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TROPICAL TUNA BIOMASS INDICATORS FROM ECHOSOUNDER BUOYS IN THE EASTERN PACIFIC OCEAN

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SUMMARY

The collaboration with certain tropical tuna vessel-owners associations operating in the eastern Pacific Ocean, as well as buoy-providers, has granted us access to information collected by their satellite-linked GPS tracking echosounder buoys since 2010. These buoys are equipped with instruments that relay real-time data to fishermen, including the precise geolocation of fish aggregating devices (FADs) (FADs) and information about the presence and abundance of fish under these devices. 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 differentiate 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 composition and average size. In this paper, we present an updated preliminary estimation of an abundance index for skipjack tuna in the eastern Pacific Ocean using echosounder buoys for the period 2012-2022. This index is utilized in the interim stock assessment.

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 state and evolution of fish stocks, providing information on relative trends in fish abundance (Quinn and Deriso 1999). Catch-Per-Unit-Effort (CPUE) based relative abundance indices are used, which are related to abundance through the catchability coefficient (q). However, various factors such as changes in fishing efficiency, species or fleet spatial dynamics, and 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;

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Torres-Irineo et al. 2014; Gaertner et al. 2016). However, scientists have faced challenges in standardizing FAD fishing Catch-Per-Unit-Effort (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 2021Consequently, 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 improve the CPUE standardization process (Wain 2021) and ultimately, tropical tuna assessments.

The introduction of satellite-linked echosounder buoys attached to FADs (Scott 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 beneath 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 (Orúe et al., 2019). This information has proven to be useful for science enabling investigation of tuna behaviour and ecology around FADs and provide buoy-derived abundance indices (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 achievement, 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 specie including skipjack, yellowfin and bigeye tuna. Preliminary results of the collaborative project were presented at the Fifth meeting of the Ad-hoc Permanent Working Group on FADs, along with a list of ideas and tasks to further improve these indicators. This document presents updated results of the previous index, including Cape Fisheries data from 2019 onwards into the series, and highlighting the progress made in specific aspects of the methodology over the past year.

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 Fish Aggregating Devices (FADs) used in the Eastern Pacific Ocean (EPO) tropical tuna purse-seine fishery. Specifically, only 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 2021) (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 43,891 individual buoys. We excluded data from the years 2010 and 2011 due to the low number of records available (see 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, 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*", estimated 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 because 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 and FAD-06-01 – 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 calculate 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 at a reasonable rate, 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 is 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 calculate 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 Target Strength (TS) of one species, skipjack, to provide the biomass in tons, and thus, 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 (SKJ), bigeye (BET) and yellowfin (YFT), which were raised to the catch in the sampled wells. Weights were estimated using IATTC weight-length conversion factors. Then, the following Target Strength-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) and Oshima (2008) 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 species distribution data from the same 5ºx5º grid, year, and month. If such data was not available, we proceeded to the second step, which involved using the same quarter and 5ºx5º grid. Lastly, if the previous options were not feasible, we utilized the mean values of species distribution 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 skipjack tuna.

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

It seems that there is a repetition of the text. However, based on the information provided, the covariates used in the standardization process and fitted as categorical variables were year-quarter, 5x5^o area, and buoy model. Additionally, a proxy of 1^{o}x1^o 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 performed 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 ($\chi2$) 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 ($\chi2$) 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 43,891buoys spanning from 2012 to 2022, resulting in 85,59observations 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 5ºx5º grid is shown in Figure 6.

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 44% of the total deviance, and the most significant explanatory variables were year-quarter, 5ºx5º 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 index are presented in Table 2 and Figure 9. Three periods showed higher values: 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 16-23%.

4. CONCLUSIONS

This paper presents preliminary results on a fisheries-independent abundance index for skipjack tuna 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) 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 new historical acoustic data from new companies or associations and integrate them into the previously presented indices for previous years. It would also be interesting to determine whether the contribution of new data from new areas, such as that provided by TUNACONS for 2022, can produce an index that covers the same area or if it generates two different indices: one based on offshore data and the other on more coastal data. This will reveal whether these indices are independent of fishing efforts and areas explored by the fleet or if two separate indices are required for each region. For instance, in the previous year's assessment of skipjack stock, new areas were identified for floating object fishery, necessitating a readaptation of the entire series to these new areas.

In addition to using updated data from as much of the fleet as possible, to represent most of the distribution area of each species, only one of the major buoy brands on the market has been used to date. Therefore, it is crucial to integrate data from different brands to determine if acoustic data can be standardized and if it is necessary to create indices based on brands or if all data can be integrated into a standardized unique index.

Furthermore, it is highly likely that new proposals for modifications at the level of areas of interest in each ocean will be made in the near future, as was done in the last evaluation of the skipjack population in the OPO in 2022 (Figure X), as well as new variations in methodology. Therefore, it is necessary to make the analysis as adaptable as possible and have the ability to analyze the entire series while accommodating any differences that may arise due to annual data submissions.

Methodology Update

The first step should be to review the filters used to clean the database of artifacts and evaluate whether they are suitable for the trajectories generated by different models. It is important to apply these filters based on the specific characteristics of each model to prioritize a particular set of models, if necessary.

