Standardized CPUE of oceanic whitetip shark bycaught by the French Reunion-based pelagic longline fishery operating in the South West Indian Ocean (2007-2024)

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Abstract

The oceanic whitetip shark *Carcharhinus longimanus* is a relatively common bycatch of the French swordfish-targeting longline fishery operating in the southwestern Indian Ocean. Using observer and self-reported data collected aboard these longliners between 2007 and 2024, we present a standardized CPUE series for oceanic whitetip shark. The index was estimated using a Generalized Additive Mixed Model (GAMM) with a Negative Binomial distribution, which appropriately handled the high proportion of zero catches in the data. For the upcoming stock assessment, we recommend using the standardized CPUE for the period comprised between 2011 and 2024 where the monitoring effort has been consequent in comparison with previous years. Throughout this period, the standardized CPUE for the oceanic whitetip shark shows a slight but significant increasing trend.

Keywords

Oceanic whitetip shark | CPUE standardization | Longline | Western Indian Ocean

1. Introduction

Primary indices of abundance of target (e.g. tunas) and non-target species (e.g. sharks) are based on catch and effort data from commercial fisheries in the absence of fishery-independent abundance indicators. Fishery-based indices need to be standardized to remove the influence of various fishery-dependent factors such as the fishing effort variability, fishing strategy, habitat overlap, etc., so they can be used for stock assessment (Maunder and Punt, 2004).

The French longline fishery based in Reunion Island operates in the southwestern Indian Ocean around Reunion Island, Mauritius, and Madagascar and mainly targets swordfish (*Xiphias gladius*) with relatively shallow night sets. The oceanic whitetip shark *Carcharhinus longimanus* is the third most common bycatch species among sharks and represents about 2.4% of the total bycatch in number of individuals caught (Ob7 pers. comm.).

In this paper, we provide an index of abundance for this species based on observer and self-reported data of the French swordfish-targeting fishery based in Reunion Island for the period 2007-2024.

2. Material and methods

2.1. Data

We used data collected by sea-going observers on French longline vessels (Bach et al., 2008) as well as data collected by fishermen themselves called "self-reported data" (Bach et al., 2013). Data were collected through CAPPER (2007-2008) and EU Data Collection Framework (2009-2024; Reg 199/2008 and 665/2008). The coverage in number of hooks monitored is presented in Figure 1. We retained a total of 5214 fishing operations monitored between 2007 and 2024 from the core fishing area that consists of 5°x5° squares with more than 120 fishing operations (Figure 2).

2.2. CPUE standardization

The response variable modeled was the number of sharks caught (*nb_caught*) per fishing operation. The fishing effort, defined as the number of hooks deployed (*total_hooks_count*), was included in the model as a log-transformed offset (*offset(log(total_hooks_count))*). This approach allowed for the direct modeling of the catch per unit of effort (CPUE) using a distribution adapted to count data.

The proportion of zeros in the data is important (79%) and the catch distribution highly skewed (Figure 3), which justifies using models adapted for overdispersed count data. We estimated the standardized CPUE with a Generalized Additive Mixed Model (GAMM) using both the *glmmTMB* and the *gam* functions, respectively from *glmmTMB* and *mgcv* R packages (Brooks et al., 2017; Wood, 2017). We compared several distributions, including Poisson (P), Zero-Inflated Poisson (ZIP), Negative Binomial (NB) and Zero-Inflated Negative Binomial (ZINB) models.

The list of candidate covariates was determined based on previous work of CPUE standardization for oceanic whitetip shark (Brodziak and Walsh, 2013) and standardization for blue shark carried out with the same dataset (Sabarros et al., 2017; Sabarros et al., 2021; Sabarros et al., 2025). The potential non-linearity of continuous covariates was checked by performing univariate GAM models (Figure 4).

Candidate covariates were:

- Fixed effects:
    - *year* (factor): 2007 to 2024.
    - *quarter* (factor): Q1 to Q4.
    - *longitude* (continuous): longitude of the fishing operation, specifically the longitude where the line starts being retrieved (hauling).
    - *latitude* (continuous): latitude of the fishing operation, specifically the latitude where the line starts being retrieved (hauling).
    - *cwp55* (factor): 5°x5° square of the fishing operation, specifically the square where the line starts being retrieved (hauling).
    - *quarter:cwp55* (factor): interaction between quarter and 5°x5° square.
    - *soaking_time* (continuous): time in hours from when the first hook is deployed to when the last hook retrieved.
    - *setting_start_time* (continuous): time (hh:mm) when the first buoy is deployed.
    - *hauling_end_time* (continuous): time (hh:mm) when the last buoy is retrieved.
    - *hooks_per_basket* (continuous): number of hooks per basket as a relative index of fishing depth range/targeting.
    - *percentage_circle_hooks* (continuous): relative proportion of circle hooks to other types of hooks (J-hooks, tuna hooks, Teracima hooks).
    - *percentage_squid_bait* (continuous): proportion of squid bait relatively to other bait used (mackerel, etc.).
- Random effects:
    - *vessel* (factor): the vessel name was used as a random effect given that we wanted to incorporate the vessel effect variability in the model but without estimating specific parameters for each vessel.

We applied a forward-stepwise model selection procedure, adding covariates sequentially and comparing models using the Akaike Information Criterion (AIC) to select for relevant and significant covariates.

The comparison between different distributions: P, ZIP, NB, and ZINB, showed that ZIP and NB provided better results than P and ZINB (not shown). The best model with a ZIP distribution is called hereafter Mod 1; the best with a NB distribution is called Mod 2.

The deviance tables (Type III ANOVA with Chi Square test) of Mod 1 and Mod 2 are provided in Table 1. The summary table of the retained model (Mod 2) is presented in Table 2, the partial effects of the different continuous covariables in Figure 5, and the graphical analysis of scaled residuals using the *DHARMa* R package (Hartig et al., 2024) in Figure 6. Finally, we present the yearly standardized CPUE series from the retained model computed (Table 3; Figure 7) as well as the scaled (by the mean) standardized CPUEs series (Figure 8).

