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**Standardized CPUE of Pacific saury (*Cololabis saira*) caught by the China’s stick-held dip net fishery up to 2024**

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**Summary**

China’s Pacific saury fishery in the Northwest Pacific Ocean began in 2003. The main fishing gear of Pacific saury fishery is the stick-held dip net. In this paper, catch per unit effort (CPUE) was standardized 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), fishing ability variables (Vessel length) and environmental variables (SST and SSTG). Log-CPUE was treated as the dependent variable and its error was assumed to follow normal distribution in each model. Bayesian information criterion (BIC) was employed to select the best GLM and GAM model. From the results, Higher Spearman’s correlation and lower mean squared error were observed by GAM. Hence, we prefer to choose the best GAM model to estimated standardized CPUE of Pacific saury in the Northwest Pacific Ocean. Additionally, we compared the standardized CPUE results derived from the full dataset versus the June-September subset to test the sensitivity of CPUE standardization to changes in the duration of fishing seasons. The *t*-test analysis revealed no statistically significant difference between the two groups (*p*>0.05). Therefore, we maintain our preference for using the standardized CPUE calculated from the full dataset.

**1. Background of the Pacific saury fishery**

Pacific saury(*Cololabis saira*) is a highly migratory fish, widely distributed in the high seas of the Northwest Pacific Ocean (NPO) (Lin, 2003; Sun et al., 2003). At the beginning of the 20th century, the first stick-held net fishing vessel (changed from squid jigging vessel) from China went to the high seas for fishing Pacific saury in the NPO, and has become one of the most important fisheries for China since then. Now, about 50 Pacific saury vessels from China operate in the NPO, after developing for almost two decades.

**2. Method**

**2.1. The data**

Commercial fishery data of Pacific saury were derived from Pacific Saury Fishery Technical Working Group, Distant-water Fishery Society of China from 2013 to 2024. Monthly fishing ground of China’s stick-held dip net fishery from 2013 to 2024 was shown in Figure 1.

The Pacific saury is a highly migratory fish, and the distribution of its fishing grounds shows significant variation during the fishing period (June-November) each year (Tian, 2003); therefore, temporal variables (Year and Month), spatial variables (Longitude and Latitude) were considered in the analysis. The Pacific saury fishing grounds is significantly affected by oceanographic factors (Zhu, 2006). Thus, the Sea surface temperature(SST) and Sea surface temperature gradients (SSTG) were in the analysis. In addition, the vessel performance may limit the catchability, so, vessel length was considered in this study.

SST data were derived from National Oceanic and Atmospheric Administration (NOAA; [ftp.nodc.noaa.gov](ftp://ftp.nodc.noaa.gov)). The spatial-temporal resolution of the SST data is daily at 0.05°×0.05° grid. SSTG data were calculated by Gradient Magnitude (GM) method (Ortiz, 2004; Howell, 2006; Hua, 2020). The formula is:



where , , and are SST values of 4 consecutive grids respectively, *i* and *j* is the numbering of row and column, is the longitudinal distance (km) between (*j*-1)th and (*j*+1)th columns, is the latitudinal distance (km) between (*i*-1)th and (i+1)th rows, is SSTG value of the current grid (°C/km).

The corresponding oceanographic grid data was used which nearest to the position where the fishery data observed in the same date. Nominal CPUE was 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 12 years (2013-2024). *Month* is a categorical variable including the eight calendar months from May to December. *Longitude* and *Latitude* are categorical variables, which divided at intervals of 1°. *Sst*, *Sstg*, *Vessellength* are categorical or continuous(splined) variable (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 2.

**2.2. Full model description and model selection**

Generalized linear model (GLM) and generalized additive model (GAM) were used to estimate standardized CPUE.

The full model of GLM was:

*log(CPUE) =Year + Month + Longitude + Latitude + Sst + Sstg* *+ Vessellength + interaction + ε*

The full model of GAM was:

*log(CPUE)*= *Year* + *Month* + *Longitude* + *Latitude + Sst + Sstg +* *Vessellength + interaction + ε*

whereis the residual, which is assumed to have a normal distribution. *interaction* is the interactive terms of spatial and temporal factors for the Pacific saury. Full model interaction includes all the possible combination of *Year, Month, Longitude, Latitude.*

Bayesian information criterion (BIC) was employed to select the optimal GLM and optimal GAM model. Spearman’s correlation and mean squared errors (MSE) between the predicted and observed CPUEs were calculated by 5 fold cross-validation to select well-performance model between two optimal models.

