# CPUE STANDARDIZATION OF SKIPJACK TUNA (KATSUWONUS PELAMIS) CAUGHT BY BRAZILIAN BAITBOAT FLEET IN SOUTHWESTERN ATLANTIC OCEAN 

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#### Abstract

SUMMARY Catch and effort data from the Brazilian baitboat fishery in the southwestern Atlantic Ocean, from 2000 to 2021, were analyzed in this working paper. The effort was distributed between $19^{\circ}$ $S$ and $35^{\circ}$ S. Bayesian Spatial-Temporal Hierarchical models using Integrated Nested Laplace Approximations with a Lognormal distribution were used to standardize CPUE series for the stock assessment of the West Skipjack Stock. The covariates used in the models were: year, quarter, vessels and lat-long squares of $0.5^{\circ} \times 0.5^{\circ}$. The estimated Bayesian Spatial-Temporal lognormal model showed interesting movements of the abundance of the stock. The lognormal index showed two distinct periods. The first one between 2000 and 2012, in general, marked by a stable trend over the years, with a pike in the last year of this period. And the second period, between 2012 and 2021, was marked by a steep one-way downward trend with a small stabilization trend in the last four years of the period.


## RÉSUMÉ

Les données de capture et d'effort de la pêcherie brésilienne de canneurs dans le Sud-Ouest de l'océan Atlantique, de 2000 à 2021, ont été analysées dans ce document de travail. L'effort a été réparti entre $19^{\circ} S$ et $35^{\circ} S$. Des modèles hiérarchiques bayésiens spatio-temporels utilisant des approximations de Laplace intégrées et imbriquées avec une distribution lognormale ont été utilisés pour standardiser les séries de CPUE pour l'évaluation du stock de listao occidental. Les covariables utilisées dans les modèles étaient: l'année, le trimestre, les navires et les carrés latlong de 0,5 $x$ 0,5 . Le modèle lognormal bayésien spatio-temporel estimé a montré des mouvements intéressants de l'abondance du stock. L'indice lognormal a montré deux périodes distinctes. La première période, entre 2000 et 2012, en général, a été marquée par une tendance stable au cours des années, avec un pic dans la dernière année de cette période. La deuxième période, entre 2012 et 2021, a été marquée par une forte tendance à la baisse à sens unique avec une petite tendance à la stabilisation dans les quatre dernières années de la période.

## RESUMEN

En este documento de trabajo se analizan los datos de captura y esfuerzo de la pesquería brasileña de cebo vivo en el sudoeste del océano Atlántico, desde 2000 hasta 2021. El esfuerzo se distribuyó entre $19^{\circ}$ S y $35^{\circ}$ S. Se utilizaron modelos jerárquicos espaciotemporales bayesianos que utilizan aproximaciones de Laplace anidadas integradas con una distribución lognormal para estandarizar las series de CPUE con miras a la evaluación de stock de listado occidental Las covariables utilizadas en los modelos fueron: el año, el trimestre, los buques y las cuadrículas de lat-long de 0,5 $5^{\circ}$ 0,5 . El modelo lognormal bayesiano espaciotemporal estimado mostró interesantes movimientos de la abundancia del stock. El índice lognormal mostraba dos períodos diferenciados. El primero entre 2000 y 2012, en general, marcado por una tendencia estable a lo largo de los años, con un pico en el último año de este periodo. Y el segundo periodo, entre 2012 y 2021, se caracterizó por una fuerte tendencia unidireccional a la baja con una pequeña tendencia a la estabilización en los últimos cuatro años del periodo.

## KEYWORDS

Abundance index; Tropical tuna; Pelagic fisheries; Catch/Effort; Bayesian models; INLA

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## 1. Introduction

Important fisheries of the Atlantic Ocean have your management process and referenced points estimations based on stocks assessments commonly structured over the utilization of catch per unit effort (CPUE) information, examples include the Yellowfin tuna stock (ICCAT, 2019), Bigeye tuna stock (ICCAT, 2021), Albacore tuna stock (ICCAT, 2020) and other species/stocks in the pelagic compartment of the Atlantic Ocean ecosystem. In terms of the Atlantic skipjack (Katsuwonus pelamis) west stock (W-SKJ), the assessment process is the same. One of the most important pieces of information used in the stock assessment is the CPUE series provided by each CPC that have fisheries involved in the exploration of this stock. This specific tropical tuna stock had an important role for commercial fisheries from Brazil. Almost $90 \%$ of the total catches of the W-SKJ are caught by the Brazilian fisheries fleets, in mainly, by the baitboat fleet.

