# Standardized CPUE of swordfish (Xiphias gladius) from Indonesian tuna longline fleets in the north-eastern Indian Ocean 

Bram Setyadji ${ }^{1,5}$, Matthew Spencer ${ }^{1}$, Laurence Kell ${ }^{2}$, Serena Wright ${ }^{3}$, Scott Ferson ${ }^{4}$, Aris Budiarto ${ }^{6}$, Yayan Hernuyadin ${ }^{6}$<br>${ }^{1}$ Department of Earth, Ocean, and Ecological Sciences, University of Liverpool, United Kingdom<br>${ }^{2}$ Centre for Environmental Policy, Imperial College London, United Kingdom<br>${ }^{3}$ Centre for Environment, Fisheries and Aquaculture Science (CEFAS), Lowestoft, United Kingdom<br>${ }^{4}$ Department of Civil Engineering and Industrial Design, University of Liverpool, United Kingdom<br>${ }^{5}$ Research Center for Fishery, National Research and Innovation Agency (BRIN), Indonesia<br>${ }^{6}$ Directorate of Fish Resources Management, Directorate General of Capture Fisheries, Indonesia


#### Abstract

The main objective of this study was to assess the abundance index of swordfish (Xiphias gladius) in the northeastern Indian Ocean, using fishery-independent data collected by scientific observers. The study aimed to address the existing information gap associated with low coverage in this region. A total of 3,302 observer data points were obtained from the Indonesian scientific observer program, spanning the years 2006 to 2022. These data were spatially disaggregated into one-degree blocks and were collected alongside commercial longline fleets. To analyze the dataset, Poisson and negative binomial models were considered, with number of fish serving as the response variable. Six covariates were included in the models, and a backward procedure based on AIC was employed to identify the best-fitting model. The results revealed that, overall, the trend in swordfish CPUE remained relatively stable over time, although there were inter-annual fluctuations. These fluctuations were attributed to natural population variations rather than operational changes or inter-annual environmental factors. Despite the lower spatial coverage compared to logbook data, the scientific observer data proved to be reliable and generated a robust abundance index for swordfish in the northeastern Indian Ocean. This highlights the effectiveness of utilizing scientific observer data to enhance our understanding of the population dynamics of swordfish in the region.


## Introduction

Swordfish (Xiphias gladius) is a large oceanic apex predator inhabits all the world's oceans. It is predominantly known as a subject of exploitation worldwide, mainly in the Pacific Ocean, Atlantic Ocean, and Mediterranean Sea (Tserpes and Tsimenides, 1995). Throughout the Indian Ocean, swordfish are primarily caught by longline fisheries, and the commercial harvest was first recorded by the Japanese in the early 1950s as bycatch of their tuna longline fisheries (IOTC-WPB20, 2022). Since 1990s the catches of swordfish increased sharply to a peak of 35,000 tons in 1998 (IOTC-WPB20, 2022) due to the growing shift of catching tunas to swordfish by Taiwanese longline fleets, the increasing number of longline fleets operations from various nations (e.g. Indonesia, Australia, La Reunion, Seychelles and Mauritius), and arrival of longline fleets from the Atlantic Ocean (e.g. Portugal, Spain and United Kingdom). In recent years (2018-2022), Indonesian fleets are responsible for approximately $7 \%$ of the total catch of swordfish in the Indian Ocean ( $\sim 2,500 \mathrm{MT}$ ) or the third largest after Sri Lanka (27\%), and Taiwan (19\%) (IOTC-WPB20, 2022). The recent catch figure was due to the refined methodology on catch estimation provided by the IOTC secretariat (IOTC-WPDCS14, 2018), which also aligned with the impact of Ministerial Regulation No. 56/2014 and No. 57/2014 about the moratorium on foreign fishing vessels and prohibition of transshipment at sea within Indonesia national jurisdiction, resulted in a significant reduction of longline vessel operations from 584 in 2015 to 271 in 2016. Our analytic
objective was to investigate how the data-limited of swordfish fishery can construct a fairly robust relative abundance indices amid the "spatial gap" of the existing dataset for standardized CPUE in the north-eastern Indian Ocean (e.g., Japanese and Taiwanese longline dataset). We believe the results are valuable as an important information to assess the status of swordfish in the Indian Ocean.

## Materials and Methods

## Data Source

This research analyzes the data collected by Indonesian scientific observers on commercial tuna longline vessels, primarily located at Benoa Fishing Port in Bali. The observation program was initiated in 2005 through a collaborative effort between Australia and Indonesia (Project FIS/2002/074 of the Australian Centre for International Agricultural Research). From 2012 onwards, the Research Institute for Tuna Fisheries (RITF Indonesia) conducted the program. However, in 2022, the program was discontinued following the establishment of the National Research and Innovation Agency (BRIN). Consequently, the data utilized in this study were obtained from the Directorate General of Capture Fisheries under the Ministry of Marine Affairs and Fisheries.

