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EFFECTS OF THE INDIVIDUAL VESSEL THRESHOLD PROGRAM ON TROPICAL TUNA CATCHES AND FLEET BEHAVIOR IN THE EASTERN PACIFIC OCEAN

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EXECUTIVE SUMMARY

The conservation measures for tropical tunas in Resolution C-21-04 implemented what has come to be known as an "Individual Vessel Threshold" (IVT) program for bigeye tuna (BET) catches in the eastern Pacific Ocean (EPO). This IVT program went into effect in 2022. Under this program, applicable purse-seine vessels receive increased closure days provided that they exceed certain annual catch values, with the amount of closure days increasing as a function of the amount by which a vessel exceeds the threshold. As part of the IVT program, an enhanced port-sampling program ("Enhanced Monitoring Program", EMP) for estimation of trip-level BET catch was mandated by Resolution C-21-04, to support member countries and their purse-seine vessels in their conservation efforts. The EMP began data collection in March 2023, and sampling will continue through December 2024. Results from EMP for 2023, as well as a summary of scientific research currently being conducted with EMP data, can be found in SAC-15 INF-H.

In response to a research recommendation made by the IATTC's Scientific Advisory Committee (recommendation 3.1 in SAC-14-16), this report evaluated evidence for the impacts of this IVT program on the fleet's behavior and catches of tropical tunas, particularly BET, in the EPO in 2022 and 2023 using multiple lines of evidence. All analyses presented in this document were based on AIDCP observer data for Class-6 vessels.

BET purse-seine catches in 2022 and 2023 were the lowest they have been in the last decade, continuing a downward trend in catches that began in roughly 2018 (Figure 2). Understanding to what extent these lower catch levels can be explained by the IVT requires some method for separating out the effects of the IVT from other factors that can influence catches such as tuna abundance and/or environmental, economic, or technological changes. Approximately 25% of vessels accounted for 75% of the BET catch of class 6 purse-seine vessels in the EPO in recent years (Figure 4). We classified class 6 purse seine vessels into a group of "highliners" that historically caught levels of BET that could put them at risk of exceeding the IVT, and "non-highliners" that did not. Our assumption is that this group of "highliner" vessels were affected by the IVT while the "non-highliner" were not. Under this assumption, the non-highliner vessels can serve as a control for other shared factors (e.g. changes in tuna abundance or environmental conditions) that might have affected tuna catches in the EPO in 2022 and 2023 besides the IVT.

Highliner and non-highliner vessels had relatively parallel trends in number of total sets and sets broken out by set-type up until 2020 at which point non-highliners experienced a marked increase in sets on floating objects (OBJ) sets and decrease in sets on unassociated schools (NOA) that was not mirrored by the highliner group (Figure 7,Figure 8).

BET catch per OBJ set (CPUE) declined steadily over the past decade in the non-highliner group, but was relatively stable in the highliner group until 2020 after which BET CPUE declined rapidly, with a particularly sharp drop in OBJ BET CPUE in 2022 and 2023 (Figure 10), coinciding with the implementation of the IVT. We compared CPUE trends between highliner and non-highliner vessels in the west (defined as west of 115 degrees west) and east (east of 115 degrees west) sections of the EPO to examine whether the differences in CPUE trends between the highliner and non-highliner groups might be explained by spatial differences in fishing grounds and BET CPUE (Figure 12, Figure 13). If space alone was the cause of these differences in CPUE trends, we would expect highliner and non-highliner vessels fishing the same area (e.g. the western EPO) to have similar CPUE of BET on OBJ sets. Instead, non-highliners fishing in both the east and west showed the same general downward trend, whereas highliners in the east and west had largely the same stable CPUE followed by a sharp decline coinciding with the IVT years (Figure 14). This result lends support to the hypothesis that the differences in CPUE trends between the highliner and non-highliner groups are driven more by fine-scale differences in fishing practices than large-scale fishing location choices.