Although CPUE has been classically used as an index of relative abundance, the relationship between the CPUE and the actual abundance of the stock is not linear, being affected by several factors, which may, therefore, lead to interpretation errors and make its utilization rather complex. Commonly, as a result of market changes over the years, several fleets have presented changes in their fishing strategies in order to increase the catching efficiency of a given species. These changes are less observed in the Brazilian baitboat fishery fleet that had presented a considerable stable market for the skipjack tuna. However, climatic changes, such as sudden variations in ocean surface temperatures, can promote considerable effects on the distribution pattern and abundance of this species. In this sense, the CPUE standardization method used in this working paper brings a form to try to include the spatial-temporal (and seasonal) variations in the relative abundance index as a proxy to try to understand the movement behaviour of the W-SKJ tuna stock at the southwestern of the Atlantic Ocean. Also, in order to contribute with information for the assessment of the W-SKJ, a standardized time series of CPUE for the species, caught by the Brazilian baitboat fleet are presenting spanning information for the last 21 years, from 2000 to 2021.

## 2. Data and methods

### 2.1 Catch and effort data

Information about fishing effort and skipjack tuna caught in the Southwest Atlantic Ocean by the Brazilian baitboat fleet used here in this working paper was provided by fisheries landings monitoring projects conducted by the Universidade do Vale do Itajaí (http://pmap-sc.acad.univali.br/). This database is composed of fishing effort and catches information collected between the years 2000 and 2021. This information was collected by interviews conducted with each skipper at the end of each cruise, logbooks fulfilled and provided by the fishing skippers also at the end of each cruise and/or from data collected onboard the vessels through historical official observer monitoring programmes and recently scientific observer programmes.

It was analyzed here information from 2,894 fishing trips, this information corresponds to $57.7 \%$ of all fishing trips conducted by the Brazilian baitboat fleet during the period between 2000 and 2021. Baitboats have been fishing offshore of Brazil since 1981, unfortunately, the information available for the models for the early period between 1981 and 1999 does not have the same spatial granularity and general detailing required here. The spatial distribution of the catches, effort and nominal CPUE can be observed in Figure 1. The spatial resolution was $0.5^{\circ}$ $\mathrm{x} 0.5^{\circ}$. The reports of skipjack catch equal to zero are scarce, less than $1.6 \%$.

### 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 4.1.0 (R Core Team, 2021). At the cleaning process, in the first step, vessels that had never caught a skipjack tuna before were removed from the dataset.

### 2.3 CPUE standardization

For the CPUE standardization of the skipjack caught in the Southwest of the Atlantic Ocean were applied Hierarchical Bayesian models structured through the Integrated Nested Laplace Approximations (INLA) (Rue et al., 2009; Lindgren et al., 2011). This approach allows understanding the spatial, temporal and seasonal trends in the abundance index estimated for a species. In this sense, effects that may be contained and directly related to spatial-temporal or even seasonal variations can be minimized due to this model structuring format. Thus, providing a cleaner view of the behaviour of the abundance index of the species being evaluated. Similarly to

Generalized Linear Models, this type of model assumes that the response variable belongs to the exponential distribution families, here used as a Lognormal distribution and that its parameters ( $\theta$ ) are linked to the linear predictor addictive structure $(\eta)$ through a logarithmic canonic connection function $g($.$) , such as g(\theta)=\eta$ (Agresti, 2002; Cosandey-Godin et al., 2014). The model differs from the traditional linear component specification $x_{i}^{T} \beta$ due the inclusion of the term $f($.$) , so that:$

$$
\eta_{i}=g\left(\mu_{i}\right)=\beta_{0}+\sum_{j=1}^{J} \beta_{j} x_{i j}+\sum_{k=1}^{K} f_{k}\left(z_{i k}\right)
$$

