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UPDATED TROPICAL TUNA BIOMASS INDICES FROM ECHOSOUNDER BUOYS IN THE EASTERN PACIFIC OCEAN

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SUMMARY

The collaboration with some tropical tuna vessel-owners associations operating in the eastern Pacific Ocean, as well as buoy-providers, allowed access to information collected by their satellite-linked GPS tracking echosounder buoys since 2010. These instrumented buoys remotely provide fishers real-time data on the precise geolocation of fish aggregating devices (FADs) and the presence and abundance of fish aggregations underneath them. As a result, echosounder buoys serve as effective observation platforms for providing catch-independent data and potentially assessing the abundances of tunas and accompanying species at FADs. Current echosounder buoys provide a single biomass value and do not discriminate between species or consider size composition of the fish. Therefore, to obtain specific-species indicators, the echosounder buoy data must be combined with fishery data, including species and size composition information. In this document, we present updated preliminary abundance indices for skipjack, bigeye and yellowfin tunas in the eastern Pacific Ocean using echosounder buoys for the period 2012-2022. A previous version of this index was used in the interim stock assessment of skipjack (SAC-13-07) and its use will be considered in future tropical tuna assessments in the EPO.

1. INTRODUCTION

Historically, tropical tuna stock assessments have almost exclusively relied on abundance estimators that depend on commercial catches and fishing effort obtained from captain's logbooks or observer data (Maunder and Punt 2004). These data are integrated into fish stock assessment models to evaluate the status and evolution of fish stocks, providing information on relative trends in fish abundance (Quinn and Deriso 1999). Relative abundance indices based on Catch-Per-Unit-Effort (CPUE) are related with the abundance, through the catchability coefficient (q). However, various factors such as changes in fishing efficiency, species or fleet spatial dynamics, and

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environmental conditions can affect this proportionality (Maunder and Punt 2004; Maunder et al. 2006). Therefore, CPUE standardization is used to eliminate these effects and identify changes related to population abundance.

The incorporation of new technology and the use of Fish Aggregating Devices (FADs) in the tropical tuna purse-seine fishery, have led to a significant increase in fishing efficiency (Lopez et al. 2014; Torres-Irineo et al. 2014; Gaertner et al. 2016). However, scientists have faced challenges in standardizing FAD fishing CPUE due to the difficulties of providing new covariates based on fine scale data to reflect technological changes and effort creep, as well as the lack of a good proxy for purse seine effort, in particular on FADs (Gaertner et al. 2016; Katara 2018; Wain 2021). Consequently, the purse-seine FAD CPUE has not been included in tropical tuna stock assessment models. However, successful science-industry collaborative projects have begun to provide valuable information on the adoption of technological advances in this fleet as a mean to improve the CPUE standardization process (Wain 2021) and ultimately, tropical tuna assessments.

The introduction of satellite-linked echosounder buoys attached to FADs (Scott and Lopez, 2014) offers an alternative method to observe the dynamics of aggregations and estimate catch-independent indices. These instrumented buoys provide daily information on buoy position and a rough estimate of the fish biomass underneath FADs, making them effective observation platforms for remotely monitoring tuna and other species aggregations in a systematic non-invasive way. In recent years, industry-research collaborations have allowed for the collection of buoy-derived data, and scientific methodological frameworks have been developed to extract reliable information from these data (e.g., Orúe et al., 2019). This information has proven to be useful for science, allowing to better understand tuna behavior and ecology around FADs and provide buoy-derived abundance indices (e.g., Lopez et al. 2014; Capello et al. 2016; Moreno 2016; Orúe et al., 2019; Santiago et al. 2019; Baidai 2020).

Recently, the Buoy-derived Abundance Index (BAI) has been integrated into the ICCAT yellowfin and bigeye stock assessments as a measure of the proportional relationship between echosounder buoy biomass estimates and total tuna abundance (ICCAT 2019, 2021). Building on this, a collaborative framework was established with the support of the International Seafood Sustainability Foundation (ISSF), between the Inter-American Tropical Tuna Commission (IATTC) and AZTI, in partnership with echosounder buoy providers and some tropical tuna purse seiner fishing companies operating in the eastern Pacific Ocean (i.e., companies integrated in the fishing vessel association OPAGAC-AGAC and Cape Fisheries). The goal of this collaboration is to produce reliable BAI for tropical tuna species in the region. This paper focuses on the application of this novel method to generate an index of abundance for skipjack tuna in the EPO from echosounder buoy information between 2012 and 2022. This index has been included in the interim skipjack assessment conducted by IATTC staff in 2022 (SAC-13-07) and can inform future abundance indices for all three major tropical tuna species, including skipjack, yellowfin, and bigeye tuna. Preliminary results of the collaborative project were presented at the fifth, sixth and seventh meetings of the ad-hoc permanent Working Group on FADs of the IATTC, along with a list of research ideas to further improve these indicators in the future. This document presents updated results of the previous indices for all three tropical tuna species and highlights the progress made in specific aspects of the methodology over the past year. Future research lines are also identified and discussed.

2. MATERIAL AND METHODS

2.1 Acoustic data pre-filtering

The primary data used in this analysis was collected by satellite-linked echo-sounder buoys attached to FADs used in the EPO tropical tuna purse-seine fishery. Specifically, the data provided by the buoy manufacturer Satlink was used in this analysis. Technical specifications for each buoy model are presented in Table 1. The buoys record information from a depth of 3 to 115 meters, divided into ten uniform vertical layers, each with a resolution of 11.2 meters. Note that the first 3 meters are considered the blind zone and do not provide usable data. Five different buoy models (DS+, DSL, ISD, ISL, and SLX) were used during the analyzed period (January 2012 to December 2022) (Table 1).

The data collected by echosounder buoys were provided by fishing companies such as Albacora, Calvo, Garavilla, Ugavi, and Cape Fisheries. These companies operated a total of 23 purse-seine vessels from 5 different countries (Panama, Spain, Ecuador, El Salvador, USA) in the IATTC convention area.

The database for this analysis included a total of 27,16 million acoustic records from 43891 individual buoys. We excluded data from the years 2010 and 2011 due to the low number of records available (Figure 1). Additionally, acoustic records from areas with a low number of observations (less than 50 records in 5ºx5º statistical rectangles) and those west of 150ºW were excluded from this analysis.

From each single data record, transmitted via satellite, the following information was extracted: "*Name*", unique identification number of the buoy, given by the model code (DS+, DSL, ISL, ISD, SLX) followed by 5-6 digits; "*OwnerName*", name of the buoy owner assigned to a unique purse seine vessel; "*MD*", message descriptor (160, 161 and 162 for position data without echosounder data, and 163, 168, 169 and 174 for echosounder data); "*StoredTime*", date (dd/mm/yyyy) and hour (HH:MM) of the position and the echosounder records; "*Latitude" and "Longitude*", record-associated GPS latitude and longitude information (in decimals); "*Bat*", battery charge level of the buoy, as a percentage (not provided, except for the D+ and DS+ models, in voltage); "*Speed*", speed of the buoy in knots; "*Layer1-Layer10*", estimated tons of tuna by layer (values are estimated by a manufacturer´s method which converts raw acoustic backscatter into biomass in tons using a depth layer echo-integration procedure based exclusively on an algorithm using the target strength (TS) and weight of skipjack tuna); "*Sum*", sum of the biomass estimated for all layers; "*Max*", maximum biomass estimated at any layer; and "*Mag1, Mag3, Mag5 and Mag7*", magnitudes corresponding to the counts of detected targets according to the TS of the detection peak.

To eliminate artifacts, we applied a set of five filters to the original data. These filters were designed to remove: 1) isolated, duplicated, and ubiquitous rows, which are often caused by satellite communication issues; 2) buoys located within 1 km of land or in continental shelf areas (i.e., those with bottom depths shallower than 200 m), which were identified and removed using shoreline data from the GSHHG database (Wessel 1996) and a worldwide global bathymetry information (Amante and Eakins 2009); and 3) "on-board" or "at sea" positions, which were identified using a Random Forest algorithm (Orue et al. 2019; Santiago et al. 2020). These cases typically occur when a buoy is activated onboard a vessel prior to deployment or post-retrieval.

