable to set h as the water depth when estimating fishing effort.

(6) Analysis of fishing intensity

Using the kernel function (Equation (4)) to analyze the fishing effort of each net can visually reflect the distribution of the *A. chinensis* fishing intensity in the sea area.

$$\boldsymbol{D} = \frac{3\left(1 - Scale^2\right)^2}{\pi r^2} \tag{4}$$

In Equation (4), r is the search radius of the nuclear analysis of the fishing effort, and *Scale* is the ratio of the distance from the raster center point to the net position point to the finding radius. In this study, the r and grid resolution were set to 3000 m and 10 m, respectively.

Parts (2) to (6) were processed using ArcGIS 10.8.

3. Results

3.1. Effects of the Neural Networks

Neural network 1 (based on the speed and positioning time, with 98.56% accuracy) performed better in identifying the position states of the vessels than neural network 2 (based on the heading and positioning time, with 51.44% accuracy) (Tables 2 and 3). The identification accuracy of casting, hauling, and sailing states based on neural network 1 were 98.33%, 100.00%, and 97.33%, respectively. In contrast, the identification accuracy states based on neural network 2 were significantly lower, at 67.00%, 41.00%, and 46.33%, respectively.

Table 2. Identified results of vessel states using the back-propagation natural work based on the speed and positioning time data.

Actual States	Number of Samples	Predicted States			Correct Percentage
		Casting	Hauling	Sailing	
Casting	300	295	3	2	98.33%
Hauling	300	0	300	0	100.00%
Sailing	300	8	0	292	97.33%
Total	-	-	-	-	98.56%

Table 3. Identified results of vessel states using the BP natural work based on the heading and positioning time data.

Actual States	Number of Samples	Predicted States			Correct Percentage
		Casting	Hauling	Sailing	
Casting	300	201	23	76	67.00%
Hauling	300	115	123	62	41.00%
Sailing	300	117	44	139	46.33%
Total	-	-	-	-	51.44%

3.2. Characteristics of Fishing Behaviors

The trained neural network, based on speed and positioning time, was used to identify the states of all vessels and detect the characteristics of fishing behavior. The results showed significant differences in the speed of vessels in different states ($p < 0.01$) (Table 4). Among them, the sailing speed was the highest at 8–12 knots. The casting speed was 4.5–7.5 knots, and the hauling speed was 0.5–2.5 knots (Figure 4).

There were also significant differences in the positioning time of the vessels in the different states ($p < 0.05$) (Table 5). The VMS data in the casting state were mainly between 4:00 a.m. and 5:00 p.m. during the TACs project (Figure 5). The hauling state occurred after the casting and waiting states and was mostly distributed from 6:00 a.m. to 10:00 p.m. daily. The duration of each fishing event was the time lag when the vessels were in hauling and casting states or corresponded to the highest value of their normal distribution probability density. Therefore, it was 2.5–3.5 h (Table 5 and Figure 5).

Table 4. Multiple comparisons of vessel speeds in different states based on a one-way analysis of variance.

Vessel States	Contrast States	Average Difference	Standard Error	Significance	99% Confidence Interval	
					Lower Limit	Upper Limit
casting	hauling	4.75 **	0.03	0.00	4.66	4.84
	sailing	−2.84 **	0.03	0.00	−2.93	−2.75
hauling	casting	−4.75 **	0.03	0.00	−4.84	−4.66
	sailing	−7.59 **	0.03	0.00	−7.68	−7.50
sailing	casting	2.84 **	0.03	0.00	2.75	2.93
	hauling	7.59 **	0.03	0.00	7.50	7.68

"**" indicate that the correlations were significant at the 0.01 levels.