3. Results

Between the ZIP and NB models, the NB model (Mod 2) was selected, as it achieved the lowest AIC score and provided the best fit to the data. The final model, identified through the forward variable selection procedure, was as follows:

Mod 2: *nb_caught ~ year + quarter + s(longitude) + s(latitude) + quarter:cwp55 +* s*(hooks_per_basket) + s(percentage_circle_hooks) + s(percentage_squid_bait) + (1|vessel) + offset(log(total_hooks_count))*

The deviance analysis (Type III Wald Chi-square test) of the final model indicates that *year* ($p < 2e\text{-}16$) and *quarter:cwp55* ($p < 2e\text{-}16$) have a significant effect on the number of oceanic whitetip sharks caught (Table 1). The smooth terms for *latitude* ($p = 0.000192$), *hooks_per_basket* ($p = 0.019725$), *percentage_circle_hooks* ($p = 0.026269$) and *percentage_squid_bait* ($p < 1.13e\text{-}05$) were also significant. However, the effects of *quarter* ($p = 0.25$) and the smooth term for *longitude* ($p = 0.322554$) were not statistically significant in the final model. These covariates were nevertheless retained in the final model as the forward selection procedure indicated their inclusion improved the model's overall fit based on AIC.

The random effect for *vessel* had a significative p-value ($p = 0.006788$), indicating considerable variability in catch rates among vessels. The dispersion parameter for the Negative Binomial distribution was 1.317, confirming significant overdispersion in the data.

Weights (Chi-square) of the model showed that *year* ($\chi^2 = 132.727$) and interaction term *quarter:cwp55* ($\chi^2 = 187.699$) were the most influential factors explaining the variability in the number of oceanic whitetip sharks caught. The smooth term for *percentage_squid_bait* ($\chi^2 = 32.619$) and the random effect of *vessel* ($\chi^2 = 20.678$) also had a relatively important explanatory power. The smooth terms for *latitude* ($\chi^2 = 16.952$), *hooks_per_basket* ($\chi^2 = 11.285$) and *percentage_circle_hooks* ($\chi^2 = 7.608$) had significant but lesser effects.

Overall, the retained standardized CPUE follows the nominal CPUE (Figure 7; Table 3). Acknowledging the relatively low coverage rate in the first years of the program, we focused on the period between 2011 and 2024. The standardized CPUE series exhibits a period of fluctuation at low levels between 2011 and 2018, and an increasing trend since 2018. Throughout 2011-2024, the overall trend of the standardized CPUE is weak but significantly increasing (linear regression: b = 0.008656, p-value = 0.0231). Between 2011 and 2018, the evolution is not significant (b = -0.004729, p-value = 0.406). The increase is more pronounced but also not significant between 2018 and 2024 (b = 0.02314, p-value = 0.0731).

The residual analysis of the final model (Figure 6) confirms a good overall fit. The scaled residuals showed no significant deviation from the expected uniform distribution (Kolmogorov-Smirnov test, p = 0.6179), indicating that the Negative Binomial model structure is appropriate for the data. No residual patterns were detected against the predicted values, and specific tests confirmed the absence of: significant remaining overdispersion (p = 0.236), too many outliers (p = 0.28), or zero-inflation (p = 0.904). Overall, the diagnostics suggest that the model is robust and appropriate for standardizing the CPUE of this species.

4. Discussion

The standardization of the oceanic whitetip shark CPUE series successfully accounted for the influence of several operational and environmental factors. The resulting index is considered a more reliable indicator of abundance trend than the nominal CPUE.

Significant effects on oceanic whitetip shark CPUE

The final model identified several environmental, temporal, and operational factors significantly influencing the oceanic whitetip shark CPUE. Among them, year and the interaction between quarter and 5°×5° squares emerged as the most influential variables, reflecting strong spatiotemporal variability in catch rates across the study period. The year effect, central to the standardization process, revealed pronounced inter-annual fluctuations, suggesting that broader ecosystem dynamics and fishing practices may influence shark availability and catchability.

Latitude also exhibited a significant non-linear effect (edf = 2.28), with higher catch rates recorded in the northern portion of the fishing grounds, around 15°S. This pattern is consistent with the known distribution of the species, which is more abundant in warmer, low-latitude waters (Bonfil et al., 2008). Although quarter and longitude were not significant in the final multivariate model, their inclusion during forward-stepwise selection ensured control of potential confounding effects and improved overall model robustness.

Operational variables were also important. The number of hooks per basket, a proxy of fishing depth, showed a significant non-linear effect (edf = 2.05). CPUE generally decreased with increasing numbers of hooks per basket, indicating lower catch rates in deeper sets. This result aligns with the epipelagic behavior of oceanic whitetip sharks (Tollotti et al., 2017). In the Reunion Island fishery, hooks are typically deployed from 10 m below the surface down to ~120 m during night sets (Bach et al., 2014). However, deeper configurations, more common in daytime sets targeting tunas, extend further into the water column and likely reduce encounter rates with this species. This pattern merits further investigation to better quantify depth-related vulnerability.

The percentage of circle hooks in the gear configuration was positively associated with catch rates, showing a nearly linear effect. This result is consistent with previous findings that circle hooks tend to increase shark catchability compared to J-hooks (Santos et al., 2019). Mechanistically, circle hooks are more likely to secure in the jaw rather than internally (e.g., J-hooks), reducing the likelihood of bite-offs and subsequent escape, which may explain the higher CPUE observed.

Bait type also influenced catch rates. The percentage of squid bait exhibited a non-linear effect, with CPUE peaking at intermediate use levels (30–40%) and declining as squid use increased further. This suggests that oceanic whitetip sharks may show a relative preference for fish-based baits over squid, in line with the findings of Santos et al. (2019). Such results highlight the potential role of bait choice in modulating shark bycatch risk.

Finally, the random effect of vessel was significant, confirming consistent inter-vessel differences in fishing efficiency. Accounting for this variability was essential to avoid biased estimates and to ensure that the observed effects were not confounded by vessel-specific fishing practices.

Relevance of the retained standardized CPUE series

This standardization was based exclusively on the core fishing grounds of the Reunion Island longline fleet (Figure 2). Restricting the analysis to this area avoided the potential biases associated with the inclusion of a small number of sets conducted in peripheral regions such as the northern Mozambique Channel or the high seas, where different environmental conditions and fishing strategies may influence catch rates. This conservative approach, also adopted in the standardization of blue shark CPUE for the same fleet (Sabarros et al., 2025), ensures that the resulting index is more representative and reliable.

Compared with the nominal CPUE, the standardized series is smoother but still captures meaningful temporal variability. Model diagnostics indicated a good fit and reliable residual structure, lending confidence to the robustness of the derived abundance index.

However, some caution is warranted for the early years of the series. Observer coverage was relatively low (<3% of effort in hooks observed) between 2007 and 2010 (Figure 1), raising concerns about data representativeness. For this reason, we recommend discarding this initial period and focusing on the 2011–2024 series for stock assessment and management purposes.

