Heliyon 10 (2024) e33298

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Quantifying the spatial nonstationary response of environmental factors on purse seine tuna vessel fishing

Wei Wang [a,c,d], Wei Fan [c,d], Yumei Wu [c,d], Shengmao Zhang [b,c,d], Weifeng Zhou [c,d], Xiumei Fan [c,d], Jiashu Shi [e], Weiguo Jin [f], Guolai Wang [f], Shenglong Yang [c,d,*]

[a] *College of Information, Shanghai Ocean University, Shanghai, 201306, China*
[b] *Laoshan Laboratory, Qingdao, 266237, China*
[c] *Key Laboratory of East China Sea & Oceanic Fishery Resources Exploitation and Utilization, Ministry of Agriculture, East China Sea Fisheries Research Institute, Chinese Academy of Fishery Sciences, Shanghai, 200090, China*
[d] *Key and Open Laboratory of Remote Sensing Information Technology in Fishing Resources, Chinese Academy of Fishery Sciences, Shanghai, 200090, China*
[e] *School of Navigation and Naval Architecture, Dalian Ocean University, Dalian, 116023, China*
[f] *Shanghai Kaichuang Deep Sea Fisheries Co., Ltd., Shanghai, 200131, China*

ARTICLE INFO

Keywords:
Tuna
Western and Central Pacific Ocean
Fishing effort
GWR
Spatial distribution
Spatial heterogeneity

ABSTRACT

To investigate the spatial and temporal patterns of environmental factors influencing the activity of purse seine tuna fishing vessels, data on fishing efforts of purse seine tuna fleets and environmental factors in the Western and Central Pacific Ocean (WCPO) from 2015 to 2020 were utilized to develop a geographically weighted regression (GWR) model. The results showed that fishing activity was primarily concentrated in the area between 140°E and 175°W, and between 10°S and 5°N. The GWR model showed excellent fitting performance and was suitable for correlation analysis. The environmental factors had a significant spatially heterogeneous effect on the fishing activity of purse seine tuna fishing vessels. The sea surface temperature, primary productivity at 200 m depth, and dissolved oxygen below the surface had the greatest spatially heterogeneous effect and are important environmental variables influencing the activity of purse seine tuna vessels in the WCPO. This study provides new methods for exploring the spatial distribution of fishing vessel activity to support science-based conservation and management.

1. Introduction

Tuna is one of the most commercially valuable fishes worldwide. The Western and Central Pacific Ocean (WCPO) is the most extensive operating area worldwide for tuna purse seine fishing, accounting for a catch of 2.49 million tonnes of tuna and related species in 2021, representing 56 % of the total global marine catch. Tuna purse seine fisheries dominate here [1]. Climate and marine environmental changes influence fish population abundance, community structure succession, and marine ecosystems, predominantly through their physical impacts on marine species, subsequently affecting fisheries resource management [2–4]. The fisheries management policy aims to ensure the sustainable development and exploitation of fisheries resources by influencing the spatial fishing behavior of fishing vessels [5]. Understanding how marine environmental variables affect the spatial distribution tuna purse seine

* Corresponding author. Key Laboratory of East China Sea & Oceanic Fishery Resources Exploitation and Utilization, Ministry of Agriculture, East China Sea Fisheries Research Institute, Chinese Academy of Fishery Sciences, Shanghai, 200090, China.

E-mail address: ysl6782195@126.com (S. Yang).

https://doi.org/10.1016/j.heliyon.2024.e33298
Received 11 March 2024; Received in revised form 17 June 2024; Accepted 18 June 2024
Available online 19 June 2024

fishing operations in the WCPO and monitoring, predicting, and managing current and future fishing activities can significantly improve conservation policy effectiveness under limited regulations [6].

Vessel trajectory data derived from automatic identification systems (AISs) have been widely used to extract high-resolution temporal and spatial information, assess ecological pressure on fishing grounds, and evaluate the relationship between fishing activity and the marine environment [7–11]. Previous studies have shown that the factors influencing the spatial distribution of fishing vessels are highly complex and include socioeconomic factors, fishing experience, economic costs, and marine environmental factors [11,12]. Most of the studies focused on the relationship between the spatial distribution of the fishing effort of tuna purse seine vessels and the marine environment in the WCPO based on niche model methods [13–16]. Yang et al. [15] applied the boosted regression trees (BRT) model and the generalized additive model (GAM) to establish a non-linear relationship between the spatial distribution of purse seine tuna fishing effort and marine ecological environment factors in the WCPO. Siosaia Vaihola et al. [17,18] utilized the BRT model and the GAM to explore the nonlinear relationship between the distribution of fishing effort and marine environmental factors. Yang et al. [16] reported that purse seine tuna fishing activity is influenced by four important environmental factors according to the maximum entropy model (MaxEnt). Hsu et al. [14] created the habitat suitability index (HSI) model using the fishing activity location and vertical environmental variables to predict fishing grounds. These studies collectively indicate a strong correlation between fishing effort and the marine environment. The above ecological niche models assumed that the influence of environmental variables on species distribution was constant, i.e., assumed spatial stationarity or homogeneity among variables [19]. However, at a large spatial scale, spatial stationarity is not always present, especially in marine ecosystems. The spatial variation in the relationship between fishing vessel operations and environmental variables makes spatial non-stationarity more likely than spatial stationarity [20]. Moreover, with the passage of time, the influence of environmental factors on fish activity may also change [21], leading to temporal non-stationarity in the relationship between environmental factors and fishing vessel activities.

The geographically weighted regression (GWR) model is a statistical tool for analysing relationships between geographical spatial variables. The GWR model can reveal the non-stationarity of spatial data by assuming that relationships within geographic space may vary spatially to provide more detailed and accurate spatial patterns [22]. The GWR model can reveal complex geographical phenomena and offer a profound understanding of geographical spatial data. However, the GWR model has limitations. Multicollinearity among local regression coefficients can challenge the robustness of parameter estimates and interpretations [23]. Additionally, the goodness of fit measurements require careful consideration to ensure robust spatial analysis [24]. Despite these challenges, the GWR model has been extensively applied in geography, ecology, agriculture, and other research areas [25–27], although no reports have focused on the environmental impacts of fishing activity.

In this study, spatial information on fishing intensity was adopted to represent spatial information on fishing activity. The GWR model was applied to investigate the effect of marine environmental spatial non-stationarity on purse seine tuna vessel fishing activity in the WCPO. The effects of spatial heterogeneity and the importance of each marine variable on fishing activity were discussed based on the GWR model results. The results can provide a better understanding of the spatial distribution of fishing vessel operations and their impacts and support science-based management.

2. Data and methods

2.1. Environmental data

According to previous studies [28–30], environmental factors, including temperature, sea level height, salinity, chlorophyll, dissolved oxygen, and primary productivity, influence the habitat of tuna. Purse seine tuna fishing primarily targets areas where the water depth is less than 200 m [31]. The vertical distribution of tuna correlates with the environmental conditions beneath the surface. Three-dimensional marine variables were selected for the model (Table 1). Marine environmental data were downloaded from the Copernicus website (https://data.marine.copernicus.eu/products). Previous research revealed that factors such as temperature gradient, thermocline temperature, eddy kinetic energy, sea floor depth, distance to shore, and distance to port significantly influence the formation of tuna fishing grounds [14,32]. The temperature gradient, thermocline temperature, and eddy kinetic energy were

Table 1
Summary of environmental data and description.

Abbreviation	Variable definition	Unit	Abbreviation	Variable definition	Unit
SST	Temperature	°C	Chl100	Total Chlorophyll (100 m)	mg/m-3
SSH	Sea Surface Height	m	Tem200	Temperature (200 m)	°C
SSS	Salinity	1e-03	Salt200	Salinity (200 m)	1e-03
Mld	Mixed Layer Depth	m	O2200	Dissolved Oxygen (200 m)	mmol/m-3
U	Eastwards Sea Water Velocity	m/s	Pp200	Total Primary Productivity (200 m)	mg/m-3
V	Northwards Sea Water Velocity	m/s	Chl200	Total Chlorophyll (200 m)	mg/m-3
O20	Dissolved Oxygen	mmol/m-3	DSH	Distance to Shore	km
Pp0	Total Primary Productivity	mg/m-3	DPT	Distance to Port	km
Chl0	Total Chlorophyll	mg/m-3	Depth	Sea Floor Depth	m
Tem100	Temperature (100 m)	°C	SSTf	Sea Surface Temperature Front	°C
Salt100	Salinity (100 m)	1e-03	Therm	Temperature of the Thermocline	°C
O2100	Dissolved Oxygen (100 m)	mmol/m-3	EKE	Eddy Kinetic Energy	J
Pp100	Total Primary Productivity (100 m)	mg/m-3			

calculated based on the downloaded environmental product data. The sea floor depth, distance to shore, and distance to port data were obtained from Global Fishing Watch (https://globalfishingwatch.org/). The sea surface temperature front (SSTf) function adopts the marine front detection algorithm proposed by Belkin et al. [33], which is based on sea surface temperature satellite imagery. The temperature gradient magnitude at each point on the sea surface temperature image is calculated as follows:

$$SSTf = \sqrt{(Gx^2 + Gy^2)} \tag{1}$$

Fiedler et al. [34] defined the isotherm representing the thermocline as the thermocline temperature:

$$\begin{aligned} Therm &= T(mld) - 0.25[T(mld) - tem400], \\ T(mld) &= tem - 0.8 \end{aligned} \tag{2}$$

where T(mld) is the temperature of the mixed layer depth, tem is the sea surface temperature, and $tem400$ is the temperature at 400 m depth.