In addition to the data cleaning filters mentioned earlier, the following selection criteria (Santiago et al. 2020) were used to create the final dataset for the standardization analysis. Firstly, shallower layers (<25m) were excluded as they are considered to potentially reflect non-tuna species (e.g., Orue et al. 2019). Secondly, only data recorded around sunrise, between 4 a.m. and 8 a.m. in local time, were considered for the analysis as they are believed to better capture the biomass under the FADs (e.g., Moreno et al. 2007, FAD-06-01 and FAD-07-01 – the hours around sunrise are preferred setting times for fishers on FADs). Finally, acoustic data belonging to "virgin segments" were selected to use the segment of a buoy trajectory whose associated FAD likely represents a new deployment that has been potentially colonized by tuna and not fished yet. To estimate virgin segments, single buoy information was divided into smaller segments where the difference between two consecutive observations of the same buoy was larger than 30 days. Although this may represent buoys that have been re-deployed, it seems unlikely. However, segments with less than 30 observations and those having a time difference between any of the consecutive observations longer than 4 days during the first 35 days were removed. Finally, from the remaining data, information corresponding to 20-35 days at sea was used as this seems to be the time period for which FADs seem to be colonized (Orue et al. 2019). Figure 2 shows a diagram with an example of "virgin" segments used to estimate the BAI index.

2.2 From acoustic data to a species-specific abundance indicator

To calculate the biomass aggregated under a FAD from the acoustic signal, Satlink uses the TS of one species, skipjack, and thus, the biomass data from Satlink has to be converted to decibels (acoustic information) reversing their formula for the biomass computation. Once the raw acoustic information is available, this can be recomputed into biomass per species using standard acoustic abundance estimation equations (Simmons and MacLennan 2005):

$$Biomass_i = \frac{s_V \cdot Vol \cdot p_i}{\sum_i \sigma_i \cdot p_i}$$

where s_V is the volume backscattering strength, *Vol* is the sampled volume of the beam and p_i and σ_i are the proportion and linearized target strength of each species *i* respectively.

Species proportions in weight at 1ºx1º and month resolution were extracted from logbooks (for class 1-5 vessels, ≤ 363 mt) and observers data (for class 6 vessels, >363mt) for 14 flags. Mean fish lengths (L_i), for 5°x5° area - month resolution were obtained from IATTC port-sampling data for skipjack, bigeye, and yellowfin, which were raised to the catch in the sampled wells. Weights were estimated using IATTC weight-length conversion factors. Then, the following TS-length relationships were used to obtain linearized TS per kilogram:

$$\sigma_i = \frac{10^{(TS)/10}}{w_i}$$

where w_i is the mean weight of each species and TS is the backscattering cross-section of each species individual fish. The linear value of TS is assumed to be proportional to the square of the fish length (Simmons and MacLennan 2005).

$$TS = 20log(Li) + b20$$

Given that each brand uses different operating frequencies, we used different b20 values for each species (b20 is the so-called reduced target strength). For Satlink, the b20 values were obtained from Boyra et al. (2018) for SKJ, from Bertrand and Josse (2000), Oshima (2008) and Sobradillo et al. (2023) for YFT, and from Boyra et al. (2018) for BET.

To obtain information on catch composition for the corresponding time-area strata of acoustic records, we followed a three-step hierarchical process. Firstly, we used catch species composition data from the same 1ºx1º grid, year, and month (5ºx5º for length composition). If such data was not available, we proceeded to the second step, which involved using the same quarter and 1ºx1º grid (5ºx5º for length composition). Lastly, if the previous options were not feasible, we utilized the mean values of catch and length composition data at a quarter and regional resolution, as shown in Figure 3.

The results presented in this document specifically pertain to the fraction of the acoustic signal estimated to be informative for the biomass of the three major species of tropical tuna: skipjack, yellowfin and bigeye tunas.

2.3 The BAI index: Buoy-derived Abundance Index

The abundance estimator, BAI, was determined as the 0.9 quantile of the integrated acoustic energy observations in each of the "virgin" sequences. A high quantile was chosen because it is likely that large values are produced by tuna, as opposed to other species. This assumption is also used by all buoy manufacturers in the market, who use the maximum value as the biomass summary for each time interval. In this study, a high quantile was selected instead of the maximum to provide a more robust estimator by avoiding outlier values. The total number of "virgin" sequences analyzed, and hence the number of observations included in the model, was 8559, of which 8424 (98.42%) had positive values.

2.4 The model

The covariates used in the standardization process and fitted as categorical variables were year-quarter, 5ºx5º area, and buoy model. Additionally, a proxy of 1ºx1º and monthly FAD densities and the following environmental variables were included as continuous variables in the model: ocean mixed layer thickness, chlorophyll, sea surface temperature (SST), and SST and chlorophyll fronts. The model assumes that the signal from the echosounder is proportional to the abundance of fish under the FAD, which is similar to the fundamental relationship between CPUE and abundance used in quantitative fisheries analysis.:

$$BAI_t = \varphi \, . \, B_t$$

where BAI_t is the Buoy-derived Abundance Index and B_t is the abundance in time t (Santiago et al., 2016).

Although it would appear to be obvious, there is not a lot of literature available on the relationship between acoustic indicators and fishing performance. In general, it is assumed that acoustic echo-integration is a linear process, i.e., proportional to the number of targets (Simmons and MacLennan 2005) and has been experimentally proven to be correct with some limitations (Foote, 1983; Røttingen, 1976). Therefore, acoustic data (echo-integration) are commonly taken as a proxy for abundance and are used to obtain acoustic estimates of abundance for many pelagic species (Hampton 1996; ICES 2015; Masse et al. 2018).

As with catchability, the coefficient of proportionality ϕ is not constant for many reasons. In order to ensure that ϕ can be assumed to be constant (i.e., to control the effects other than those caused by changes in the abundance of the population) a standardization analysis should be performed by aiming to remove factors other than changes in abundance of the population. This can be achieved standardizing nominal measurements of the echosounder using a Generalized Linear Mixed Modelling (GLMM) approach.

Because of the low proportion of zeros in the dataset (1.58%), they were excluded from the analysis and therefore the delta lognormal approach (Lo et al. 1992) was not considered. A GLMM with a log-normal error structured model was applied to standardize the non-zero acoustic observations. A stepwise procedure was used to fit the model with all the explanatory variables and interactions in order to determine those that significantly contributed to explaining the variability in the data. For this, deviance analysis and summary tables were created, and the final selection of explanatory variables was conducted using: a) the relative percent increase in deviance explained when the variable was included in the model (variables that explained more than 5% were selected), and b) The Chi-square ($\chi 2$) significance test.

Interactions between the temporal component (year-quarter) with the rest of the variables were also evaluated. If an interaction was statically significant, it was then considered as a random interaction(s) within the final model (Maunder and Punt 2004).

The selection of the final model was based on the Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC), and a Chi-square ($\chi 2$) test of the difference between the log- likelihood statistic of different model formulations. The year-quarter effect least square means (LSmeans) were bias corrected for the logarithm transformation algorithms using the approach described in Lo et al. 1992. All analyses were done using the lme4 package in R (Bates et al. 2014).

3. RESULTS

A total of 27.16 million acoustic records were evaluated from 43,891 buoys ranging from 2012 to 2022, resulting in 8559 observations for the GLMM analysis. Each observation was calculated as the 90th percentile of a "virgin" segment of buoy trajectories. A virgin segment represents a deployment that has the potential to be colonized by tuna but has not yet been fished.

Figure 4 displays histograms of the BAI and log-transformed BAI nominal values. The log transformation was applied to make the data follow a normal distribution, as shown in the left panel of Figure 4. Figure 5 displays the spatial distribution of the number of "virgin" segments of buoy trajectories that were used in the GLMM analysis on a 5ºx5º grid. The quarterly evolution of the number of observations on a 5^{o}x5^{o} grid is shown in Figure 6.

Figure 7 illustrates the quarterly evolution of the nominal log BAI index by squares of 5x5 degrees from 2012 to 2022.