Within this period, the standardized CPUE shows a gradual increase in relative abundance of oceanic whitetip sharks, with an average growth rate of 0.9% per year ($p = 0.0231$). The index increased from ~0.17 in 2011 to ~0.30 in 2024, with a more pronounced upward trend in recent years (2018–

2024). While these results suggest some recovery or improved local availability of the species in the southwestern Indian Ocean, the relatively modest increase in abundance and the species' known life-history constraints underscore the need for continued monitoring and precautionary management.

5. Conclusion

The standardized CPUE time series from the Reunion-based pelagic longline fishery provides a reliable index of oceanic whitetip shark abundance between 2011 and 2024. The series shows a slight but significant increasing trend, mainly driven by higher catch rates in recent years (2018–2024). While this may suggest localized improvement, the species remains highly vulnerable. Incorporating this index into regional stock assessments will be important to support science-based management and to evaluate conservation measures such as the IOTC retention ban and bycatch mitigation strategies in pelagic longline fisheries.

6. Acknowledgments

We thank the observers and captains that collected data through CAPPER and EU DCF data collection programs.

7. References

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8. Tables

Table 1. Deviance table (Type III ANOVA) of the covariates in GAMM Mod 1 (best model with a Zero-Inflated Poisson distribution) and Mod 2 (best model with a Negative Binomial Distribution). For each covariate, we indicate the degrees of freedom or effective degrees of freedom (df or edf), the Chi Square test statistic (Chi.sq) and the significance (p-value).

Model	Covariates	df / edf	Chi.sq	p-value
Mod 1 (best model with a Zero-Inflated Poisson distribution) Random effect: *vessel* N = 5214 AIC = 6746.697	*year*	17	139.928	< 2e-16
	quarter	3	4.442	0.218
	te(longitude, latitude)	5.285	24.313	0.000329
	quarter:cwp55	28	134.691	6.57e-16
	s(hooks_per_basket)	1.938	11.189	0.017294
	s(percentage_circle_hooks)	1.314	7.985	0.027357
	s(percentage_squid_bait)	5.049	54.686	< 2e-16
Mod 2 (best model with a Negative Binomial distribution) Random effect: *vessel* N = 5214 AIC = 6708.916	*year*	17	132.727	< 2e-16
	quarter	3	4.104	0.25
	s(longitude)	0.02761	0.027	0.322554
	s(latitude)	2.27859	16.952	0.000192
	quarter:cwp55	28	187.699	< 2e-16
	s(hooks_per_basket)	2.04727	11.285	0.019725
	s(percentage_circle_hooks)	1.10567	7.608	0.026269
	s(percentage_squid_bait)	4.51508	32.619	1.13e-05

Table 2. Summary table of the retained Negative Binomial GAMM (Mod 2).

```
Family: Negative Binomial(1.317)
Link function: log

Formula:
nb_caught ~ year + quarter + s(longitude, bs = "cs") + s(latitude, bs = "cs") + quarter:cwp55 +
   s(branchlines_per_basket_count, bs = "cs") + s(percentage_circle_hooks, bs = "cs") +
   s(percentage_squid_bait, bs = "cs") +
 s(vessel, bs = "re") + offset(logtotalhooks)

Parametric coefficients:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)         -8.91893   0.68645 -12.993  < 2e-16 ***
year2008             0.19393   0.93511   0.207  0.83571
year2009             0.25129   0.62937   0.399  0.68969
year2010             0.78941   0.63881   1.236  0.21655
year2011             0.16435   0.50055   0.328  0.74266
year2012            -0.32604   0.48462  -0.673  0.50110
year2013            -0.79800   0.48978  -1.629  0.10325
year2014            -0.28342   0.48258  -0.587  0.55700
year2015            -0.41077   0.47975  -0.856  0.39188
year2016            -0.16056   0.48154  -0.333  0.73881
year2017            -0.11342   0.48252  -0.235  0.81417
year2018            -0.67094   0.49388  -1.359  0.17430
year2019            -0.01788   0.47943  -0.037  0.97025
year2020             0.29251   0.47816   0.612  0.54071
year2021             0.28405   0.47343   0.600  0.54852
year2022            -0.17448   0.48017  -0.363  0.71633
year2023             0.14689   0.47207   0.311  0.75568
year2024             0.70799   0.47265   1.498  0.13416
quarterQ2            0.56852   0.56814   1.001  0.31699
quarterQ3           -0.57546   0.71885  -0.801  0.42340
quarterQ4            0.34063   0.64926   0.525  0.59983
quarterQ1:cwp556215050  0.58764   0.54120   1.086  0.27757
quarterQ2:cwp556215050 -0.06011   0.32345  -0.186  0.85257
quarterQ3:cwp556215050  1.13431   0.58102   1.952  0.05091 .
quarterQ4:cwp556215050  0.21754   0.45024   0.483  0.62898
quarterQ1:cwp556215055 -0.21090   0.59416  -0.355  0.72263
quarterQ2:cwp556215055  0.22899   0.32644   0.701  0.48300
quarterQ3:cwp556215055  1.36754   0.56464   2.422  0.01544 *
quarterQ4:cwp556215055  0.44545   0.46309   0.962  0.33609
quarterQ1:cwp556220040  1.87600   0.57068   3.287  0.00101 **
quarterQ2:cwp556220040  1.20294   0.38900   3.092  0.00199 **
quarterQ3:cwp556220040  2.65748   0.57414   4.629 3.68e-06 ***
quarterQ4:cwp556220040  1.23016   0.48240   2.550  0.01077 *
quarterQ1:cwp556220045  0.37748   0.54890   0.688  0.49165
quarterQ2:cwp556220045 -0.13901   0.33834  -0.411  0.68118
quarterQ3:cwp556220045  0.01300   0.57381   0.023  0.98192
quarterQ4:cwp556220045  0.30919   0.50111   0.617  0.53723
quarterQ1:cwp556220050  0.48520   0.51311   0.946  0.34435
quarterQ2:cwp556220050 -0.09347   0.31444  -0.297  0.76628
quarterQ3:cwp556220050  0.22663   0.54526   0.416  0.67767
quarterQ4:cwp556220050 -0.18026   0.43987  -0.410  0.68196
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```
quarterQ1:cwp556220055  0.61802   0.52992   1.166  0.24351
quarterQ2:cwp556220055  0.18508   0.33748   0.548  0.58340
quarterQ3:cwp556220055  0.04740   0.74735   0.063  0.94943
quarterQ4:cwp556220055 -0.17016   0.45632  -0.373  0.70923
quarterQ1:cwp556225045  0.36312   1.00286   0.362  0.71729
quarterQ2:cwp556225045 -0.90483   0.61813  -1.464  0.14324
quarterQ3:cwp556225045 -0.94757   0.84489  -1.122  0.26206
quarterQ4:cwp556225045 -0.42405   0.83602  -0.507  0.61199
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                                  edf Ref.df Chi.sq  p-value
s(longitude)                  0.02761      9  0.027 0.322554
s(latitude)                   2.27859      9 16.952 0.000192 ***
s(branchlines_per_basket_count)  2.04727      9 11.285 0.019725 *
s(percentage_circle_hooks)      1.10567      9  7.608 0.026269 *
s(percentage_squid_bait)        4.51508      9 32.619 1.13e-05 ***
s(vessel)                    11.14079     43 20.678 0.006788 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.219   Deviance explained = 24.2%
-REML =   3343  Scale est. = 1        n = 5214
```