**2.3. Yearly trend extraction**

Time series of standardized CPUE was estimated using the well-performance model. Expanded grid function in R was used to generate a series of spatial homogeneous explanatory variables and the area of each 1°×1° grid cell was considered the same. Then, annual values of ln(*CPUE*) for each area (1°×1°) were predicted. Finally annual standardized CPUE were calculated as the mean of CPUE*y*:

where, is CPUE indices in *y*th year, is the spatial homogeneous explanatory variables number in *y*th year, is the *k*th fitted CPUE in *y*th year.To compare the results across different datasets, we calculated the standardized CPUE for both the full dataset and the subset restricted to the June–September period.

The fitted CPUE and 95% confidence intervals of optimal model were calculated by bootstrap resampled residuals with 1000 replications. The standardized CPUE was compared with nominal CPUE.

**3. Result and discussion**

In this study, we used two models to standardize the CPUEs. VIF and Spearman correlation coefficient among explanatory variables were calculated (Table2). The maximum VIF is less than 5, which indicates that 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 (Figure 3).

We used same explanatory variables in GLM and GAM analysis (Table 1). The results of the GLM and GAM model selections are shown in Table 3 and Table 6, respectively. The summary of fitting the optimal GLM model is shown in Table 4. All explanatory variables are significant at 0.05. The summary of fitting optimal GAM is shown in Table 7. All explanatory variables are significant at 0.05.

Comparing the results of cross validation tests in GLM and GAM analyses (Table 5 and 8), higher Spearman’s correlation and lower 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.

Figure 4 presents the annual nominal CPUE alongside the standardized CPUE calculated from two datasets. Based on the *t*-test results (Table 9), no significant difference was observed between the standardized CPUE derived from the full dataset and the June–September subset (*P* > 0.05). Therefore, we prefer to use the standardized CPUE calculated from the full dataset.

We standardized CPUE in accordance with the standardization protocol (NPFC-2017-TWG PSSA-Report Annex D). The checklist is shown in Appendix 1.

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**APPENDICES**

Appendix1. Checklist for the CPUE standardization protocol

|  |  |  |
| --- | --- | --- |
| (1) | Conduct a thorough literature review to identify key factors (i.e., spatial, temporal, environmental, and fisheries variables) that may influence CPUE values; | Yes (2.1 The data paragraph 2) |
| (2) | Determine temporal and spatial scales for data grouping for CPUE standardization; | Yes (Table 1) |
| (3) | Plot spatio-temporal distributions of fishing efforts and catch to evaluate spatio-temporal patterns of fishing effort and catch; | Yes (Fig.1) |
| (4) | Calculate correlation matrix to evaluate correlations between each pair of those variables; | Yes (Table 2 and Fig.2) |
| (5) | Identify potential explanatory variables based on (1)-(4) to develop full model for the CPUE standardization; | Yes (Table 1) |
| (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 (GLM and GAM) |
| (7) | Evaluate the models using methods such as likelihood ratio, AIC, BIC or cross validation; | Yes (Table3 and Table6) |
| (8) | Evaluate if distributional assumptions are satisfied and if there is a consistent spatial/temporal distribution of residuals in CPUE standardization modeling; | Yes (Fig.3) |
| (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 interactions between area and season or month requires careful consideration on a case by case basis; | Yes (2.3 Yearly trend extraction**)** |
| (10) | Recommend a time series of yearly standardized CPUE and associated uncertainty; | Yes (Table 10) |
| (11) | Plot nominal and standardized CPUEs over time.  Overall remarks Recommendations | Yes (Fig. 4) |

**Tables**:

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variables | Cases | Categorical or continuous | Details | Note |
| Year | *Year* | 12 categories | from 2013 to 2024 |  |
| Month | *Month* | 8 categories | from May to December |  |
| Longitude | *Lon* | 22 categories | Longitude＜149°,149°≦Longitude＜150°, 150°≦Longitude＜151, …, 168°≦Longitude＜169°, Longitude≥169° | at intervals of 1° |
| Latitude | *Lat* | 13 categories | Latitude＜39°,39°≦Latitude＜40°, 40°≦Latitude＜41°, …, 48°≦Latitude＜49°, Latitude≥49° | at intervals of 1° |
| Sea surface temperature | *Sst*  *Sst\_c* | continues（spline）  12 categories | Sst＜8℃，8℃≦Sst＜9℃，9℃≦Sst＜10℃，…; 19℃≦Sst＜20℃, Sst≥20℃ | at intervals of 1℃ |
| Sea surface temperature gradient | *Sstg*  *Sstg\_c* | continues（spline）  13 categories | Sstg<0.005℃/km; 0.005℃≦Sstg＜0.01℃/km, …, 0.075℃/km≦Sstg＜0.08℃/km | at intervals of 0.005℃/km |
| Vessel length | *Vl*  *Vl\_c* | continues（spline）  6 categories | Vessellength＜70m , 70m≦Vessellength＜71m,…, 77m≦Vessellength＜78m | at intervals of 1m |

