

North Pacific Fisheries Commission

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Standardized CPUE of Chub mackerel (*Scomber japonicas*) caught by the China's lighting purse seine fishery up to 2019

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Summary

Chub mackerel (*Scomber japonicas*) is key economic and ecological specie in the Northwest Pacific Ocean. Most of the Chub mackerel catch is harvested by the lighting purse seine fishery in China. In this paper, we standardized catch per unit fishing effort (CPUE) using generalized linear model (GLM) and generalized additive model (GAM). Four groups of independent variables were considered in the CPUE standardization: spatial variables (latitude and longitude), temporal variables (year and month), vessel length and environmental variables (SST, SSH and Chl-a). Log-CPUE was treated as the dependent variable and its error was assumed to follow normal distribution in each model. The model selections of GLM and GAM were based on the BIC. From the results, Higher Spearman's correlation and lower mean squared error were observed by GAM. Besides, the standardized CPUE trend of GAM model is similar with that of nominal CPUE. Therefore, we prefer to choose the best GAM model to estimated standardized CPUE of Chub mackerel fishery.



1. Background of the Chub mackerel fishery

Chub mackerel (*Scomber japonicas*) is a highly migratory fish, widely distributed in the high seas of the Northwest Pacific Ocean (Yukami., 2009). The annual catches of Chub mackerel recorded in 2019 were about 64,364 tons in China, which accounted for 14.00% of the global production. Now, about 50 Chub mackerel vessels from China operate in the Northwest Pacific Ocean. The main fishing area of China is shown in Figure 1.

2 METHOD

2.1 The data

Full-commercial fishery data were from 2014-2019, which were derived from Technical Group for Chub mackerel Fishery, Distant-water Fishery Society of China. Distribution of catch (ton) and fishing effort for China Chub mackerel fishing fleets in the Northwestern Pacific Ocean from 2014 to 2019 was shown in Figure 2. The catch of Chub mackerel in region 146 - 155 °E and 39 - 44 °N is higher than other regions (Fig.2a).

The Chub mackerel is a highly migratory fish, and the distribution of its fishing grounds shows large variation during the fishing period (April–November) each year (Yatsu, 2002), therefore, temporal variables (year and month), spatial variables (longitude and latitude) were included in the analysis. The distribution of the Chub mackerel fishing grounds is tightly associated with the marine environment (Zhang, 2009). Thus, Sea surface temperature (SST), Sea surface height (SSH), Chlorophyll-a concentration (Chla) were included in the analysis. In addition, the vessel length may affect the quantity of the catch, which was included in this study.

SST data were derived from National Oceanic and Atmospheric Administration (NOAA; <u>ftp.nodc.noaa.gov</u>). The spatial-temporal resolution of the SST data is daily at $0.1^{\circ} \times 0.1^{\circ}$ grid. Sea surface height (SSH) data were derived from Archiving Validation and Interpolation of Satellite Oceanographic Data (AVISO; <u>www.aviso.altimetry.fr</u>). The spatial-temporal resolution of the data is SSH daily at $0.25^{\circ} \times 0.25^{\circ}$ grid. The monthly Chla data from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the satellite Aqua platform provided by Asia-Pacific Data Research Center were used for this study, The Chla data was from website:

http://apdrc.soest.hawaii.edu/data/data.php.

This study extracted the corresponding oceanographic data from the nearest grid to the grid where the fishery data existed at the same date. Nominal CPUE were defined as catch per day per vessel, unit: ton/day/v.

Summary of explanatory variables used for CPUE standardization were listed in the table 1.

Year is a categorical variable of 6 years (2014–2019). *Month* is a categorical variable including the nine calendar months from April to December. *Longitude* and *latitude* are categorical variables, which divided at intervals of 1° . We attempted two cases (categorical and splined variable) for *SST* and investigated splined variable for *Chla* and *SSH*. *Vessellength* is a categorical or continuous variable of 44–61 m vessels, which will affect the catchability (Table1).

Variance Inflation Factor (VIF) and Spearman correlation coefficient among explanatory variables were calculated (Table 2) and correlations among variables were shown in the Figure 3.

2.2 Full model description and model selection

Both generalized linear model (GLM) and generalized additive model (GAM) were used to standardize the CPUEs.