The results of the deviance analysis are presented in Table 2. The model explained 47% of the total deviance for SKJ, 50% of the deviance for BET, and 45% of the deviance for YFT. The most significant explanatory variables were year-quarter, 5^{o}x5^{o} area, and the interaction between year-quarter and area, which was considered a random effect. No significant residual patterns were observed (Figure 8).

Quarterly series of standardized BAI indices are presented in Table 2 and Figure 9. Three periods showed higher values (at different scales for each species): a) the beginning of the series in 2012 - with wider confidence intervals due to the low number of observations; b) the years 2015 and 2016; and c) the years 2019 and 2020. Aside from the first two quarters in 2012 the coefficients of variation remained relatively stable throughout the time series at levels of 8-26% for SKJ, 10-32% for BET, and 10-31% for YFT.

4. DISCUSSION

This paper presents preliminary results on a fisheries-independent abundance indices for skipjack, yellowfin, and bigeye tunas in the EPO, based on echo-sounder buoy data attached to FADs. The series has been updated with data up to 2022, and thanks to the collaboration of Cape Fisheries, the corresponding historical data from 2019 to 2022 have been recovered and integrated into the series. For this study, the methodology previously presented for tropical tuna populations in both the Pacific and other oceans (Santiago, Uranga et al. 2019, Santiago, Uranga et al. 2020a, Santiago, Uranga et al. 2020b, Uranga 2021, FAD-06-03, FAD-07-03) has been followed, and areas for improvement have been identified. To effectively use this information into stock assessments of tropical tuna species, it is essential to explore further the areas mentioned below and adapt the methodology as much as possible to the specific needs of the EPO tuna fisheries.

Data collection

To examine the consistency of the abundance indices generated thus far, it would be beneficial to retrieve historical acoustic data from other fishing companies and integrate them into the indices developed with this methodology. The new data could determine whether the contribution of new information from new areas can produce a more robust index and explore the need and possibility to develop area-specific indices (e.g., offshore vs inshore indices). This will help better understand whether these indices are independent of fishing efforts and areas explored by the different fleet and fishing strategies and if separate indices are providing converging or conflicting results for each region. For instance, in the previous year's assessment of skipjack stock, new areas were identified for the floating object fishery, and therefore, analyzing the echo-sounder buoy data for these new areas could contribute towards improved assessments.

In the current analysis only one of the major buoy brands on the market has been used. Therefore, it is crucial to integrate data from different brands to determine if acoustic data can be standardized among brands or if brand-specific indices need to be developed.

In addition, new proposals for modifications at the level of research and data aspects of interest in each ocean are likely to be made in the near future, along with new variations in methodology. Therefore, the analysis should be as adaptable as possible and capable of accommodating any differences that may arise due to differences in fleet dynamics, fishing strategies, and annual data submissions across the entire series.

Methodology Update

To improve the accuracy of estimating relative biomasses of tropical tuna populations, we propose a series of steps. Firstly, we will review and evaluate the filters used to clean the database of artifacts, considering the specific characteristics of each model to prioritize a particular set of models, if necessary.

Additionally, we will standardize and document the method for selecting specific composition and size data from catches, which play a key role, to ensure consistent characterization of the acoustic data. This process will be periodically reviewed and updated in the coming years, including an exploration of the effect of considering new species and size composition resolutions into the analysis (i.e. strata at different spatio-temporal resolution, for example 5x5, year and month or 5x5, year and quarter, among others). In this regard, we plan to develop a protocol for hierarchically assigning these values based on their resolution or detail (e.g., observers per fishing set, fishing logbooks, 1x1-month).

To enhance the representativeness of the percentage by species throughout the year and different areas of the Eastern Pacific Ocean, we will explore the potential of different models, such as geospatial or machine learning models, and investigate whether species composition correlates with the colonization process. We may use electronic tagging studies to define the depth that different species and individuals of different sizes typically inhabit.

For colonization models, we will reconsider the assumption that days 20-35 after new deployments (Orue et al. 2019) are the best measure and find an adaptive solution that fits the different regions and seasons of the eastern Pacific Ocean. For example, FAD-specific adaptive colonization models will be explored, as well as new algorithms trained to better understand this variability.

In terms of biomass estimates, we will update the values of target strength (b20) using the latest values published in scientific journals and campaigns. For example, the new b20 value for juvenile YFT, presented at the FAD WG meeting in 2023 (Sobradillo et al. 2023), required a reanalysis of the time series with the new values. We will also make arrangements to integrate both Marine Instruments and Zunibal buoys into the study and will be taking into account new buoy models or data processing changes via direct collaborations with buoy providers. However, this needs to be done carefully, and we will consider whether to generate independent indices for each buoy provider or standardize all companies' and models' data to form a comprehensive series of indices.

We will conduct several sensitivity tests to examine the effect of using different types of measures (e.g., mean, median, 90th percentile) for the model used to standardize nominal biomass values for each quarter of the series. Additionally, we will explore different acoustic measures calculated in the virgin segment and evaluate different sizes and specific compositions of various resolutions.

We will continue exploring other environmental variables to better explain the model's variance.

Lastly, we will consider the possibility of finding data without the presence of tunas to better understand how the model behaves with a higher proportion of zeros. These steps aim to improve the accuracy and robustness of estimating the relative biomass indices of different tropical tuna species.

Progress in acoustics

To improve the methodology for estimating biomass, it's essential to cross-reference acoustic data or estimated biomass with capture data linked to the corresponding buoy. This exercise is crucial in providing robustness to the original data used in this proposal as an information source. Additionally, switching from specific measurements extracted from the virgin segment, as explained in this document, to complete echograms of the virgin segment as input for new models can lead to a significant qualitative leap. To achieve this, we need to find ways to increase the number of samples to compare echograms with their associated captures as models that use images to find patterns require a large number of samples. We should also carry out experiments to determine whether multifrequency data can be extracted from the collected information to improve species discrimination by interpreting results at the frequency response level. A significant breakthrough would be the ability to distinguish skipjack, a species without a swim bladder and the main target species of the purse seine fleet using FADs, from bigeye and yellowfin, swim bladder species.

All the specific points for improvement identified in this study point towards the need for further research in generating relative abundance indices based on buoy acoustics. Buoy acoustics can be a global monitoring platform that provides significant information about the three main tropical tuna species. The key to success in this analysis lies in knowing how to deal with the noisy nature of the data, finding solutions to discard all acoustic data that is not relevant to significant tuna presence and signal, and exploring the best way to exploit this privileged source of information until a breakthrough is achieved.

Looking to the future, promoting collaborative projects with the fleet to collect data from the vessel's acoustic devices, including echosounders and sonars, could also be beneficial. These devices are assumed to have higher resolution in the data and could provide complementary information that could offer multiple answers regarding the morphology, dynamics and behavior of the tuna schools associated with the FADs. This leap would transform fishing vessels into research platforms, allowing the retrieval of valuable data for scientific endeavors and comparisons with buoy acoustics.

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Table 1. Technical specifications of different buoy models and observed values over analysis data.

Model	Typical setup						Mean observed values over analysis data	
	Beam angle	Sounder frequency	Power	Frequency of acoustic sampling (ping rate)	Daily acoustic data recorded	Frequency of transmission	Number of buoys	Sampling frequency
DS+	32º	190.5 kHz	100 W	3	3	24h	1428	1.36
DSL+	32º	190.5 kHz	100 W	3	3	24h	12462	2.82
ISL+	32º	190.5 kHz	100 W	15 min	variable (reset at dusk)	24h	23	1.67
ISD+	32º	200/38 kHz (38 kHz not provided)	100 W	15 min	variable (reset at dusk)	24h	6214	1.21
SLX+	32º	200	100 W	5 min	variable (Sunrise or Alarms based)	24h	785	1.98

Table 2. Deviance table for the GLMM lognormal model of the 2012-2022 period: A) Skipjack, B) Bigeye, C) Yellowfin tuna.