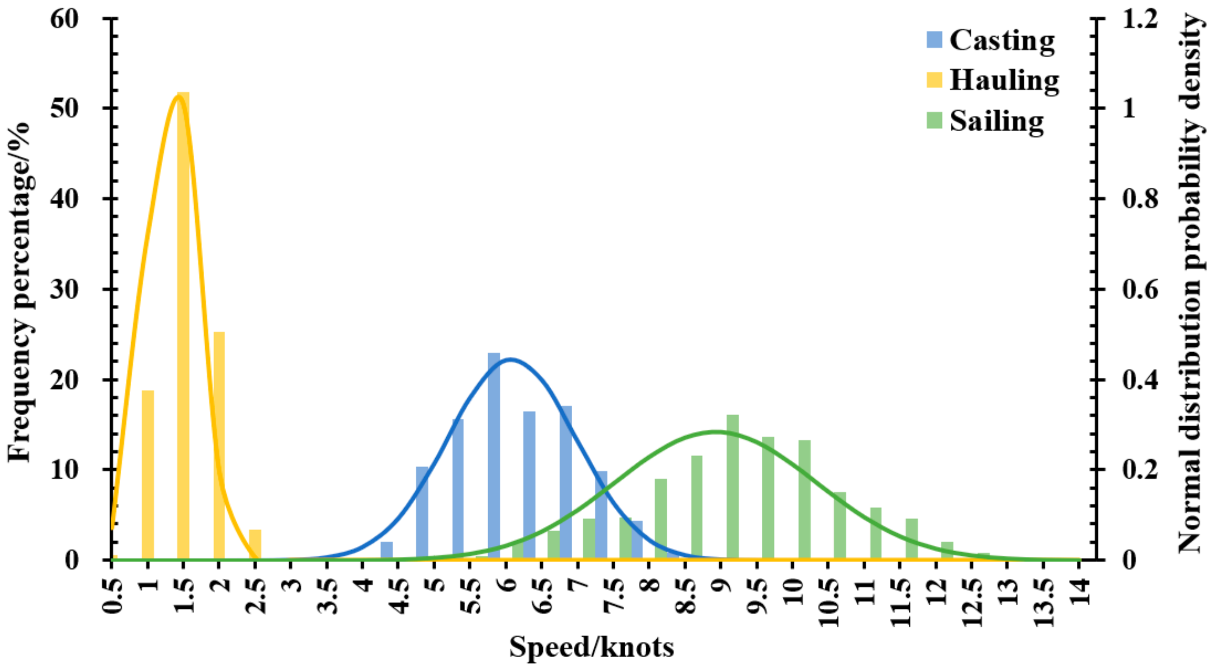

Figure 4. Speeds and frequency percentages of all vessels in different states.

Table 5. Multiple comparisons of positioning time of vessels in different states based on a one-way analysis of variance.

Vessel States	Contrast States	Average Difference	Standard Error	Significance	99% Confidence Interval	
					Lower Limit	Upper Limit
casting	hauling	−2.98 **	0.16	0.00	−3.44	−2.52
	sailing	−3.38 **	0.16	0.00	−3.84	−2.92
hauling	casting	2.98 **	0.16	0.00	2.52	3.44
	sailing	−0.40 *	0.16	0.03	−0.86	0.06
sailing	casting	3.38 **	0.16	0.00	2.92	3.84
	hauling	0.40 *	0.16	0.03	−0.06	0.86

"**" and "*" indicate that the correlations were significant at the 0.01 and 0.05 levels, respectively.

We superimposed the ocean current data of the corresponding months in Haizhou Bay from the point sets with the states of the sample vessels in June and July. The results indicated that the azimuth of fishing nets for shrimp ranged from 60 to 90° or 240 to 270° (Figure 6), which was perpendicular to the current direction of Haizhou Bay (Figure 7). In the fishing stage, the trajectory positions of the vessels were distributed in a straight line, and the length of the fishing nets of each vessel was mostly between 3500 and 4500 m.