To accurately estimate the relative biomasses of different tropical tuna populations, it is crucial to standardize and document the method for selecting specific composition and size data from catches, which play a key role in characterizing the acoustic data. In the coming years, we plan to review and update the process for assigning species percentages and size measurements to the entirety of acoustic data.

We should explore different models' potential to provide greater robustness in estimating specific compositions in space and time. Geospatial or machine learning models could be tested to improve the representativeness of the percentage by species throughout the year and different areas of the Eastern Pacific Ocean. Additionally, we could investigate whether species composition correlates with the colonization process and propose studies where the vertical behavior of different species is considered to weight the measures used in specific areas and seasons. Electronic tagging studies could be used to define the depth that different species and individuals of different sizes typically inhabit.

Through these analyses, we could develop a protocol for hierarchically assigning these values based on their resolution or detail (e.g., observers per haul, fishing logs, 1x1-month).

When it comes to colonization models, we need to reconsider the assumption that days 20-35 after new deployments (based on Orue et al. 2019) are the best measure. Ideally, we should find an adaptive solution that fits the different regions and seasons of the Eastern Pacific Ocean.

In terms of biomass estimates, we need to update the values of target strength b20 that relate to the size of individual fish, using the latest values published in scientific journals/campaigns. For example, the new b20 value for juvenile YFT, presented at current 7th Meeting of the Ad Hoc Working Group on FADs, requires a reanalysis of the series with the new values. We also need to keep a watchful eye on new buoy models or any processing changes due to collaborations with buoy providers. The top priority is to integrate both MarineInstruments and Zunibal buoys into the study. However, this needs to be done carefully, and we should discuss whether to generate an independent index for each provider or standardize all companies' and models' data to form a comprehensive index.

Concerning the model used to standardize nominal biomass values for each quarter of the series, we need to conduct several sensitivity tests to examine the effect of using different types of measures (mean, median, 90th percentile, etc.). We could try different acoustic measures calculated in the virgin segment and evaluate different sizes and specific compositions of various resolutions. Besides the variables outlined in this document, we need to continue exploring in the future to see if any set of environmental variables of a different nature can better explain the model's variance. Lastly, it would be interesting to consider the possibility of finding data without the presence of tunas to observe how another model behaves with the presence of zeros.

Progress in acoustics and future lines

In addition to improving the methodology for estimating biomass, it is crucial to keep exploring the idea of cross-referencing acoustic data or estimated biomass with capture data linked to the corresponding buoy. This exercise is essential in providing robustness to the original data used in this proposal as an information source. We also believe that switching from specific measurements, extracted from the virgin segment using the steps and assumptions 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 consider ways to increase the number of samples to compare echograms with their associated captures because these types of models that use images to find patterns require a large number of samples. Furthermore, experiments should be carried out 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) from swim bladder species (bigeye and yellowfin).

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. This is because buoy acoustics is 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, which requires finding solutions to discard all acoustic data that is not relevant to significant tuna presence, and exploring the best way to exploit this privileged source of information until a breakthrough is achieved.

Looking to the future, it would also be beneficial to promote collaborative projects with the fleet to collect data from the vessel's acoustic devices (both, echosounders and sonars). These devices are assumed to have higher spatial resolution, and with appropriate use, could provide complementary information that could offer multiple answers regarding the morphology of the schools associated with the FADs. This leap would transform fishing vessels into research platforms, allowing for the retrieval of valuable data.

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TABLE 1. Technical specifications of different buoy models and observed values over analysis data.
TABLA 1. Especificaciones técnicas de diferentes modelos de boyas y valores observados sobre datos de análisis.

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 GLM lognormal model of the 2012-2022 period.
TABLA 2. Tabla de desviación del modelo lognormal MLG del período 2012-2022.

Variable	Df	Deviance	Resid..Df	Resid..Dev	F	Pr..F.	Dev..Exp
NULL	NA	NA	7074	10472	NA	NA	NA
yyqq	43	706	7031	9766	17	0.0000	6.74 %
area	36	965	6995	8801	27	0.0000	9.21 %
model	2	43	6993	8758	22	0.0000	0.41 %
den	1	22	6992	8736	23	0.0000	0.21 %
chlfront	1	38	6991	8698	39	0.0000	0.36 %
sst	1	2	6990	8696	2	0.1997	0.02 %
sstfront	1	9	6989	8687	9	0.0022	0.09 %
yyqq:area	1050	2867	5939	5820	3	0.0000	27.38 %

TABLE 3. Nominal and standardized Buoy-derived Abundance Index for the period 2012-2022. Standard errors and coefficient of variations of the standardized series are also included.
TABLA 3. Índice de Abundancia Derivado de las Boyas nominal y estandarizado para el período 2012-2022. También se incluyen los errores estándar y el coeficiente de variación de la serie estandarizada.