Pratt et al. [35] defined eddy kinetic energy (EKE) using the current velocity components u and v:

$$EKE = \frac{u^2 + v^2}{2} \tag{3}$$

The environmental data had a 0.5° × 0.5° spatial resolution and monthly temporal resolution. The spatial coverage of the data ranged from 130°E to 150°W and from 15°S to 10°N. The temporal coverage spans from January 2015 to December 2020.

2.2. Fishing effort data

The AIS-based fishing effort information was obtained from Global Fishing Watch (https://globalfishingwatch.org/). This dataset offers information on global maritime transit and fishing operation times for vessels from 2000 to 2020. The data included the date, longitude, latitude, MMSI, transit time, and fishing time. The spatial resolution was 0.1°.

The fishing effort of purse seine tuna vessels in the WCPO from 2015 to 2020 was selected for this study. A total of 337 tuna purse seiners belonging to 24 countries and regions operated during this period (Table 2). Among all vessels, mainland America had the most vessels (44), followed by South Korea (35).

Fishing vessel activity includes transitioning, searching for fish, and fishing operations. For the tuna purse seine set, fishing operations are defined as the time the net is closed around the fish to the end of the fish baiting operation when the net is lifted out of the water, omitting searching time. The calculation of fishing effort for purse seine tuna vessels involves quantifying the time spent during purse seine operations. During this time, the fishing vessels maintain a relatively stationary state, and changes in the operational area are minimal. Fishing effort is not influenced by searching patterns (FAD school and free school) and target species.

The vast majority of these vessels were concentrated in the length range of 40–90 m, with the most numerous segments being those between 60 and 80 m (Fig. 1). The tonnage of most vessels was clustered in the lower ranges, indicating the widespread prevalence and advantage of small and medium-sized vessels in global fishing activities (Fig. 2).

In the WCPO, the total number of fishing vessels with AIS recorded information was the lowest in 2015 and peaked in 2019 (Fig. 3). There was little variation in the total number of fishing vessels in other years. The number of fishing vessels with AIS recorded information each month showed little variation.

The fishing effort data mainly span both sides of the equator. The vessel operation position was mainly located in the region (130°-210°E; 20°S-20°N); therefore, we defined (130°-210°E; 20°S-20°N) as the study area. To align with the environmental data, the spatial resolution of the fishing effort data was converted to 0.5° × 0.5°. The data from 2015 to 2019 were used as the training set for the model. To ensure the data matched the model, the environmental data and fishing effort data from 2015 to 2019 were temporally averaged.

2.3. Selection of environmental factors

Multicollinearity within marine variables may result in overfitting and instability of the model. The variance inflation factor (VIF) was used to examine multicollinearity. Variables with VIF values greater than 10 were progressively removed. Finally, the SST, SSS,

Table 2
Total number of fishing vessels per country or region.

Country	Num	Country	Num	Country	Num
USA	44	KIR	14	NZL	2
KOR	35	NRU	14	SLV	2
JPN	34	MHL	13	TUV	2
TWN	34	VUT	7	COK	1
PNG	33	ECU	5	IDN	1
PHL	29	SLB	5	MEX	1
FSM	26	COL	2	PAN	1
CHN	23	ESP	2	UNK	1

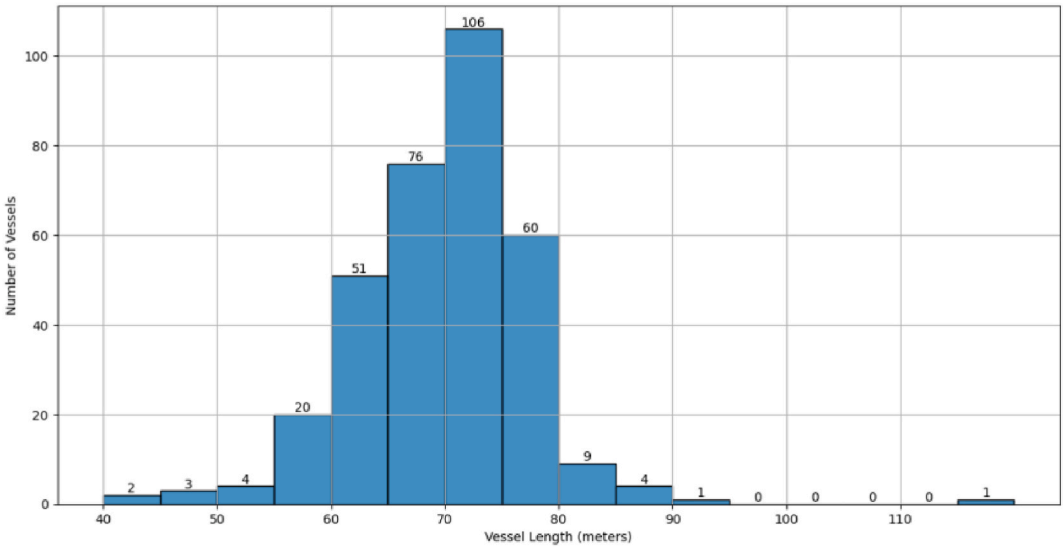


Fig. 1. Summary of length information for purse seine tuna vessels.

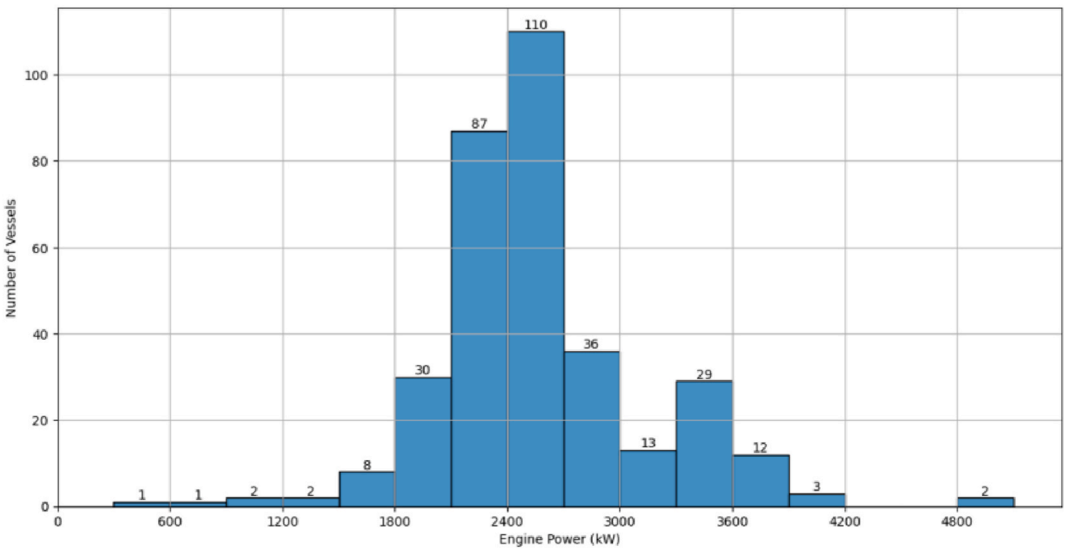


Fig. 2. Summary of power information for purse seine tuna vessels.

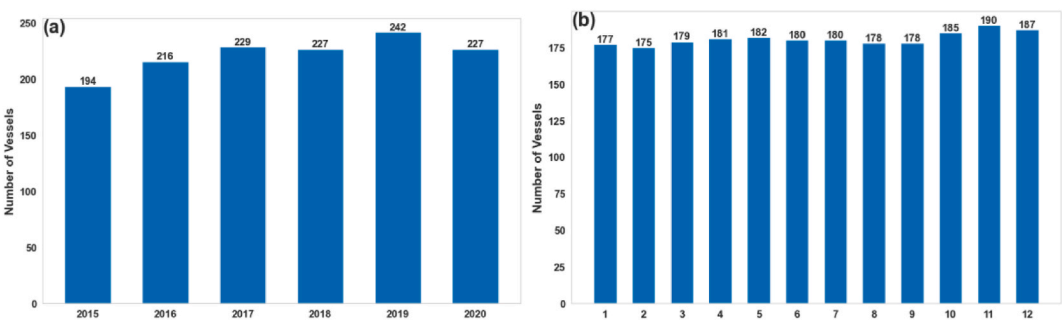


Fig. 3. (a) Number of fishing vessels each year from 2015 to 2020. (b) Average number of fishing vessels per month from 2015 to 2020.

Mld, SSTf, EKE, U, V, Salt200, Chl200, O20, O2100, O2200, Pp0, Pp100, and Pp200 variables were retained (Table 3). The Pearson correlation coefficients of the retained variables were calculated to examine the pairwise correlations (Fig. 4). SST and Salt200, Salt200 and Chl200, as well as Chl200 and Pp200, exhibited strong positive correlations. A few other variables showed moderate correlations, while most variables had low correlations with each other. Additionally, the Depth, DPT, and DSH variables were also retained.