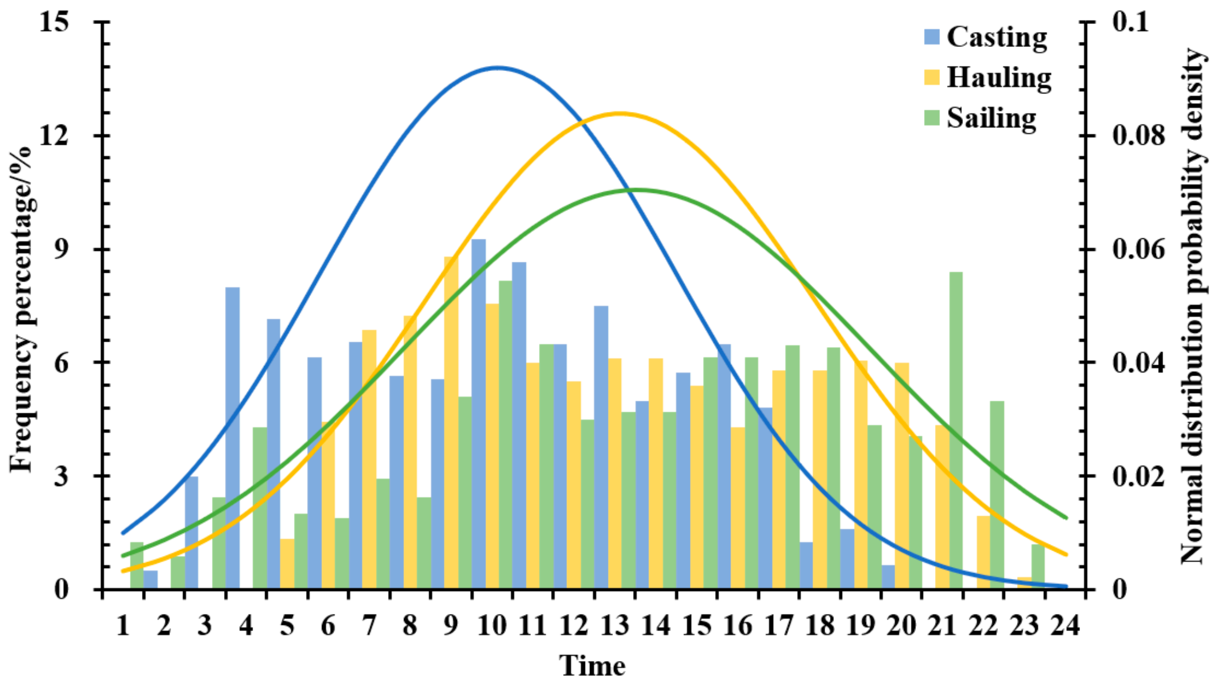

Figure 5. Positioning time and frequency percentages of all vessels in different states.

