# CATCH-PER-UNIT-EFFORT STANDARDIZATION FOR THE SOUTHERN ATLANTIC BLUE SHARK (PRIONACE GLAUCA) BASED ON BRAZILIAN AND URUGUAYAN LONGLINE FISHERY DATA (1990-2022) 

L. G. Cardoso ${ }^{1}$, R. Sant'Ana ${ }^{2}$, R. Forselledo ${ }^{3}$, B. Mourato ${ }^{4}$, E. Kikuchi ${ }^{1}$, P. Travassos ${ }^{5}$, A. Domingo ${ }^{3}$


#### Abstract

SUMMARY Catch and effort data from Brazilian and Uruguayan tuna longline fishery in the South Atlantic Ocean from 1978 to 2022 were analyzed. The effort was distributed in a wide area of the western Atlantic Ocean. The CPUE of the southern blue shark was standardized by a GLM using a Delta Lognormal approach. The factors used in the models were: year, quarter, flag, vessel, hooks per floats, hooks, and the lat-long reference for each five by 5 degrees square. After the data cleaning, an index was estimated for the period between 1992 to 2022. The estimated delta-lognormal index showed three distinct periods. Between 1992 and 2005, the index was marked by stable smooth and low values. The second one, from 2006 to 2012, presented a slight increase in relative abundance attaining its peak in 2012. The third period, from 2013 to 2022, showed a dynamic pattern with higher values than the beginning of the series but without any apparent increase or decreasing trend.


## RÉSUMÉ

Les données de prise et d'effort de la pêcherie palangrière thonière uruguayenne et brésilienne dans l'océan Atlantique Sud de 1978 à 2022 ont été analysées. L'effort était réparti dans une large zone de l'océan Atlantique occidental. La CPUE du requin peau bleue du Sud a été standardisée au moyen d'un GLM utilisant une approche delta-lognormale. Les facteurs utilisés dans les modèles étaient: l'année, le trimestre, le pavillon, le navire, les hameçons par flotteurs, les hameçons ainsi que la référence lat-long pour chaque carré de $5^{\circ}$ de $5^{\circ}$. Après le nettoyage des données, un indice a été estimé pour la période allant de 1992 à 2022. L'indice deltalognormal estimé affichait trois périodes distinctes. Entre 1992 et 2005, l'indice était marqué par des valeurs stables, lisses et faibles. La deuxième période, de 2006 à 2012, présentait une légère augmentation de l'abondance relative, qui a atteint son maximum en 2012. La troisième période, de 2013 à 2022, présentait un schéma dynamique avec des valeurs plus élevées qu'au début de la série, mais sans tendance croissante ou décroissante apparente.

## RESUMEN

Se analizaron los datos de captura y esfuerzo de la pesquería atunera de palangre brasileña y uruguaya en el océano Atlántico sur desde 1978 hasta 2022. El esfuerzo se distribuyó en una amplia zona del océano Atlántico occidental. Se estandarizó la CPUE del tiburón azul del sur mediante un GLM un enfoque delta lognormal. Los factores utilizados en el modelo fueron: año, trimestre, pabellón, buque, anzuelos por flotador y anzuelos, y la referencia lat-long para cada una de las cuadrículas de 5x5 grados. Una vez depurados los datos, se estimó un índice para el periodo comprendido entre 1992 y 2022. El índice delta-lognormal estimado mostraba tres períodos diferenciados. Entre 1992 y 2005, el índice se caracterizó por valores estables suaves y bajos. El segundo periodo, de 2006 a 2012, presentó un ligero aumento de la abundancia relativa alcanzando su máximo en 2012. El tercer periodo, de 2013 a 2022, mostró un patrón dinámico con valores más altos que al principio de la serie, pero sin ninguna tendencia aparente de aumento o disminución.

