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POTENTIAL BIAS ON THE 2020 AND 2021 TROPICAL TUNA CATCH ESTIMATES RESULTING FROM COVID-19: UPDATE

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CONTENTS

SUMMARY

The IATTC port-sampling data are used to determine the species and size composition of the tropical tuna catch, and therefore play a very important role in the current Best Scientific Estimate (BSE) catch estimation methodology. The COVID-19 pandemic generally limited the ability of IATTC port-samplers to collect data in 2020 – 2021, however, the disruption to data collection was greater in some ports than in others. This may have resulted in bias in the BSE of catch composition for 2020 – 2021 because some fleet segments preferentially unload in specific ports. An increase in the 2020 BSE for bigeye tuna (BET) in floating-object (OBJ) sets in 2020, relative to the previous year (SAC 13-03), despite a decrease in OBJ sets (SAC-13-06), and the marked disparity between the 2020 BSE and the reported catches from observers and logbooks for 2020, contributed to a concern about potential bias in the BSE at the 12th Meeting of the Scientific Advisory Committee. A study that applied the BSE methodology to data from 2010 – 2019, after simulating a systematic reduction in port-sampling data to match that which occurred in 2020, showed that bias could occur, but that the bias could be either an over-estimation or an under-estimation (SAC-13 INF-L). Therefore, to address the effect of the systematic loss of port-sampling data in 2020-2021 on the BSE, a spatio-temporal model was developed to estimate the port-sampling catch composition from observer (logbook) data for catch estimation strata for which no port-sampling data were available (SAC-13-05). Exploratory analyses showed that observer data (supplemented with logbook data, where

necessary) could be used successfully to predict the port-sampling species composition, and that prediction was improved when spatial and temporal covariates were included in the model. The spatio-temporal model performed well in terms of the percent variance explained and normalized prediction error, and the catch estimates from the model were highly correlated with the BSEs for 2010-2019, years for which no systematic data losses occurred. Through simulation, the spatio-temporal model was found to be robust to the type of systematic port-sampling data losses that occurred in 2020 and 2021. One of the reasons for this may be that long-term historical information was incorporated into the spatio-temporal model through an autoregressive process. This spatio-temporal model was used to estimate the catch by species in the OBJ fishery for 2020 and 2021, and the results indicate that the BET catch was overestimated by the BSE methodology by about 12% and 18.2% in 2020 and 2021, respectively. The results for 2021 were preliminary in SAC-13-05, because the 2021 estimates are based on data for 2020, which was also impacted by the pandemic, and possibly in a different manner than that which occurred in 2021. This document updates SAC-13-05 with analyses conducted to determine the robustness of the 2021 estimates.

2. BACKGROUND

Due to the COVID-19 pandemic, in 2020 - 2021 it was not possible to collect some of the data used to estimate the species and length composition of the tropical tuna catch (yellowfin, bigeye and skipjack) for the purse-seine fleet. Specifically, data collected in port (port-sampling data) were not collected during part of this two-year period in some of the main ports where bigeye tuna (BET) catch is unloaded (landed). As a result, there is concern that the Best Scientific Estimates (BSE) of the species and length composition of the catch for these two years may be biased, particularly for bigeye tuna (SAC-13 INF-L). The fact that the 2020 BSE of the BET catch in floating-object (OBJ) sets increased, relative to the 2019 estimate (SAC-13-03), while the number of OBJ sets in 2020 decreased relative to the number in 2019 (SAC-13-06), has added to concern about bias. Therefore, for 2020 - 2021, modification to the statistical methodology used to estimate the tropical tuna catch composition is likely necessary, placing greater emphasis on other data sources, besides the port-sampling data, in the estimation methodology.

2.1 Data sources available for catch composition estimation

There are four primary data sources available with which to estimate the species composition of the purse seine catch of tropical tunas in the eastern Pacific Ocean (EPO): (i) Observer data, (ii) Logbook data (iii) Cannery data, and (iv) Port-sampling data. These data sources differ in their coverage, collection methods, sample sizes, potential biases (both catch amounts and species identification), and the effects of COVID on data collection. A more detailed description of these data sources is provided in Appendix B.

Of the four data sources, the observer and logbook data are the most extensive in terms of spatial and temporal coverage of the fishery. The logbook data are available for all size classes of purse-seine vessels. The logbook data include details of the fishing effort and estimates of the target species catch, but they do not provide information on the size of fish and rely on the fishers to provide information. The observer data have effectively 100% coverage for large purse seiners (IATTC Class-6; > 363 mt fish carrying-capacity) and contain additional information (e.g., bycatch, tuna discards), but are only available for a small fraction of small purse-seine vessels. The observer data provide estimates of the amounts of tuna catch by species in three weight categories (‘small’: fish < 2.5 kg total weight; ‘medium’: fish between 2.5 kg and 15 kg; ‘large’: fish > 15 kg), but not actual measurements of length or weight of individual fish.