Quarter	Index nominal	BAI Index	BAI se	BAI cv
12Q1	3.412	7.072	3.858	0.546
12Q2	6.750	5.484	1.325	0.242
12Q3	4.071	3.153	0.710	0.225
12Q4	1.675	1.301	0.292	0.224
13Q1	5.581	3.582	0.705	0.197
13Q2	2.943	2.072	0.421	0.203
13Q3	1.650	1.523	0.331	0.217
13Q4	2.196	1.570	0.306	0.195
14Q1	2.556	1.955	0.419	0.215
14Q2	2.024	1.860	0.405	0.218
14Q3	1.537	1.416	0.316	0.223
14Q4	1.392	1.162	0.229	0.197
15Q1	3.231	2.890	0.602	0.208
15Q2	2.392	2.141	0.464	0.217
15Q3	1.786	1.809	0.291	0.161
15Q4	1.580	1.614	0.352	0.218
16Q1	2.329	2.091	0.452	0.216
16Q2	1.414	1.450	0.342	0.236
16Q3	2.557	2.187	0.513	0.235
16Q4	2.046	1.690	0.394	0.233
16Q4	2.046	1.690	0.394	0.233
17Q1	1.771	1.470	0.320	0.218
17Q2	1.726	1.345	0.269	0.200
17Q3	2.172	1.613	0.351	0.218
17Q4	2.107	1.560	0.349	0.223
18Q1	1.867	1.476	0.313	0.212
18Q2	1.671	1.233	0.247	0.200
18Q3	0.832	0.735	0.162	0.220
18Q4	2.513	1.806	0.393	0.218
19Q1	1.874	1.862	0.392	0.211
19Q2	2.851	1.864	0.406	0.218
19Q3	1.597	1.570	0.367	0.234
19Q4	2.510	2.248	0.527	0.234
20Q1	4.220	3.537	0.778	0.220
20Q2	2.862	2.310	0.468	0.203
20Q3	2.445	2.082	0.443	0.213
20Q4	2.867	2.373	0.490	0.206
21Q1	1.488	1.044	0.235	0.225
21Q2	1.281	0.956	0.200	0.209
21Q3	1.851	1.197	0.237	0.198
21Q4	1.323	1.089	0.246	0.226
22Q1	1.876	1.258	0.263	0.209
22Q2	1.699	1.723	0.389	0.226
22Q3	1.179	1.050	0.241	0.229
22Q4	1.420	1.459	0.341	0.234

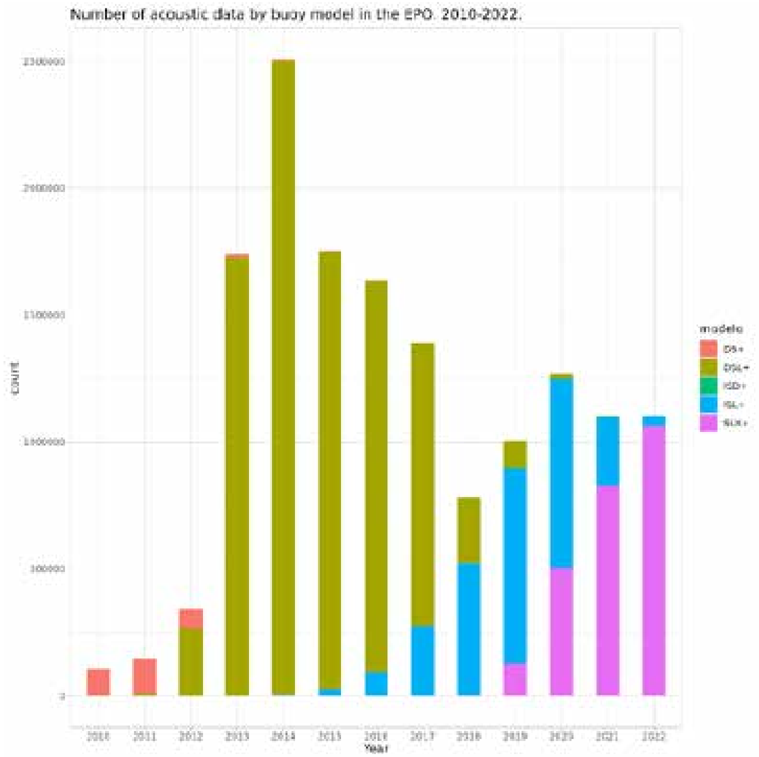

FIGURE 1. Buoy data distribution per model in the Pacific Ocean (2010-2022).
FIGURA 1. Distribución de datos de boyas por modelo en el Océano Pacífico (2010-2022).