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

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| coefficient/p value | VIF | Year | Month | Longitude | Latitude | SST | SSTG | Vessellength |
| Year | 1.42 |  | <0.001 | <0.001 | <0.001 | 0.139 | <0.001 | <0.001 |
| Month | 3.69 | -0.246 |  | <0.001 | <0.001 | <0.001 | <0.001 | 0.869 |
| Longitude | 4.47 | 0.450 | -0.832 |  | <0.001 | <0.001 | <0.001 | 0.765 |
| Latitude | 1.74 | 0.243 | -0.520 | 0.545 |  | <0.001 | <0.001 | <0.001 |
| SST | 1.61 | 0.007 | 0.504 | -0.436 | -0.515 |  | <0.001 | 0.003 |
| SSTG | 1.31 | -0.205 | 0.379 | -0.455 | -0.386 | 0.205 |  | 0.029 |
| Vessellength | 1.00 | 0.040 | 8.00E-04 | 0.001 | -0.027 | 0.014 | 0.010 |  |

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

Table 3 Result of GLM model selection

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| No | GLM model | R2 | BIC | Explained deviance |
| 1 | *Ln*(CPUE)~*Intercept+Year+Month+Longitude+Latitude+Sst +Sstg+Vl\_c* | 0.2920 | 137604 | 32.25% |
| 2 | *Ln*(CPUE)~*Intercept+Year+Month+Longitude+Latitude+Sst\_c +Sstg+Vl\_c*+*Year:Month*+*Year:Latitude* | **0.3704** | **134825** | **39.62%** |
| 3 | *Ln*(CPUE)~*Intercept+Year+Month+Longitude +Latitude +Sst\_c +Sstg +Vl\_c*+*Year:Month+ Year: Longitude* + *Year: Latitude* + *Month: Longitude* + *Month: Latitude* + *Longitude: Latitude* | 0.4092 | 136631 | 42.57% |

Table 4 Anova test for optimal GLM model

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Df | Deviance | Resid. Df | Resid. Dev | *F* | Pr(>*F*) |  |
| NULL | NA | NA | 46365 | 73187.29 | NA |  |  |
| factor(Year) | 11 | 8909.25 | 46354 | 64278.04 | 791.41 | < 2.2E-16 | \*\*\* |
| factor(Month) | 7 | 8999.58 | 46347 | 55278.47 | 1256.25 | < 2.2E-16 | \*\*\* |
| factor(Longitude) | 21 | 1406.16 | 46326 | 53872.31 | 65.43 | < 2.2E-16 | \*\*\* |
| factor(Latitude) | 12 | 897.37 | 46314 | 52974.94 | 73.07 | < 2.2E-16 | \*\*\* |
| Sst | 11 | 235.51 | 46303 | 52739.43 | 20.92 | < 2.2E-16 | \*\*\* |
| Sstg | 12 | 121.80 | 46291 | 52617.63 | 9.92 | < 2.2E-16 | \*\*\* |
| factor(Vessellength\_c) | 5 | 801.66 | 46286 | 51815.97 | 156.67 | < 2.2E-16 | \*\*\* |
| factor(Year):factor(Month) | 62 | 3710.59 | 46224 | 48105.38 | 58.48 | < 2.2E-16 | \*\*\* |
| factor(Year):factor(Latitude) | 60 | 860.73 | 46164 | 47244.65 | 14.02 | < 2.2E-16 | \*\*\* |

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

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

|  |  |  |
| --- | --- | --- |
| case | cor\_GLM\_mean | MSE\_GLM\_mean |
| 1 | 0.5725 | 1.0538 |
| 2 | 0.5661 | 1.0565 |
| 3 | 0.5629 | 1.0586 |
| 4 | 0.5779 | 1.0664 |
| 5 | 0.5703 | 1.0741 |