Cannery data are principally estimated catch amounts of target species by trip, provided to the IATTC staff by tuna canneries. They do not provide information on exact fishing locations or dates, or on operational characteristics (e.g., purse-seine set type), although information on fishing zones and trip departure and arrival dates are provided. No size information is currently available on the database; some canneries do provide estimates of catch by weight categories, but those categories differ among canneries, making the size information problematic to use for catch composition estimation. Cannery data are not available to the IATTC staff for all trips nor from all canneries. The port-sampling data are collected by IATTC field office staff when purse-seine vessels unload their catch in port and are principally samples of lengths and species composition of the catch stored in individual vessel wells. The data include length measurements to the nearest mm from a sample of fish and counts of species from another independent sample of fish (see appendix in Suter (2010) for details of the sampling protocol). They also include data on the month, area and set type associated with the catch in the well that was sampled. Although the port-sampling data collection protocol is based on 13 sampling areas, since 2000 both the sampling area and the 5° area are available for each sample. Not every trip is sampled by the port-sampling program, and the coverage of trips differs by vessel size class. The coverage in terms of the percentage of wells sampled or percentage of the catch sampled is low.

2.2 Current catch composition estimation methodology

Comprehensive and accurate information on the species and size composition of the fleet catch is not available from any one of the four primary data sources. Therefore, these data sources have to be combined to produce the BSE. More information on the BSE statistical methodology used since 2000 to estimate the purse-seine tuna catch composition for the three target tuna species is provided in Appendix C of document SAC-13-05 and citations therein. The methodology is a design-based approach to catch estimation, as opposed to a model-based approach. The methodology uses the port-sampling data to estimate the species and size composition of the total catch of tropical tunas by stratum, where strata are defined by area and month of fishing, purse-seine set type and vessel size class category. The estimate of the total purse-seine catch of tropical tunas (sum of catches of yellowfin, bigeye and skipjack) is based on catches from cannery data, if available, otherwise observer data or logbook data are used. This total tropical tuna catch is distributed to strata using observer and logbook data.

Because there are always strata with catch but no port-sampling data (SAC-13 INF-L), species and size composition in some strata are based on port-sampling data from ‘neighboring’ strata. The ‘best’ neighboring stratum is determined through a set of hierarchical rules. In general, priority is given to set type. Then priority is given to area or month, depending on the programs being used, and finally vessel size class category. Bias may be introduced by this procedure when the true species and size composition of ‘neighboring’ strata with port-sampling data are sufficiently different from that of the stratum for which no port-sampling data exist. The possibility of bias is always present, but much more likely when the overall level of port-sampling is very low or catch unloaded in some ports is not sampled for an extended period of time, as was clearly the case in 2020 and 2021 (SAC-13-INF-L).

2.3 Overview of statistical approach taken in this study

The overall approach taken in this study was to develop a statistical methodology that would use the port-sampling data to ‘adjust,’ in a statistical manner, the catch composition estimates obtained from the observer and logbook data. There are two reasons for this. First, collection of observer and logbook data was not as severely impacted by the pandemic as was the collection of port-sampling data. Second, as noted above, the observer and logbook data are also more extensive in their spatial and temporal coverage of the fishery, as compared to the port-sampling data. Thus, the goal was to develop an integrated statistical model, which could accommodate multiple sources of variation inherent in the data, so that observer and logbook data could be used to predict the port-sampling catch composition by strata (e.g., by year and set type for specific spatial units), for strata for which no port-sampling data were actually available.

Conditionally Auto Regressive spatio-temporal models (CAR; Besag *et al.* 1991) was the class of integrated statistical models used in this study. These types of models can take advantage of innate spatial and temporal correlation structure in the data and are thus more likely to make reliable estimates when large amounts of data are systematically missing (e.g., for certain ports for many months). The work to date has focused on estimation of the species composition of the catch in OBJ sets because BET is primarily caught in OBJ sets (SAC-13-03) and the systematic loss of port-sampling data caused by the pandemic likely led to bias in the BET OBJ-set BSE (SAC-13 INF-L).

Since the true species composition of the catch is unknown, in this study it was assumed that the goal is to develop a method that will produce catch estimates that are as consistent as possible with those produced by the BSE methodology prior to the pandemic (i.e., prior to 2020). Therefore, not only were standard measures of model performance used to develop the best CAR model, such as percent of variance explained by the model and prediction error, but the new methodology was also evaluated in terms of its ability to match the BSEs for 2000-2019 that are reported in the IATTC Fishery Status Report (e.g., Table A-7 of SAC-13-03).