The full GLM model was:

 $log(CPUE) = Year + Month + Longitude_c + Latitude_c + SST + SSH + Chla + Vessellength_c + interaction + \varepsilon$

The full GAM model was:

log(CPUE)= Year+ Month+ longitude_c + latitude_c + s(SST) + s(SSH) + s(Chla) + s(vessel length) + interaction + ε

where ε is the residual, which is assumed to have a normal distribution. *interaction* is an interaction term representing the interactive effect of spatial and temporal factors for the Chub mackerel. Full model interaction includes all the possible combination of year, month, longitude_c, latitude_c.

The optimal model was selected using the Bayesian information criterion (BIC). Spearman's correlation between the predicted and observed CPUEs, and mean of squared errors between two CPUEs were calculated to evaluate prediction performance.

2.3 Yearly trend extraction

The way to calculate the standardization CPUE is the yearly mean of fitted CPUE from the best model. The formula is,

$$\overline{CPUE}_i = \frac{1}{n_i} \times \sum_{k=1}^{n_i} CPUE_k^{fitted}$$

where, \overline{CPUE}_i is CPUE indices in *i*th year, n_i is the observation number in *i*th year, $CPUE_k^{fitted}$ is the *k*th fitted CPUE data in *i*th year.

The bootstrapped 95% confidence intervals of Standardized CPUE of the optimal GLM and GAM were calculated.

3 RESULT and DISCUSSION

In this study we used two models to standardize the CPUEs. Variance Inflation Factor (VIF) and Spearman correlation coefficient among explanatory variables were calculated (Table1). The Maximum VIF<5, indicates there is no serious multi-collinearity (Tien, 2011). Residuals from both approaches showed an approximately normal distribution around 0, which indicated that the model assumptions were satisfied. The results were shown in Figure 4 and Figure 5.

We used same explanatory variables in GLM and GAM analysis (Table 1). The result of the best GLM and GAM models are shown in Table 3 and Table 6 respectively. The summary of fitting a GLM for the optimal model is shown in Table 4. All explanatory variables are highly significant (p<0.01) except for SSH. The summary of fitting a GAM for the best model is shown in Table 7. All explanatory variables are highly significant (p<0.01) except for SSH.

Table 9 and Figure 6 shows the annual changes of nominal CPUE and standardized CPUE by GAM and GLM models. There are few differences between fitted CPUEs data by GLM and GAM, which may be related to the assumption of relationships between CPUEs and explanatory variables.

Comparing the results of cross validation tests in GLM and GAM analyses (Table 5 and 8), higher Spearman's correlation and lower mean squared error (MSE) between observed and predicted of test data were observed by GAM, so we prefer to choose the best GAM model to estimate standardized CPUE.

We standardized CPUE in accordance with the standardization protocol. The checklist is shown in Appendix 1.