2.4. Model and methods

Geographically weighted regression (GWR) is a method of geographic data analysis adept at addressing issues related to spatial heterogeneity present within spatial data. The GWR model is generally formulated as follows [36]:

$$y_i = \beta_0(u_i, v_i) + \sum_{m=1}^{p} \beta_m(u_i, v_i) x_{im} + \varepsilon_i \tag{4}$$

In the formula, $\beta_0(u_i, v_i)$ is the intercept term, x_{im} is the m-th independent variable of the *i*-th sample point $(i = 1, 2, \ldots n)$, y_i is the dependent variable of the *i*-th sample point, (u_i, v_i) are the coordinates of the *i*-th sample point within the study area (usually using longitude and latitude), $\beta_m(u_i, v_i)$ is the regression coefficient of the m-th variable of the *i*-th sample point, and ε_i represents the residuals from model fitting.

The validation of the model was performed using the corrected Akaike information criterion (AICc) [37], the coefficient of determination R^2 [38], and the adjusted R^2. A lower AICc value coupled with R^2 and adjusted R^2 values near 1 indicate a more proficient fit of the model. The implementation of the GWR method was facilitated using MGWR 2.2 software.

3. Results

3.1. Spatial distribution of fishing effort

The fishing effort of purse seine tuna vessels in the WCPO region gradually increased from 2015 to 2017, peaking in 2017 (Fig. 5). From 2017 to 2020, there was a slight decline in fishing effort. Throughout these six years, fishing effort primarily focused on the region spanning 140°E to 175°W longitude and 10°S to 5°N latitude, identifying it as the area with the highest fishing intensity (Fig. 6). The main fishing areas for the Western Pacific tuna purse seine fleet were the low-latitude exclusive economic zones near the equator. The fishing intensity was relatively lower east of 170°W, north of 5°N, and south of 10°S. There was a slight westwards shift in the areas with high fishing intensity.

3.2. Model parameter results

The GWR model exhibited an AICc of 6917.446, an R^2 of 0.886, and an adjusted R^2 of 0.842. Overall, the GWR model demonstrated good performance. Superior performance was observed in the region from 10°S to 7°N and 150°E to 180°W (Fig. 7). The general model R^2 exceeded 0.729 in the region and was mostly greater than 0.816. An inferior performance of the GWR model was observed only in the region from 6°N to 10°N and 170°E to 180°W, where the overall R^2 was less than 0.212. The region east of 160°W exhibited relatively poor model performance, with R^2 values ranging from 0.212 to 0.599.

3.3. GWR model results

A descriptive analysis of the geographically weighted regression coefficients for various marine environmental parameters is shown in Table 4. SST had the highest absolute mean value of 7.36, followed by Pp200, with an absolute mean value of 5.538. The absolute mean values of the other variables were all less than 2. Similarly, SST had the highest standard deviation of 16.57, followed by Pp200, with a standard deviation of 11.149. The standard deviation values of the other variables were all less than 4. A large absolute mean and standard deviation indicate high importance and spatial heterogeneity.

Table 3
Variance inflation factor for the selected variables.

Variable	VIF	Variable	VIF
Chl200	7.440	Pp100	3.600
Pp200	7.282	Mld	3.013
SST	7.222	O2200	2.431
Salt200	5.837	SSTf	1.761
Pp0	4.356	U	1.247
O2100	4.124	EKE	1.203
O20	4.062	V	1.173
SSS	3.800		

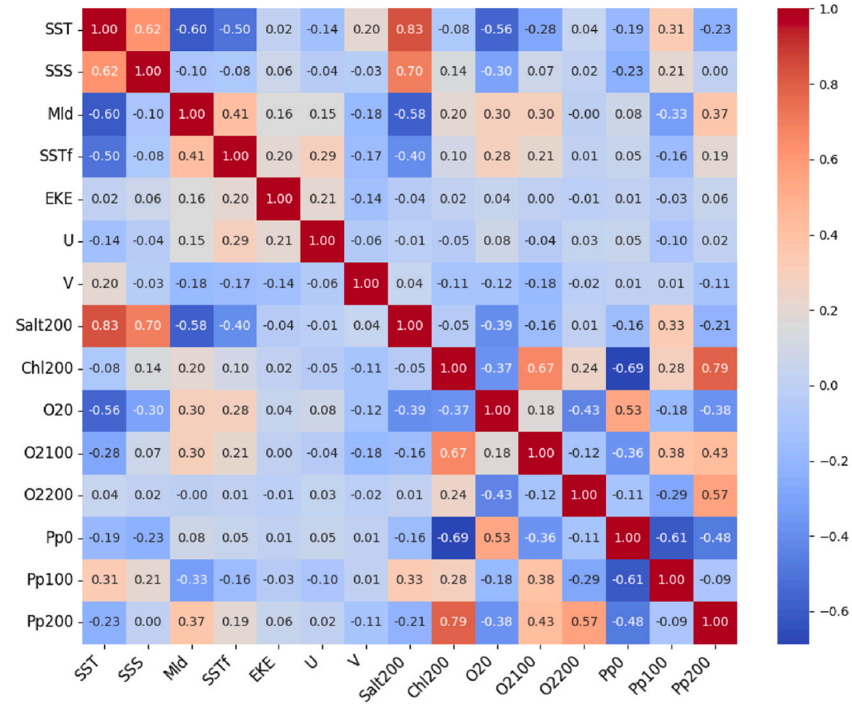


Fig. 4. Pearson correlation coefficients among the retained environmental variables.

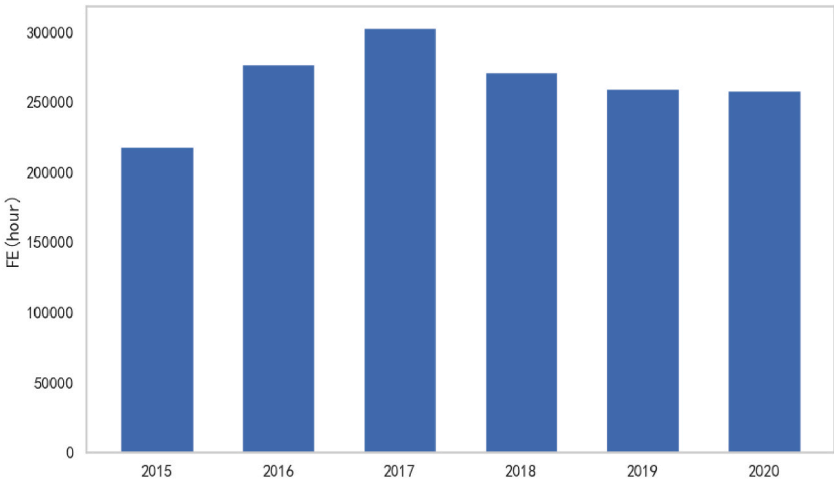


Fig. 5. Fishing effort of purse seine tuna vessels in the WCPO region from 2015 to 2020.

3.4. Analysis of spatial heterogeneity characteristics

The impact of each environmental factor on fishing activity exhibited significant spatial heterogeneity (Fig. 8, Fig. 9). The local regression coefficients of each environmental factor exhibited variations across spatial locations, indicating that a single factor influences fishing activity differently at disparate locations.

The span of local regression coefficients can signify the extent of spatial heterogeneity in the influence of various environmental factors on fishing effort [39]. The degrees of spatial heterogeneity in the influence of various environmental factors on the operations of Western and Central Pacific purse seine tuna boats are shown in Fig. 10. The spatial heterogeneity of SST was the greatest, displaying a positive effect on fishing activity in 57.6 % of the areas and a negative effect in 42.4 % of the areas. SST primarily had a positive effect on fishing activity in the region from 150°E to 170°E, 5°S to 8°N and a negative effect east of 170°W. The spatial heterogeneity of Pp200 followed that of SST, with 44.86 % of its local regression coefficients being positive and 55.14 % being negative. The region between 155°E and 170°E was predominantly negatively affected, with the maximum positive impact occurring in the area from 170°E