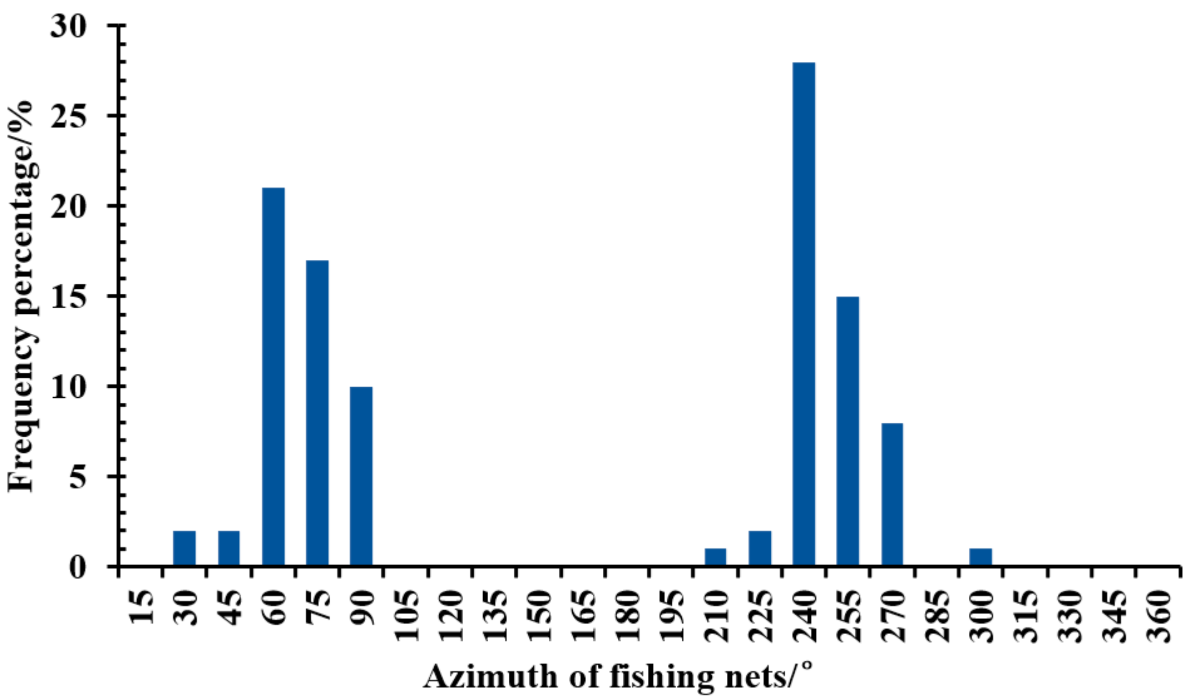

Figure 6. Azimuths and frequency percentages of fishing nets.