We used a mixture of cluster analyses and difference-in-difference models to estimate whether the IVT may have caused a decrease in the probability of highliner vessels catching meaningful amounts of BET in OBJ sets. We estimated that the probability of highliner vessels catching ≥ 10MT of BET in a set decreased sharply in 2022 and 2023 relative to the historic trend (Figure 19), and that this was driven by an decrease in catch events in sets that historically would have been more likely to catch BET given their attributes (for example fishing time, location, and FAD depth) (Figure 21). These effects are in addition to any effects from the background level of estimated vulnerable BET biomass, indicating that the drop in the probability of highliner vessels catching BET coinciding with the years of the IVT is due to some other attribute of the fishery for which we do not currently have data.

We used synthetic control models to estimate the effect of the IVT on total OBJ catch of BET and other tropical tunas by highliner vessels. This approach controls for observed confounders such as the biomass of BET vulnerable to OBJ sets, as well as unmeasured time-varying and vessel-specific confounders (conditional on the assumptions of the model). This synthetic control approach estimated that the IVT decreased highliner OBJ BET catches by on average approximately 8,500 MT in 2022 and 2023, equivalent to a 23% reduction from the predicted catch levels in the absence of the IVT (Figure 25). While the precise number is somewhat uncertain, the model has strong support for an effect size of this order of magnitude.

We found no evidence that the IVT alone might explain a meaningful portion of the recent increases in yellowfin tuna (YFT) catches (Figure 17). Both highliner and non-highliner vessels increased their YFT catch substantially in 2021 and 2022, and decreased their catches in 2023. Highliner vessels did not have a disproportionate increase in YFT catches coinciding with the IVT.

In summary, we estimate that the IVT meaningfully decreased catches of BET in OBJ sets by class 6 purse seine vessels. This change appears to have been driven largely by a decrease in CPUE in OBJ sets, as opposed to a decrease in the number of total sets or a shift from OBJ to NOA sets. This estimated reduction in BET catches caused by the IVT takes into account the effects of best available estimates of underlying BET abundance. These results are further supported by our analysis showing that highliner vessels appeared to have decreased their probability of catching ≥ 10MT of BET in an OBJ set relative to other background trends in this rate (Figure 21).

Alternative explanations for these results may exist, but would need to explain why highliner BET CPUE dropped at the same time as the IVT was implemented and why this drop in CPUE at the time of the IVT was not seen in the non-highliner vessels (Figure 10), and why these differences in CPUE trends between the highliner and non-highliner vessels persist even when these two groups of vessels fished the same general area (Figure 14). We found no clear evidence of changes in fishing strategy that might explain these changes, given the attributes of fishing sets for which we have set-level data. Further research is needed to understand what if any changes in fishing strategy by the highliner vessels explain these results.

1. INTRODUCTION

In determining the conservation measures for tropical tunas for the period 2022-2024, the staff recommended the adoption of measures in addition to a 72-day seasonal closure of the purse-seine fishery to prevent fishing mortality from increasing above the *status quo* levels, defined as the average fishing mortality during 2017-2019. In that regard, two proposals were presented by Members for an Individual Vessel catch limit scheme for bigeye tuna (BET), considering that a small fraction of vessels were responsible for a large fraction of the BET catches. As a result, the conservation measures for tropical tunas in Resolution C-21-04 implemented an "Individual Vessel Threshold" (IVT) program for BET catches. This IVT program went into effect in 2022. Under this program, applicable purse-seine vessels receive increased closure days provided that they exceed certain annual catch values, with the amount of closure days increasing as a function of the amount by which a vessel exceeds the threshold (Table 1).

As part of the IVT program, an enhanced port-sampling program ("Enhanced Monitoring Program", EMP) for estimation of trip-level BET catch was mandated by Resolution C-21-04, to support member countries and their purse-seine vessels in their conservation efforts. The EMP began data collection in March 2023, and sampling will continue through December 2024. For sampled trips, the EMP provides an independent estimate of BET catch, as well as a measure of precision on that estimate (SAC-15 INF-H). Data collected by the EMP are also being used for scientific research, including modeling of the relationship between EMP and observer well-level estimates of BET catch (SAC-15 INF-H), potentially leading to the incorporation of observer data into future research on spatio-temporal models for fleet-level estimates of species composition.