Table 3. Standardized CPUE (stdCPUE) time series for oceanic whitetip shark caught in the French longline fishery for the period 2007-2024. nCPUE designates the nominal CPUE. The stdCPUE is provided with 95% confidence interval (CI).

Year	nCPUE	stdCPUE	Lower CI	Upper CI
2007	0.2391	**0.1470**	0.0367	0.5891
2008	0.0928	**0.1784**	0.0267	1.1929
2009	0.1357	**0.1890**	0.0493	0.7247
2010	0.1631	**0.3237**	0.0834	1.2568
2011	0.2547	**0.1732**	0.0571	0.5252
2012	0.1129	**0.1061**	0.0361	0.3113
2013	0.0777	**0.0662**	0.0224	0.1954
2014	0.1560	**0.1107**	0.0391	0.3135
2015	0.1349	**0.0975**	0.0331	0.2868
2016	0.1687	**0.1252**	0.0430	0.3644
2017	0.1582	**0.1312**	0.0459	0.3753
2018	0.1690	**0.0751**	0.0252	0.2236
2019	0.2404	**0.1444**	0.0490	0.4257
2020	0.2920	**0.1969**	0.0673	0.5764
2021	0.3440	**0.1953**	0.0674	0.5657
2022	0.2453	**0.1234**	0.0421	0.3618
2023	0.3935	**0.1702**	0.0588	0.4929
2024	0.5721	**0.2983**	0.1040	0.8557

9. Figures

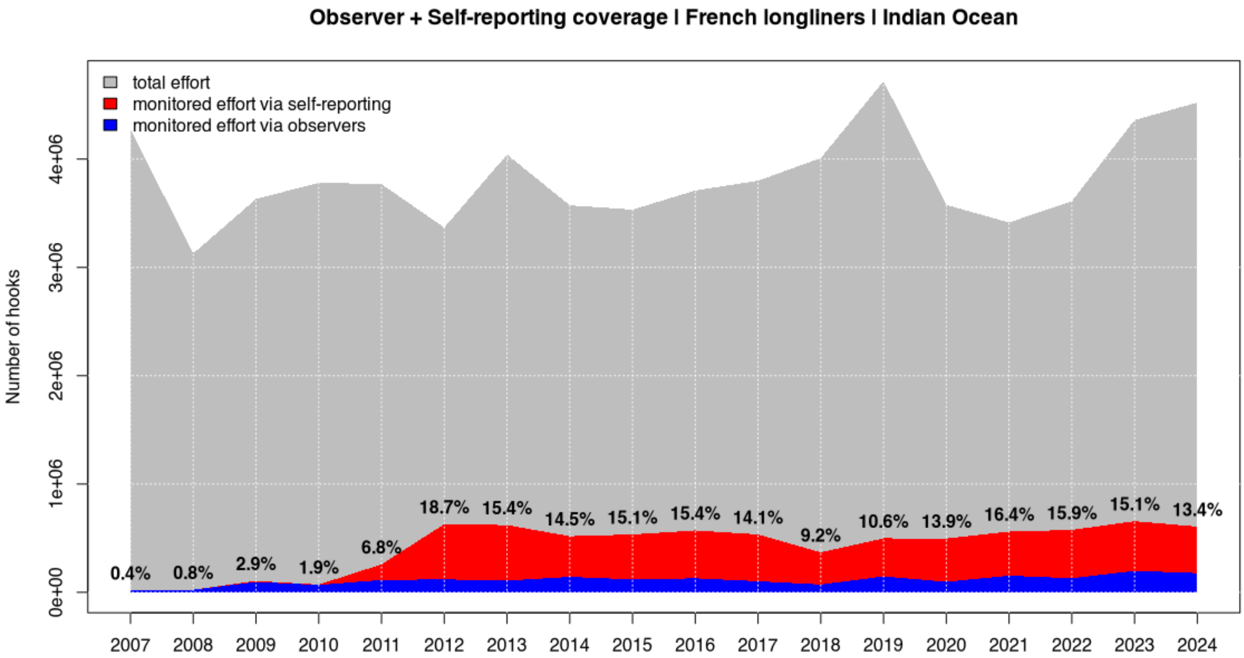

Figure 1. Observer and self-reporting effort coverage in number of hooks deployed in the French longline fishery operating in the south-west Indian Ocean between 2007 and 2024.