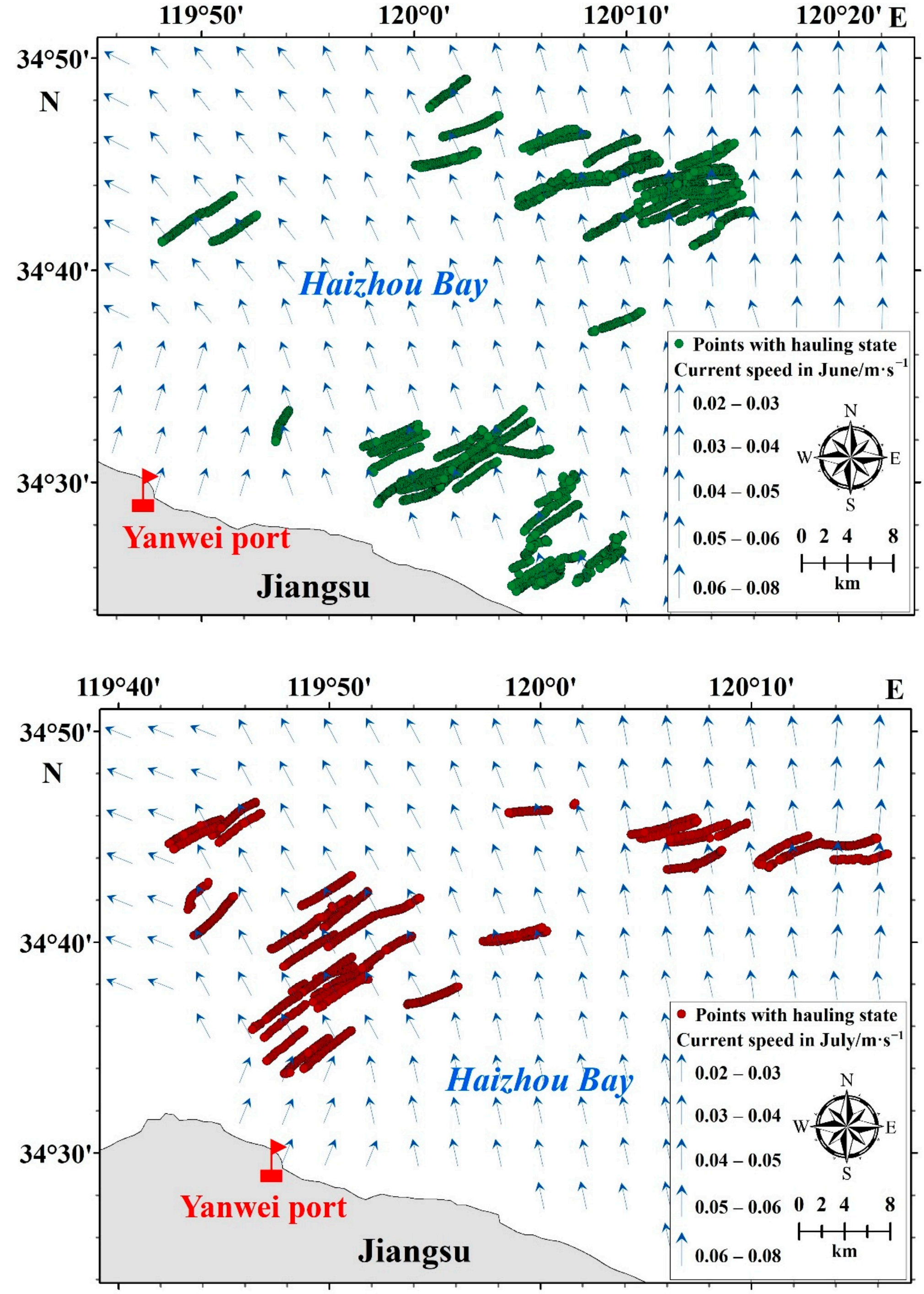

Figure 7. Distribution of the current in Haizhou Bay, Yellow Sea, showing the hauling state points by the sample vessels in June and July.

3.3. Distribution of Fishing Intensity

A kernel density analysis was performed based on the fishing efforts of all net positions. The fishing efforts of the vessels in Haizhou Bay in 2021 showed an obvious aggregated distribution pattern (Figure 8). The main core area was at 120°04′–120°16′ E, 34°42′–34°46′ N, whereas fishing intensity ranged from 120,000 to 280,000 $m^2 \cdot h/km^2$. The secondary core area was distributed from 119°46′ to 119°54′ E and 34°36′ to 34°44′ N, and the fishing intensity was 80,000–200,000 $m^2 \cdot h/km^2$.

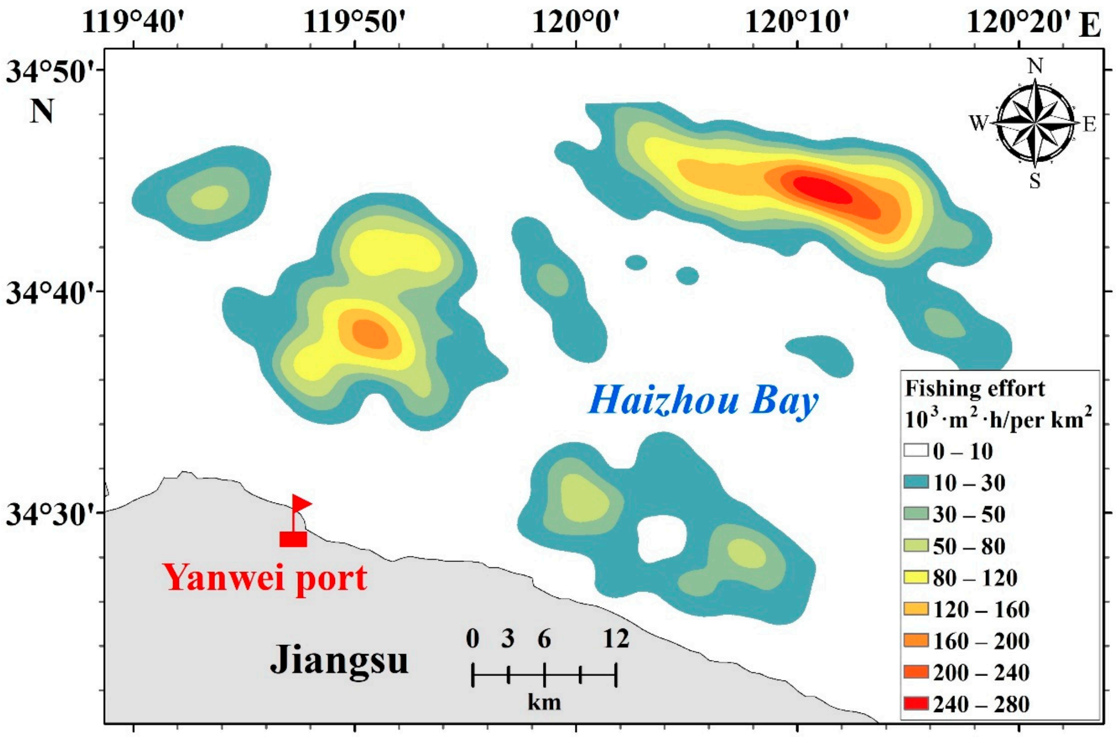

Figure 8. Distribution of fishing intensity during the total allowable catch system (TACs) project in Haizhou Bay, Yellow Sea.