In this document we present further work on the new methodology to estimate the species composition of the tropical tuna catch, focusing on OBJ sets. First, we describe some of the exploratory analyses used to investigate the relationship between port-sampling and observer species composition estimates. Next, we describe the new integrated statistical methodology developed to estimate the species composition of the catch from both observer (logbook) data and port-sampling data in 2020 and 2021. Then we estimate the potential bias caused by the reduced port sampling in 2020 and 2021 by assuming similar missing data in prior years. We conclude with revised estimates of catch by species for 2020 and 2021.

3. DATA EXPLORATORY ANALYSIS

Several types of exploratory analyses, focusing on the data of IATTC Class-6 vessels, were conducted to investigate the relationship between the species composition estimates from port-sampling and those from observer data. First, the magnitude of differences in species catch composition between observer and port-sampling data was evaluated, by strata, using graphical techniques (Figure 1 and 2). Then, multiple regression analyses were carried out to: (i) understand the strength and nature of the relationship between the observer and port-sampling species composition estimates; and (ii) to identify any spatial and temporal structure that may be present in the port-sampling species composition estimates. Further details are in SAC-13-05.

4. STATISTICAL SPATIO-TEMPORAL MODELING

In SAC-13-05 Section 4, the CAR spatio-temporal model (Besag *et al.* 1991) implemented in this study is described. This section describes the key aspects of the statistical modeling that were needed to address the data characteristics identified by the exploratory analyses. The details and the 'best' spatio-temporal CAR model and the results related to model fit and prediction performance, as well as estimates of the species composition of the catch, which are compared to the BSEs presented in SAC-13-03 are in SAC-13-05 Section 4.

The key aspects of the statistical modeling that are needed to address the data characteristics are:

1. The statistical model needs to allow flexibility for spatial pattern (mean at each spatial location) and spatial variation (variance at each spatial location) in the data to change from year to year, all in one integrated model. The presence of spatial pattern implies that observations from units closer to each other are more similar than those from units farther from each other. If there is no spatial pattern and the spatial variance is also constant, for example, the data can be assumed to be distributed randomly in space. However, in the exploratory analyses, it was found that the BET species proportions exhibited spatial pattern and spatial variation that changed over the years. Specifically, the box-and-whisker plots of Figure 5 have different medians and different interquartile ranges, and these values depend on longitude, which suggests that there may be residual spatial pattern and spatial variation after regressing port-sampling proportions on observer proportions.
2. The statistical model needs to address data sparsity in space and time. Data sparsity is a function of the spatio-temporal resolution of the data used to fit the model. While statistical models can be fitted to relatively fine-resolution data (e.g., 5°-monthly data), the sparsity of the port-sampling data in space and time, compared to spatio-temporal extent of the catch data (observer, logbook), made such modeling of the port-sampling species proportions problematic in preliminary analyses. An example of spatial data sparsity in the monthly 5° data is shown in Figure 6. One way to address this issue is to aggregate the data in space and time to compensate for low sample sizes in certain areas of the EPO, especially in some years where data were particularly spatially scarce. However, sparsity is still present in the annual data, as shown in Figures 3 - 4. An additional way to deal with data sparsity is to take advantage of correlation structure within the data, either in space at the same time point, or through time, by incorporating data from multiple years into one model. In this way, the model can take advantage of spatial pattern that is evolving in a correlated manner through time to help mitigate the issue of data sparsity).
3. The statistical model must be able to predict for new areal units to be able to estimate species proportions for areal units where port-sampling data were missing in 2020-2021.

After several attempts to develop models using finer-resolution data, e.g., monthly and quarterly data at a 5° spatial resolution, which resulted in models with poor performance (but see Discussion section), it was decided to aggregate the data in time to a yearly resolution and in space to the 13 sampling areas (Figure 7) used in BSE catch estimation methodology (Tomlinson 2002). The spatial aggregation works well in reducing the variability of the proportions – leading to better fitting models, presumably because there are more data points in these larger regions compared that for smaller spatial 'cells'. Thus, spatio-temporal CAR models, described in SAC-13-05 (Section 4), were fitted to the aggregated data to estimate p_{kt}.

4.1 Catch estimation

Once the estimated values for the port-sampling species proportions have been obtained, the next step is to estimate the total catch of a species for OBJ sets for the entire EPO, by year. To estimate the total catch, estimated species proportions, p_{ktm} , were obtained by spatial region (k), year (t) and vessel size class category (m; Classes 1-5 and Class-6). For Class 1-5 vessels, the CAR models used both observer and logbook data to compute q_{ktm}, whereas for Class-6 vessels, the q_{ktm} were based only on observer data. If the total tropical tuna catch for the EPO in year t is given by U_t, then U_t is prorated to area and vessel size class category using the proportion of tropical tuna catch within each stratum, as estimated from observer and logbook data. This procedure produces stratum-level estimates of total tropical tuna catch, U_{ktm}. Then the estimated catch for that stratum for a species is $U_{ktm}\, p_{ktm}$, and the total catch for OBJ sets is obtained as the sum $C_t = \sum U_{ktm}\ p_{ktm}$ over the corresponding strata. Once total catch estimates for BET and SKJ are obtained in this way, we obtain the total catch estimate for the YFT by subtracting their sum from the total OBJ catch of tropical tunas of that year. That is, $C_{t\_YFT} = U_t - C_{t\_BET} - C_{t\_SKJ}$.