## KEYWORDS

Abundance; Southern Blue Shark; Pelagic fisheries; Catch/Effort

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## 1. Introduction

Standardized catch per unit of effort (CPUE) are critical for stock assessments of large pelagic fish stocks. Temporal changes of human-related factors like fishing strategies, fishing power, technologies and market demands as well as natural factors like seasonal changes of species distribution may induce catchability oscillations introducing serious errors when analyzing the nominal CPUEs trajectories. For example, since 1956, when longline fishing operations began in the South Atlantic Ocean, a number of changes in fishing operations and strategies were observed affecting directly the relative catch composition (Amorim e Arfelli, 1984; Hazin et al., 2007; Carvalho et al., 2010). This prevents the direct comparison of effort units from previous years to the following. Two decades after, in 1981, the Uruguayan tuna fleet began its activities targeting mainly bigeye tuna, Thunnus obesus. Since 1992, the fleet has operated with American-type longline, except for some units that operate with Spanish-type longline, targeting mainly swordfish, Xiphias gladius (Domingo et al. 2008).

The blue shark, Prionace glauca (BSH) is an important component of longline fleets catches in southwestern Atlantic (Hazin et al., 2007; Carvalho et al., 2010, Pons and Domingo, 2008, Forselledo et al. 2016). The species is presumed to be captured since the beginning of the longline fishing in the southwestern Atlantic (1960s), despite not always being retained and frequently discarded onboard. From the early 1990's the species began to be retained and reported in logbooks of Brazilian (Hazin et al., 2007; Carvalho et al., 2010) and Uruguayan fishing fleets (Pons and Domingo, 2008, Forselledo et al., 2016).

In this study, in order to contribute with information for the assessment of the blue shark in the south Atlantic Ocean, catch and effort data from Brazilian and Uruguayan longline fishing fleets was gathered to produce standardized abundance indices for the species, from 1992 to 2022, spanning 30 years.

## 2. Data and methods

### 2.1 Catch and effort data

In the present study, we analyzed catch and effort data from the 1978-2022, totalizing 122,259 longline sets, which were obtained from logbooks reported by the Brazilian tuna longline fleet, including both national and foreign chartered vessels and the Uruguayan longline fishing fleet. The longline sets were distributed in a wide area of the equatorial and South Atlantic Ocean, ranging from $18^{\circ}$ to $55^{\circ} \mathrm{W}$ of longitude, and from $10^{\circ} \mathrm{N}$ to $57^{\circ} \mathrm{S}$ of latitude (Figure 1). The resolution of $0.5^{\circ} \times 0.5^{\circ}$, per fishing set, was used for the analysis of the geographical distribution of fishing effort. The BIL ICCAT sampling areas were considered to select data based on its geographical distribution. The final standardized index were obtained from sets performed inside the BIL96 sampling area (Figure 1).

### 2.2 Data cleaning and preparation

Data cleaning and preparation for the analysis were based on the approaches proposed by Hoyle et al. (2015), Hoyle et al. (2016) and Hoyle et al. (2018). All analyses were carried out in R version 4.2.2 (R Core Team, 2022). At the cleaning process, in the first step, vessels that had never caught a blue shark before were removed from the dataset. We also selected data for vessels that had fished for at least two quarters in that specific region. Besides, we also selected vessels in the final dataset if they reported at least 50 sets. Spatial cells and year-quarters were only included in the final dataset if it comprised at least five sets. Year-quarter $* 5^{\circ}$ cell strata with less than five sets were also removed, to avoid giving too much statistical weight to individual sets via the area-weighting process.

### 2.3 CPUE standardization

The factors used in the models were: year, quarter, flag, the lat-long reference for each $5^{\circ} \times 5^{\circ}$ spatial squares, hooks, hooks per floats and individual vessels. For the standardization of the CPUE, we performed a single model for the BIL96 ICCAT sampling area (Figure 1).

CPUE standardization methods followed the approaches used in Hoyle et al. (2018). A Generalized Linear Models (GLM) using a Delta Lognormal approach was implemented. Delta lognormal analyses (Lo et al. 1992; Maunder \& Punt 2004) use a binomial distribution for the probability $w$ of catch rate being zero and a probability distribution $f(y)$, where $y$ was $\log$ (catch in number/hooks set) ${ }^{*} 1000$, for non-zero (positive) catch rates. The index estimated for each year-quarter was the product of the year effects for the two model components $(1-w) *(y \mid y \neq 0)$.