4. Discussion

Vessel monitoring systems and fishing logs effectively monitor and quantify fishing activities. The two data sets are complementary, and combining them has important implications for marine spatial planning and biodiversity conservation [28]. VMStools is a common open-source software for processing, analyzing, and visualizing fishing logs and VMS data [29]. It has some functional modules, such as fishing activity identification and vessel trajectory interpolation and reconstruction, which are widely used for estimating fishing efforts by vessels and assessing the impact of fishing activities on ecosystems [30,31]. VMStools uses two standardized data formats, EFLALO (EU logbook data) and TACSAT (the VMS positions). Based on the vessel ID and voyage number, it matches the fishing log data to the corresponding VMS data for reconstructing the fishing vessel trajectory and analyzing fishing activities. Besides the limited input data format, the tool depends heavily on the completeness of the VMS data and the fishing logs and the ability to merge these data successfully and to estimate real fishing activity [29]. This study adopted another method based on matching the BeiDou VMS data of a small number of sample vessels with their fishing logs. First, we marked the real vessel state of each trajectory point of the sample vessels and then trained and verified the neural network model with a high identification accuracy. Finally, we used the model to identify the states of the non-sample vessels. The method of this study only needed to ensure the quality of the fishing logs of the sample vessels. There was no requirement for the quantity and integrity of the fishing logs of the non-sample vessels, which was perfectly applicable to the situation where the authenticity and timeliness of China's fishing logs could not be fully ensured [15]. However, it is best used for fishing activities with similar operating habits by fishing vessels because, in this case, the characteristics of fishing behavior extracted from sample vessels are more suitable for identifying fishing activities by non-sample vessels. In addition, if the trajectory reconstruction does not accurately capture the true path of a fishing vessel, it will lead to greater under- or overestimation of the fishing effort of the vessel [30]. The BeiDou VMS data have a temporal resolution of 3 min and a spatial resolution of approximately 10 m. Compared with that of other VMS data [32,33], the extremely high spatial and temporal resolution of the BeiDou VMS data enabled this study to accurately evaluate the spatiotemporal distribution of fishing activities without the trajectory interpolation or reconstruction. Moreover, based on the BeiDou VMS data of the vessels of different fishing operation types, its temporal and spatial resolution could be reduced artificially to the same as other VMS data. We could use the original Beidou VMS data with high spatial and temporal resolution as a validation set, and we could train and test to obtain the trajectory interpolation or reconstruction models, which were suitable for other VMS data of the vessels with the corresponding fishing operation type, thereby effectively improving the spatiotemporal resolution and applicability of other VMS data.

Different types of operating nets refer to different elements for identifying vessel states. At present, there are two major methods to identify the states based on VMS data: the first one is to judge the state by analyzing the changes in vessel speed. However, Lee et al. [4] performed statistics on the speed identification thresholds of the fishing state in different studies and found that no speed threshold was suitable for all vessel state identifications. Meanwhile, Bertrand et al. [32] noted that simply identifying the vessel state by the speed threshold would overestimate the number of vessel positions in the fishing state. The second method is to judge the vessel state by analyzing characteristic data, such as vessel speed and heading, to form a vector. Russo et al. [34] used the speed, heading, operation depth, and other vessel factors to discriminate the types of operating nets with the help of a neural network. They found that some factors, such as speed and heading, significantly impacted the discrimination results, which were more sensitive to the distinction of different nets, because they could better reflect fishing behaviors. *A. chinensis* stow nets are quite different from other stow nets and trawl in their structure and operation, which is an exclusive net for shrimp fishing. In this study, artificial neural networks were used to identify the position state of the vessels based on speed and positioning time or heading and positioning time, and the more similar these elements of fishing behavior of fishers, the higher the identification accuracy of vessel states based on them. The results showed that the artificial neural network based on speed and positioning time could identify the position states of the vessels, verifying the high degree of similarity in fishers' operation habits [23,24]. In contrast, the accuracy of identifying the states based on heading and positioning time was significantly lower (Tables 2 and 3) because there were significant differences in the speed characteristics of the vessels when fishing for shrimp (Table 4). Moreover, through the verification of the actual operation of the vessel at sea, it was found that the lower the speed of the fishing vessel, the greater the influence of the tidal current on its heading data, which means that there was no significant difference in the heading characteristics of different vessel states. Therefore, the heading of the vessel could not be used as a reference element for the neural network model to identify the vessel's state.