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

Table 6 Result of GAM model selection

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| No | GAM model | R2 | BIC | Explained deviance |
| 1 | *Ln(CPUE)~Intercept+Year+Month+Longitude +Latitude + Sst+Sstg+Vl* | 0.2914 | 137483.4 | 29.25% |
| 2 | *Ln(CPUE)~Intercept+Year+Month+Longitude +Latitude + Sst+Sstg+Vl+Year:Month+Year:Latitude* | **0.3592** | **134484.9** | **36.25%** |
| 3 | *Ln(CPUE)~Intercept+Year+Month+Longitude +Latitude + Sst+Sstg+Vl*+*Year:Month+ Year: Longitude* + *Year: Latitude* + *Month: Longitude* + *Month: Latitude* + *Longitude: Latitude* | 0.4002 | 136379.4 | 40.99% |

Table 7 Anova test for optimal GAM model

Parametric Terms:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | df | *F* | P-value |  |
| factor(Year) | 11 | 28.81 | < 2.2E-16 | \*\*\* |
| factor(Month) | 7 | 7.45 | 5.59E-9 | \*\*\* |
| factor(Longitude) | 21 | 25.05 | < 2.2E-16 | \*\*\* |
| factor(Latitude) | 12 | 12.59 | < 2.2E-16 | \*\*\* |
| factor(Vessellength\_c) | 5 | 165.62 | < 2.2E-16 |  |
| factor(Year):factor(Month) | 66 | 56.59 | < 2.2E-16 | \*\*\* |
| factor(Year):factor(Latitude) | 69 | 18.35 | < 2.2E-16 | \*\*\* |

Approximate significance of smooth terms:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Edf | Ref.df | *F* | p-value |  |
| s(Sst) | 8.55 | 8.95 | 41.04 | < 2.2E-16 | \*\*\* |
| s(Sstg) | 6.72 | 7.86 | 5.98 | < 2.2E-16 | \*\*\* |

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

Table 8 The cross validation for the optimal GAM.

|  |  |  |
| --- | --- | --- |
| case | cor\_GAM\_mean | MSE\_GAM\_mean |
| 1 | 0.5889 | 1.0184 |
| 2 | 0.5671 | 1.0211 |
| 3 | 0.5875 | 1.0274 |
| 4 | 0.5803 | 1.0309 |
| 5 | 0.5834 | 1.0320 |

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

Table 9 T-test results for standardized CPUE between the two datasets.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Group | mean | SD | n | *t* | *P* |
| June–November | 8.60 | 3.38 | 12 | 1.61 | 0.122 |
| June–September subset | 6.64 | 2.49 | 12 |  |  |

Table 10 Nominal CPUE and standardized CPUE by GAM from 2013 to 2024.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Year | Nominal CPUE | Standardized CPUE | CV(%) | 95% CI | |
| 2013 | 20.80 | 11.34 | 0.07 | [11.338 | 11.341] |
| 2014 | 22.11 | 12.93 | 0.05 | [12.931 | 12.933] |
| 2015 | 23.48 | 12.11 | 0.07 | [12.104 | 12.107] |
| 2016 | 15.02 | 6.67 | 0.04 | [6.671 | 6.672] |
| 2017 | 12.12 | 7.73 | 0.04 | [7.734 | 7.735] |
| 2018 | 23.13 | 14.11 | 0.04 | [14.107 | 14.108] |
| 2019 | 10.78 | 7.10 | 0.03 | [7.099 | 7.101] |
| 2020 | 9.53 | 4.71 | 0.04 | [4.706 | 4.707] |
| 2021 | 7.13 | 4.77 | 0.04 | [4.772 | 4.773] |
| 2022 | 6.22 | 4.09 | 0.03 | [4.092 | 4.093] |
| 2023 | 10.06 | 8.94 | 0.03 | [8.939 | 8.940] |
| 2024 | 10.25 | 8.67 | 0.03 | [8.672 | 8.673] |

**Figures**:

图表

AI 生成的内容可能不正确。

Fig. 1 Annual fishing ground of China’s stick-held dip net fishery for Pacific saury from 2013 to 2024



Fig. 2 Correlation matrix of explanatory variables used in the analysis.



(a)



(b)

Fig. 3 Normal distribution checks, Q-Q plot and histogram of residuals for the GLM(a) and GAM(b) optimal model.



Fig.4 Annual changes of nominal CPUE and standardized CPUE by GAM model up to 2024.