	Variable	Df	Deviance	Resid_Df	Resid_Dev	F	Pr_F	Dev_Exp
A) SKJ	NULL	NA	NA	22789	31673	NA	NA	NA
	yyqq	43	2192	22746	29481	66	0	6.92
	area	33	2845	22713	26636	112	0	8.98
	model	3	166	22710	26470	72	0	0.52
	den	1	34	22709	26436	44	0	0.11
	chlfront	1	64	22708	26372	83	0	0.2
	sst	1	0	22707	26372	0	0.8921	0
	sstfront	1	36	22706	26336	46	0	0.11
	mld	1	5	22705	26331	6	0.0154	0.01
	yyqq:area	996	8645	21709	17687	11	0	27.29
	yyqq:model	33	276	21676	17411	11	0	0.87
	yyqq:den	39	487	21637	16923	16	0	1.54
	yyqq:sst	43	145	21594	16779	4	0	0.46
	yyqq:mld	42	131	21552	16648	4	0	0.41
B) BET	NULL	NA	NA	22457	46316	NA	NA	NA
	yyqq	43	3402	22414	42914	73.1057	0	7.35
	area	33	5615	22381	37298	157.243	0	12.12
	model	3	286	22378	37012	88.2148	0	0.62
	den	1	107	22377	36905	98.8709	0	0.23
	chlfront	1	30	22376	36875	27.6809	0	0.06
	sst	1	80	22375	36794	74.2552	0	0.17
	sstfront	1	33	22374	36761	30.8957	0	0.07
	mld	1	0	22373	36761	0.1948	0.66	0
	yyqq:area	988	12186	21385	24575	11.3974	0	26.31
	yyqq:model	32	414	21353	24161	11.9587	0	0.89
	yyqq:den	39	745	21314	23415	17.6541	0	1.61
	yyqq:sst	43	187	21271	23229	4.0168	0	0.4
	yyqq:mld	42	255	21229	22974	5.6048	0	0.55
C) YFT	NULL	NA	NA	22663	41844	NA	NA	NA
	yyqq	43	2881	22620	38963	63	0	6.88
	area	33	2963	22587	36000	85	0	7.08
	model	3	177	22584	35823	56	0	0.42
	den	1	436	22583	35387	413	0	1.04
	chlfront	1	66	22582	35321	62	0	0.16
	sst	1	23	22581	35298	22	0	0.06
	sstfront	1	25	22580	35273	24	0	0.06
	mld	1	0	22579	35273	0	0.8898	0
	yyqq:area	994	11477	21585	23796	11	0	27.43
	yyqq:model	32	302	21553	23494	9	0	0.72
	yyqq:den	39	472	21514	23021	11	0	1.13
	yyqq:sst	43	145	21471	22876	3	0	0.35
	yyqq:mld	42	228	21429	22648	5	0	0.55

Table 3. Nominal and standardized Buoy-derived Abundance Indices for Skipjack (A), Bigeye (B) and Yellowfin (C) tunas for the period 2012-2022.
Standard errors and coefficient of variations of the standardized series are also included.

		Quarter	Index nominal	BAI Index	BAI se	BAI cv
A)	SKJ	12Q1	5.409	10.34	2.765	0.267
		12Q2	7.366	5.777	1.169	0.202
		12Q3	3.254	2.722	0.616	0.226
		12Q4	1.433	1.189	0.26	0.219
		13Q1	5.217	3.335	0.488	0.146
		13Q2	2.47	1.854	0.33	0.178
		13Q3	1.688	1.577	0.336	0.213
		13Q4	2.042	1.56	0.258	0.165
		14Q1	2.533	2.129	0.398	0.187
		14Q2	1.816	1.612	0.322	0.2
		14Q3	1.66	1.629	0.322	0.198
		14Q4	1.551	1.099	0.203	0.185
		15Q1	3.553	3.171	0.559	0.176
		15Q2	2.667	2.293	0.419	0.183
		15Q3	1.872	1.879	0.162	0.086
		15Q4	1.982	1.784	0.292	0.163
		16Q1	2.469	2.019	0.3	0.148
		16Q2	1.496	1.464	0.304	0.208
		16Q3	2.632	2.075	0.436	0.21
		16Q4	2.282	1.919	0.437	0.228
		17Q1	2.003	1.458	0.266	0.183
		17Q2	1.889	1.379	0.238	0.173
		17Q3	2.632	1.775	0.403	0.227
		17Q4	2.278	1.672	0.44	0.263
		18Q1	1.857	1.561	0.309	0.198
		18Q2	1.788	1.289	0.253	0.196
		18Q3	0.764	0.712	0.158	0.221
		18Q4	2.704	1.829	0.368	0.201
		19Q1	2.173	2.151	0.367	0.171
		19Q2	3.205	1.878	0.404	0.215
		19Q3	1.974	1.806	0.484	0.268
		19Q4	2.922	2.322	0.493	0.212
		20Q1	4.355	3.816	0.669	0.175
		20Q2	2.929	2.387	0.407	0.17
		20Q3	2.717	2.292	0.386	0.168
		20Q4	3.362	2.592	0.468	0.181
		21Q1	1.593	0.976	0.204	0.209
		21Q2	1.458	1.053	0.214	0.204
		21Q3	2.06	1.122	0.214	0.191
		21Q4	1.428	1.162	0.24	0.207
		22Q1	2.102	1.304	0.241	0.185
		22Q2	1.838	1.862	0.452	0.243
		22Q3	1.104	1.025	0.247	0.241
		22Q4	1.447	1.373	0.292	0.213

B) BET	12Q1	3.244	11.982	3.525	0.294
	12Q2	2.92	2.623	0.629	0.24
	12Q3	1.147	0.972	0.264	0.272
	12Q4	0.435	0.407	0.104	0.255
	13Q1	1.985	1.443	0.256	0.178
	13Q2	1.046	0.978	0.208	0.212
	13Q3	0.625	0.609	0.154	0.252
	13Q4	0.742	0.638	0.127	0.2
	14Q1	1.215	1.192	0.27	0.226
	14Q2	0.962	0.936	0.222	0.237
	14Q3	0.462	0.503	0.12	0.239
	14Q4	0.618	0.5	0.112	0.225
	15Q1	1.676	1.913	0.41	0.214
	15Q2	1.54	1.511	0.334	0.221
	15Q3	0.637	0.64	0.067	0.104
	15Q4	0.793	0.779	0.154	0.198
	16Q1	1.015	0.764	0.122	0.16
	16Q2	0.737	0.687	0.176	0.256
	16Q3	0.929	0.801	0.203	0.253
	16Q4	0.82	0.734	0.192	0.261
	17Q1	0.832	0.75	0.157	0.209
	17Q2	0.756	0.72	0.15	0.208
	17Q3	1.058	0.7	0.199	0.284
	17Q4	0.628	0.497	0.151	0.303
	18Q1	0.819	0.691	0.166	0.24
	18Q2	0.737	0.505	0.111	0.221
	18Q3	0.276	0.23	0.063	0.274
	18Q4	1.067	0.731	0.182	0.249
	19Q1	0.83	0.918	0.189	0.206
	19Q2	1.143	0.762	0.201	0.264
	19Q3	0.595	0.618	0.2	0.324
	19Q4	1.132	1.015	0.258	0.254
	20Q1	1.496	1.479	0.318	0.215
	20Q2	0.997	0.898	0.187	0.208
	20Q3	0.935	0.852	0.169	0.198
	20Q4	0.873	0.805	0.173	0.216
	21Q1	0.714	0.477	0.114	0.238
	21Q2	0.591	0.48	0.117	0.243
	21Q3	0.309	0.257	0.058	0.227
	21Q4	0.43	0.364	0.094	0.258
	22Q1	0.62	0.507	0.112	0.222
	22Q2	0.628	0.74	0.219	0.296
	22Q3	0.346	0.4	0.118	0.295
	22Q4	0.39	0.459	0.116	0.253
C) YFT	12Q1	6.896	9.503	2.948	0.31
	12Q2	1.322	1.634	0.38	0.232
	12Q3	0.842	0.768	0.203	0.264
	12Q4	0.264	0.328	0.083	0.254
	13Q1	1.224	1.316	0.226	0.171
	13Q2	0.706	0.783	0.154	0.197