Fishing behaviors were related to the biological characteristics of *A. chinensis*, fishing characteristics of nets, management of fishing policy, and the state of the marine environment. In spring, *A. chinensis* migrates to shallow coastal waters for food and fattening as the water temperature of the coastal water rises. The shrimp gonads mature in May, whereafter they spawn and breed in low-salt coastal waters. Hereafter, some of the parent shrimp die naturally, while the juveniles are distributed in the coastal waters for feeding and growth [35,36]. During the fishing moratorium in China, a special fishing period for *A. chinensis* was set from 15 June to 15 July to protect and utilize shrimp resources scientifically. In terms of speed characteristics, there were obvious differences in the vessel speeds in different states (Figure 4). The vessel speed was the highest when departing from the port or exploring to maximize fishing time and production during the TACs project. In addition, the speeds of vessels in the same state were also slightly different and were mainly determined by the marine environmental conditions, such as current speed and wind speed and the quantity of catch in the fishing nets. In terms of positioning time characteristics, the set of VMS points with a casting state appeared at 4:00 a.m. and ended at 5:00 p.m. daily. (Figure 5). Waiting for a catch occurred between the casting and hauling states. Therefore, the waiting state was mainly distributed in the daytime, which was related to the fishing characteristics of the nets and the vertical movement of the shrimp during the day and night. Under the scientific setting of the buoyancy of floats and the gravity of sinkers and nets, combined with the impact of the ocean current, the mouths of the nets were mainly suspended above the sea bottom. At midnight, *A. chinensis* gradually migrated to the bottom of the sea [37]. Therefore, the occurrence times of casting and hauling were closely related to the fishing time of *A. chinensis* (i.e., the state of waiting for the catch) in the daytime. In addition, the duration of each fishing excursion was 2.5–3.5 h, significantly shorter than that of other stow nets [38]. The shrimp were rushed into the nets with the current, and escaping was difficult. Waiting too long for the catch would cause the shrimp to be compacted, decreasing the catch quality. The economic value of processed products obtained from fresh shrimp is extremely high (400–800 RMB/kg). Therefore, fishers have set a short waiting duration for fishing to pursue the high economic value of fresh-quality shrimp. Through the spatial visualization of the point sets with the hauling state and the ocean current data of Haizhou Bay, it was found that the azimuth of fishing nets were mainly in a perpendicular state with the current direction of the bay (Figure 7) because of the swimming ability of the shrimp and fishing characteristics of the nets. Haizhou Bay is affected by the coastal currents of southern Shandong, northern Jiangsu, and the Yellow Sea Warm Current. The current in this sea area is relatively rapid [39]. *A. chinensis* is a small planktonic shrimp, whose autonomous swimming ability is weak and is classified as drifting [37]. The *A. chinensis* stow net mainly relies on ocean currents to carry shrimp into the nets. By arranging the azimuth of the net and the direction of the current in a perpendicular state, it is difficult for shrimp to escape from the nets due to the continuous impact of the current. Therefore, the purpose of fishing for *A. chinensis* is achieved.