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APPENDICES

Appendix1. Checklist for the CPUE standardization protocol

 Conduct a thorough literature review to identify key factors (i.e., spatial, temporal, environmental, and fisheries variables) that may influence CPUE values; Determine temporal and spatial scales for data grouping for CPUE standardization; Plot spatio-temporal distributions of fishing efforts and catch to evaluate spatio-temporal patterns of fishing effort and catch; Calculate correlation matrix to evaluate correlations between each pair of those variables; Identify potential explanatory variables based on (1)-(4) to develop full model for the CPUE standardization; Fit candidate statistical models to the data (e.g., GLM, GAM, Delta-lognormal GLM, Neural Networks, Regression Trees, Habitat based models, and Statistical habitat based models); Evaluate the models using methods such as likelihood ratio, AIC, BIC or cross validation; Evaluate if distributional assumptions are satisfied and if there is a consistent spatial/temporal distribution of residuals in CPUE standardization modeling; Extract yearly standardized CPUE and standard error by a method that is able to account for spatial heterogeneity of effort, such as least squares mean or expanded grid. If the model includes area and the size of spatial strata differs or the model includes interactions between time and area, then standardized CPUE should be calculated with area weighting for each time step. Model with 	11	nuix1. Checklist for the CI OE standardization protocor	
fisheries variables) that may influence CPUE values; Image: CPUE values; (2) Determine temporal and spatial scales for data grouping for CPUE standardization; Yes (see table 1) (3) Plot spatio-temporal distributions of fishing efforts and catch; Yes (see Fig.2) (4) Calculate correlation matrix to evaluate correlations between each pair of those variables; Yes (see table 1 and Fig.3) (5) Identify potential explanatory variables based on (1)-(4) to develop full model for the CPUE standardization; Yes (GLM and GAM) (6) Fit candidate statistical models to the data (e.g., GLM, GAM, Delta-lognormal GLM, Neural Networks, Regression Trees, Habitat based models, and Statistical habitat based models); Yes (see Table3 and Table6) (7) Evaluate the models using methods such as likelihood ratio, AIC, BIC or cross validation; Yes (see Fig.5 and Fig.6) (8) Evaluate if distributional assumptions are satisfied and if there is a consistent spatial/temporal distribution of residuals in CPUE standardization modeling; Yes (see 2.3 Yearly trend extraction) (9) Extract yearly standardized CPUE and standard error by a method that is able to account for spatial heterogeneity of effort, such as least squares mean or expanded grid. If the model includes area and the size of spatial strata differs or the model includes interactions between time and area, then standardized CPUE should be calculated with area weighting for each time step. Model with	(1)	Conduct a thorough literature review to identify key	Yes (see 2.1 The data
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		and area, then standardized CPUE should be calculated	
		with area weighting for each time step. Model with	
interactions between area and season or month requires		interactions between area and season or month requires	
careful consideration on a case by case basis;		careful consideration on a case by case basis;	

(10)	Recommend a time series of yearly standardized CPUE	Yes (see Table 9)
	and associated uncertainty;	
(11)	Plot nominal and standardized CPUEs over time.	Yes (see Fig. 6)
	Overall remarks Recommendations	

Tables:

Table 1 Summary of explanatory variables used for GLM and GAM analysis

Variables	Cases	Categorical or	Details	Note
		continuous		
Year	Year	6 categories	6 years from 2014 to2019	
Month	Month	9 categories	9 months from April to December	
Longitude	Longitude_c	22 categories	Longitude<144°; 144°≤Longitude<	at intervals
			145°; 145°≤Longitude<146;,	of 1°
			Longitude>164°	
Latitude	Latitude_c	12 categories	Latitude<33°; 33°≤Latitude<34°; 34°	at intervals
			≤Latitude<35;, Latitude>44°	of 1°
Sea surface	SST	spline		
temperature	SST_c	12 categories	SST<10°C;10°C≤SST<11°C;11°C≤	at intervals
			SST<12°C;, 19°C≤SST≤20°C;	of 1°C
			Sst>20°C	
Sea surface	SSH	continues (spline)		
height				
Chlorophyll-a	Chla	continues (spline)		
concentration				
Vessel length	Vessellength	spline	Vessellength≤44m; 44m≤Vessellength	at intervals
	Vessellength_c	10 categories	<46m;, Vessellength≥60m	of 2m

Table 2 Variance Inflation Factor (VIF) and Spearman correlation coefficient among explanatory variables

coefficient/p	VIF	Year	Month	Longitude	Latitude	SST	SSH	Chl-a	vessellength
value									
Year	1.04		0.0081	0.3231	< 0.001	< 0.001	0.3330	0.0487	< 0.001
Month	1.34	-0.0548		< 0.001	< 0.001	< 0.001	< 0.001	0.0029	0.5529
Longitude	1.39	0.0205	0.0682		< 0.001	< 0.001	< 0.001	0.0015	0.2670

Latitude	1.70	0.0898	0.2298	0.4585		< 0.001	< 0.001	< 0.001	< 0.001
SST	1.48	-0.1062	0.2487	0.0712	-0.3021		< 0.001	< 0.001	< 0.001
SSH	1.27	-0.0200	0.3463	-0.0558	-0.1043	0.3582		0.0573	< 0.001
Chl-a	1.03	0.0408	-0.0616	0.0657	0.0757	-0.1433	-0.0393		0.4543
Vessellength	1.04	0.1160	0.0123	-0.0230	-0.0770	0.0988	0.0944	-0.0155	

1) Spearman correlation coefficient are under the slope line; p values are above the slope line.