In response to a research recommendation made by the IATTC's Scientific Advisory Committee (SAC) (recommendation 3.1 in SAC-14-16), this report evaluated evidence for the impacts of this IVT program on fleet's behavior and catches of tropical tunas, particularly BET, in the eastern Pacific Ocean (EPO) in 2022 and 2023 using multiple lines of evidence. All analyses presented in this document were based on observer data collected for Class-6 vessels under the Agreement on the International Dolphin Conservation Program (AIDCP). While the IVT provides an incentive for vessels not to exceed the established threshold, it is not clear *a priori* exactly how strong this incentive is and what the resulting changes in tropical tuna catches would be (as opposed to say a top-down control like an annual catch quota). In addition, impacts of the IVT may be confounded with other concurrent economic and ecological changes in the EPO. To address these challenges, we evaluated multiple lines of evidence in an effort to measure the impacts of the IVT on catches of tropical tunas in 2022 and 2023, with a particular focus on catches of bigeye tuna (BET, *Thunnus obesus*). Our results indicate that the IVT likely did result in a meaningful reduction in the catch of BET in 2022 and 2023, and does not appear to explain the recent increases in yellowfin tuna (*Thunnus albacares*, YFT) catches.

1.1. Objectives

This report had three primary objectives:

1. Evaluating the impact of the IVT on general fishing strategies employed by purse-seine vessels in the EPO (Section 4.1)
2. Evaluating the impact of the IVT on catches of tropical tunas, with a particular focus on catches of bigeye tuna (Section 4.2).
3. Evaluating whether there is any indication that the IVT program might in part explain recent increases in yellowfin tuna catches (Section 4.3).

2. METHODS

This report explores evidence for effects of the Individual Vessel Limit (IVT) program that went into effect January 1st 2022 per Resolution C-21-04. Specifically, changes in catches of BET by class 6 vessels, as well as changes in fishing strategy and species composition of the catch, resulting or at least coinciding with the implementation of the IVT. The challenge with any policy evaluation is separating out the effect of the policy itself from other factors that altered the outcome of interest at the same time. In the case of tropical tunas, catches vary year-to-year due to a large number of factors, including changes in abundance that are driven by recruitment fluctuations, as well as environmental, economic, and policy factors. While it can be instructive to begin by looking for clear changes coinciding with the implementation of the IVT program, on their own this type of approach can be misleading; any observed changes in catches coinciding with the IVT could have occurred for any number of other reasons. All analyses were conducted using R (Team, 2024).

2.1. Data

The main data used for this analysis are AIDCP observer data from the Daily Activity Records (DAR) form, for 2009 through 2023. We performed some filtering of these data for this analysis. We only included purse-seine vessels with capacity greater than 363 metric tons (t) fish-carrying capacity (IATTC Class-6 vessels), and sets on floating-objects (OBJ) and unassociated (NOA) sets made east of 150°W.

Prior to running the analyses, the data were further limited to vessels with a similar overall fishing behavior. Part of the goal of this study is to compare trends in vessels that are broadly similar in their overall fishing behavior but that had very different histories of BET catch. To identify general types of fishing behavior, we ran a cluster analysis using the methods described in Lennert-Cody et al. (2018) and FAD-07-01, assigning each vessel to one cluster over the time period of 2010 to 2020.

To identify fishing strategies, the cluster analysis was applied to vessel-level summaries of the following variables:

- The proportion of sets by set type (all three set types).
- The proportion of OBJ sets upon by object type (e.g., fish aggregating devices (FADs) deployed by the vessel.
- FADs encountered by chance, natural floating objects.
- Proportion of OBJ sets made in the western region of the EPO.

Vessels used in this analysis were those that made a larger percentage of their sets on FADs that they deployed themselves, with proportionally few sets on natural floating objects and on tunas associated with dolphins. These vessels also made proportionally more OBJ sets than NOA sets. This set of vessels corresponds to clusters 1 and 4 of those shown in Figure 1. It is assumed that this subset of vessels represents an overall fishing behavior focused on FAD fishing, but one that also opportunistically makes NOA sets.