13Q3	0.707	0.571	0.136	0.239
13Q4	0.447	0.546	0.106	0.195
14Q1	0.955	1.157	0.254	0.219
14Q2	0.912	0.724	0.165	0.228
14Q3	0.372	0.474	0.11	0.232
14Q4	0.515	0.391	0.086	0.219
15Q1	1.318	1.395	0.29	0.208
15Q2	1.016	1.148	0.245	0.213
15Q3	0.542	0.545	0.055	0.102
15Q4	0.474	0.519	0.1	0.194
16Q1	0.689	0.745	0.128	0.172
16Q2	0.465	0.459	0.109	0.238
16Q3	0.702	0.627	0.152	0.243
16Q4	0.595	0.657	0.17	0.258
17Q1	0.662	0.582	0.124	0.213
17Q2	0.467	0.659	0.131	0.199
17Q3	0.699	0.717	0.201	0.28
17Q4	0.495	0.596	0.18	0.301
18Q1	0.423	0.508	0.117	0.23
18Q2	0.643	0.625	0.144	0.23
18Q3	0.272	0.29	0.074	0.256
18Q4	0.585	0.588	0.138	0.235
19Q1	0.63	0.933	0.186	0.199
19Q2	0.807	0.843	0.209	0.247
19Q3	0.504	0.601	0.187	0.311
19Q4	0.976	0.738	0.182	0.247
20Q1	1.174	1.337	0.273	0.204
20Q2	0.914	0.923	0.186	0.201
20Q3	0.884	1.006	0.195	0.194
20Q4	0.846	0.816	0.173	0.212
21Q1	0.644	0.548	0.133	0.243
21Q2	0.294	0.461	0.109	0.237
21Q3	0.349	0.246	0.055	0.222
21Q4	0.386	0.401	0.098	0.243
22Q1	0.505	0.545	0.114	0.21
22Q2	0.721	0.827	0.246	0.297
22Q3	0.371	0.425	0.117	0.275
22Q4	0.452	0.474	0.118	0.248

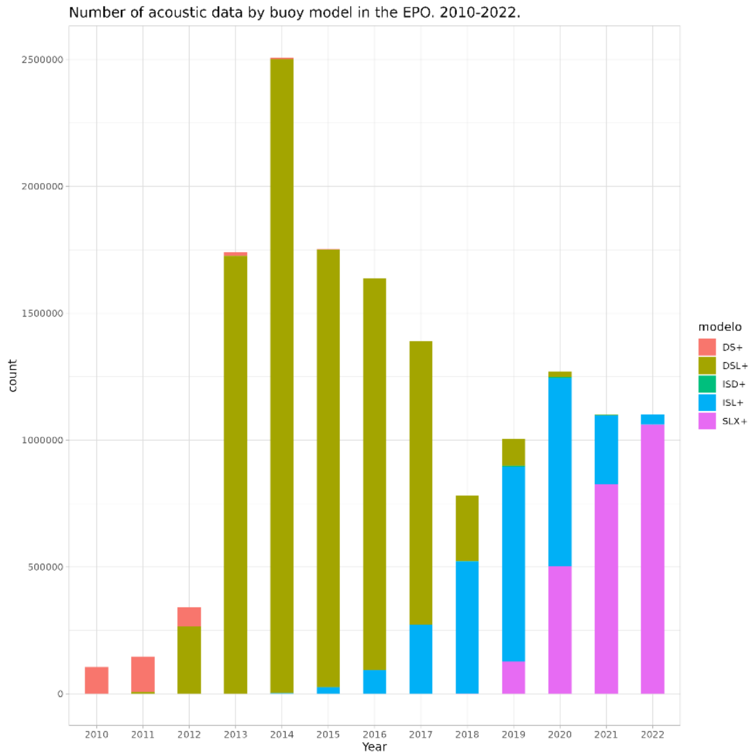


Figure 1. Buoy data distribution per model in the Pacific Ocean (2010-2022)

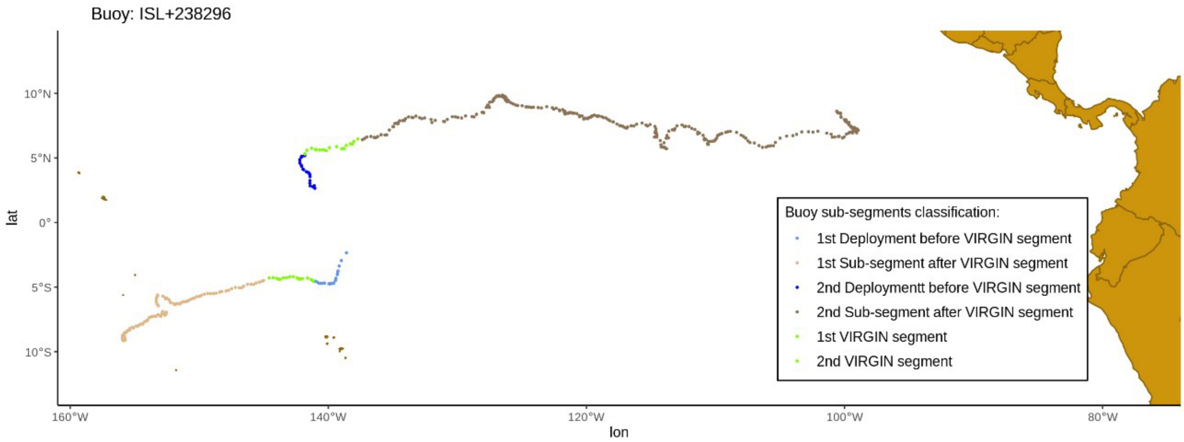


Figure 2. Example of "virgin" segments used for the calculation of the BAI index. Trajectories correspond to buoy ISL+284966 with two different paths representing drifts of different FADs. A virgin segment is defined as the segment of a buoy trajectory whose associated FAD likely represents a new deployment, which has been potentially colonized by tuna and not already fished. We consider as virgin segments (i.e. when tuna has aggregated to FAD) those segments of trajectories from 20-35 days at sea. "Virgin" segments are shown in green.

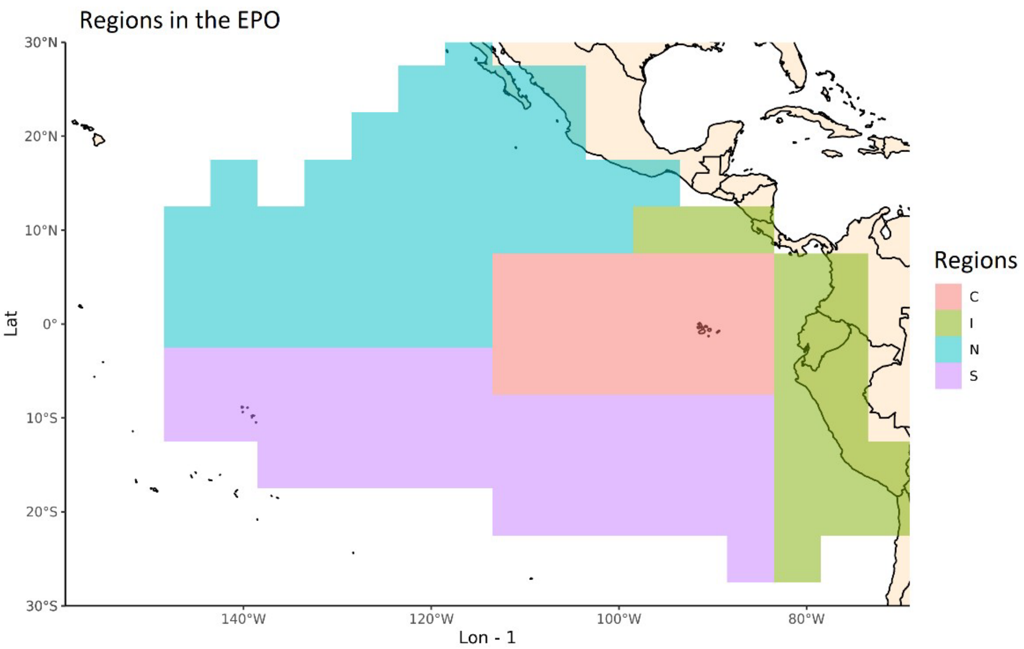


Figure 3. Length-frequency sampling areas defined by the IATTC staff for analyses of tropical tuna catches associated with floating objects.