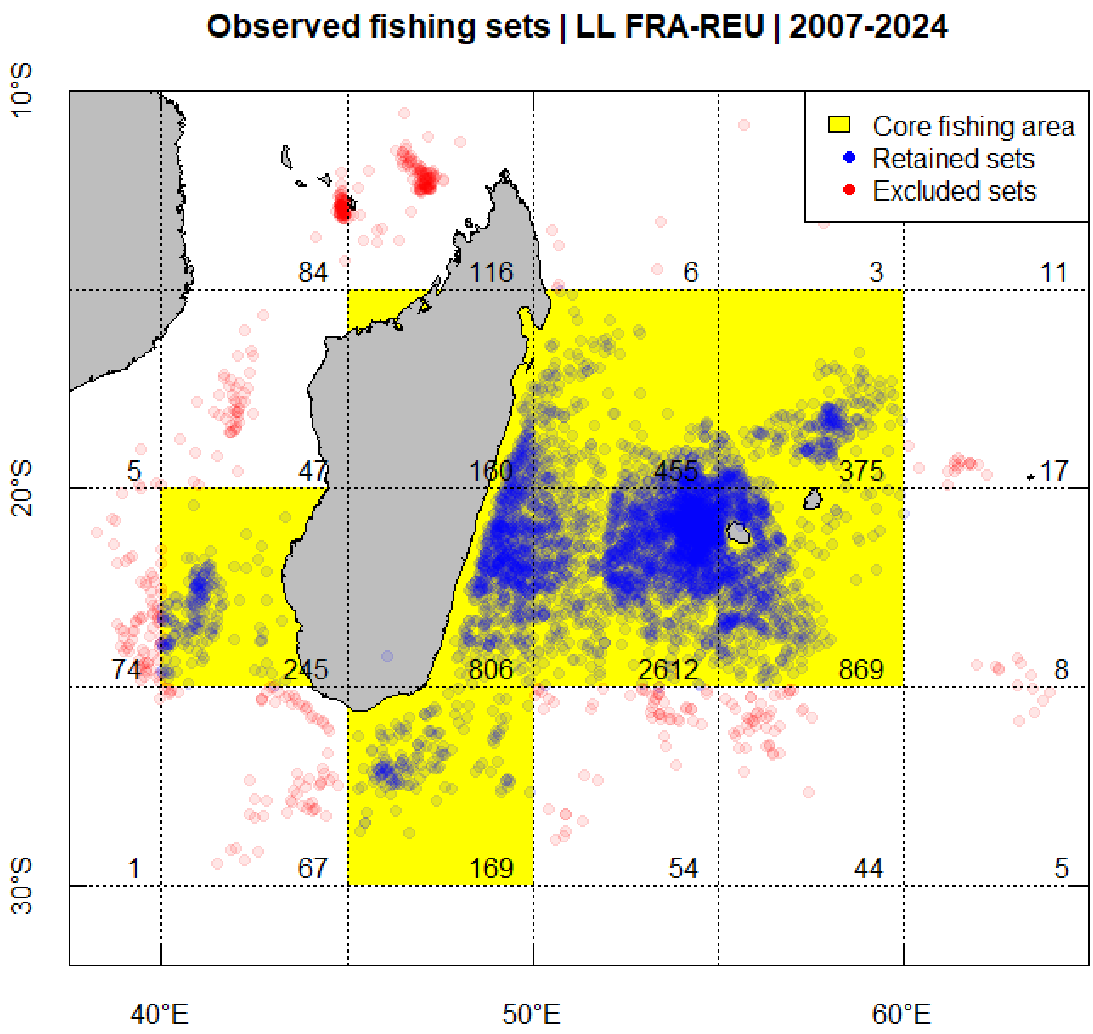

Figure 2. Distribution of fishing sets (hauling start position) between 2007 and 2024. The yellow area represents the core fishing area with retained sets in blue. Excluded sets are shown in red. Numbers in the corners of 5°x5° squares are the number of sets.

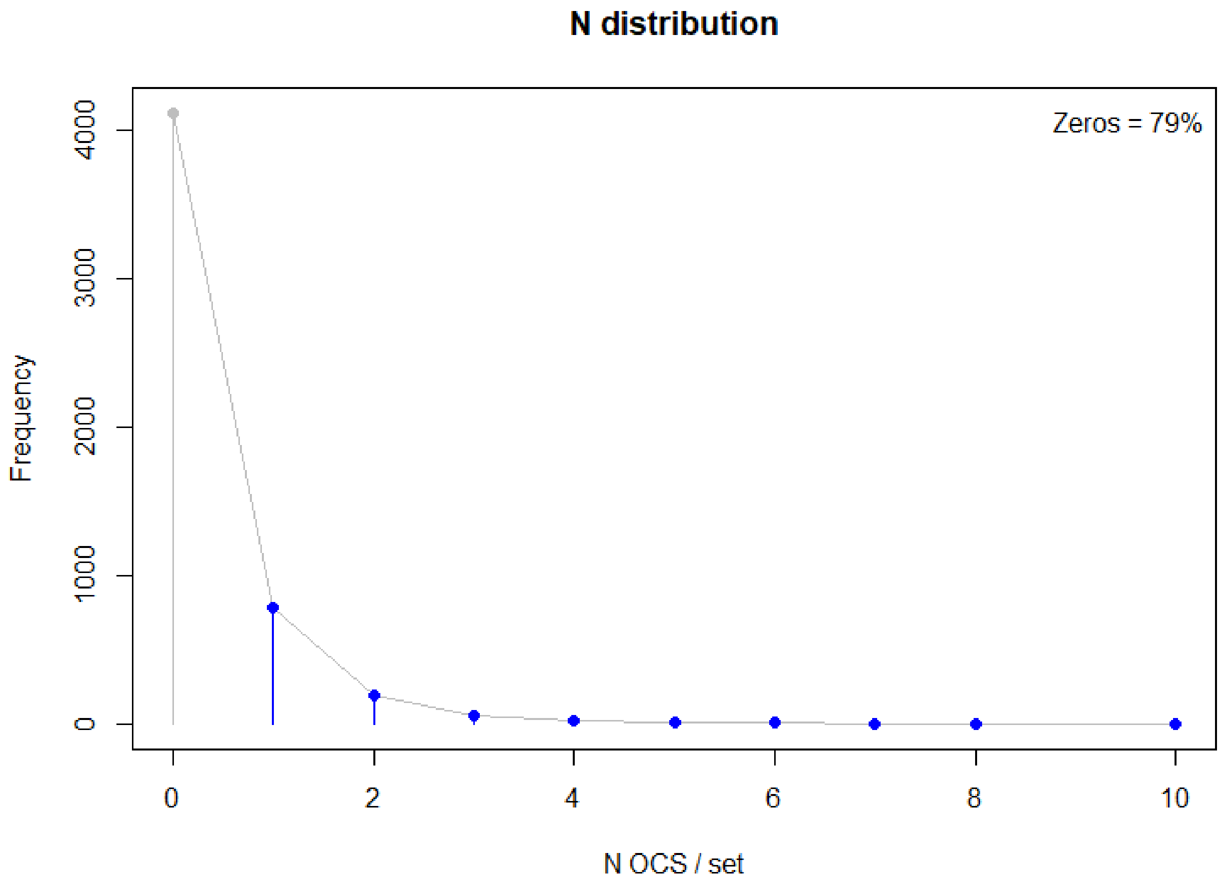

Figure 3. Frequency distribution of oceanic whitetip shark catches per set, showing a high proportion of zeros (79%).