A comprehensive dataset consisting of 3,302 set-by-set records was obtained from Indonesia's scientific observer program. The dataset provides detailed information on a 1 x 1 degree latitude and longitude grid, covering the period from January 2006 to December 2022. The data primarily pertains to commercial tuna longline vessels predominantly operating from the Port of Benoa in Bali. Fishing trips typically range from three weeks to three months in duration.

The fishing grounds explored in this study extend from the western to the southern parts of Indonesian waters, spanning approximately from $75^{\circ} \mathrm{E}$ to $35^{\circ} \mathrm{S}$ (refer to Figure 1). The dataset includes valuable information on various aspects such as the species-specific catch quantities, total number of hooks, number of hooks between floats (HBF), start time of the set, start time of haul, soak time, and geographic positions where the longline sets were deployed.

## CPUE Standardization

Two Generalized Linear Model (GLM) models were considered in this present study. Whereas nominal catch (number of fish) acted as response variable while effort (total hooks) was included in the models as an offset caught. These models are Poisson and negative binomial, which we refer to as the standard models. The models were simply conducted with the main effects considered in this analysis were as follows:
a. Year: List of observation year (2006-2022), set as categorical variable;
b. Month: List of months of given year (1-12), set as categorical variable;
c. $H B F$ : Number of hooks between floats was set as a categorical variable in the model. It was assigned as 1 if $\mathrm{HBF}<10$ hooks (surface longline), and 2 if HBF $>10$ hooks (deep longline) following (Sadiyah et al., 2012);
d. Moon: Moon phase information is referring to the eight shapes of the directly sunlit portion of the moon that we can see from Earth. The moon phase was calculated using lunar package (Lazaridis, 2014);
e. Lat/Lon: Geographical information (latitude and longitude) in $5 \times 5$ degree blocks and incorporated as a continuous variable.

The interactions between main effects were not incorporated into the models to avoid overfitting. The model for either Poisson or Negative Binomial was conducted as follows:

Poisson model:

$$
\begin{equation*}
\text { Catch }=\mu+Y e a r+\text { Month }+L a t+L o n+\text { Moon }+H B F+o f f s e t(\log (H o o k s))+\epsilon^{\text {Poisson } / \text { NegativeBinomial }} \tag{1}
\end{equation*}
$$

We used a forward selection procedure to select explanatory variables for the full model. The procedure began by fitting simple models with one variable at a time. The variable that was included in the model with the lowest residual deviance was selected first. The selected variable was then added to the model, and another simple model was fit with one additional variable. The variable that was included in the model with the lowest residual deviance was then selected. This process was repeated until the residual deviance did not decrease as new variables were added to the model. Finally, all main effects were considered, and a backward procedure based on Akaike Information Criterion (AIC) (Akaike, 1974) was used to select the final model.

## Results

## Fishing dynamics

Observers recorded catch and operational data at sea following Indonesian tuna longline commercial vessels from 2006-2022. The final dataset contained 122 trips, 3302 sets, and almost 4.5 million hooks observed, respectively (Table 1). The distribution of sets mainly gathered in area of eastern Indian Ocean with most of the positive catches occurred in the area south of Indonesian waters, between $0-20^{\circ} \mathrm{S}$ and $75-125^{\circ} \mathrm{E}$ (Figure 1).

Table 1. Summary of observed effort from Indonesian tuna longline fishery during 2006-2022. Results are pooled and also presented by year of observation