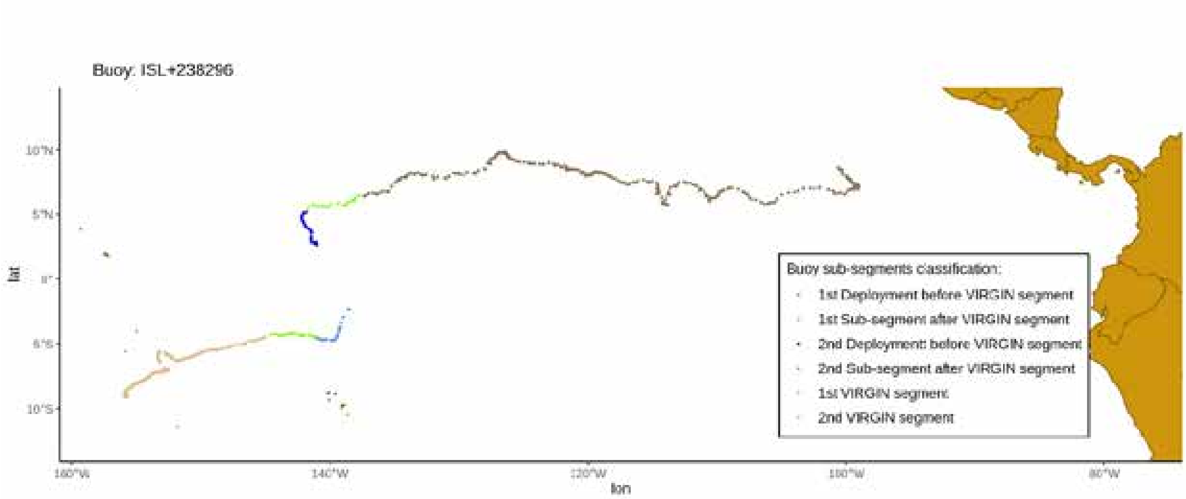

FIGURE 2. Example of "virgin" segments used for the calculation of the BAI index. Trajectories correspond to buoy ISL+284966 with two different paths representing drifts of different FADs. A virgin segment is defined as the segment of a buoy trajectory whose associated FAD likely represents a new deployment, 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.
FIGURA 2. Ejemplo de segmentos "vírgenes" utilizados para el cálculo del índice IAB. Las trayectorias corresponden a la boya ISL+284966 con dos rutas distintas que representan derivas de diferentes plantados. Un segmento virgen se define como el segmento de la trayectoria de una boya cuyo plantado asociado probablemente representa una nueva siembra, que ha sido potencialmente colonizado por atunes y que aún no se ha pescado. Consideramos como segmentos vírgenes (es decir, cuando el atún se ha agregado a un plantado) aquellos segmentos de trayectorias de 20 a 35 días en el mar. Los segmentos "vírgenes" se muestran en verde.

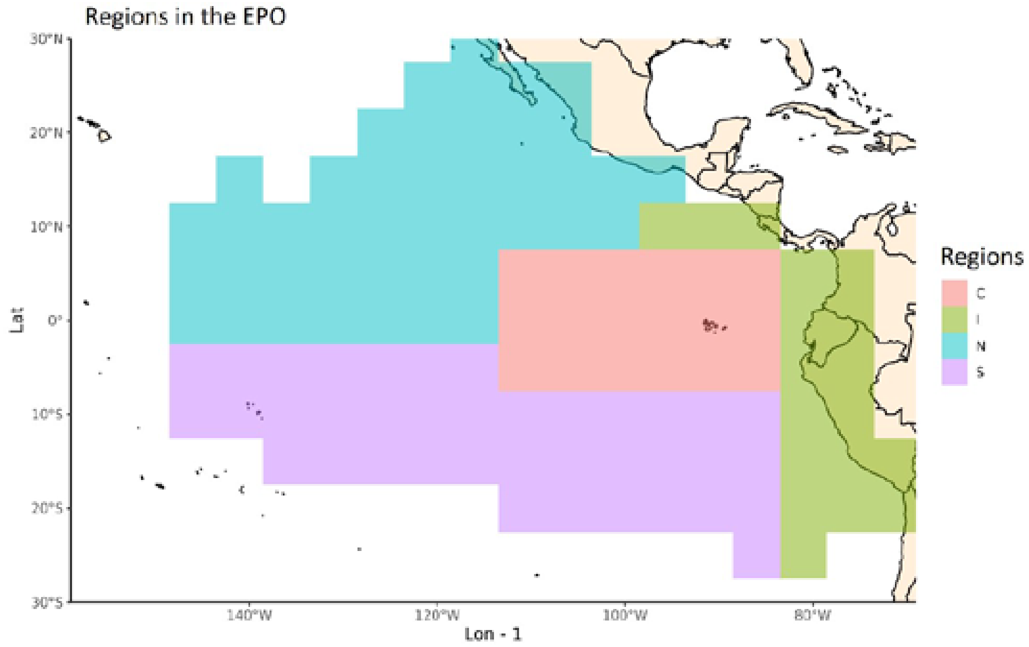

FIGURE 3. Length-frequency sampling areas defined by the IATTC staff for analyses of tropical tuna catches associated with floating objects.

FIGURA 3. Áreas de muestreo de frecuencia de tallas definidas por el personal de la CIAT para análisis de capturas de atunes tropicales asociadas con objetos flotantes.

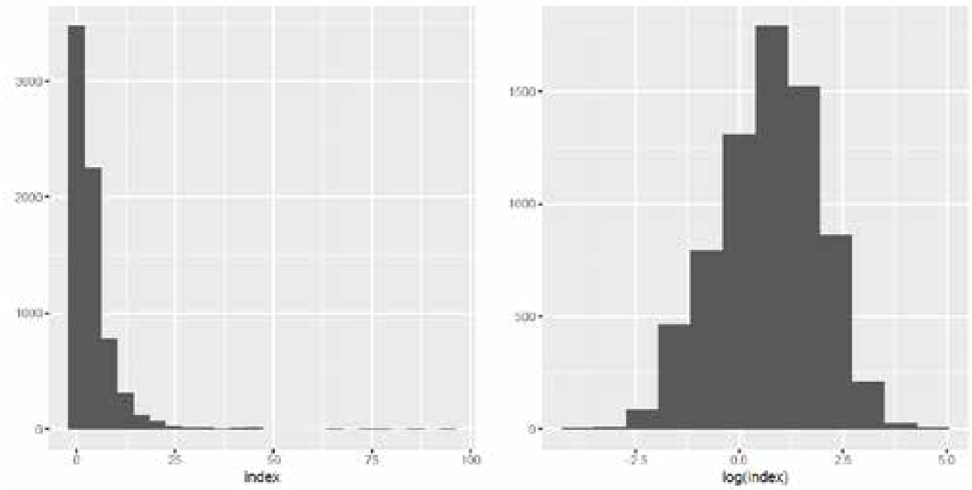

FIGURE 4. Histograms of the nominal values (left) and the log transformed nominal values (right) of the Buoy-derived Abundance Index (0.9 quantile of the integrated acoustic energy observations in "virgin" sequences).