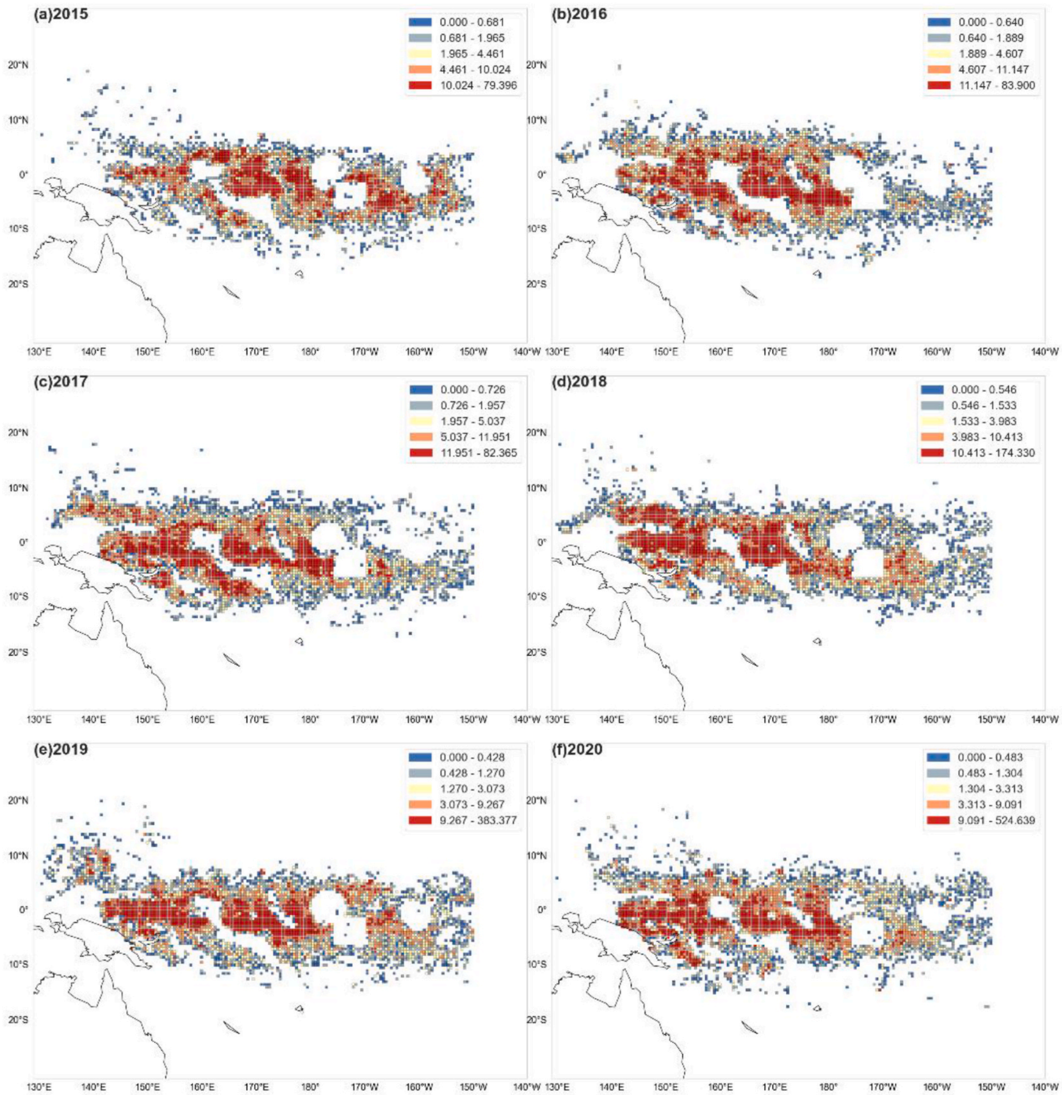


Fig. 6. (a) Spatial distribution of purse seine tuna fishing efforts in the WCPO region in 2015. (b) Spatial distribution of purse seine tuna fishing efforts in the WCPO region in 2016. (c) Spatial distribution of purse seine tuna fishing efforts in the WCPO region in 2017. (d) Spatial distribution of purse seine tuna fishing efforts in the WCPO region in 2018. (e) Spatial distribution of purse seine tuna fishing efforts in the WCPO region in 2019. (f) Spatial distribution of purse seine tuna fishing efforts in the WCPO region in 2020.

to 180°W and north of the equator.

O20, O2100, DPT, O2200, Pp100, Pp0, Chl200, Salt200, DSH, and U showed a much smaller spatially heterogeneous effects on fishing activity than did SST and Pp200, but these effects were still significant. The size of the spatially heterogeneous effects on fishing activity caused by Mld, EKE, SSS, SSTf, Depth, V, and other environmental factors were relatively small.

3.5. Key environmental factor analysis

The importance of the influence of each environmental factor on fishing activity was represented by the absolute mean value of the local regression coefficient (Fig. 11). The absolute mean value of the local regression coefficient of SST was 7.36, which suggests that SST had the most important influence on fishing activity. The SST was followed by the Pp200, and the absolute mean value of its local regression coefficient was 5.538. The absolute mean values of the local regression coefficients of O20, O2100, O2200, Chl200, Pp0, Pp100, and Salt200 ranged from 1 to 2 and these variables considerably affected fishing activity. The absolute mean values of the local regression coefficients of Mld, SSS, DPT, DSH, EKE, U, SSTf, V, and Depth were less than 1, and these variables had little influence on fishing activity. SSTf, V, and Depth had no significant impact on fishing vessel operations because their regression coefficients were less than 0.3.

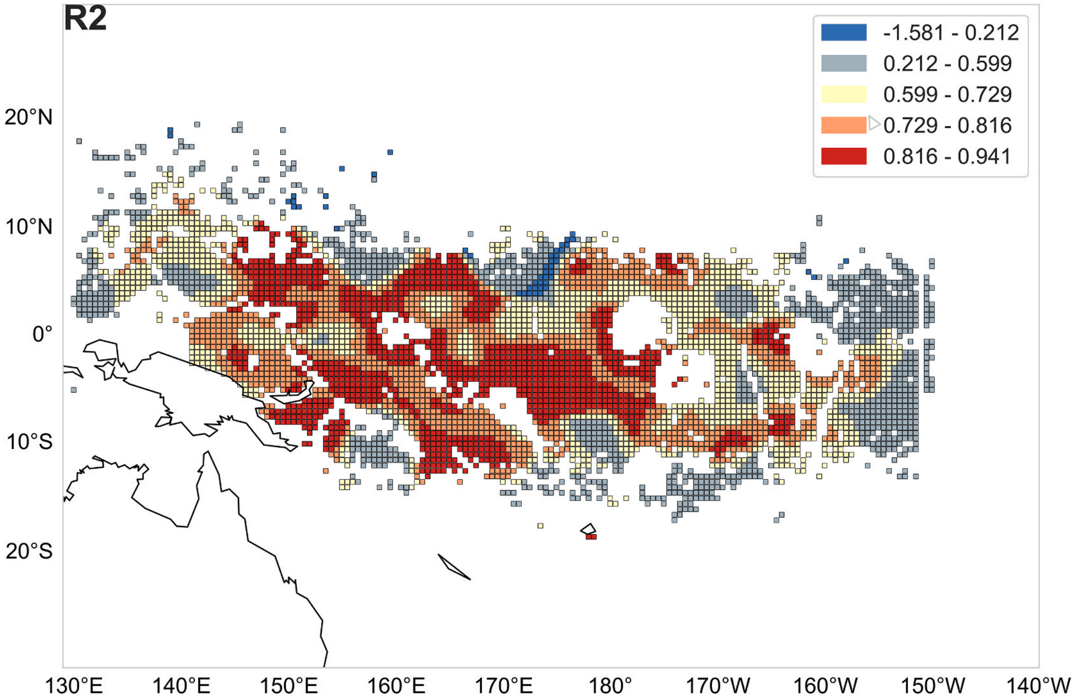


Fig. 7. Spatial distribution of the coefficient of determination (R^2) of the GWR model
Note: There are 25 location points in the figure with negative R^2 values, indicating that the model fit is poor at these points, even worse than a simple mean model (i.e., using the sample mean instead of regression predictions).

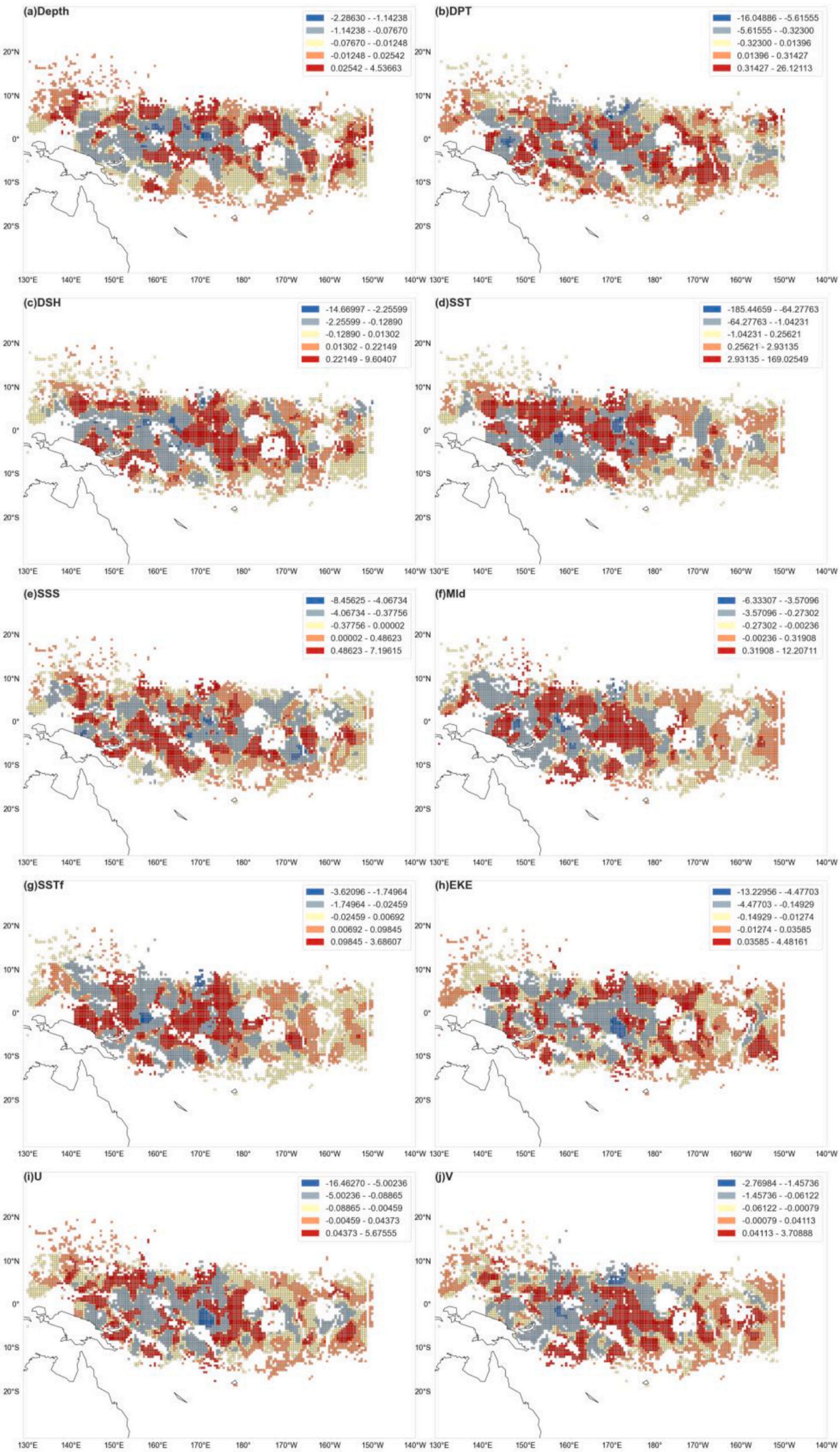
Table 4
Statistical description of the local coefficients of each environmental factor based on GWR.