Table 3 The best GLM model			
GLM model	R ²	BIC	Explained deviance (%)
<i>Ln</i> (CPUE)~ <i>Intercept</i> + <i>Year</i> + <i>Month</i> + <i>Longitude_c</i> + <i>Latitude_c</i> + <i>SST</i> + <i>SSH</i> + <i>Chla</i> + <i>Year</i> : <i>Month</i> + <i>Year</i> : <i>Longitude_c</i>	0.3552	6313.59	59.59%

	Table 4 Anova test for best GLM model						
	Df	Deviance	Resid. Df	Resid. Dev	F	$\Pr(>F)$	
NULL			2335	1370.70			
factor(Year)	5	22.45	2331	1348.26	13.24	1.19E-10	***
factor(Month)	8	113.74	2323	1234.52	33.54	< 2.2E-16	***
factor(Longitude_c)	47	84.91	2276	1149.61	4.26	< 2.2E-16	***
factor(Latitude_c)	35	55.83	2241	1093.77	3.76	1.21E-12	***
SST	1	1.98	2240	1091.79	4.68	< 2.2E-16	***
SSH	1	1.45	2239	1090.34	3.42	0.0464	*
Chla	1	0.81	2238	1089.53	1.92	0.0069	**
factor(Year):factor(Month)	29	73.61	2209	1015.91	5.99	< 2.2E-16	***
<pre>factor(Year):factor(Longitude_c)</pre>	124	132.02	2085	883.90	2.51	< 2.2E-16	***

Significant code: *** 0.001, **0.01, *0.05

Table 5 The Five-fold cross validation for the best GLM.								
case	cor_GLM_test	MSE_GLM_test						
1	0.5247	1.3254						
2	0.5198	1.1578						
3	0.5219	1.2629						
4	0.5458	1.3142						
5	0.5392	1.1561						

Table 5 The Five-fold cross validation for the best GLM.

The spearman's correlation coefficient is showed in the table.

Table 6 The best GAM model			
GAM model	R ²	BIC	Explained deviance (%)
Ln(CPUE)~Intercept+Year+Month+Longitude_c+Latitude_c+s(SS T)+s(SSH)+s(Chla)+ Year:Month	0.3851	5690.01	60.61%

Parametric Terms:

			df	F	P-value	
factor(Year)			5	7.141	1.04E-05	***
factor(Month)			8	16.602	< 2.2E-16	***
factor(Longitude_c)			47	2.618	1.95E-8	***
factor(Latitude_c)			35	3.113	3.04E-9	***
factor(Year):factor(M	onth)		31	5.294	< 2.2E-16	***
Approximate significar	nce of smooth term	ns:				
	Edf	Ref.df		F	p-value	
s(SST)	7.76	8.49		4.49	0.000158	***
s(SSH)	4.14	5.20		5.98	0.0048	*
s(Chla)	7.72	8.53		3.65	0.00016	***

Significant code: *** 0.001, **0.01, *0.05

Tab	Table 8 The cross validation for the best GAM.						
case	cor_GAM_test	MSE_GAM_test					
1	0.6345	0.9357					
2	0.6615	0.9214					
3	0.6438	0.9579					
4	0.6946	0.9042					
5	0.6713	0.9316					

The spearman's correlation coefficient is showed in the table.

able 9 Nominal and standardized CPUE from 2014 to 2019.

Year	Nominal CPUE	SD of Nominal CPUE	Standardized CPUE by GLM	SD by GLM	95% CI by GLM		Standardized CPUE by GAM	SD by GAM	95% CI by GAM	
2014	22.59	13.68	19.24	11.14	[18.63	22.15]	19.57	8.84	[18.17	21.00]
2015	18.61	11.91	15.66	6.81	[14.92	16.46]	15.10	5.56	[14.36	15.75]
2016	16.41	10.28	14.40	3.70	[13.96	14.85]	14.34	3.54	[13.94	14.71]
2017	15.47	9.99	13.45	5.65	[12.91	14.02]	13.29	5.33	[12.75	13.82]
2018	16.48	10.05	14.61	4.05	[14.10	15.05]	14.45	3.41	[14.07	14.87]
2019	19.24	12.43	17.08	7.69	[16.42	17.64]	16.85	6.57	[16.41	17.24]