FIGURA 4. Histogramas de los valores nominales (izquierda) y los valores nominales transformados logarítmicamente (derecha) del Índice de Abundancia Derivado de las Boyas (cuantil de 0.9 de las observaciones de energía acústica integrada en secuencias "vírgenes").

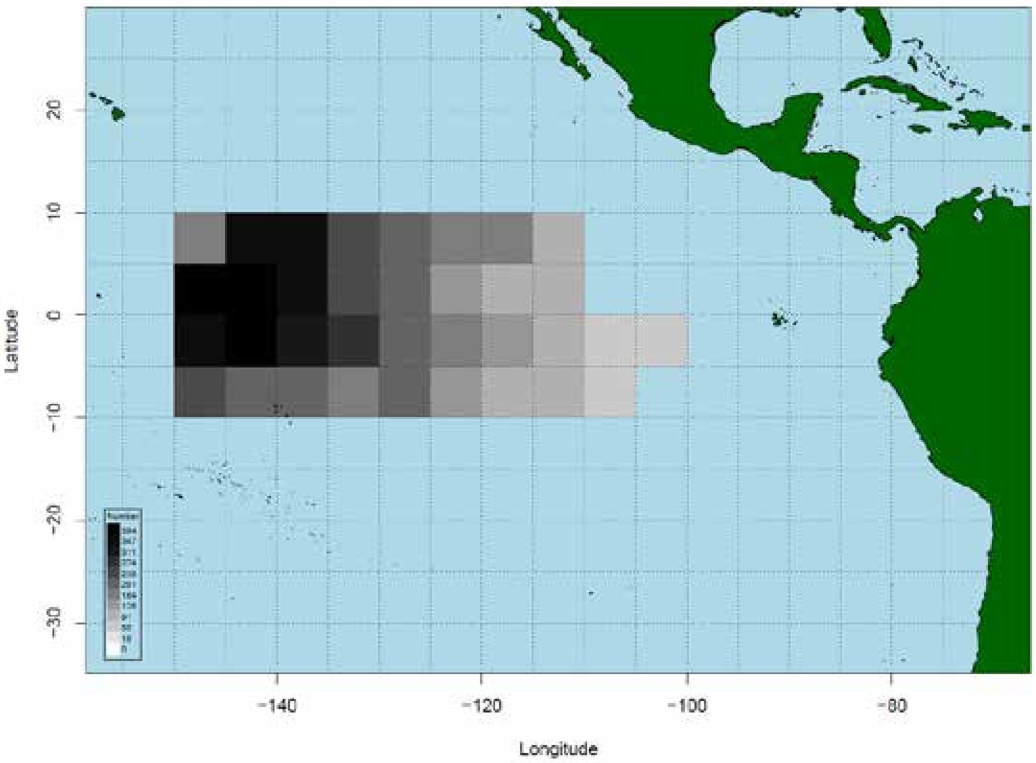

FIGURE 5. Spatial distribution [5ºx5º] of the "virgin" sequences of buoy trajectories that have been used in the GLM analysis.

FIGURA 5. Distribución espacial [5ºx5º] de las secuencias "vírgenes" de trayectorias de boyas que se han utilizado en el análisis MLG.