The final filtered database used in this analysis has 145,309 sets by 106 vessels. Taking 2023 as a benchmark, this filtered database accounts for 29,996 t of BET, out of the total of 38,768 t reported in the DAR in that year (77%). This database contains both OBJ and NOA sets. We use both types of sets throughout, but for BET we primarily focus on OBJ sets, as BET catches in NOA sets are extremely low (Figure 9).

We augmented this database with information on the abundance of BET vulnerable to the fishing gears in question. To calculate this, we gathered the estimated biomass at age of BET from the latest stock assessment (SAC-15-02). We calculated the vulnerable ages for OBJ and NOA based on the estimated selectivity curves for these gear types, which resulting in quarters 4 through 15 being vulnerable to NOA sets and quarters 3 through 6 being vulnerable in OBJ sets. We then calculated the total biomass in each of these age groups to provide two separate biomass indices for the NOA and OBJ sets. Vessel-specific estimates of vulnerable biomass were calculated as the weighted average of the NOA and OBJ vulnerable biomass trends, with weighting based on the relative amount of NOA and OBJ sets conducted by a given vessel in a given year.

2.2. Defining Vessel Groups and Time Periods Affected by the IVT

Throughout this report we examined a range of strategies for exploring changes in fishing outcomes resulting from the IVT and isolating the effects of the IVT program from changes brought about by other factors, as much as possible. Many of these methods are based on the assumption that we can separate out purse-seine vessels covered by the IVT program into two broad groups: a set of “highliners” that historically caught relatively large amounts of BET and as such are more likely to be directly impacted by the IVT program and a set of “non-highliners” that historically did not catch much bigeye and as such as likely to continue on with operations as normal regardless of the presence of the IVT. Many of our analyses make the assumption that these "non-highliner" vessels can serve as an indicator of broad unobserved environmental and/or abundance and/or market trends in the fishery that might affect catches regardless of the presence of the IVT.

We tested a variety of methods for defining this highliner group, but the primary approach presented here is to define highliners based on catches of BET from 2017 through 2021. During this period, we calculated the total catch of BET per year per vessel. The IVT program stipulates that vessels exceeding catches of 1,200 t of bigeye in a year receive increased closure days, providing vessels an incentive to avoid crossing this threshold. Vessels typically track their catches at the level of fishing trips. Given this, we quantified the standard deviation of BET catch per trip per vessel from 2017 through 2021. A simple assumption then is that a vessel might expect BET catches on any given trip to be within $\pm$ ~ 2 standard deviations (340) of the average catch per trip. The cutoff then was calculated as the threshold value of 1,200 t minus roughly two standard deviations, rounded down to 800 t.

We then calculated the proportion of years between 2017 and 2021 in which each vessel caught greater than or equal to 800 t of BET, and defined "highliners" as vessels that caught more than or equal to 800 t of BET in 50% or more of the years. The rationale is that during these reference years, these vessels were consistently catching enough BET to be at risk of crossing the current IVT threshold, which may be indicative of their exposure to the IVT policy once it came into effect.

Several other methods for defining the "highliner" group were evaluated, including only vessels included in the EMP program, the vessels in the top 80th percentile of BET catch, and variations on the cutoff of 800 t used here. Results were insensitive to these variations of highliner definition.

This process resulted in 25 vessels in the highliner group and 81 vessels in the non-highliner group.

We generally assigned the years 2009 through 2021 as the "before" IVT period, and 2022 through 2023 as the "after" IVT period, though in some sensitivity analyses we assigned placebo IVT years to test the validity of different model assumptions.

2.3. Fishing Strategy Clusters

One hypothesis is that the IVT program might cause some vessels to modify their fishing strategies, if by doing so they are able to better avoid undesirably high levels of BET catches. To test this hypothesis, we ran a clustering algorithm on the trimmed data set that assigned each fishing set from 2009 to 2023 to a particular fishing strategy cluster. We then examined whether vessels in the highliner group (which we hypothesize are more likely to respond to the IVT program) showed any systemic changes in the frequency of sets within different fishing clusters following the implementation of the IVT program.