Variable	Mean	Absolute mean	STD	Min	Max	Positive ratio	Negative ratio
Intercept	0.470	5.533	10.803	−58.292	114.376	45.99 %	54.01 %
Depth	−0.022	0.159	0.380	−2.286	4.537	40.39 %	59.61 %
DPT	−0.092	0.782	1.492	−16.049	26.121	52.19 %	47.81 %
DSH	0.054	0.460	0.880	−14.670	9.604	53.88 %	46.12 %
SST	0.704	7.360	16.570	−185.447	169.025	57.60 %	42.40 %
SSS	0.045	0.793	1.276	−8.456	7.196	50.00 %	50.00 %
Mld	0.114	0.827	1.471	−6.333	12.207	49.46 %	50.54 %
SSTf	0.053	0.235	0.499	−3.621	3.686	59.61 %	40.39 %
EKE	−0.178	0.330	0.941	−13.230	4.482	38.66 %	61.34 %
U	−0.137	0.309	1.040	−16.463	5.676	46.12 %	53.88 %
V	0.000	0.200	0.461	−2.770	3.709	48.93 %	51.07 %
Salt200	−0.038	1.070	1.797	−13.792	10.780	51.42 %	48.58 %
Chl200	−0.188	1.296	2.314	−13.180	14.373	46.18 %	53.82 %
O20	−0.298	1.898	3.682	−34.124	24.123	48.96 %	51.04 %
O2100	0.312	1.812	3.606	−23.232	30.566	56.64 %	43.36 %
O2200	−0.229	1.422	2.588	−13.777	20.492	47.39 %	52.61 %
Pp0	−0.245	1.289	2.180	−14.609	13.372	45.36 %	54.64 %
Pp100	0.081	1.238	2.442	−13.291	20.133	45.20 %	54.80 %
Pp200	0.080	5.538	11.149	−71.265	90.285	44.86 %	55.14 %

4. Discussion

4.1. Spatial distribution characteristics of fishing activity

In this study, we focused on fishing effort information for tuna purse-seine fleets in the WCPO. The spatial precision was set to 0.1°. Tuna purse seine vessels employ various fishing strategies at different times. The purse seine fishery operation consists of FAD schools and free schools (as well as dolphin-associated schools in the eastern Pacific). These two types of schools operate differently when it comes to locating fish schools and executing net setting. The fishing effort of tuna purse seine is defined as the time from when the net is closed around the fish to the completion of the fish is lifted out of the water. Throughout this period, the purse seine vessel remains



(caption on next page)

Fig. 8. (a) Spatial distributions of the local regression coefficients of Depth. (b) Spatial distributions of the local regression coefficients of DPT. (c) Spatial distributions of the local regression coefficients of DSH. (d) Spatial distributions of the local regression coefficients of SST. (e) Spatial distributions of the local regression coefficients of SSS. (f) Spatial distributions of the local regression coefficients of Mld. (g) Spatial distributions of the local regression coefficients of SSTf. (h) Spatial distributions of the local regression coefficients of EKE. (i) Spatial distributions of the local regression coefficients of U. (j) Spatial distributions of the local regression coefficients of V.

more or less stationary. This fishing action is similar across all purse-seine fleets, we did not account for the diverse schooling patterns in this study. Additionally, we used the total time of catching fishing, which disregards the varying sizes of different fishing vessels.

Analyses based on AIS data can reveal the spatio-temporal distribution characteristics of fisheries activities [16,40] and assess the effectiveness of fisheries management measures. Fishing effort and catch are positively correlated within a certain period [41]. Determining the scope of fisheries activities can indirectly predict the location of central fishing grounds and changes in fisheries resources. The spatial distribution of fishing vessel activities obtained in this study is similar to the spatial distribution of fisheries resources [39]. Despite some limitations associated with using AIS data, such as fishing vessels potentially turning off AIS devices in certain situations and poorly received in certain areas, which can lead to data incompleteness. According to Welch et al. [42], the practice of vessels disabling AIS is particularly prominent in areas like the Exclusive Economic Zones (EEZ) of Argentina and West African countries, as well as the Northwest Pacific region. This behavior may be linked to avoiding competition, concealing high-yield fishing grounds, or evading illegal, unreported, and unregulated (IUU) fishing activities. Nevertheless, even with these limitations, AIS data remains an effective tool for analyzing fisheries activities.

Most of the fishing activities were located within the warm pool region with relatively high seawater temperatures, wherein relatively elevated seawater temperatures craft an optimal environment conducive to the proliferation of tuna populations. However, the high-latitude regions on both sides of the equator exhibited relatively lower tuna fishing efforts. Several factors may explain this phenomenon. First, these areas are far from the land; therefore, the cost of fishing activities is relatively high. Second, the frequency of tuna aggregation in these areas is lower than that in other areas. Hence, the reduced fishing effort for tuna in these areas is driven by the combination of these two factors.

Tuna fishing activities are influenced by a combination of natural environmental changes and human-imposed management measures. In the exclusive economic zones (EEZs) of the WCPO, the legality of fishing activities hinges on the acquisition of permits and the procurement of operational days. In contrast, the high seas region of the WCPO lacks a stringent quota system; instead, the management of fishing vessels and resources is orchestrated through the establishment of marine protected areas (MPAs) and the restriction of fishing operation times. For instance, while fishing methods such as surface fishing are permitted year-round, driftwood fishing is subject to seasonal bans, specifically from July to September. Additionally, countries are required to select either April to May or November to December each year to enforce a fishing ban [43].

4.2. Importance of environmental factors

Environmental variables influence the distribution of tuna habitats. Within the realm of modern fisheries practices, the utilization of marine environmental information by ship captains to identify propitious fishing locations has emerged as a critical strategy for augmenting fishing efficiency and sustainability [44,45]. The results suggest that the SST and Pp200 are also critical environmental variables influencing the spatial distribution of tuna purse seine fishing vessel operation in the WCPO, followed by the concentration of dissolved oxygen on the sea surface and at 100 and 200 m.

The results reflect the ecological characteristics of the primary target species [13,46]. Tuna caught by purse seine tuna fishing fleets mainly swim in waters shallower than 200 m below the surface, concentrating approximately 100 m [47]. SST has important effects on the spatial and vertical distributions of tuna. In addition, high primary productivity indicates a high abundance of planktonic organisms and phytoplankton, which attract fish and other organisms, thereby increasing fishing effort. Pp0 and Pp100 had little influence on fishing effort, implying that primary productivity primarily affects fishing activities at 200 m. Tuna purse seine fleets often target small tuna, which have poor low-oxygen tolerance and thus tend to aggregate in areas with high dissolved oxygen concentrations.

These results suggest that SSTf has little influence on tuna purse seine fishing vessel activity, which contrasts with the conclusions of Hsu et al. [14]. This may be due to different time scales. Daily data were adopted by Hsu et al. [14]. Monthly data were used in this study. The SSTf provides detailed information on marine dynamics. The monthly average data smoothed the detailed information.

Tem100 was excluded from the collinearity analysis. Longitude and latitude were the input parameters of the GWR model. Therefore, the results did not include Tem100, longitude or latitude. Considering the characteristics of the model and the fact that other influencing factors were not included in the model, it is possible that the above important variables are not the sole critical factors affecting fishing effort. However, this insight provides a direction for future research in selecting key factors from a multitude of environmental variables.