5. RESULTS

5.1. Spatio-temporal modeling

a) Model parameters

The parameter estimates for the best CAR model for each year are given in Appendix B in SAC-13-05 document.

b) Catch estimates

The catch estimates of each species for OBJ sets based on the best CAR model for each of years 2010-2019 are given in Table 2 in SAC-13-05, and those for 2020 and 2021 are shown separately in Table 1.

c) Model performance

The results of model performance are summarized in Tables 4 – 5 in SAC-13-05. The proportion variance explained by these models ranges from 74-100%, and is mostly higher than 90%, indicating that the models fit the data well. The normalized prediction errors are mostly small (i.e., less than 1) indicating overall good prediction performance.

d) Estimated bias

One of the main objectives of this work was to investigate the potential bias in the BSE due to the pandemic-driven port-sampling data loss in 2020-2021. The spatio-temporal CAR models that were developed to be consistent with BSE during non-pandemic years 2010-2019, were found to perform similarly well (see Section 5.3, SAC-13-05) when port-sampling data for some ports for which data were systematically missing 1) in 2020 and 2) in both 2020 and 2021 (SAC-13 INF-L) were excluded in the years prior to 2020 (see Section 5.2). This robustness was taken to indicated that these best spatio-temporal CAR models would likely produce reliable estimates in 2020 -2021. Given this, the bias of the BSE for a particular species was defined as the difference between the BSE estimate and the CAR estimate (Table 1). The estimated bias was greatest for BET (12% and 18% for 2020 and 2021, respectively) and was lowest for SKJ (6% and -4% for 2020 and 2021, respectively).

5.2. Retrospective analysis of bias

To evaluate the effect of the pandemic-driven loss of port-sampling data on the 2020 OBJ BET BSE, the BSE estimation methodology was run for each of years 2010 - 2019, using all available cannery, observer and logbook data, but with only a subset of the port-sampling data; details of this analysis can be found in SAC-13 INF-L. The results indicate that the systematic pandemic-related loss of port-sampling data in 2020 for ports where much of the EPO BET is estimated to be unloaded may have led to a bias in the OBJ BET BSE. Although the median difference between estimates, with and without the simulated data loss, was close to 0, both negative and positive biases of about 20% or more were seen over the 2010 – 2019 period (Figures 10-11). A similar analysis for 2021 has not yet been completed.

5.3. Sensitivity analysis of the best CAR model in 2020 and 2021

To test the sensitivity of the CAR methodology to a systematic loss of port-sampling data in the year for which estimates were desired, a sensitivity analysis with data from 2019 and earlier was conducted, mimicking 1) the 2020 data loss in the year of interest and 2) the 2021 data loss in the year of interest and the 2020 data loss in the previous year to the year of interest. Specifically, in (1) the port-sampling data from the ports of Manta (April-December), Mazatlan (April) and Posorja (April-May) (see SAC-13 INF-L for an explanation of why these ports and time periods were selected) were excluded for the year of interest and the catch totals for that year re-estimated using the same best CAR model. In (2) the port-sampling data from the ports of Manta (April-December), Mazatlan (April) and Posorja (April-May) were excluded for the previous year to the year of interest and Manta (Feb-July) Guayaquil (Jan-June) were excluded for the year of interest (see Figure 3 for an explanation of why these ports and time periods were selected) were excluded for the year of interest and the catch totals for that year re-estimated using the same best CAR model. This was done for each of years 2010 – 2019. Comparison of these estimates to the BSEs, and to the CAR estimates based on the full data sets for 2010- 2019, demonstrates that even after excluding some of the port-sampling data, the CAR estimates seem robust, since they are close to the estimates obtained when the data were not excluded (Figure 12, SAC-13-05 and Figure 4).

To further demonstrate the robustness of the CAR estimates, Table 4 shows the correlation coefficients of the CAR estimates for the best model with the BSE (i) when no port-sampling data were excluded, (ii) when some port-sampling data were excluded mimicking the systematic port-sampling data loss in 2020, and (iii) when some port-sampling data were excluded mimicking the systematic port-sampling data loss in 2020 and 2021. The correlation coefficients are similar for (i), (ii) and (iii).