where $\eta_{i}$ is the linear predictor; $g\left(\mu_{i}\right)$ is the link function for the expected values of the $i$ observations $\left(E\left(y_{i}\right)\right)$; $\beta_{0}$ is the intercept of the model; the coefficients $\beta=\left\{\beta_{1}, \ldots, \beta_{j}\right\}$ quantify the fixed effect of some covariates $x=$ $\left(x_{1}, \ldots, x_{j}\right)$ on the response; and $f=\left\{f_{1}(),. \ldots, f_{k}().\right\}$ is the collection of functions defined in terms of a set of covariates $z=\left(z_{1}, \ldots, z_{k}\right)$. The terms $f_{k}($.$) can assume different forms such as smooth and nonlinear effects of$ covariates, time trends and seasonal effects, random intercept and slopes as well as temporal or spatial random effects (Blagiardo and Cameletti, 2015). These components define the latent field as $\theta=\left\{\beta_{0}, \beta, f\right\}$, where $\beta$ and $f$ are the covariates and smooth functions and/or random effects included in the linear predictor with their appropriate prior distributions $(\psi)$.

Similar to Generalized Additive Model (GAM), the $f_{k}$ are semi-parametric functions defining the spatial, temporal and random effects included in the models (Table 1). Four distinct criteria were used to compare the performance of the different models: (i) reduction in deviance; (ii) Watanabe-Akaike Information Criteria (WAIC) (Watanabe, 2010); (iii) Deviance Information Criterion (DIC) (Spiegelhalter et al., 2002) and (iv) Conditioning Predictive Ordinate (CPO) (Roos and Held, 2011). Additionally, as a measure of diagnostic, the Probability Integral Transform (PIT) was used (Schrödle and Held, 2011). Thus, the variable selection process and structure for the random effect for each covariate were based on the same four criteria. As proposed by Cosandey-Godin et al. (2014), the process was conducted in three hierarchical steps, as is: (1) it was evaluated the structure for temporal and seasonal covariates as listed in Table 1; (2) it was evaluated the contribution of each covariate with structure defined in the last step including the random effect (IID) for the covariate boat, and; (3) finally, were evaluated the structure for the spatial and spatial-temporal and seasonal interaction effect. A description of the three spatial and spatial-temporal and seasonal interaction effects teste in this working paper are shown in Table 3.

## 3. Results and Discussion

The exploratory analysis shown that skipjack caught by the Brazilian baitboat fleet consists of almost $95 \%$ of its total catches (Figure 2). The temporal variation in the representativeness of the skipjack in the catch times series was quite stable over the 21 years here analysed. As described in the Methods section, the proportion of zero catches was relatively small, in general, less than $1.6 \%$ of the total fishing trips evaluated (Figure 3). Boxplots for the nominal catch-per-unit effort are presented in Figure 4. Although a general overlap between the annual boxplots was observed, there is a gentle reduction in the central tendencies in more recent years, starting in 2016.

All process for the selection of the final model was presented in Tables $\mathbf{1 , 2}$ and 3. The best fit structure for the temporal and seasonal covariates was an autoregressive function with order 01 for "year" and also an autoregressive function of order 01 with a cyclic interaction for "quarter". In the second step, the model based on year, quarter and boat presented the best fit. Finally, the model with spatial structure repeating over the years with a cyclic spatial correlation between seasons (quarters) with an autoregressive function of order 01 was elected as a final model based on both information criteria used in this study.

Diagnostics of the predictive capability of the final model can be observed in Figure 6. Conditional predictive ordinates do not present any failure. The same pattern was observed in predictive integral probabilities. The contrast between observed CPUE and the predicted by the model shown a general correlation of 0.8035 . In general, the final model shows less predictive capabilities in to predict the zero CPUE. Although, these cases was very rare in all database. The analysis of the residuals of the final model shown an approximated normal distribution and independent and identically distributed (Figure 7).