4.3. Spatial heterogeneity of various factors

Biogeographic zones are natural geographic ecological units that differentiate species and productivity and hence they also strongly influence natural fluctuations of fish stocks [48] and the hierarchy of biodiversity [49]. Tuna in sub-tropical and equatorial areas of the Pacific, showed relatively restricted movements and regional fidelity [50]. The marine environmental variables in different

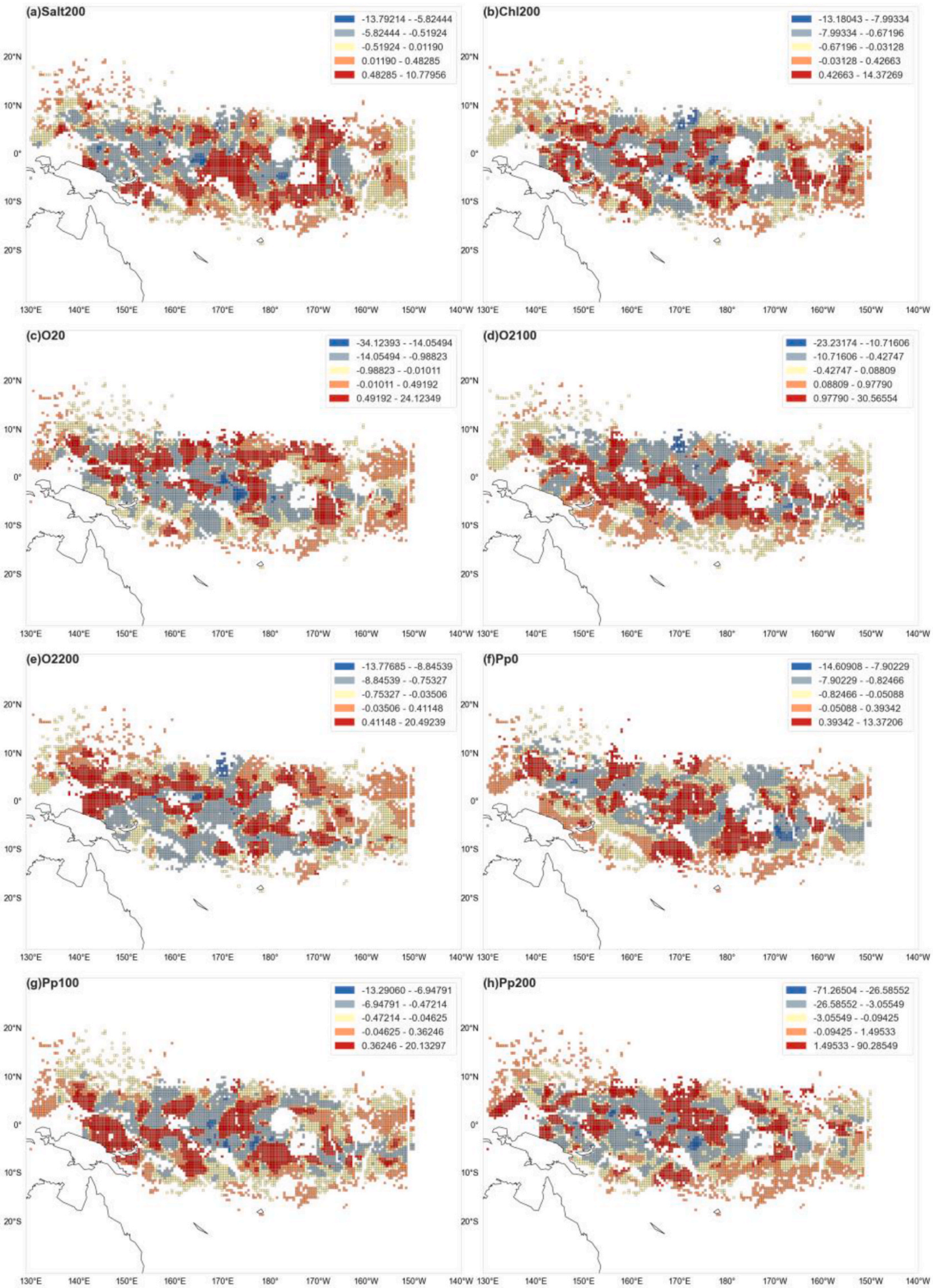


Fig. 9. (a) Spatial distributions of the local regression coefficients of Salt200. (b) Spatial distributions of the local regression coefficients of Chl200. (c) Spatial distributions of the local regression coefficients of O20. (d) Spatial distributions of the local regression coefficients of O2100. (e) Spatial distributions of the local regression coefficients of O2200. (f) Spatial distributions of the local regression coefficients of Pp0. (g) Spatial distributions of the local regression coefficients of Pp100. (h) Spatial distributions of the local regression coefficients of Pp200.

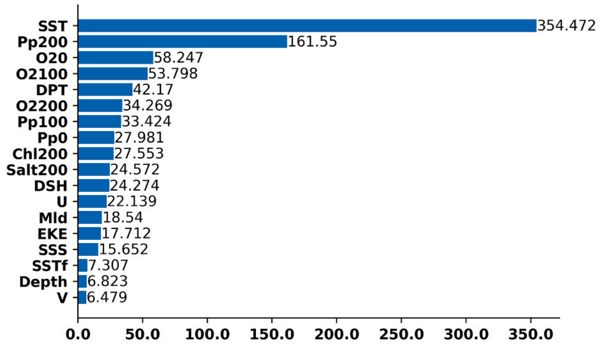


Fig. 10. Interval range of the local regression coefficients for each environmental variable.

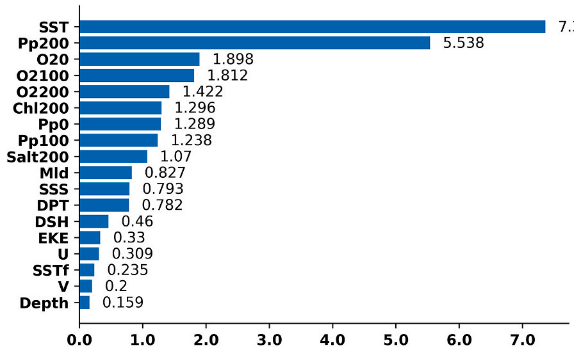


Fig. 11. Absolute mean of local regression coefficients for each environmental variable.

biogeographic zones of tuna show spatial heterogeneity. Few studies have discussed the spatial heterogeneity of marine environmental impacts on the spatial distribution of skipjack tuna (*Katsuwonus pelamis*) resources in the WCPO [39,51]. Tuna purse seine fishing vessels track and catch tuna schools. The marine environment indirectly influences the spatial distribution of fishing activity. This study confirmed that the marine environment also has spatially heterogeneous impacts on fishing activity in the WCPO. The spatial heterogeneity levels of various environmental factors differ from previous results due to different research subjects and environmental variables.

The spatial heterogeneity of sea surface temperature (SST) is the most prominent. Existing research has shown that SST plays a crucial role in the distribution of tuna fishing grounds [52]. Tang et al. have suggested that the optimal SST range for the distribution of tuna fishing grounds in the WCPO is between 28 and 30 °C [53]. Within the 140°E−180° range of the WCPO, SST generally falls within this optimal range (Fig. 12(a)), decreasing from the center towards the east and west. However, within this region, the impact of SST on purse seine fishing operations varies between the northern and southern directions: south of 5°S, SST generally has a negative impact on fishing operations, whereas north of 5°S, it has a positive impact (Fig. 8(d)). The same SST exerts spatially heterogeneous impacts on fishing activities in the north-south direction, which may be due to multiple factors influencing tuna distribution. For instance, in the 150°E−180° and 15°S-8°S regions, although SST is within the optimal range, fishing effort is relatively low (Fig. 5). This could be due to the low primary productivity (Pp200) in the 150°E−160°E and 15°S-8°S regions (Fig. 12 (c)), and the lowest dissolved oxygen concentration in the 150°E−180° and 15°S-8°S regions (Fig. 12 (b)). Even if SST is optimal, low primary productivity and low dissolved oxygen concentration lead to reduced fishing effort, resulting in a negative impact of the same SST in this region.

The spatial heterogeneity of primary productivity at a depth of 200 m (Pp200) on fishing activities is second only to that of SST. Primary productivity affects the growth of plankton, and regions with higher primary productivity are generally more conducive to tuna survival. Although the distribution of Pp200 exhibits a certain regularity, the distribution of its local regression coefficients is more complex and irregular compared to SST (Fig. 9(h)). This may be because tuna are significantly influenced by a combination of various environmental factors, leading to a chaotic distribution of Pp200's local regression coefficients.

Environmental factors such as O20, O2100, and DPT also exhibit significant spatial heterogeneity in their impact on the distribution of fishing operations. Various environmental factors collectively influence the distribution of tuna fishing grounds, resulting in spatial heterogeneity, where the same environmental factors can have different impacts in different regions.