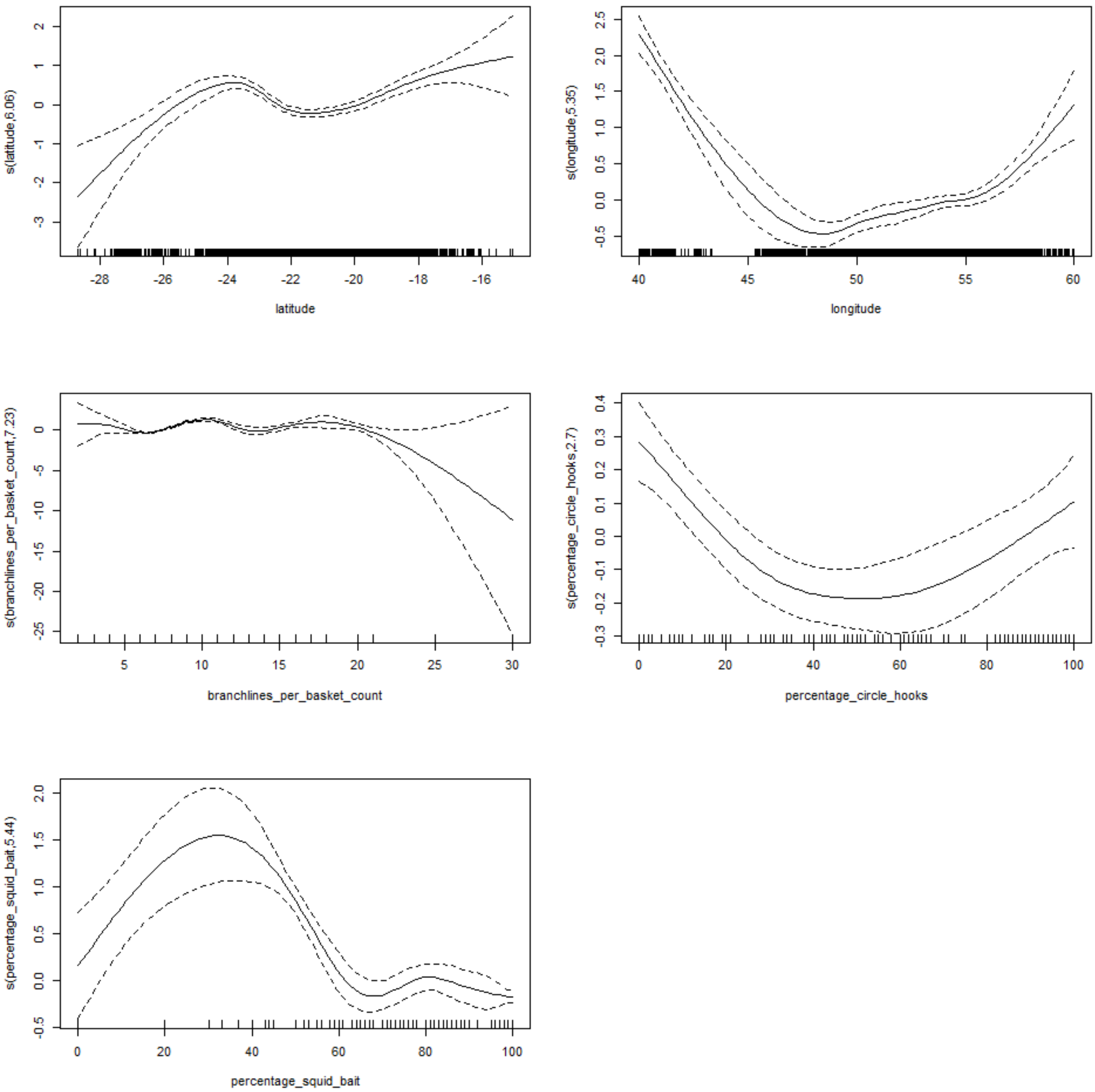

Figure 4. Individual univariate GAMMs for each continuous covariate used to explain CPUE in the retained model (Mod 2).