Figures 8 and 9 were shown the posteriors distributions of (1) the precisions (inverse of variances) for the Gaussian observations, year, boat and spatial effect, and; (2) the hyperparameters temporal autocorrelation for the year and spatial autocorrelation between seasons or quarters. For all posteriors were also presented the $95 \%$ highest probability density intervals (hpd). This last one showed an hpd crossing the absolute zero, this can be interpreted as a non-significant trend in spatial correlations along the seasons.

The summary of random effects can be observed in Figures 10, 11 and 12. The year random effect showed a decreasing trend after 2012 until 2017. This pattern apparently stabilises after this last year. In the case of the boat random effect, it is possible to observe a relatively constant pattern among vessels, showing a quite similar fishing efficiency among the fleet. While the spatial correlation between seasons had shown a probability to be equal to zero, Figures 11 and $\mathbf{1 2}$ show some interesting trends in the spatial-temporal and seasonal changes in relative abundance index. In the examples presented here, it is possible to observe an increasing trend in the index from the North area to South during the first quarter of 2000, 2006 and 2012. This same positive trend can be observed in 2006 and 2012 for the third quarter. Here are presented only some examples of the movement of the stock, these results can be access to all 21 years analyzed in this working paper.

The estimated lognormal index showed two distinct periods. The first one between 2000 and 2012, in general marked by a stable trend over the years, with a pike in the last year of this period. And the second period, between 2012 and 2021, marked by a steep one-way downward trend with a small stabilization trend in the last four years of the period (Figure 13; Table 4). This trend in the lognormal index, mainly in the second part of the time series, could be affected by different factors, among them (a) the effect of availability of the species to the fishing effort in the area for the recent years could reflect in a sub-estimation of the relative abundance index; (b) existence of some unreported information or sub-notification that could be implying in a sub-estimation of the relative abundance index also for recent years and, (c) there is a real reduction in the biomass of the W-SKJ stock in the recent years and the relative abundance index could be reflecting an answer to the historical removals over the time.

## References

Agresti, A., 2002. Categorical data analysis. Second ed. John Wiley \& Sons, New York.
Amorim, A. F E Arfelli, C. A. 1984. Estudo biológico pesqueiro do espadarte, Xiphias gladius Linnaeus, 1758, no sudeste e sul do Brasil (1971 a 1981). B. Inst. Pesca, São Paulo, 11(único):35-62.
Bentley N., Kendrick T.H., Starr P.J., Breen P.A. 2011. Influence plots and metrics: tools for better understanding fisheries catch-per-unit-effort standardizations. ICES Journal of Marine Science 69(1): 84-88.

Blangiardo, M.; Cameletti, M. 2015. Spatial and Spatio-temporal Bayesian Models with R-INLA. Chichester: John Wiley \& Sons.
Cosandey-Godin, A.; Krainski, E. T.; Worm, B.; Flemming, J. M. Applying Bayesian Spatio-Temporal Models to Fisheries Bycatch in the Canadian Arctic. Can. J. Aquat. Sci. 72 (2), 186-197.
Dobson, A. J. 2002. An Introduction to Generalized Linear Models. New York: Chapman \& Hall.
Hoyle S.D., Okamoto H., Yeh Y.-m., Kim Z.G., Lee S.I., Sharma R. 2015. IOTC-CPUEWS02 2015: Report of the 2nd CPUE Workshop on Longline Fisheries, 30 April - 2 May 2015. 126 p.

Hoyle S.D., Kim D., Lee S., Matsumoto T., Satoh K., Yeh Y. 2016. Collaborative study of tropical tuna CPUE from multiple Indian Ocean longline fleets in 2016.

Hoyle, S.D., Huang, H., Kim, D. N., Lee, M. K., Matsumoto, T., Walter, J. Collaborative study of bigeye tuna CPUE from multiple Atlantic Ocean longline fleets in 2018. Collect. Vol. Sci. Pap. ICCAT, 75(7): 20332080.

Lindgren F.; Rue, H.; Lindstrom, J. 2011. An Explicity Link Between Gaussian Fields and Gaussian Markov Random Fields: the stochastic partial differential equation approach (with discussion). Journal of Royal Statistical Society, Series B, 73(4): 423-498.
Lindgren F.; Rue, H. 2013. Bayesian Spatial Modeling with R. Journal of Statistical Software. 63(19): 1-25.
R Core Team 2021. R: A Language and Environment for Statistical Computing. Vienna, Austria, R Foundation for Statistical Computing.
Roos, M.; Held, L. 2011. Sensitivity Analysis in Bayesian Generalized Linear Mixed Models for Binary Data. Bayesian Analysis. 6(2): 259-278.