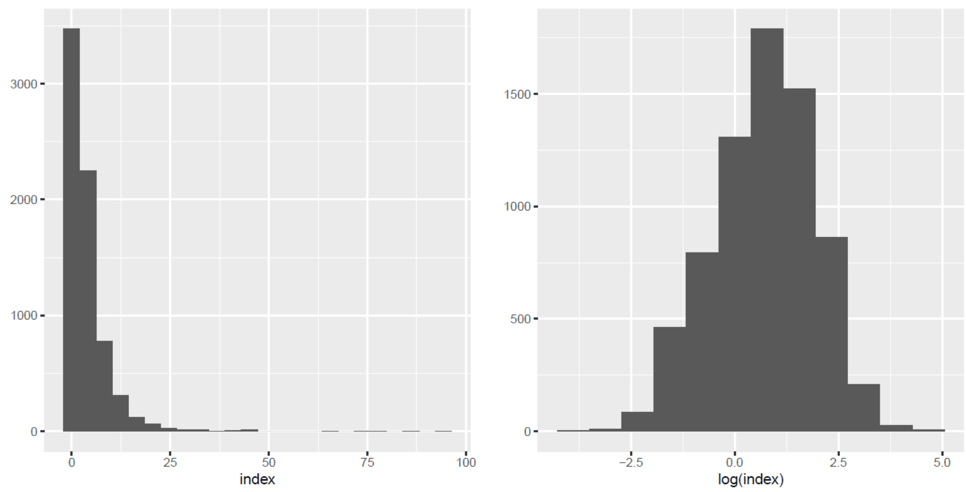


Figure 4. Histograms of the nominal values (left) and the log transformed nominal values (right) of the Buoy-derived Abundance Index (0.9 quantile of the integrated acoustic energy observations in "virgin" sequences).

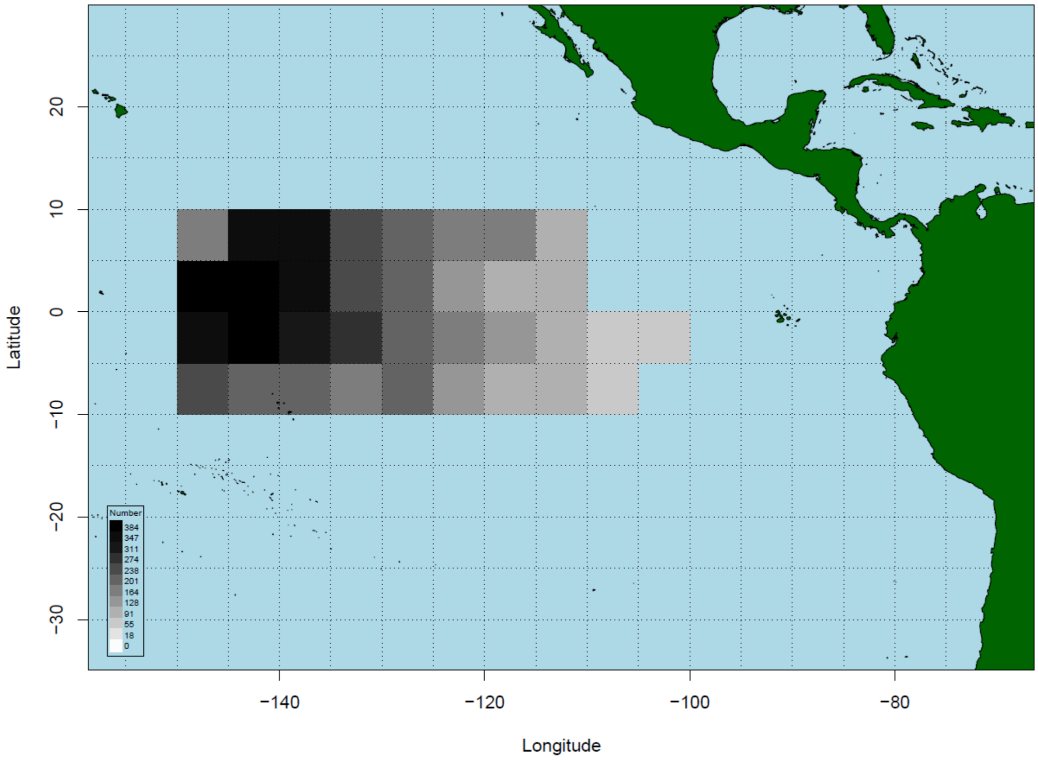


Figure 5. Spatial distribution [5^{o}x5^o] of the “virgin” sequences of buoy trajectories that have been used in the GLMM analysis.

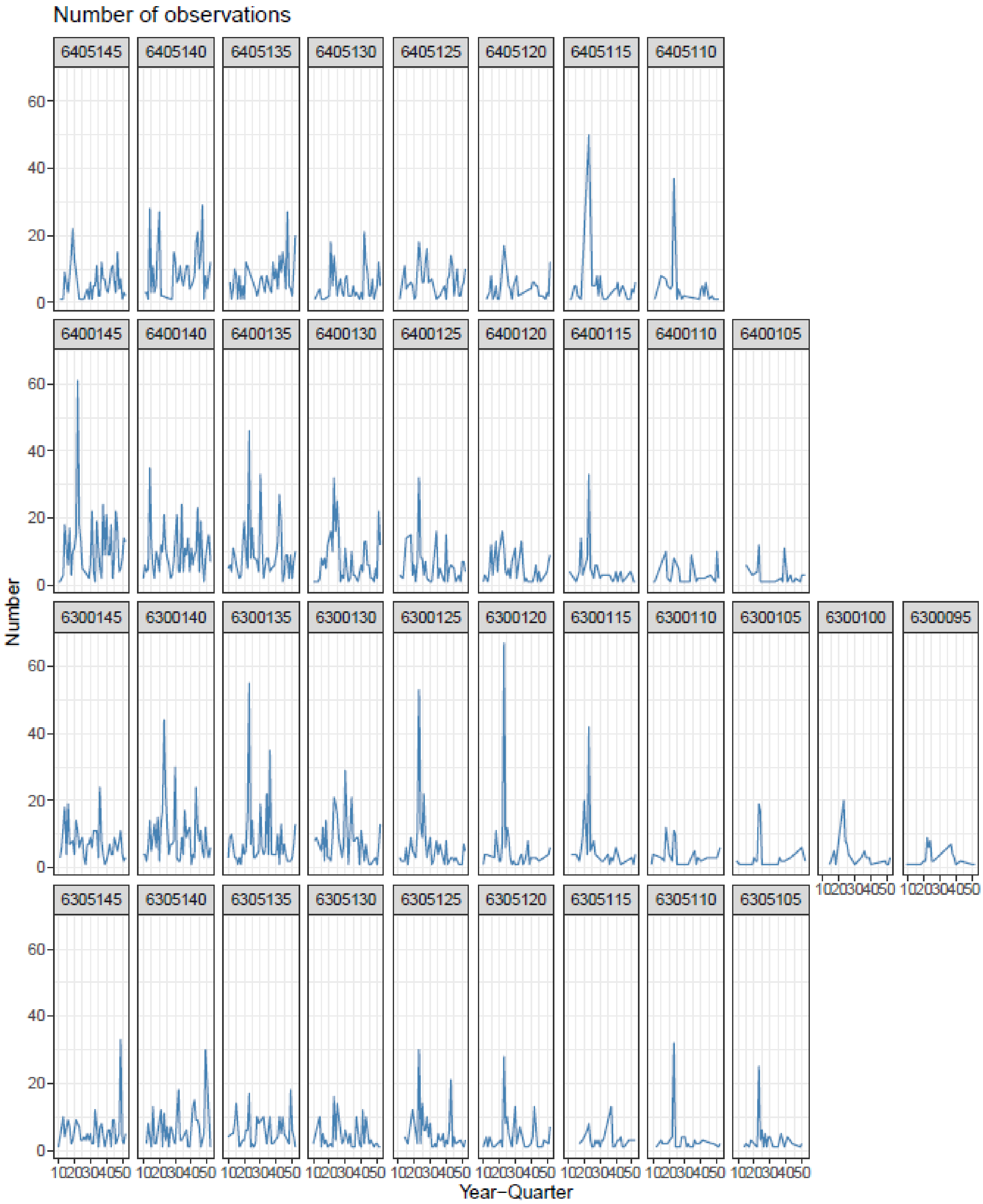


Figure 6. Quarterly evolution of the number of observations ("virgin" sequences of buoy trajectories) on a 5^{o}x5^o grid from 2012 to 2022.