6. DISCUSSION

To address the systematic loss of port-sampling data from some ports during 2020 - 2021, a lognormal spatio-temporal CAR model was developed to obtain annual estimates of the species composition of the catch in OBJ sets. This modeling approach makes use of the observer (logbook) data, as well as the spatial and temporal structure inherent in the available port-sampling data, to predict the species catch composition for estimation strata for which no port-sampling data were collected. The spatial correlation structure of the CAR model was specifically designed to mimic the spatial dependencies inherent in the current BSE methodology. Thus, this CAR model can be viewed as an extension of the current BSE methodology, one which can take advantage of other data sources to mitigate the normal sparseness of the port-sampling data – a feature exacerbated by the effect of the pandemic on data collection in 2020 - 2021. This CAR model was shown to have good performance in terms of percent variation explained and normalized prediction error, and the annual estimates produced by the CAR model had reasonably high correlation with the 2010-2019 BSEs for OBJ sets. In addition, the estimates of the CAR model were reasonably consistent with the BSE estimates even when trips were excluded systematically in the years prior to 2020 to simulate the pandemic-driven data loss. One of the reasons for this may be that the CAR model incorporated long-term historical information in a structured manner, which may be a reliable method to correct for short-term systematic data loss.

The CAR model was used to estimate the potential 'bias' in the BSE for OBJ sets for 2020 and 2021, for each of the three tropical tuna species. From these results it seems that the BET catch may have been over-estimated by the BSE methodology for the years 2020 and 2021 by 12% and 18.2%, respectively. This percent bias for BET was much higher than the differences between the BSE and the CAR estimates in 2010-2019, years for which no bias in the BSE would be expected because there was no systematic loss of port-sampling data. In contrast, the 'bias' values for YFT and SKJ for 2020 and 2021 were within the range of values obtained for the earlier years, i.e., 2010 - 2019. This suggests that, of the three species' estimates for 2020 – 2021, those for BET were the most likely to have been impacted by pandemic-related data loss.

The pandemic appears to have had less of an impact on the fishery and sampling in 2021, as compared to 2020. The number of OBJ sets and fishing capacity increased in 2021 compared to 2020 (SAC-13-06) as did the number of wells sampled by the port sampling (there were 447 well samples used in the analysis for 2020 and 611 for 2021). However, despite the increase in fishing effort, the BSE estimate of bigeye tuna catch decreased (SAC-13-06). In addition, the estimated bias in the BSE estimates for BET were about the same as in 2020 and 2021, despite the increase in wells sampled by the port-sampling program. There may be several reasons for these unexpected changes. The retrospective analysis of the BSE catch estimates showed that there may be bias in the BSE estimates in the case of systematic data loss, but there could be both over and under estimation of catch in different years. In addition, the time series nature of the CAR estimator means that the 2020 port-sampling data, which had significant data gaps for some ports, were used in the estimation of the 2021 catch composition (although, to compensate for this a longer time series was used). Other factors such as bigeye tuna abundance could also impact the estimates.

7. CONCLUSION

- The COVID-19 pandemic limited the ability of port samplers to take samples, resulting in a reduction in OBJ-set samples for 2020 and 2021 of 66% and 35%, respectively, compared to 2019.
- The port sampling data are used to calculate the species and size composition of the catch, and therefore play a very important role in the current BSE catch estimation methodology.
- Port-sampling data collection was disrupted by the pandemic in some ports more than others and this may result in bias in the estimates of catch by species because certain fleet segments preferentially unload in specific ports.
- Applying the same systematic reduction in sampling by port to the data of years prior to 2020 showed that bias could occur, but that the bias could be either an over-estimation or an under-estimation (SAC-13 INF-L).
- Exploratory analysis showed that observer data (supplemented with logbook data, where necessary) could be used successfully to predict the port-sampling species composition, and that prediction was improved when spatial and temporal covariates were included in the model.
- A spatio-temporal model was developed to estimate the port-sampling species proportions from observer (logbook) data in catch estimation strata for which port-sampling data were not available.
- Using the spatio-temporal model to estimate the catch composition of earlier years (2010-2019), after simulating the same systematic reduction in port-sampling data that occurred 1) in 2020 and 2) in both 2020 and 2021 showed that the catch composition estimates from the spatio-temporal model were robust to systematic port-sampling data loss for the year for which catch estimates were desired.
- The spatio-temporal model was used to estimate the catch by species in the OBJ fishery for 2020 and 2021, and the results indicated that the BET catch was overestimated by about 12% and 18.2% for 2020 and 2021 respectively.