Covariates included year-quarter (yq), and $5^{\circ}$ cell (latlong5) fitted as categorical variables. Analyses including the continuous variable hooks fitted it using a cubic spline function $h$ with 10 degrees of freedom. Analyses including the vessel identifier (vessid) fitted it as a categorical variable nested in flag identifier (BRA or URU). Analyses including hooks between floats (hbf) fitted it as a continuous variable using a cubic spline $\phi$ (Hoyle et al., 2018). As proposed by Hoyle et al. (2018), data in all models, except for the binomial model, were 'area-weighted', with the weights of the sets adjusted so that the total weight per year-quarter in each $5^{\circ}$ square would sum to 1

In the binomial component of the model, fitted probabilities of 0 or 1 may occur, associated with categories of the vessel, year-quarter, or $5^{\circ}$ cell. This is known as 'perfect separation' and is problematic for uncertainty estimation (Venables \& Ripley 2002). This is one of the reasons why the binomial component of the uncertainty is not used. Perfect separation should not bias prediction of the year-quarter effects, as long as a category at which separation occurs is not used in the predictor. Perfect separation in year-quarter results in an accurate prediction of 0 or 1 (Hoyle et al., 2018). The effects of covariates were examined using influence plots, by means of the R package influ (Bentley et al., 2011).

As Hoyle et al. (2018) proposed, indices of abundance were obtained by applying the R function predict.glm to model objects. The datasets used for prediction included all year-quarter values, with all other variables fixed at either the median for continuous variables or the mode for categorical variables. Binomial time effects were obtained by a) generating logit time effects from the GLM, and b) adding a constant to these logit time effects so that the mean of the back-transformed proportions was equal to the proportion of positive sets across the whole dataset. The main aim with this approach is to obtain a CPUE that varies appropriately, since variability for a binomial is greater when the mean is at 0.5 than at 0.02 or 0.98 , and the multiplicative effect of the variability is greater when the mean is lower. The outcomes were normalized and reported as relative CPUE with mean of 1 . Uncertainty estimates were provided by applying the R function predict.glm with type= "terms" and se.fit $=$ TRUE and taking the standard error of the year-quarter effect. This process concerns only the uncertainty in the positive component. Residual distributions and Q-Q plots were produced for the lognormal positive analyses. For those components that included cluster in the model, median residuals were plotted by the cluster.

## 3. Results and Discussion

The joint landings time series of the Brazilian and Uruguayan longline fishing fleets presented a steady increase from 1994 to 2012 and a steep dynamic increase generated by the Brazilian catches (Figure 2). The proportion of BSH on the total reported catches also increased over time, reaching more than $40 \%$ around 2010 and in the series' final years (Figure 3). For Brazilian and Uruguayan fleets, it increased from the mid-1990s, reaching more than $80 \%$ in the 2010s, the final years of the Uruguayan series, and more than $40 \%$ in the final years of the Brazilian series. After the data cleaning, the final data set was composed by 103,605 sets.

Diagnostic plots for the Lognormal model showed that the assumption of the lognormal distribution for the positive dataset is adequate, as indicated by the QQ plots (Figure 4). Residuals were homoscedastic, and no systematic biases were observed. The annual influence of each explanatory variable in explaining the variation in the abundance index varied among the different covariates in the standardization model (Figure 5). The influence plot for the annual trend in flag: vessel nested effect shows a continuously increasing trend along the time series analyzed. The hook per float effect trend presented some pulses during 1998 and 2006. After this period, the influence plot showed a decreased trend until 2019, whereas the trend increased sharply after this year.

The estimated delta-lognormal index showed three distinct periods. Between 1992 and 2005, the first was marked by stable smooth and low values. The second one, from 2006 to 2012, presented a slight increase in relative abundance, attaining its peak in 2012. The third period, from 2013 to 2022, showed a dynamic pattern with higher values than the beginning of the series but without any apparent increase or decreasing trend. (Figures 6; Table 1).