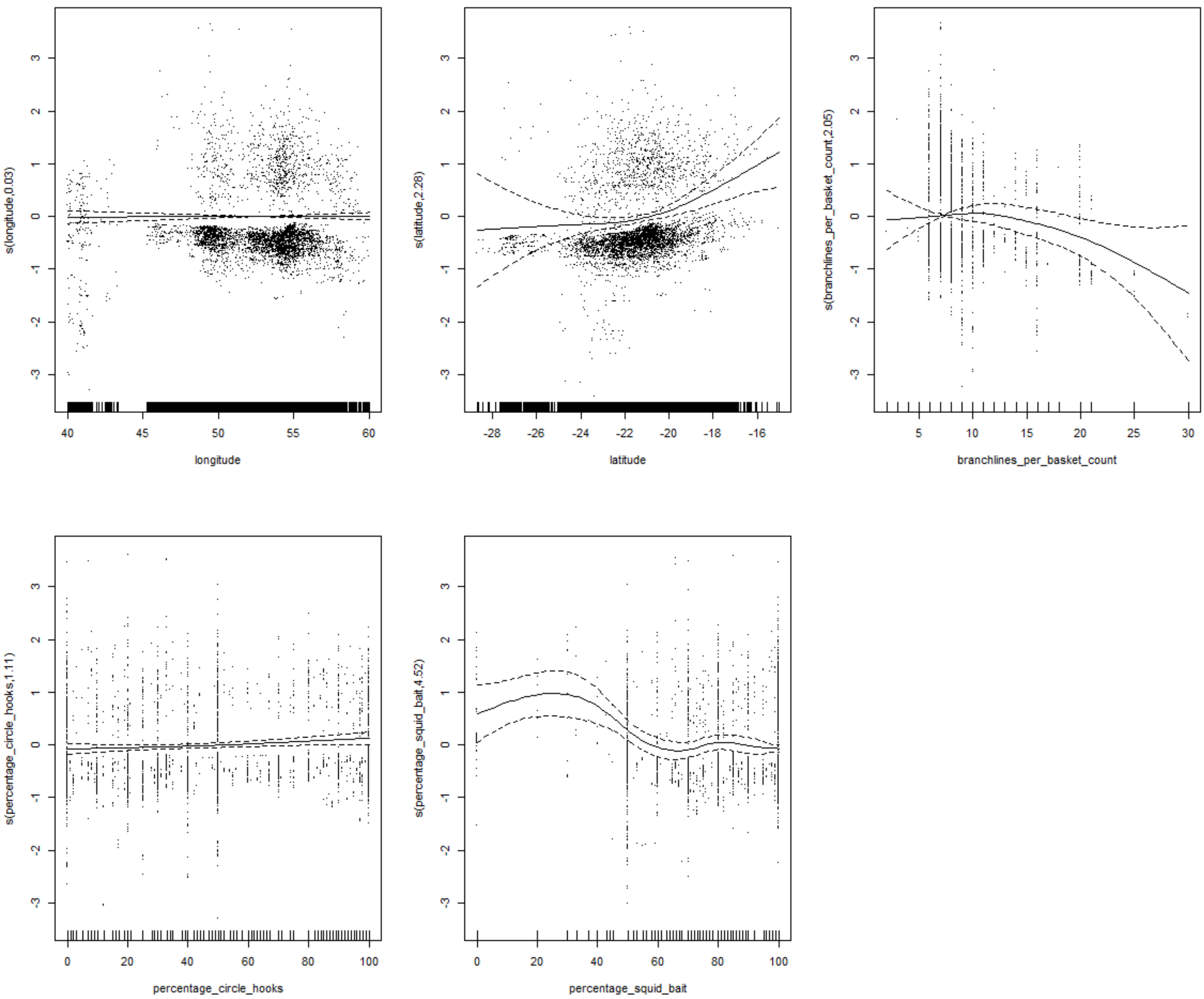

Figure 5. Partial effects (splines) of the continuous covariates used to explain CPUE in the retained Negative Binomial GAMM (Mod 2).

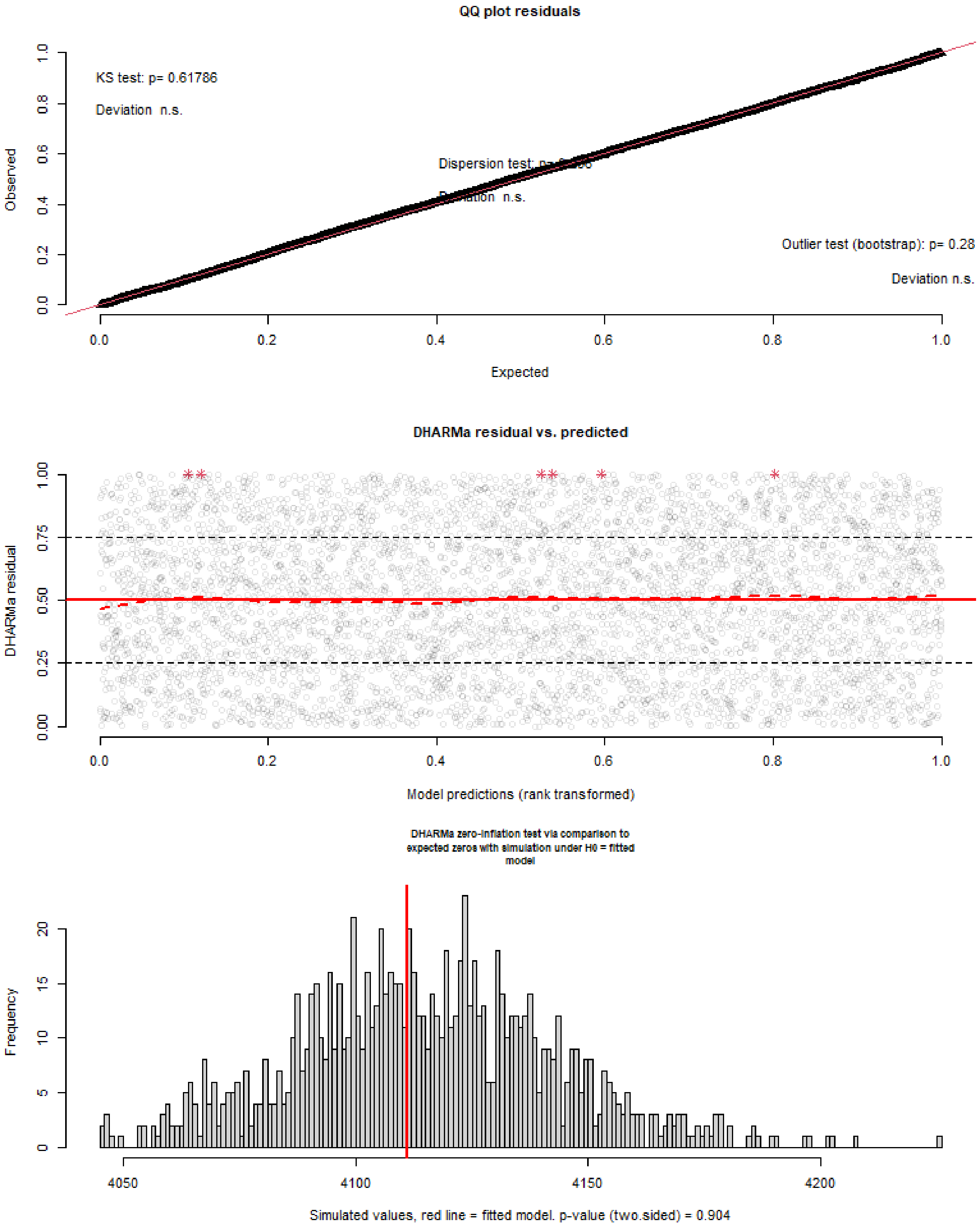

Figure 6. Residual analysis of model selected for oceanic whitetip shark CPUE standardization including the covariates selected by the forward-stepwise model selection.