8. REFERENCES

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Appendix A: Estimates and Performance Measures

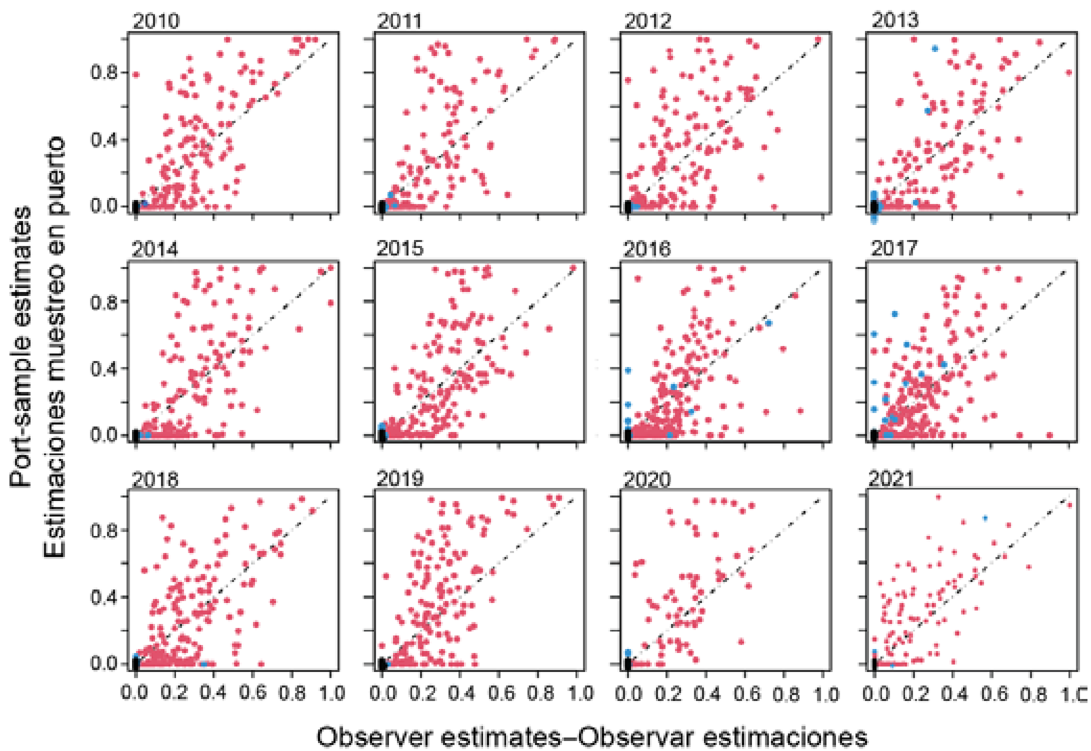

FIGURE 1. Scatter plots of the observer versus the port-sampling proportions for BET at a resolution of 5°area x month, for 2010 – 2021, plotted for `cells' that had both port-sampling and observer data. Red dots: OBJ sets; black dots: NOA sets; and blue dots: DEL sets.

FIGURA 1. Diagramas de dispersión de las proporciones de observadores frente a las proporciones de muestreo en puerto para BET en una resolución de área de 5° por mes, para 2010–2021, trazados para "celdas" que tenían datos de muestreo en puerto y de observadores. Puntos rojos: lances OBJ; puntos negros: lances NOA; puntos azules: lances DEL.