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Table 1. Annual standardized CPUEs and associated CVs and $95 \%$ confidence intervals, with vessel effects for the southern Blue Shark caught by the Brazilian and Uruguayan longline fleets for the BIL96 area.

| Year | Index | CV | Lower 95\% CI | $\begin{gathered} \text { Upper } 95 \% \\ \text { CI } \\ \hline \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: |
| 1992 | 1.13 | 0.147 | 0.852 | 1.513 |
| 1993 | 0.75 | 0.147 | 0.563 | 1.004 |
| 1994 | 0.48 | 0.101 | 0.393 | 0.583 |
| 1995 | 0.94 | 0.093 | 0.78 | 1.124 |
| 1996 | 0.55 | 0.072 | 0.478 | 0.634 |
| 1997 | 0.57 | 0.051 | 0.519 | 0.634 |
| 1998 | 0.80 | 0.041 | 0.743 | 0.872 |
| 1999 | 0.61 | 0.044 | 0.558 | 0.665 |
| 2000 | 0.67 | 0.042 | 0.614 | 0.725 |
| 2001 | 0.70 | 0.041 | 0.644 | 0.756 |
| 2002 | 0.63 | 0.035 | 0.588 | 0.675 |
| 2003 | 0.66 | 0.041 | 0.608 | 0.713 |
| 2004 | 0.58 | 0.035 | 0.537 | 0.616 |
| 2005 | 0.67 | 0.036 | 0.623 | 0.717 |
| 2006 | 0.48 | 0.038 | 0.442 | 0.514 |
| 2007 | 0.68 | 0.039 | 0.627 | 0.73 |
| 2008 | 0.86 | 0.039 | 0.8 | 0.932 |
| 2009 | 0.91 | 0.033 | 0.853 | 0.973 |
| 2010 | 0.82 | 0.049 | 0.743 | 0.902 |
| 2011 | 1.14 | 0.042 | 1.05 | 1.239 |
| 2012 | 1.58 | 0.036 | 1.472 | 1.697 |
| 2013 | 1.14 | 0.051 | 1.032 | 1.259 |
| 2014 | 0.93 | 0.042 | 0.856 | 1.009 |
| 2015 | 1.19 | 0.044 | 1.094 | 1.3 |
| 2016 | 0.88 | 0.049 | 0.795 | 0.964 |
| 2017 | 1.02 | 0.102 | 0.838 | 1.25 |
| 2018 | 1.24 | 0.042 | 1.14 | 1.342 |
| 2019 | 1.28 | 0.055 | 1.15 | 1.427 |
| 2020 | 0.72 | 0.072 | 0.629 | 0.834 |
| 2021 | 1.49 | 0.044 | 1.366 | 1.626 |
| 2022 | 1.00 | 0.046 | 0.914 | 1.096 |



Figure 1. Spatial distribution of the total fishing effort done by the Brazilian tuna and Uruguayan longline fishing fleets in the Atlantic Ocean from 1978 to 2018 (left). Spatial representation of the ICCAT BIL sampling areas (right).


Figure 2. Catch time series of the Brazilian tuna and Uruguayan longline fishing fleets in the South Atlantic Ocean from 1978 to 2018.


Figure 3. Time series for the blue shark proportion of the total reported catch of the Brazilian tuna and Uruguayan longline fishing fleets in the South Atlantic Ocean from 1978 to 2018.


Figure 4. Diagnostics plots for southern Blue Shark deltalog model - positive component.


Figure 5. Annual and seasonal influence values for each explanatory variable in GLM model.


Figure 6. Upper panel: Nominal CPUE (white dots) and scaled index by year for southern Atlantic blue shark and respective $95 \%$ confidence intervals. Lower panel: Nominal CPUE (white dots) and scaled index by year and quarter for southern Atlantic blue shark and respective $95 \%$ confidence intervals.


[^0]:    ${ }^{1}$ Federal University of Rio Grande - FURG
    ${ }^{2}$ University of Itajaí Valey - UNIVALI
    ${ }^{3}$ Dirección Nacional de Recursos Acuáticos - DINARA
    ${ }^{4}$ Federal University of São Paulo - UNIFESP
    ${ }^{5}$ Federal Rural University of Pernambuco - UFPRE