The results of fishing intensity estimated using different measurement methods and grid resolutions have been different, and it is desirable to analyze fishing intensity at the finest resolution possible [30]. In this study, the net positions were used to represent the fishing positions of the vessels. The Kernel density analysis was performed to analyze the fishing effort of each net position at a high resolution of 10 m to obtain the distribution of fishing intensity for *A. chinensis*. Compared with the traditional method of obtaining fishing intensity by directly calculating the total fishing efforts in the fishing area at different resolutions [40], the kernel density analysis considered the spatial relationship between the fishing nets of the vessels. The fishing effort for shrimp in the Yellow Sea in 2021 showed a clear aggregated distribution pattern. Due to the economic cooperation between the fishers and the timeliness of the data feedback on the catch of *A. chinensis* in each net, a larger number of fishing vessels are generally gathered for coordinated fishing in waters with a high production. Therefore, the fishing effort distribution of all the vessels represents the spatial distribution of the shrimp resource to some extent. This verifies the biological characteristics of *A. chinensis* spawning in shallow coastal waters during early summer [36].

Detecting the characteristics of fishing behavior and intensity could provide an important basis for managing the TACs project and exploring the *A. chinensis* resource distribution. Scientific fishing measures, such as strictly controlling the number of nets carried by each vessel and delimiting the fishing area for *A. chinensis* [41], have been established for the sustainable development of shrimp and other resources. Moreover, only the fishing vessels with fishing licenses can participate in the fishing activities of *A. chinensis*. In this study, the fishing effort of all the vessels in the fishing area during the TACs project was extracted through the BeiDou VMS data. It is possible to check whether the vessels participating in fishing activities have obtained fishing licenses according to their ID number, which would provide direct evidence to combat IUU (Illegal, Unreported, and Unregulated) fishing activities. Furthermore, the length of the fishing nets of each vessel was mostly 3500–4500 m, which was in line with the maximum length corresponding to the regulation that the number of nets carried by a single vessel did not exceed 25. Therefore, the maximum length of the net distribution extracted from the VMS data of each vessel could be used to check whether the number of nets held by each vessel meets the TAC regulations and then standardize the fishing behavior of each fishing vessel. In addition, the distribution of fishing intensity for *A. chinensis* was determined based on the fishing efforts of all net positions. This is vital for delimiting the fishing area for the following year. In the future, by appropriately increasing the number of sample vessels and recording the actual production of each netting of the sample vessels, which can be set as two parts of the training and the validation sets, models predicting catch volumes could be established. First, the fishing effort and corresponding catches of the fishing vessels in the training set at different temporal and spatial scales can be calculated to explore the resource abundances of *A. chinensis*. Then, some predicted productions of the fishing vessels in the validation set can be estimated by calculating these resource abundances and their fishing efforts at different temporal and spatial scales. Finally, these predicted productions from the validation set can be compared with the actual productions, and the prediction model with the smallest overall error will be selected. This idea is an important method for rectifying the reported catch of each vessel and controlling the total fishing quota for that year. It also provides a scientific basis for setting the number of vessels allowed to fish, the upper limit of the annual catch of *A. chinensis*, and the quotas given to each vessel for the next year. Based on the spatiotemporal distribution of all the vessel productions, the relationship between the distribution of *A. chinensis* resources and marine environmental elements (including water temperature, salinity, and chlorophyll-a concentration) could be explored for accurately forecasting the fishing grounds and periods of *A. chinensis* in further studies.

5. Conclusions

By combining the VMS data with the fishing logs from three sample vessels during the TACs project for *A. chinensis* in the Yellow Sea, a high-accuracy artificial neural network for identifying the position states of the vessels fishing shrimp was trained, verified, and obtained. Then, the fishing activities of all vessels, such as net positions, azimuths, and fishing efforts, were characterized. This study is the first application of BeiDou VMS data and artificial neural networks to manage TACs projects. This objectively reflects the distribution characteristics of species resources based on the distribution of fishing intensity. With the advent of the big data era, machine learning, as a science of artificial intelligence, should closely follow the massive and diversified characteristics of big data and mine valuable information from the data to provide a basis for fishery management. Taking this study as a case, the combination of big data mining and machine learning can be used as an effective method to control elements in international TACs projects and to track the spatiotemporal distribution of marine species in the future.

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