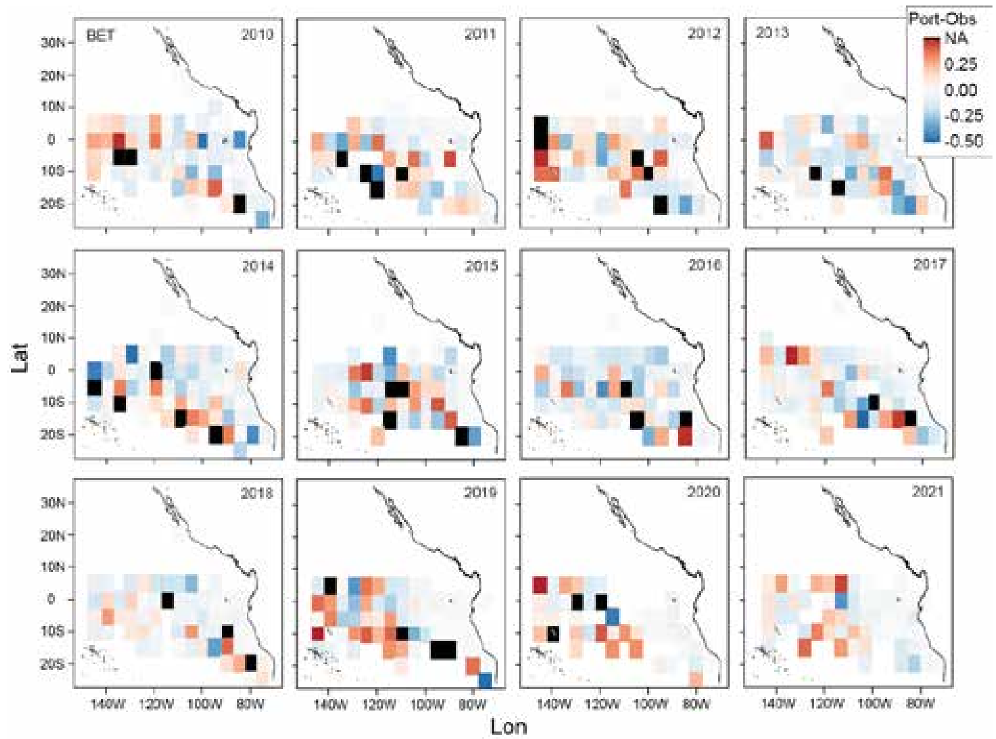

FIGURE 2. Annual maps of differences between port-sampling and observer proportions $(p_{kt} - q_{kt})$ for BET (Class-6 OBJ), at a 5° resolution. The black color indicates 5° areas for which port-sampling data were unavailable.

FIGURA 2. Mapas anuales de las diferencias entre las proporciones de muestreo en puerto y las proporciones de observadores $(p_{kt} - q_{kt})$ para BET (OBJ clase 6), en una resolución de 5°. El color negro indica áreas de 5° para las que no se disponía de datos de muestreo en puerto.

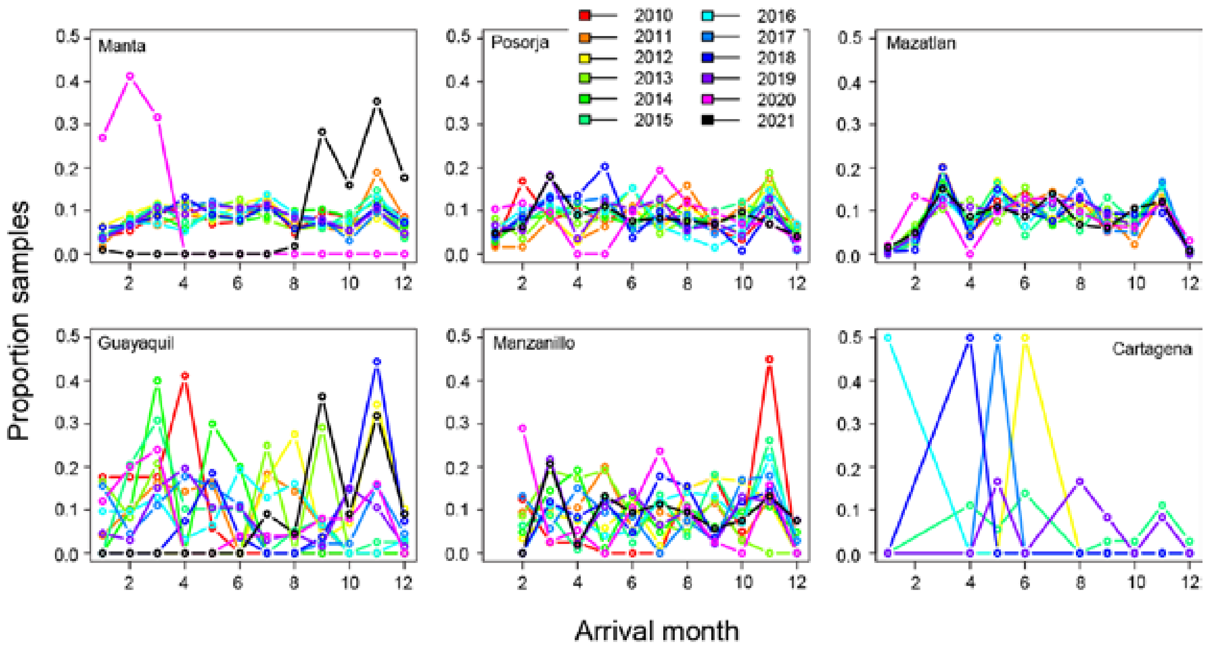

FIGURE 3. Port-sampling proportions of BET OBJ (monthly) for years 2010-2021 for various ports. The black line stands for 2021 port-sampling proportions BET OBJ.

FIGURA 3. Proporciones de muestreo en puerto de BET en lances OBJ (mensual) para los años 2010-2021 para varios puertos. La línea negra representa las proporciones de muestreo en puerto de BET en lances OBJ en 2021.