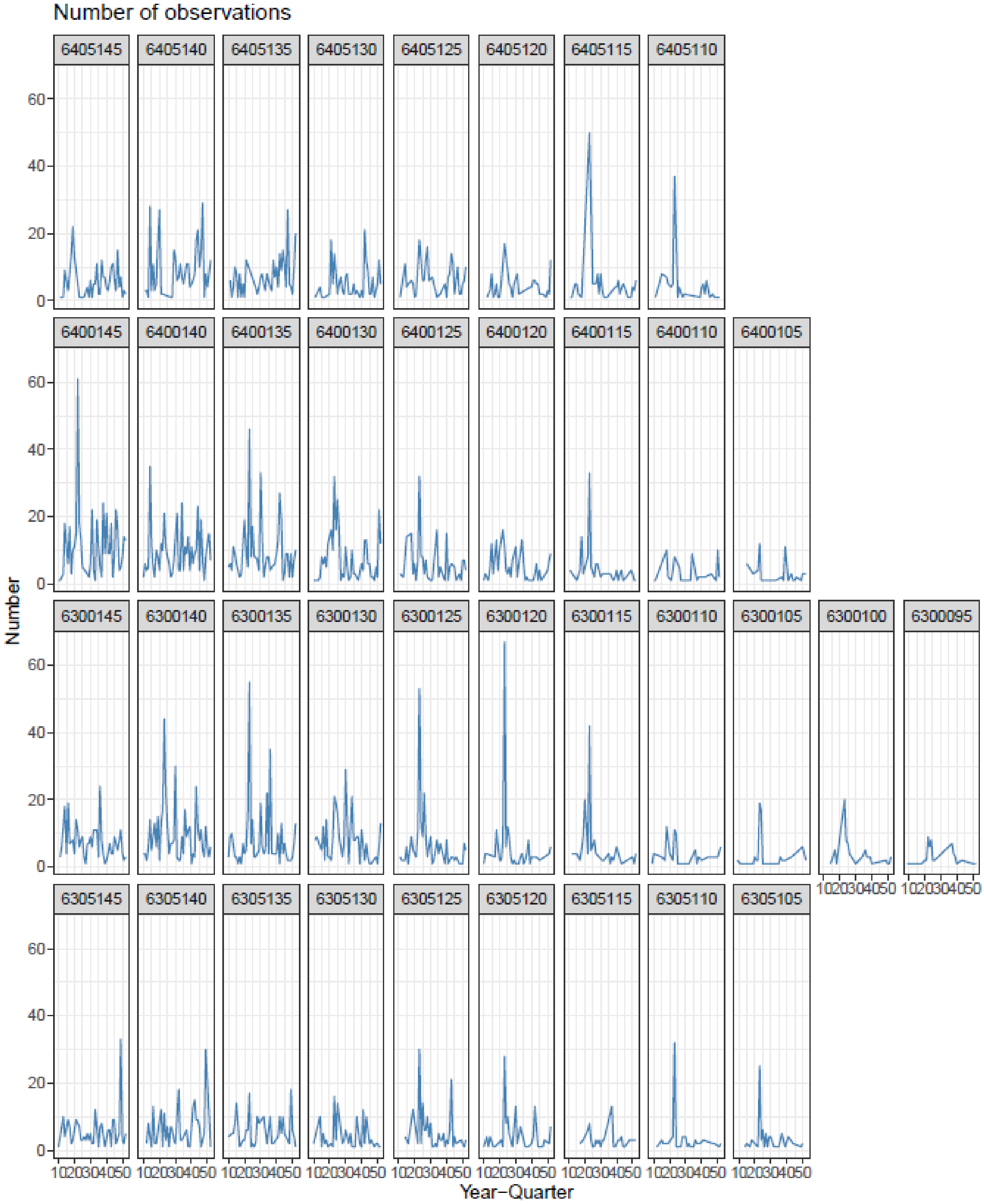

FIGURE 6. Quarterly evolution of the number of observations ("virgin" sequences of buoy trajectories) on a 5ºx5º grid from 2012 to 2022.
FIGURA 6. Evolución trimestral del número de observaciones (secuencias "vírgenes" de trayectorias de boyas) en una cuadrícula de 5ºx5º de 2012 a 2022.