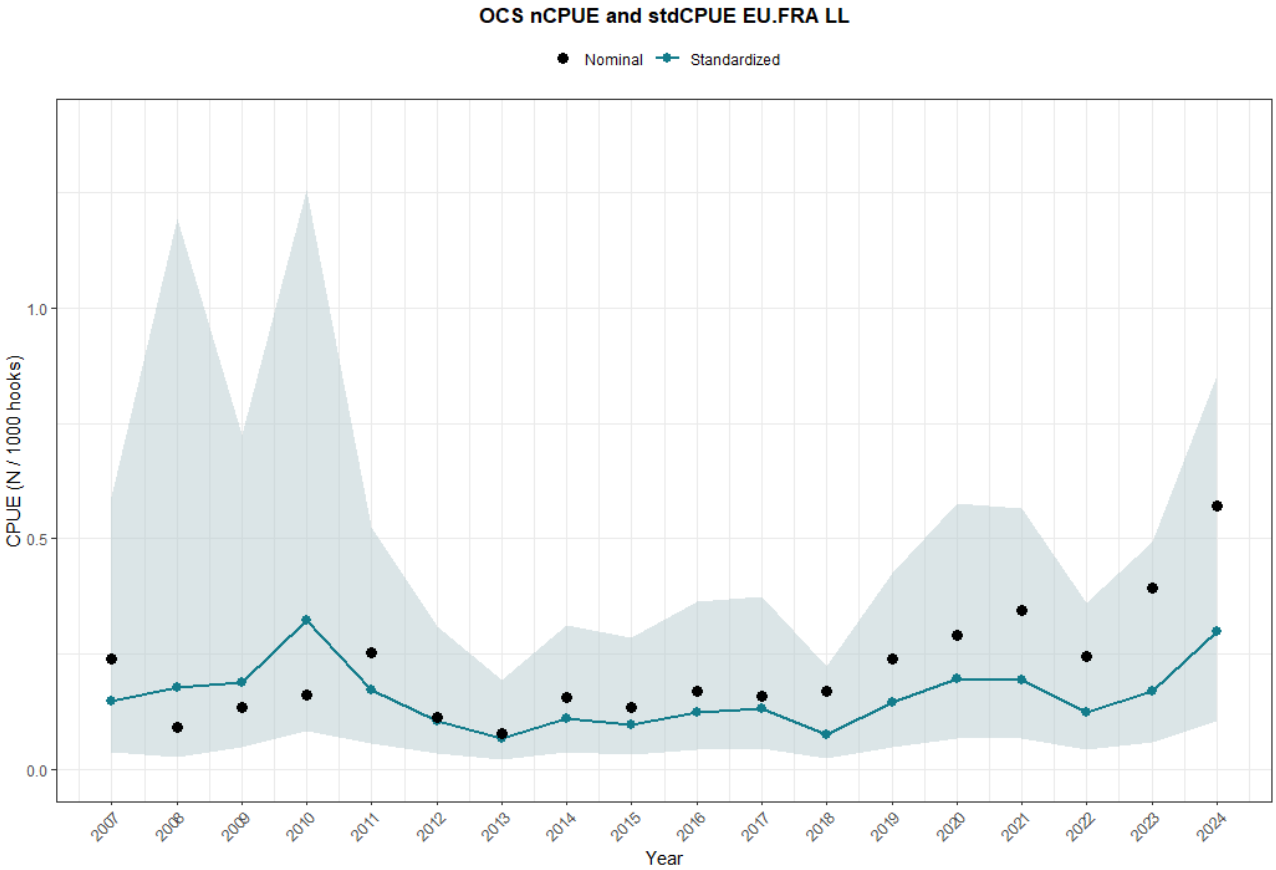

Figure 7. Nominal and standardized CPUE (N/1000 hooks) time series for the oceanic whitetip shark (OCS) caught by the French longline fishery based in Reunion Island (EU.FRA LL) for the period 2007-2024. The standardized index is derived from the final Negative Binomial GAMM. The gray envelope represents the 95% confidence intervals.

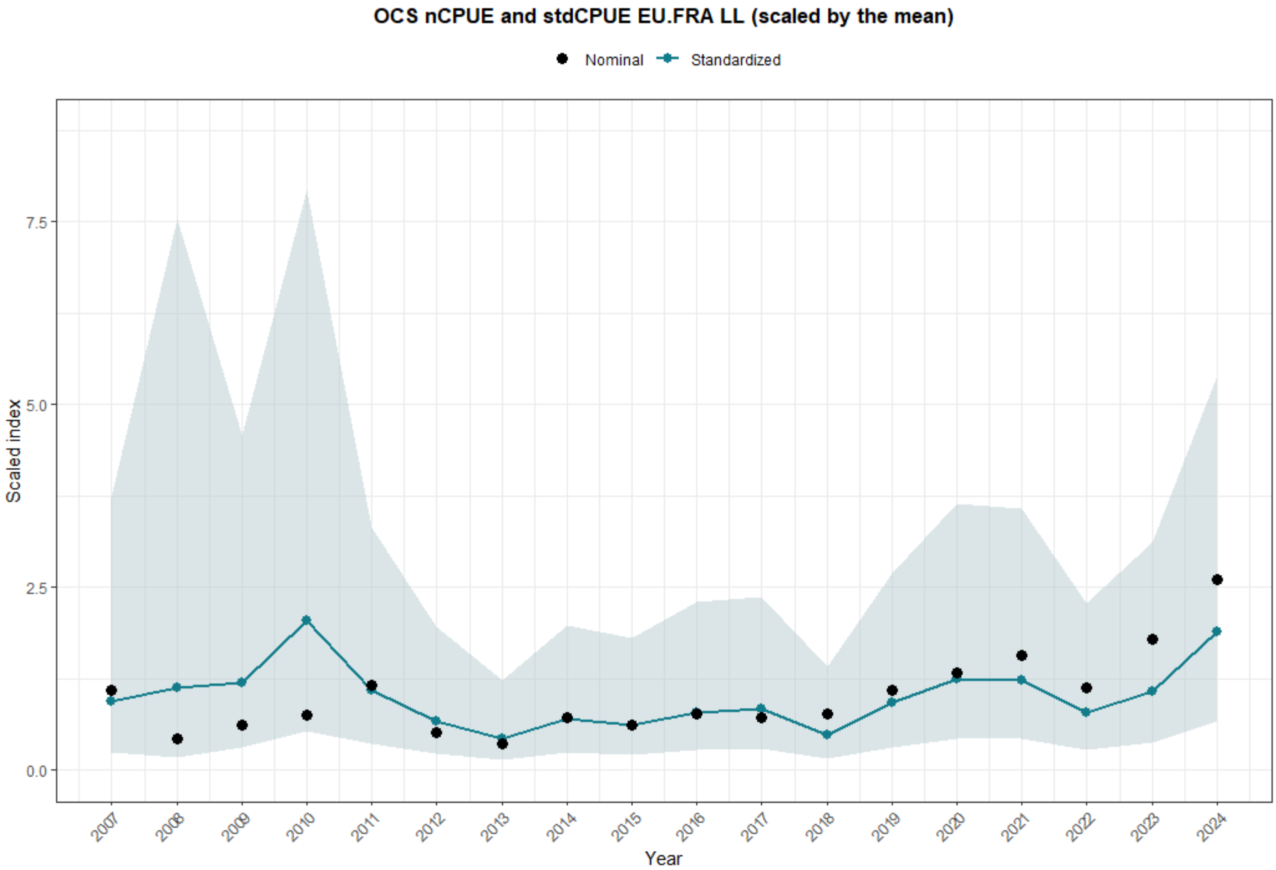

Figure 8. Scaled (by the mean) nominal and standardized CPUE time series for the oceanic whitetip shark (OCS) caught by the French longline fishery based in Reunion Island (EU.FRA LL) for the period 2007-2024. The standardized index is derived from the final Negative Binomial GAMM. The gray envelope represents the 95% confidence intervals.