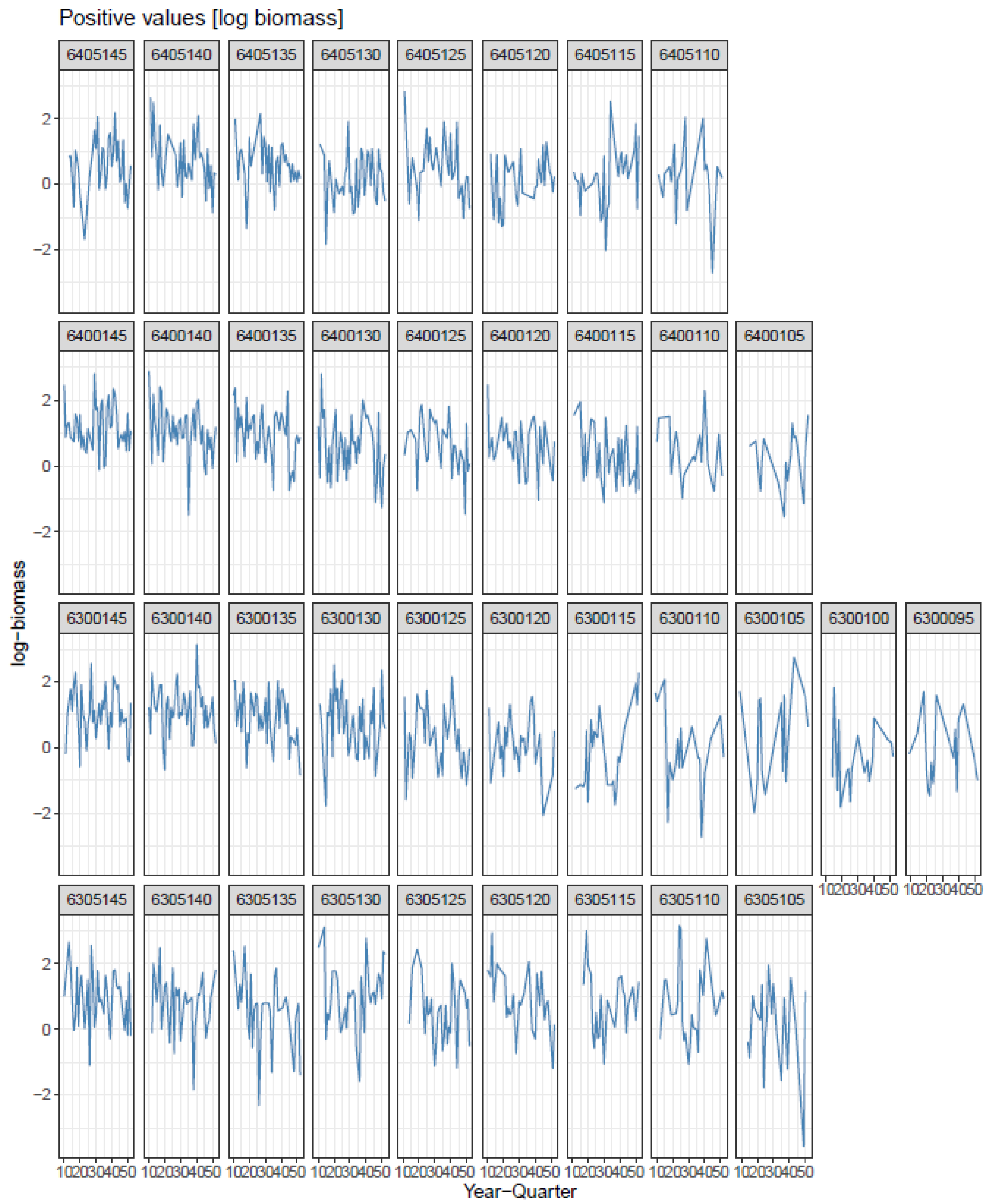
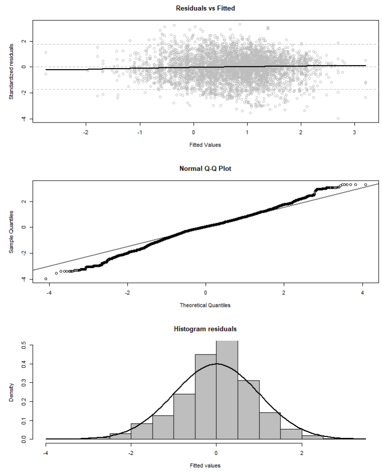
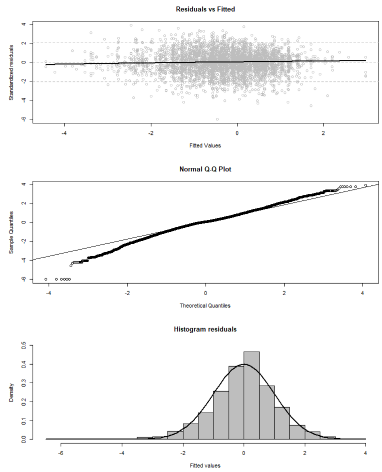


Figure 7. Quarterly evolution of the nominal log BAI index in the Atlantic Ocean by squares of 5x5 degrees from 2012 to 2022.

A)



B)



C)

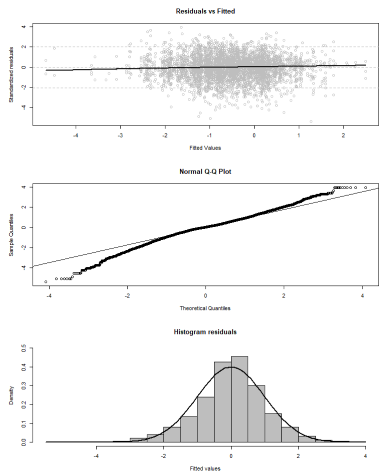


Figure 8. Diagnostics of the lognormal model selected for the period 2012-2022: residuals vs fitted, Normal Q-Q plot and frequency distributions of the residuals: A) Skipjack; B) Bigeye, C) Yellowfin tuna.