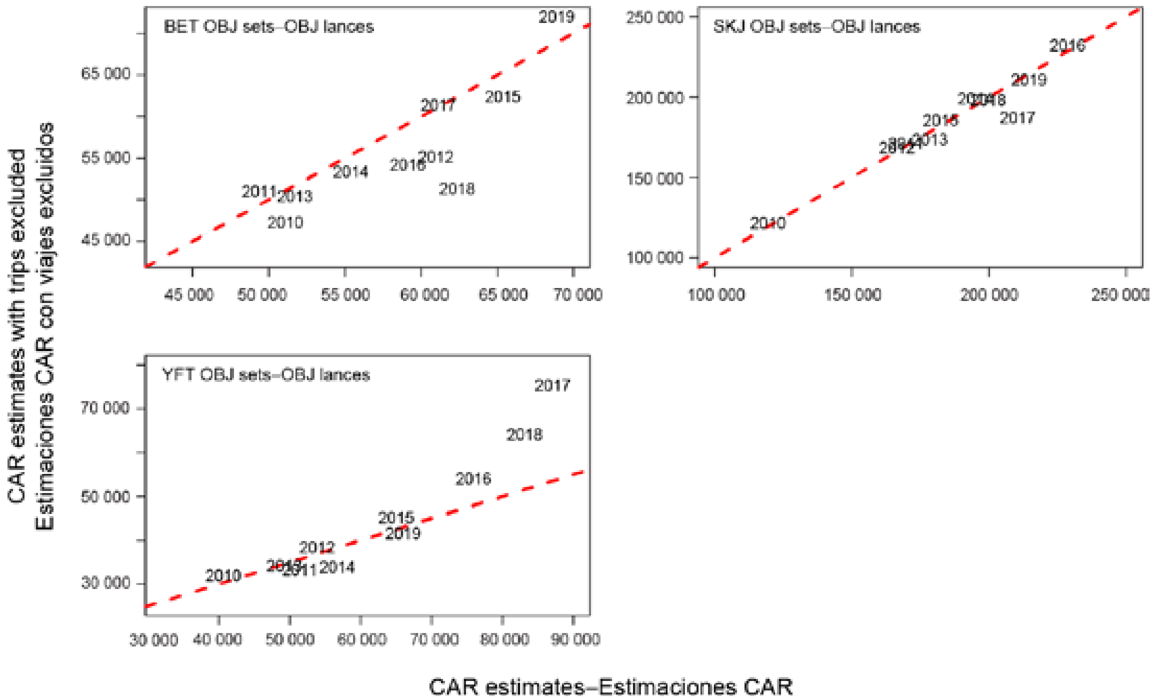

FIGURE 4. The CAR estimates with no port-sampling data excluded (on the x-axis) *versus* the CAR estimates for 2010-2019 with some data excluded: (a) BET (upper left panel); (b) SKJ (upper right panel); and, (c) YFT (lower left panel).

FIGURA 4. Las estimaciones CAR sin datos de muestreo en puerto excluidos (en el eje 'x') *versus* las estimaciones CAR para 2010-2019 con algunos datos excluidos: (a) BET (panel superior izquierdo); (b) SKJ (panel superior derecho); y, (c) YFT (panel inferior izquierdo).

TABLE 1. OBJ catch estimates of BET, YFT, SKJ (metric tons) for 2020-2021 based on the `best' CAR model. The BSE values were taken from Table A-7 of SAC-13-03.

TABLA 1. Estimaciones de captura de BET, YFT, SKJ en lances OBJ (toneladas métricas) para 2020-2021 basadas en el 'mejor' modelo CAR. Los valores BSE se tomaron de la Tabla A-7 del documento SAC-13-03.

Estimated values	2020 CAR	2020 BSE	2021 CAR	2021 BSE
BET	69,901	78,208	48,087	56,861
SKJ	190,243	191,399	239,692	225,132
YFT	53,924	44,461	60,701	66,488

TABLE 2. Absolute (in metric tons) and percent bias of the BSE in 2020-2021 as estimated from the best CAR model. Bias is defined as the BSE minus the CAR estimate.

TABLA 2. Sesgo absoluto (en toneladas métricas) y porcentual de la BSE en 2020-2021 según la estimación del mejor modelo CAR. El sesgo se define como la estimación BSE menos la estimación CAR.

Bias	2020	2021
BET	8,307 (12%)	8,774 (18.2%)
SKJ	1,156 (0.6%)	-14,560 (-6%)
YFT	-9,463 (-17.5%)	5,787 (9.5%)

TABLE 3. OBJ estimates for BSE program divided by CAR model, for 2020-2021 for the three species of tuna.

TABLA 3. Estimaciones OBJ del programa BSE divididas por el modelo CAR, para 2020-2021, para las tres especies de atunes.

Ratio	2020	2021
BET	1.12	1.18
SKJ	1.01	0.94
YFT	0.82	1.1

TABLE 4. Correlation of BSE with the best CAR models for the three tuna species in 2010-2019.
TABLA 4. Correlación de la BSE con los mejores modelos CAR para las tres especies de atunes en 2010-2019.

Correlation coefficients	**2010-2019 BET**	**2010-2019 SKJ**	**2010-2019 YFT**
Best CAR model	0.78	0.98	0.95
Best CAR model with trips excluded mimicking 2020 pandemic data loss situation	0.73	0.98	0.92
Best CAR model with trips excluded mimicking 2020, 2021 pandemic data loss situation	0.68	0.95	0.91