Rue, H.; Martino, S.; Chopin, N. 2009. Approximate Bayesian Inference for Latent Gaussian Model By Using Integrated Nested Laplace Approximations (with discussion). Journal of Royal Statistical Society, Series B, 71, 319-392.

Spiegelhalter. D.; Best, N.; Carlin, B.; Van Der Linde, A. Bayesian measures of model complexity and fit, Journal of the Royal Statistical Society B, v. 64, p. 583-639, 2002.
Schrodle, B.; Held, L. Spatio-temporal disease mapping using INLA, Environmetrics, v. 22, p. 725-734, 2011.
Watanabe, S. 2010. Asymptotic Equivalence of Bayes Cross Validation and Widely Applicable Information Criterion in Singular Learning Theory. Journal of Machine Learning Research 11: 3571-3594.

Table 1. Descriptive results table for temporal and seasonal models fitted to define the structure for the covariates year and quarter in the spatial-temporal models.

| Covariate | Model | Deviance | WAIC | DIC |
| :---: | :---: | :---: | :---: | :---: |
| ジ | Null | 7527.23 | 7529.34 | 7528.38 |
|  | Fixed | 7152.07 | 7175.07 | 7173.54 |
|  | Random (IID) | 7152.10 | 7173.81 | 7172.30 |
|  | Autoregressive (AR1) | 7151.51 | 7169.21 | 7168.89 |
|  | Autoregressive (AR2) | 7213.30 | 7219.99 | 7219.80 |
|  | Autoregressive (AR3) | 7151.49 | 7170.40 | 7170.13 |
|  | Autoregressive (AR4) | 7152.08 | 7172.43 | 7170.80 |
|  | Random Walk (RW1) | 7183.33 | 7193.44 | 7193.01 |
|  | Null | 7527.23 | 7529.34 | 7529.27 |
|  | Fixed | 7381.64 | 7386.67 | 7386.68 |
|  | Random (IID) | 7421.12 | 7424.66 | 7423.60 |
|  | Autoregressive (AR1) | 7525.32 | 7526.86 | 7526.83 |
|  | Random Walk (RW1) | 7381.99 | 7386.98 | 7386.98 |
|  | Autoregressive (AR1 - Cyclic) | 7381.28 | 7385.56 | 7385.61 |
|  | Random Walk (RW1 - Cyclic) | 7381.79 | 7386.76 | 7379.66 |

Table 2. Descriptive results table of the lognormal model fitted without spatial structure to selection final variables to the spatial-temporal models.

| Model | Deviance | WAIC | DIC |
| :---: | :---: | :---: | :---: |
| logCPUE ~ f(Y, "ar1") | 7151.79 | 7171.68 | 7170.88 |
| $\operatorname{logCPUE} \sim \mathrm{f}(\mathrm{Y}$, "arl") + f(Q, "arl", cyclic) | 6985.96 | 7009.13 | 7008.25 |
| $\operatorname{logCPUE} \sim \mathrm{f}(\mathrm{Y}$, "arl") $+\mathrm{f}(\mathrm{B}$, "iid") | 6793.17 | 6875.27 | 6868.83 |
| $\operatorname{logCPUE} \sim \mathrm{f}(\mathrm{Y}$, "arl") $+\mathrm{f}(\mathrm{Q}$, "arl", cyclic $)+\mathrm{f}(\mathrm{B}$, "iid") | 6583.69 | 6671.36 | 6665.47 |

Table 3. Descriptive results table of the lognormal model fitted with spatial-temporal structure.