4.4. Model analysis

This study employs the GWR model to investigate the spatio-temporal heterogeneity of the impacts of marine environmental factors

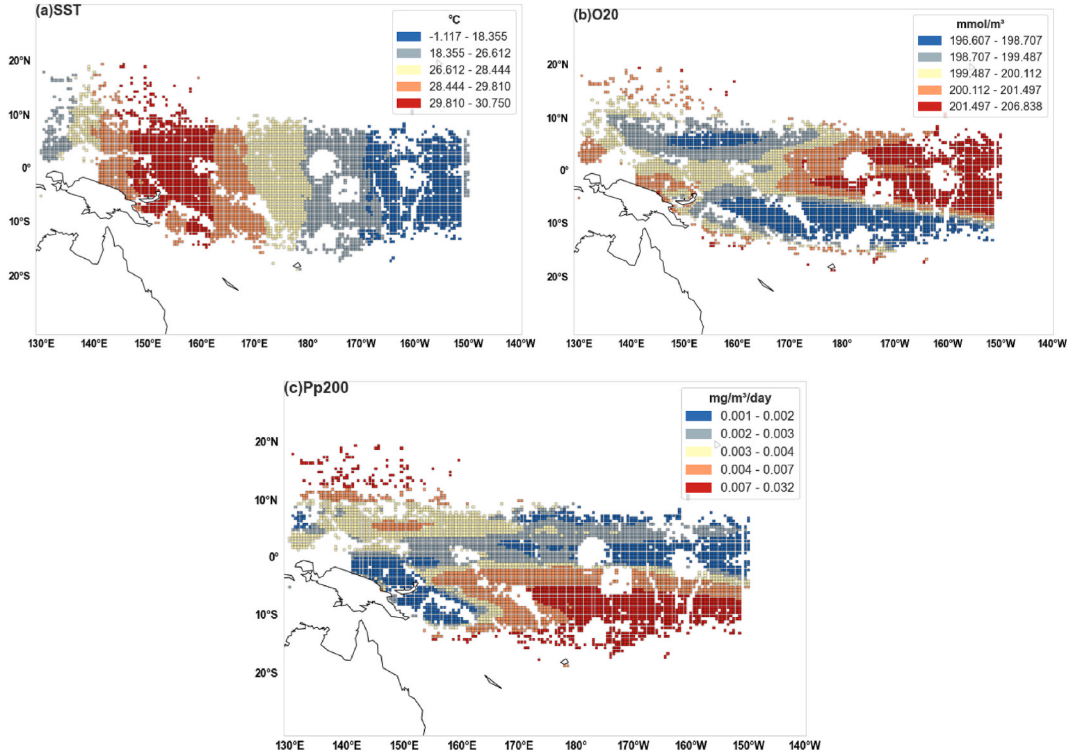


Fig. 12. (a)Average spatial distribution of SST in the WCPO region from 2015 to 2019. (b)Average spatial distribution of O20 in the WCPO region from 2015 to 2019. (c)Average spatial distribution of Pp200 in the WCPO region from 2015 to 2019.

on purse seine tuna fishing activities. The essence of the GWR model lies in the localization of parameters of the traditional regression model, allowing for independent parameters at different data points to address the spatial non-stationarity of the data. The use of the GWR model facilitates the drawing of spatial distribution maps of parameters, aiding in the intuitive understanding of the spatial heterogeneity of variables [36].

Nevertheless, the GWR model fails to account for temporal non-stationarity. Kininmonth et al.'s study found that from 2004 to 2014, the impact of environmental factors (such as salinity) on cod populations weakened compared to previous years, while the abundance of benthic invertebrates, habitat rugosity, and flatfish biomass became more influential in predicting cod biomass [21]. Therefore, exploring the temporal non-stationarity of environmental factors on fishing vessel activities could also be a potential research direction in the future.

However, the annual interval of modelling limits its ability to make fine-scale predictions. In the future, leveraging key environmental variables and fishing effort data and employing advanced spatio-temporal prediction models could enable more refined predictions on a monthly, weekly, or even daily basis.

5. Conclusions

This study employed the GWR model to explore the spatial heterogeneity impact of marine environmental factors on purse seine tuna fishing vessels in the WCPO. The GWR model shows a very good fit in most regions of the Western and Central Pacific. The GWR model can explore the influence of the spatial heterogeneity of marine environmental variables well. The influence of environmental factors on the fishing activity of purse seine tuna fishing vessels in the WCPO exhibited significant spatial heterogeneity. SST and Pp200 have the greatest spatially heterogeneous effects and are critical environmental variables influencing the operation of purse seine tuna vessels in the WCPO. The impact of SST on the spatial distribution of fishing vessels is mainly positive, while the impact of PP200 is mainly negative. Monitoring, predicting, and managing fishing activities can be based on several key environmental variables.

Funding

This research was funded by the Laoshan Laboratory (LSKJ202201804, LSKJ202201801), the Special Funds of Basic Research of Central Public Welfare Institute (2019T09).

Institutional review board statement

Not applicable.

Informed consent statement

Not applicable.

Data availability statement

Publicly available datasets of vessel numbers and marine environment were analyzed in this study. The vessel number data can be found here: https://globalfishingwatch.org/, accessed on May 8, 2023. The marine environment data can be found here: https://data.marine.copernicus.eu/products, accessed on May 8, 2023.

Question	Response
Data and Code Availability Sharing research data helps other researchers evaluate your findings, build on your work and to increase trust in your article. We encourage all our authors to make as much of their data publicly available as reasonably possible. Please note that your response to the following questions regarding the public data availability and the reasons for potentially not making data available will be available alongside your article upon publication. Has data associated with your study been deposited into a publicly available repository?	No
Please select why. Please note that this statement will be available alongside your article upon publication. As follow-up to "**Data and Code Availability** Sharing research data helps other researchers evaluate your findings, build on your work and to increase trust in your article. We encourage all our authors to make as much of their data publicly available as reasonably possible. Please note that your response to the following questions regarding the public data availability and the reasons for potentially not making data available will be available alongside your article upon publication. Has data associated with your study been deposited into a publicly available repository?"	Data included in article/supp. material/ referenced in article

CRediT authorship contribution statement

Wei Wang: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Data curation, Conceptualization. **Wei Fan:** Software, Methodology, Formal analysis. **Yumei Wu:** Methodology. **Shengmao Zhang:** Software, Project administration. **Weifeng Zhou:** Validation. **Xiumei Fan:** Validation. **Jiashu Shi:** Visualization. **Weiguo Jin:** Supervision. **Guolai Wang:** Supervision. **Shenglong Yang:** Writing – review & editing, Project administration, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors of this research would like to thank all the researchers who contributed to the research process during our study. Thanks for the data provided by Global Fishing Watch Data.

References

[1] P. Williams, T. Ruaia, Overview of Tuna Fisheries in the Western and Central Pacific Ocean, Including Economic Conditions – 2021, 2022.
[2] X.F. Wang, L.X. Xu, C. Zhou, G.P. Zhou, H. Tang, The relationship between the thermocline features and the rate of fishing success for free school caught by the tuna purse seiner in the Western and Central Pacific Ocean, Journal of Shanghai Ocean University 22 (2013) 763–769.
[3] Q.S. Tang, Research Report on the Current Situation and Development Trend of Fisheries Science, Ocean Press, Beijing, 2013.
[4] S. Dueri, L. Bopp, O. Maury, Projecting the impacts of climate change on skipjack tuna abundance and spatial distribution, Global Change Biol. 20 (2014) 742–753.
[5] J.R. Watson, E.C. Fuller, F.S. Castruccio, J.F. Samhouri, Fishermen follow fine-scale physical ocean features for finance, Front. Mar. Sci. 5 (2018) 46.
[6] G.O. Crespo, D.C. Dunn, G. Reygondeau, K. Boerder, B. Worm, W. Cheung, D.P. Tittensor, P.N. Halpin, The environmental niche of the global high seas pelagic longline fleet, Sci. Adv. 4 (2018) eaat3681.
[7] M. James, T. Mendo, E.L. Jones, K. Orr, A. McKnight, J. Thompson, AIS data to inform small scale fisheries management and marine spatial planning, Mar. Pol. 91 (2018) 113–121.
[8] M. Le Tixerant, D. Le Guyader, F. Gourmelon, B. Queffelec, How can Automatic Identification System (AIS) data be used for maritime spatial planning? Ocean Coast Manag. 166 (2018) 18–30.