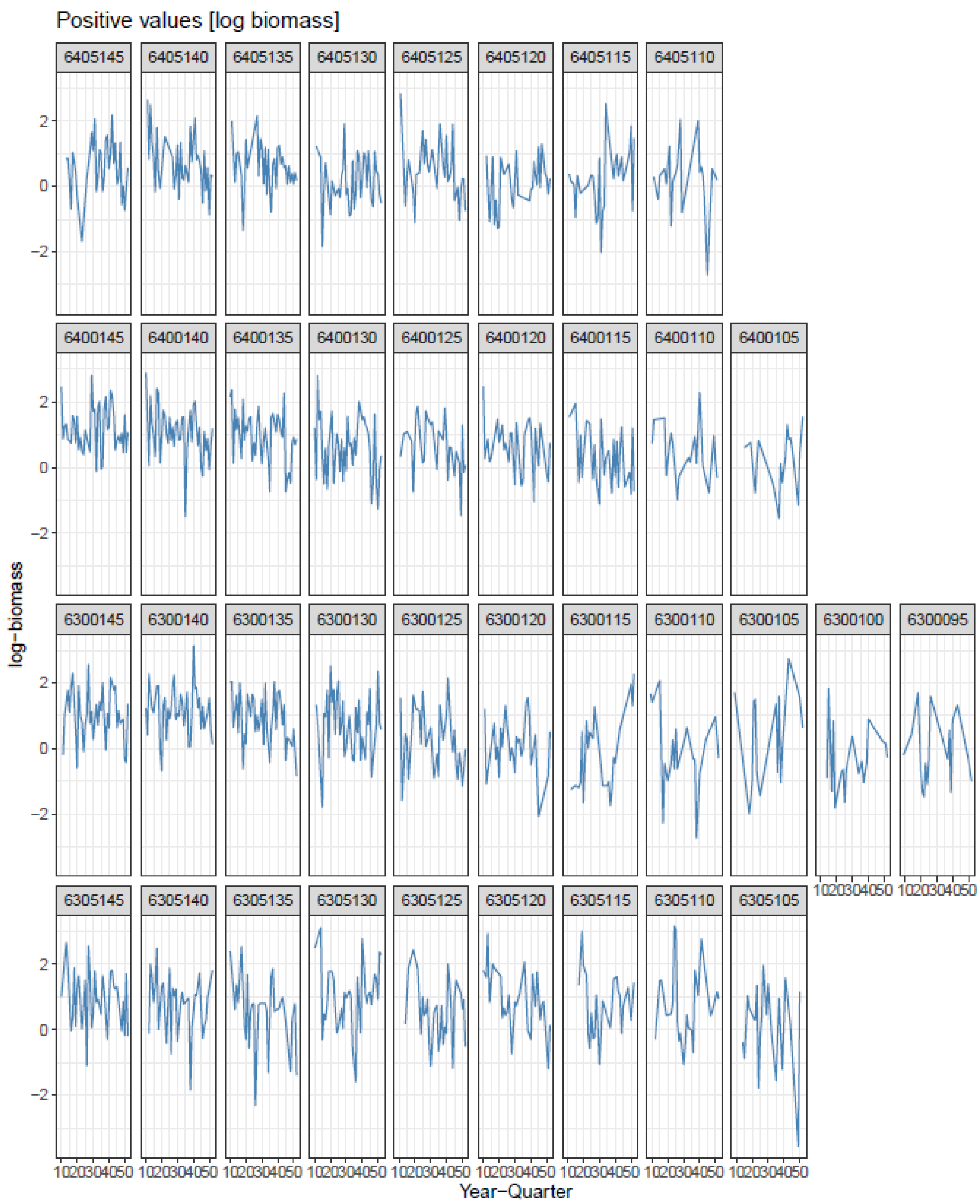

FIGURE 7. Quarterly evolution of the nominal log BAI index in the Atlantic Ocean by squares of 5x5 degrees from 2012 to 2022.

FIGURA 7. Evolución trimestral del índice IAB logarítmico nominal en el Océano Atlántico por cuadrados de 5x5 grados de 2012 a 2022.

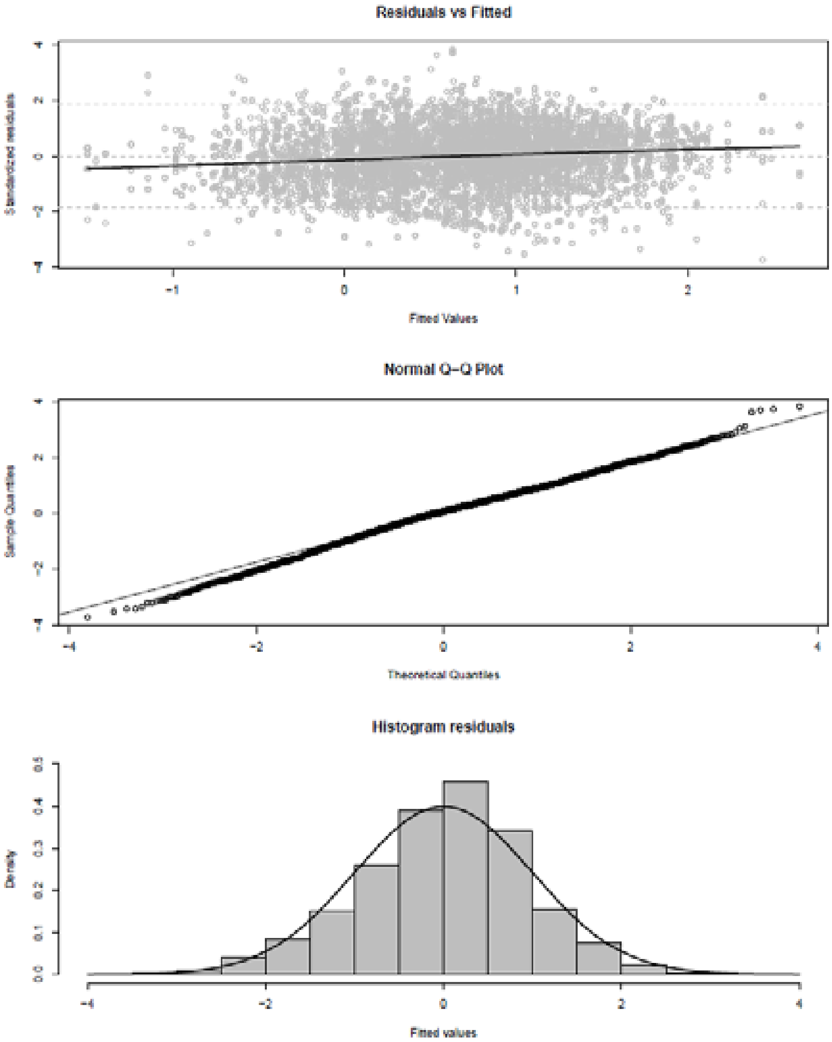

FIGURE 8. Diagnostics of the lognormal model selected for the period 2012-2022: residuals vs fitted, Normal Q-Q plot and frequency distributions of the residuals.
FIGURA 8. Diagnóstico del modelo lognormal seleccionado para el periodo 2012-2022: residuales vs. ajustados, gráfico Q-Q normal y distribuciones de frecuencia de los residuales.