| Year | Trips | Sets | Total Hooks | Mean Hooks | se | Mean HBF | se |
| ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| 2006 | 13 | 400 | 575989 | 1439.97 | 10.77 | 11.21 | 0.20 |
| 2007 | 13 | 262 | 403333 | 1539.44 | 19.96 | 14.03 | 0.27 |
| 2008 | 15 | 396 | 510702 | 1289.65 | 19.28 | 12.72 | 0.22 |
| 2009 | 13 | 288 | 328718 | 1141.38 | 13.82 | 12.18 | 0.29 |
| 2010 | 6 | 166 | 221274 | 1332.98 | 35.51 | 13.61 | 0.40 |
| 2011 | 3 | 105 | 110384 | 1051.28 | 16.97 | 12.00 | 0.00 |
| 2012 | 8 | 198 | 290265 | 1465.98 | 39.73 | 14.12 | 0.16 |
| 2013 | 7 | 210 | 231990 | 1104.71 | 14.11 | 12.40 | 0.15 |
| 2014 | 6 | 184 | 216705 | 1177.74 | 13.35 | 15.01 | 0.14 |
| 2015 | 5 | 150 | 174655 | 1164.37 | 11.81 | 14.15 | 0.26 |
| 2016 | 3 | 130 | 175868 | 1352.83 | 18.33 | 11.31 | 0.29 |
| 2017 | 4 | 139 | 192188 | 1382.65 | 33.82 | 15.32 | 0.15 |
| 2018 | 6 | 195 | 262856 | 1347.98 | 16.52 | 14.81 | 0.18 |
| 2019 | 9 | 164 | 216836 | 1322.17 | 15.14 | 10.79 | 0.35 |
| 2020 | 2 | 63 | 86845 | 1378.49 | 18.20 | 13.48 | 0.11 |
| 2021 | 5 | 130 | 197424 | 1518.65 | 27.32 | 11.34 | 0.29 |
| 2022 | 6 | 122 | 221196 | 1813.08 | 33.58 | 12.66 | 0.37 |



Figure 1. Indonesian tuna longline fishing efforts distribution based on scientific observer reports from 2006 to 2022

## CPUE Data Characteristics

In general, the catches of SWO remained relatively stable with few fluctuations over the last two decades. The lowest CPUE was recorded in $2011(0.122 \pm 0.43)$, while the highest was observed in $2019(0.61 \pm 1.76)$. On the other hand, the proportion of zero catches for SWO was initially quite high but showed a tendency to decline. In contrast to the nominal CPUE, this trend varied annually, with a maximum of $90 \%$ in 2011 and a minimum of $48 \%$ in 2022 (Figure 2). The average proportion was $68 \%$ per year.



Figure 2. Nominal CPUE series (N/1000 hooks) (left panel) and Proportion of zero-catch-per-set (right panel) for BUM from 2006 to 2021. The error bars refer to the standard errors.

## CPUE Standardization

After applying the AIC model selection criteria for Poisson and Negative Binomial models, no main effects were omitted. However, for the Poisson and Negative Binomial models, longitude didn't affect the number of swordfish caught (Table 2,

Table 3). The current catch was more likely driven by temporal (Year and Month), specific spatial distribution (Latitude), environmental (Moon Phase) and current operational aspect, i.e., number of hooks between floats (HBF).

Table 2. The deviance table for Poisson model.

|  | Df | Deviance | Residual Df | Residual Dev | $\operatorname{Pr}(>$ Chisq) |
| :--- | ---: | ---: | ---: | ---: | ---: |
| NULL | NA | NA | 3301 | 4639.211 | NA |
| Year | 16 | 126.5963610 | 3285 | 4512.615 | 0.0000000 |
| Month | 11 | 113.5746092 | 3274 | 4399.040 | 0.0000000 |
| Lat | 1 | 16.6860217 | 3273 | 4382.354 | 0.0000441 |
| Lon | 1 | 0.0645907 | 3272 | 4382.289 | 0.7993819 |
| Moon | 7 | 252.9788345 | 3265 | 4129.310 | 0.0000000 |
| HBF | 1 | 114.6102114 | 3264 | 4014.700 | 0.0000000 |

Table 3. The deviance table for Negative Binomial Model.

|  | Df | Deviance | Residual Df | Residual Dev | $\operatorname{Pr}(>$ Chisq) |
| :--- | ---: | ---: | ---: | ---: | ---: |
| NULL | NA | NA | 3301 | 2919.783 | NA |
| Year | 16 | 82.9681675 | 3285 | 2836.815 | 0.0000000 |
| Month | 11 | 68.6125913 | 3274 | 2768.202 | 0.0000000 |
| Lat | 1 | 12.0519462 | 3273 | 2756.151 | 0.0005174 |
| Lon | 1 | 0.0108326 | 3272 | 2756.140 | 0.9171059 |
| Moon | 7 | 144.8033377 | 3265 | 2611.336 | 0.0000000 |
| HBF | 1 | 55.7354499 | 3264 | 2555.601 | 0.0000000 |

In general, the standardized CPUE trend remained relatively stable over time with minimal noise throughout the series. However, the persisting issue of high uncertainties is primarily due to the limited coverage of scientific observer data. The implementation of the National Observer Program by the Directorate General of Capture Fisheries, Ministry of Marine Affairs and Fisheries is anticipated to improve observer coverage in the coming years, addressing this concern.


Figure 3. Standardized catch-per-unit-effort (CPUE) calculated using Poisson and Negative Binomial model. Values were scaled by dividing them by their means.

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