[9] M.A. Cimino, M. Anderson, T. Schramek, S. Merrifield, E.J. Terrill, Towards a fishing pressure prediction system for a western Pacific EEZ, Sci. Rep. 9 (2019) 461.
[10] E. Debrah, G. Wiafe, K. Agyekum, D. Aheto, An assessment of the potential for mapping fishing zones off the coast of Ghana using ocean forecast data and vessel movement, J. Appl. Ecol. 26 (2018) 26–43.
[11] D.A. Kroodsma, J. Mayorga, T. Hochberg, N.A. Miller, K. Boerder, F. Ferretti, et al., Tracking the global footprint of fisheries, Science 359 (2018) 904–908.
[12] B. He, F. Yan, H. Yu, F. Su, V. Lyne, Y. Cui, L. Kang, W. Wu, Global fisheries responses to culture, policy and COVID-19 from 2017 to 2020, Rem. Sens. 13 (2021) 4507.
[13] H.N. Feng, H.J. Lu, J.T. Wang, Spatial-temporal distribution of CPUE and its relation with environmental factors for skipjack tuna (Katsuwonus pelamis) from purse-seine fishery in western and central Pacific Ocean, Journal of Guangdong Ocean University 43 (2023).
[14] T.-Y. Hsu, Y. Chang, M.-A. Lee, R.-F. Wu, S.-C. Hsiao, Predicting skipjack tuna fishing grounds in the western and central Pacific Ocean based on high-spatial-temporal-resolution satellite data, Rem. Sens. 13 (2021) 861.
[15] S. Yang, H. Zhang, W. Fan, H. Shi, Y. Fei, S. Yuan, Behaviour impact analysis of tuna purse seiners in the western and central pacific based on the BRT and GAM models, Front. Mar. Sci. 9 (2022) 881036.
[16] S. Yang, L. Yu, F. Wang, T. Chen, Y. Fei, S. Zhang, W. Fan, The environmental niche of the tuna purse seine fleet in the western and central Pacific Ocean based on different fisheries data, Fishes Sahul 8 (2023) 78.
[17] S. Vaihola, S. Kininmonth, Environmental factors determine tuna fishing vessels' behavior in Tonga, Fishes Sahul 8 (2023) 602.
[18] S. Vaihola, D. Yemane, S. Kininmonth, Spatiotemporal patterns in the distribution of albacore, bigeye, skipjack, and yellowfin tuna species within the exclusive economic zones of Tonga for the years 2002 to 2018, Diversity 15 (2023) 1091.
[19] L. Ciannelli, P. Fauchald, K.-S. Chan, V.N. Agostini, G.E. Dingsør, Spatial fisheries ecology: recent progress and future prospects, J. Mar. Syst. 71 (2008) 223–236.
[20] C. Liu, R. Wan, Y. Jiao, K.B. Reid, Exploring non-stationary and scale-dependent relationships between walleye (Sander vitreus) distribution and habitat variables in Lake Erie, Mar. Freshw. Res. 68 (2016) 270–281.
[21] S. Kininmonth, T. Blenckner, S. Niiranen, J. Watson, A. Orio, M. Casini, S. Neuenfeldt, V. Bartolino, M. Hansson, Is diversity the missing link in coastal fisheries management? Diversity 14 (2022) 90.
[22] M. Jia, L. Huang, J. Chu, C. Liu, Studies on the nonlinear and spatial nonstationary effects of environmental factors on the distribution of Antarctic krill (Euphausia superba), Per, Ocean Univ. China. 49 (2019) 19–26.
[23] D. Wheeler, M. Tiefelsdorf, Multicollinearity and correlation among local regression coefficients in geographically weighted regression, J. Geogr. Syst. 7 (2005) 161–187.
[24] Y. Leung, C.-L. Mei, W.-X. Zhang, Statistical tests for spatial nonstationarity based on the geographically weighted regression model, Environ. Plann. 32 (2000) 9–32.
[25] P. Propastin, Multiscale analysis of the relationship between topography and aboveground biomass in the tropical rainforests of Sulawesi, Indonesia, Int. J. Geogr. Inf. Sci. 25 (2011) 455–472.
[26] M. Imran, A. Stein, R. Zurita-Milla, Using geographically weighted regression kriging for crop yield mapping in West Africa, Int. J. Geogr. Inf. Sci. 29 (2015) 234–257.
[27] P.J.H. Dong L L, W.G. Wang, et al., Spatiotemporal pattern of summer thermal field and its relationship with land cover in Lanzhou based on RS and GWR, Soils (2018) 404–413.
[28] A.L. Deary, S. Moret-Ferguson, M. Engels, E. Zettler, G. Jaroslow, G. Sancho, Influence of central Pacific oceanographic conditions on the potential vertical habitat of four tropical tuna species1, Pac. Sci. 69 (2015) 461–475.
[29] S.H.M. Yang S L, X.M. Fan, et al., Spatial analysis of suitable habitat for yellowfin tuna in the tropical central and western Pacific Ocean, J. Agric. Sci. Technol. (2022) 183–191.
[30] C.L.L. Zhou W F, X.S. Cui, et al., Effects of thermocline and space-time factors on yellowfin tuna fishing ground distribution in the central and western pacific in abnormal climate, Agricultural Science and Technology (2021) 192–201.
[31] T. Matsumoto, H. Okamoto, M. Toyonaga, Behavioral study of small bigeye, yellowfin and skipjack tunas associated with drifting FADs using ultrasonic coded transmitter in the central Pacific Ocean, Second Regular Session of the Scientific Committee, Western and Central Pacific Fisheries Commission Information Paper. 7 (2006).
[32] S. Yang, Y. Zhang, H. Zhang, D. Wang, J. Ma, J. Zhang, X. Cui, The relationship between the temporal-spatial distribution of fishing ground of yellowfin tuna (Thunnus albacares) and themocline characteristics in the tropic Indian Ocean, Acta, Ecol. Sin. 32 (2012) 671–679.
[33] I.M. Belkin, J.E. O'Reilly, An algorithm for oceanic front detection in chlorophyll and SST satellite imagery, J. Mar. Syst. 78 (2009) 319–326.
[34] P.C. Fiedler, Comparison of objective descriptions of the thermocline, Limnol Oceanogr. Methods 8 (2010) 313–325.
[35] L. Pratt, J. Earles, P. Cornillon, J.-F. Cayula, The nonlinear behavior of varicose disturbances in a simple model of the Gulf Stream, Deep Sea Res. A. 38 (1991) S591–S622.
[36] A.S. Fotheringham, C. Brunsdon, M. Charlton, Geographically Weighted Regression: the Analysis of Spatially Varying Relationships, John Wiley & Sons, 2003.
[37] P. Beier, Model Selection and Inference: a Practical Information-Theoretic Approach, JSTOR, 2001.
[38] M.J. Windle, G.A. Rose, R. Devillers, M.-J. Fortin, Exploring spatial non-stationarity of fisheries survey data using geographically weighted regression (GWR): an example from the Northwest Atlantic, ICES (Int. Counc. Explor. Sea) J. Mar. Sci. 67 (2010) 145–154.
[39] Y.X.M. Jiang S, J.F. Zhu, Analysis of spatial and temporal heterogeneity of the relationship between skipjack tuna fishery and marine environment in the Western and Central Pacific Ocean, Fishery Sciences of China (2022) 744–754.
[40] F. Natale, M. Gibin, A. Alessandrini, M. Vespe, A. Paulrud, Mapping fishing effort through AIS data, PLoS One 10 (2015) e0130746.
[41] J. Lee, A.B. South, S. Jennings, Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data, ICES (Int. Counc. Explor. Sea) J. Mar. Sci. 67 (2010) 1260–1271.
[42] H. Welch, T. Clavelle, T.D. White, M.A. Cimino, J. Van Osdel, T. Hochberg, D. Kroodsma, E.L. Hazen, Hot spots of unseen fishing vessels, Sci. Adv. 8 (2022) eabq2109.
[43] Conservation and Management Measures (CMMs) and Resolutions of the Western Central Pacific Fisheries Commission, Western Central Pacific Fisheries Commission, vols. 48–49, 2024.
[44] N.A. Olsen, F. Bahr, N.D. Bethoney, A.M. Mercer, G. Gawarkiewicz, Integrating Fishers' knowledge with oceanographic observations to understand changing ocean conditions in the Northeast United States, Front. Mar. Sci. 10 (2023), https://doi.org/10.3389/fmars.2023.1144178.
[45] C. Van Vranken, J. Jakoboski, J.W. Carroll, C. Cusack, P. Gorringe, N. Hirose, et al., Towards a global Fishing Vessel Ocean Observing Network (FVON): state of the art and future directions, Front. Mar. Sci. 10 (2023), https://doi.org/10.3389/fmars.2023.1176814.
[46] R.W. Brill, K.A. Bigelow, M.K. Musyl, K.A. Fritsches, E.J. Warrant, Bigeye tuna (Thunnus obesus) behavior and physiology and their relevance to stock assessments and fishery biology, Col. Vol. Sci. Pap. ICCAT. 57 (2005) 142–161.
[47] T. Matsumoto, K. Satoh, Y. Semba, M. Toyonaga, Comparison of the behavior of skipjack (Katsuwonus pelamis), yellowfin (Thunnus albacares) and bigeye (T. obesus) tuna associated with drifting FAD s in the equatorial central Pacific Ocean, Fish. Oceanogr. 25 (2016) 565–581.
[48] V. Klemas, Fisheries applications of remote sensing: an overview, Fish. Res. 148 (2013) 124–136.
[49] P.R. Last, V.D. Lyne, A. Williams, C.R. Davies, A.J. Butler, G.K. Yearsley, A hierarchical framework for classifying seabed biodiversity with application to planning and managing Australia's marine biological resources, Biol. Conserv. 143 (2010) 1675–1686.
[50] K. Schaefer, D. Fuller, J. Hampton, S. Caillot, B. Leroy, D. Itano, Movements, dispersion, and mixing of bigeye tuna (Thunnus obesus) tagged and released in the equatorial Central Pacific Ocean, with conventional and archival tags, Fish. Res. 161 (2015) 336–355.

[51] H.H. Zheng, X. Yang, J.F. Zhu, Environmental impact mechanism of skipjack tuna fishery in western and central Pacific Ocean based on multi-scale geographical weighted regression model (MGWR), South China Fisheries Science 19 (2023) 1–10.
[52] T. Ye, B. Feng, Y. Yan, H. Lu, The relationship between skipjack katsuwonus pelamis catch and vertical water temperature and salinity in the west-central Pacific Ocean, Trans. Oceanol. Limnol. 1 (2012) 51–57.
[53] H. Tang, L. Xu, X. Chen, G. Zhu, C. Zhou, X. Wang, Effects of spatiotemporal and environmental factors on the fishing ground of Skipjack Tuna (Katsuwonus pelamis) in the western and central Pacific Ocean based on generalized additive model, Mar. Environ. Sci. 32 (2013) 518–522.