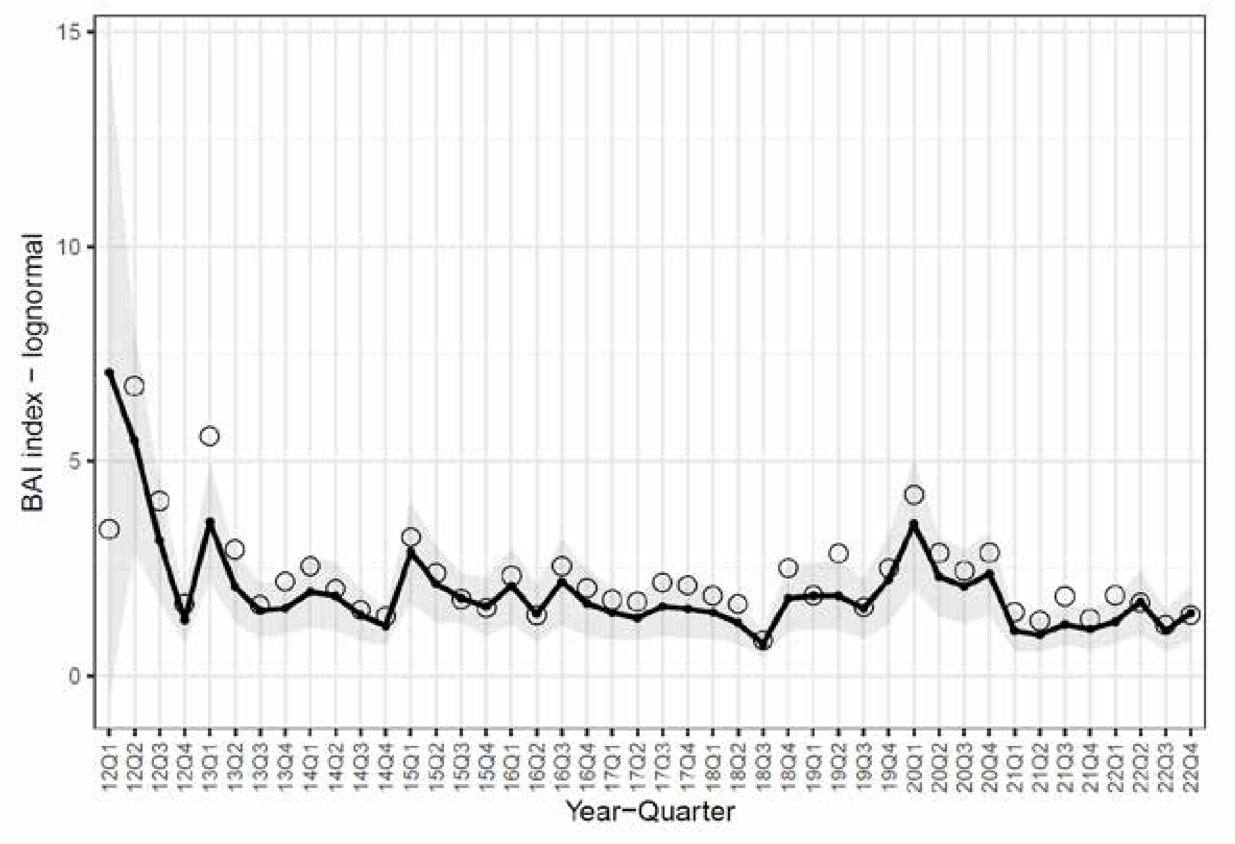

FIGURE 9. Time series of nominal (circles) and standardized (continuous line) Buoy-derived Abundance Index for the period 2012-2022. The 95% upper and lower confidence intervals of the standardized BAI index are shown by the grey shaded area.

FIGURA 9. Serie de tiempo del Índice de Abundancia Derivado de Boyas nominal (círculos) y estandarizado (línea continua) para el período 2012-2022. Los intervalos de confianza superior e inferior del 95% del índice IAB estandarizado se muestran en el área sombreada en gris.

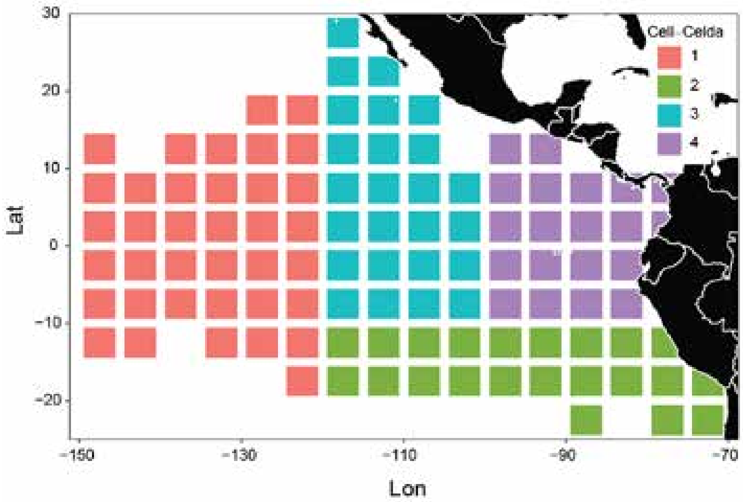

FIGURE 10. Areas corresponding to the floating-object fishery definitions used in the stock assessment of skipjack tuna in the EPO in 2022.

FIGURA 10. Áreas correspondientes a las definiciones de la pesquería sobre objetos flotantes utilizadas en la evaluación de la población de atún barrilete en el OPO en 2022.