| Model | Deviance | WAIC | DIC |
| :--- | :---: | :---: | :---: | :---: |
| Spatial structure fixed along the years and cyclic spatial <br> correlation between quarters with an autoregressive <br> function with order 1 | 8423.28 | 8586.57 | 8587.77 |
| Spatial structure repeating over the years and cyclic spatial <br> correlation between quarters with an autoregressive <br> function with order 1 | 7923.79 | 8381.01 | 8376.61 |
| Spatial structure with an autoregressive function of order 1 <br> over the years. | 8382.96 | 8561.00 | 8558.95 |

Table 4. Relative abundance index and associated standard deviation and $95 \%$ credibility intervals for the skipjack tuna caught by the Brazilian baitboat fleet.

| Year | Index | Std. Deviation | Lower 95\% CI | Upper 95\% CI |
| :---: | :---: | :---: | :---: | :---: |
| 2000 | 1.214 | 0.1237 | 0.927 | 1.577 |
| 2001 | 1.073 | 0.1010 | 0.829 | 1.346 |
| 2002 | 1.020 | 0.1000 | 0.811 | 1.283 |
| 2003 | 0.768 | 0.1013 | 0.600 | 0.973 |
| 2004 | 0.935 | 0.1004 | 0.743 | 1.190 |
| 2005 | 1.029 | 0.1053 | 0.795 | 1.303 |
| 2006 | 1.310 | 0.1073 | 1.055 | 1.660 |
| 2007 | 1.355 | 0.1010 | 1.089 | 1.712 |
| 2008 | 1.300 | 0.1010 | 1.045 | 1.630 |
| 2009 | 1.303 | 0.1039 | 1.029 | 1.608 |
| 2010 | 1.076 | 0.1023 | 0.855 | 1.363 |
| 2011 | 1.525 | 0.0980 | 1.238 | 1.895 |
| 2012 | 1.854 | 0.0979 | 1.499 | 2.266 |
| 2013 | 1.167 | 0.1045 | 0.921 | 1.453 |
| 2014 | 0.917 | 0.1096 | 0.710 | 1.175 |
| 2015 | 0.819 | 0.1242 | 0.607 | 1.083 |
| 2016 | 0.620 | 0.1973 | 0.369 | 0.982 |
| 2017 | 0.442 | 0.1083 | 0.318 | 0.598 |
| 2018 | 0.488 | 0.1086 | 0.356 | 0.637 |
| 2019 | 0.520 | 0.1117 | 0.378 | 0.682 |
| 2020 | 0.679 | 0.1028 | 0.516 | 0.868 |
| 2021 | 0.585 | 0.1076 | 0.437 | 0.764 |




Figure 1. Spatial distribution of the total catch, fishing effort and nominal CPUE off the Brazilian tuna baitboat fishery in the Southwestern Atlantic Ocean from 2000 to 2021.


Figure 2. General diagram the Brazilian baitboat catches discriminated by species and year.


Figure 3. Distribution of the proportion of zero skipjack tuna catches in the Brazilian baitboat fleet discriminated by year, quarter and vessel (light colour represents the proportion of zero catches over the trips and dark colour represents the respective proportion of positive catches).


Figure 4. Logarithm of the catch-per-unit-effort (t/fishing days) in each year, quarter and for each vessel monitored during the period.


Figure 5. Spatial neighbor structure defined for the model.


Figure 6. General diagram with the predictive model diagnostics.


Figure 7. Standard diagnostic plots for the fitting of the lognormal model.


Figure 8. Posteriors distributions for the precisions of the covariates of the final model. Gray areas represents the $95 \%$ highest posterior density (HPD) credible interval.


Figure 9. Posteriors distributions for the hypeparameters in the final model. Gray areas represents the 95\% highest posterior density (HPD) credible interval.


Figure 10. Random effect estimated for the covariates Year and Vessel.


Figure 11. Random effect estimated for the Spatial interaction with temporal (Year) and seasonal (Quarter) covariates. Examples for the years 2000 (top-left); 2006 (top-right); 2012 (bottom-left) and 2021 (bottom-right).


Figure 12. Spatial-temporal random effect distribution. Examples for the years 2000 (top-left); 2006 (top-right); 2012 (bottom-left) and 2021 (bottom-right).


Figure 13. Standardized abundance index time series and associated $95 \%$ credibility intervals estimated for the skipjack tuna caught by Brazilian baitboat fleet.


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