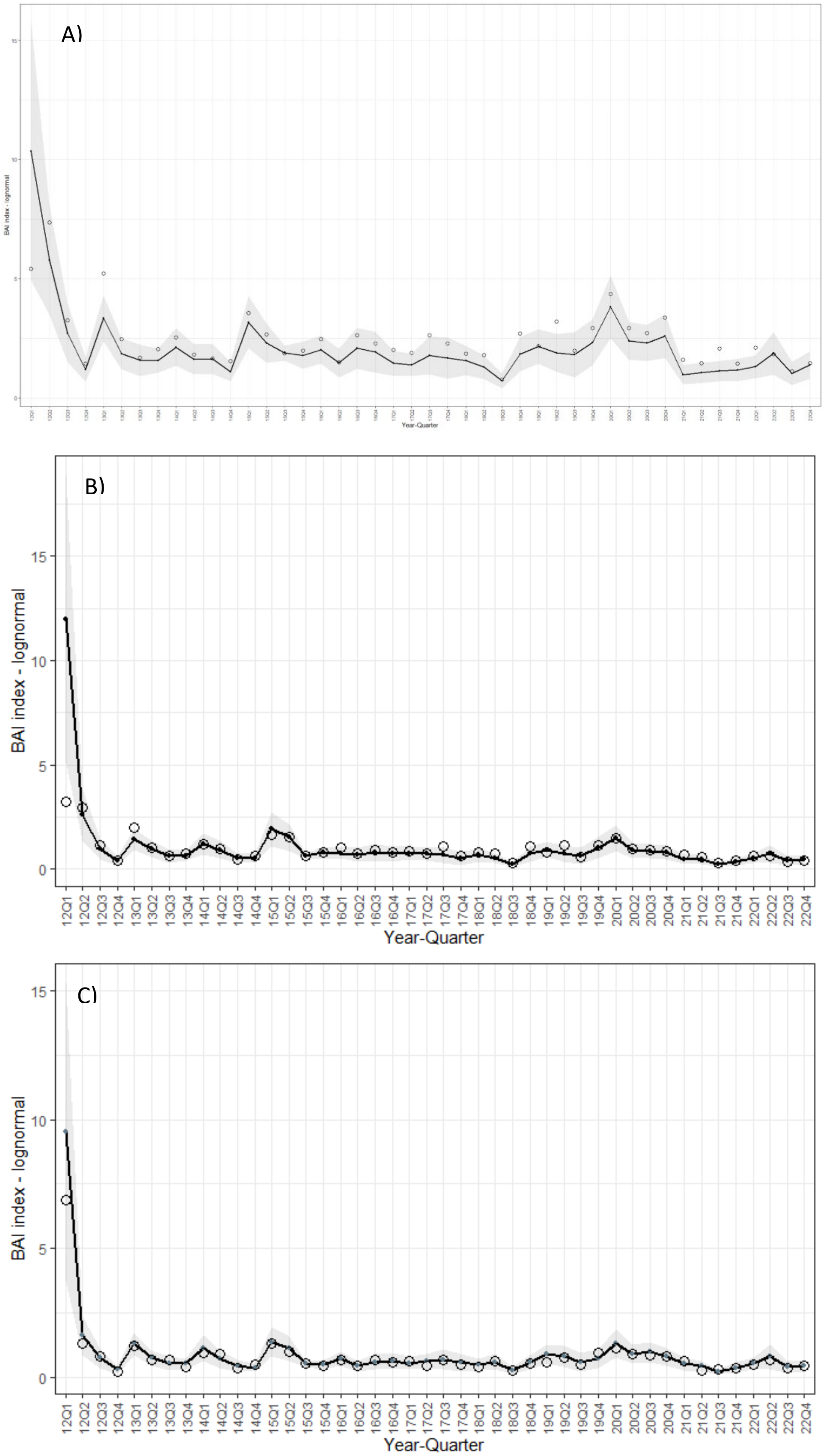


Figure 9.a Time series of nominal (circles) and standardized (continuous line) Buoy-derived Abundance Indices for Skipjack (A), Bigeye (B) and Yellowfin (C) tuna for the period 2012-2022. The 95% upper and lower confidence intervals of the standardized BAI index are shown by the grey shaded area.

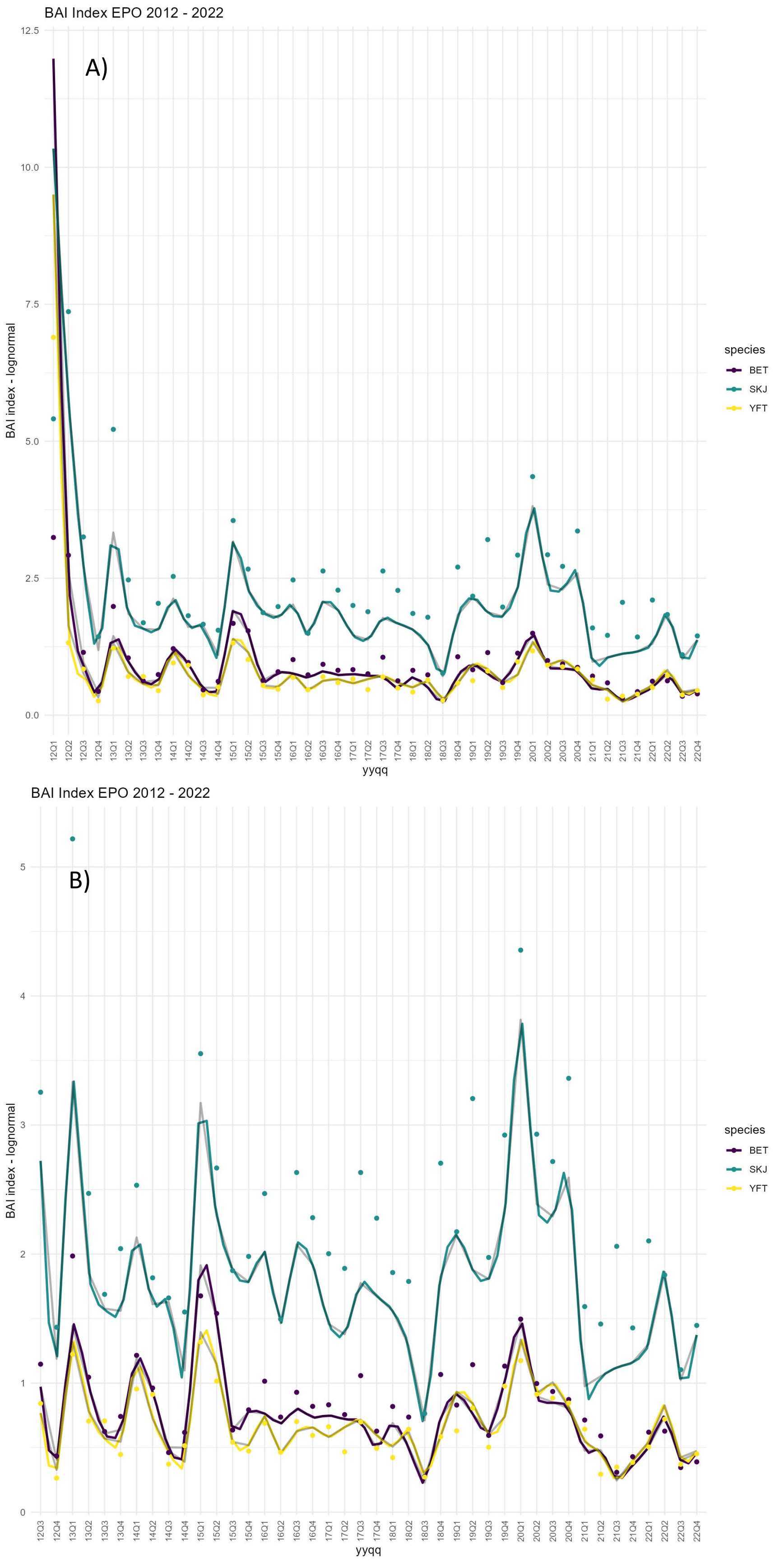


Figure 9.b Time series of nominal (circles) and standardized (continuous line) Buoy-derived Abundance Indices for Skipjack, Bigeye and Yellowfin tuna for the period 2012-2022 (A) and without 2012 Q1 and Q2 (B)

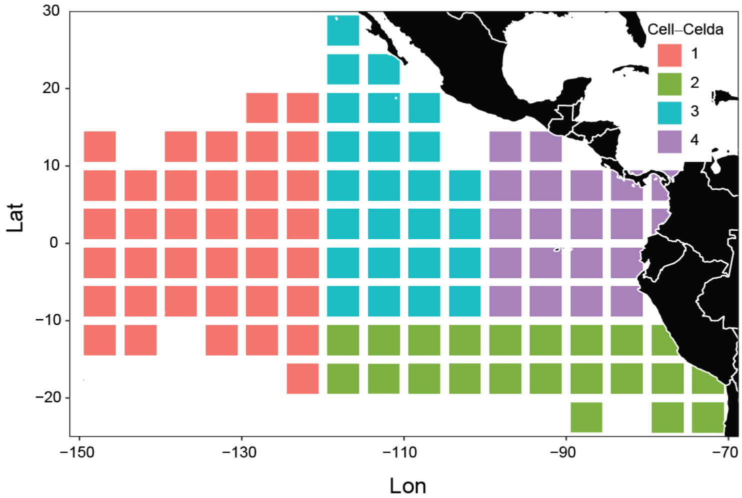


Figure 10. Areas corresponding to the floating object fishery definitions used in the stock assessment of skipjack tuna in the EPO in 2022.