Figures:

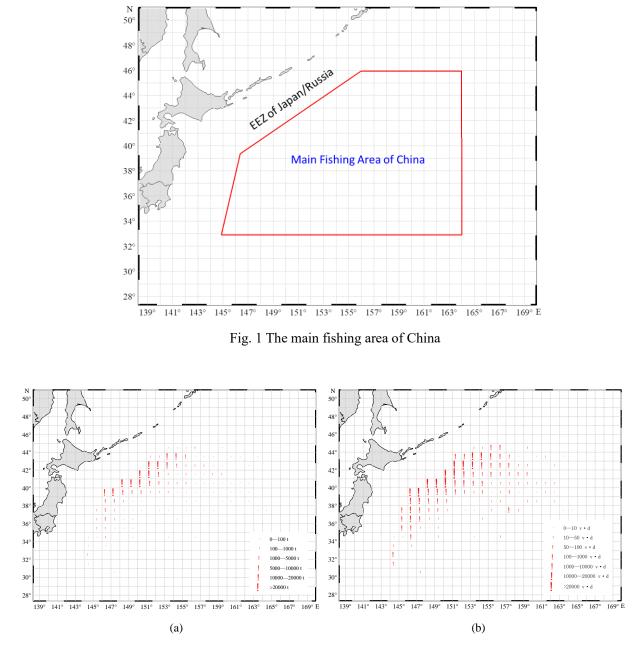


Fig. 2 Distribution of catch (a) and fishing effort(b) for China Chub mackerel fishing fleets in the Northwestern Pacific Ocean from 2014 to 2019

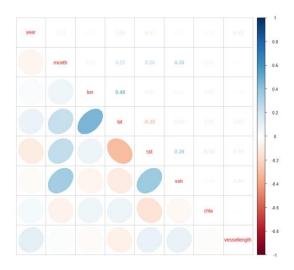


Fig. 3 Correlation matrix of explanatory variables used in the analysis

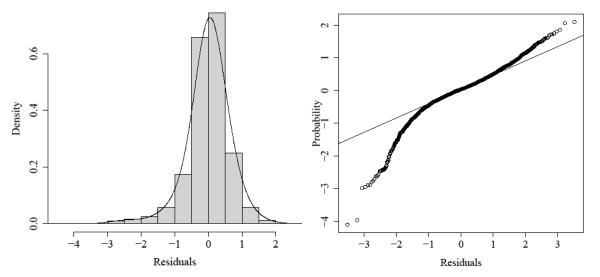


Fig. 4 Normal distribution checks, Q-Q plot and histogram of residuals for the GLM optimal model.

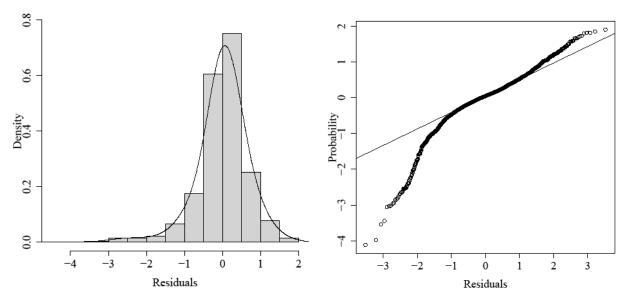


Fig. 5 Normal distribution checks, Q-Q plot and histogram of residuals for the GAM optimal model.

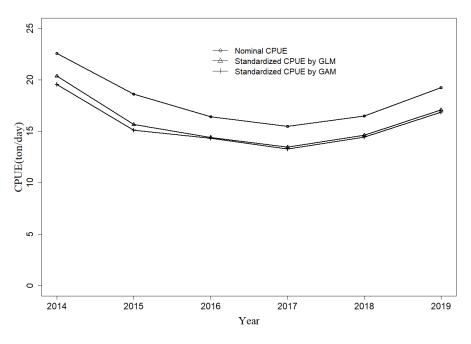


Fig.6 Annual changes in nominal, GAM and GLM estimated standardized CPUEs.