Clustering was performed using the following variables:

- Set type (OBJ, NOA, dolphin-associated (DEL)).
- Latitude and longitude.
- Distance to coast.
- Sea surface temperature.
- Net depth.
- Month.

Net depth refers to the maximum vertical extent of the purse-seine net (i.e., it is not actual in-water depth, which will be affected by currents and other factors). To perform the set-by-set clustering, we first randomly sampled 25,000 sets from the subset used in this study. We then calculated the Gower dissimilarity matrix among all sets in this sub-sampled database, based on the above listed clustering covariates. The reason for this step is that it was not computationally feasible to calculate the dissimilarity matrix across the over 100,000 observed sets included in the study. We then clustered the sets based on this dissimilarity matrix using the hclust function in R, limiting the final set of clusters to 5.

We then trained a random forest model using the ranger package in R to assign all observed sets to one of the clusters developed in the sub-sampling step. The initial clustering step assigned vessels to clusters based on dissimilarities in the above listed attributes among sets. We used the random forest model to predict the cluster based on these same clustering attributes; in other words, the random forest model learns how the clustering algorithm ultimately used these variables to partition sets into clusters. This step allowed us to then estimate the cluster that every set not included in the initial cluster definition likely would have been assigned to by the clustering algorithm had it been included.

2.4. Difference-In-Difference

Difference-in-difference (DiD) is a common technique used to attempt to estimate the causal effect of a policy (see Ovando et al., 2021 for an ecological example), given data on a "treatment" and "control" group before and after implementation of a policy. In our case, we treated the highliner and non-highliner groups as our treatment and control groups, respectively, and our "before" period as the years prior to 2022 and the "after" period as years 2022 and 2023.

The basic DiD equation is:

$$outcome = \left(Highliner_{after} - Highliner_{before}\right) - \left(NonHighliner_{after} - NonHighliner_{before}\right) \qquad (1)$$

"outcome" in this case could be for example tuna catch per OBJ set. We used DiD-style approaches for examining the effect of the IVT on several different kinds of outcomes in this report. Conditional on the assumption that the highliner and non-highliner groups would have had parallel trends in the outcome in the absence of the IVT, this approach both controls for different baseline outcome levels between the two groups, and for baseline differences in the before and after time periods unrelated to the policy intervention.

This DiD approach can be expressed through the following general regression structure:

$$outcome_{i,t} \sim \beta_0 + \beta_1 IVT_t + \beta_2 highliner_i + \beta_3 IVT_t \times highliner_i + \boldsymbol{\beta_x}\mathbf{covariates_{i,t}}$$

Where *outcome* is the outcome of interest for unit *i* in time period *t*, *IVT* is a dummy variable indicating whether we are in the before or after the IVT period, and *highliner* is a dummy variable indicating whether a given unit is in the treatment (highliner) or control (non-highliner) group, and **covariates** is a vector of additional covariates. In this structure, β_0 is the baseline level of the outcome for a non-highliner in the pre-IVT period, β_1 is the additional effect of being a non-highliner in the IVT period, β_2 is the additional effect of being a highliner, and β_3 is the additional effect of being a highliner in the IVT period. $\boldsymbol{\beta_x}$ is a vector of additional covariate coefficients.

The β_3 parameter is our estimated effect of the policy, the additional effect of being a highliner unit in the IVT period. In order to interpret this β_3 coefficients "causally", we have to invoke the parallel trends assumption, i.e. that *prior* to treatment the treated and non-treated groups had parallel trends in the outcome, which we can observe prior to treatment, but can never observe post-treatment. When *outcome* is in log-space, the coefficients β can be roughly interpreted as a multiplicative effect, rather than an additive effect.

2.5. Residual Change-Point Model

The catch of BET is a complex function of both the availability of bigeye and the fishing practices used in a particular set. To the extent that we know the important attributes and can accurately measure them, we can in theory build a model to predict the probability of catching bigeye as a function of these attributes. However, we often do not have data on every attribute of the fishing process that might be relevant, and the effect of a given attribute on the fishing process can change between time periods used to train the model and time periods in which the model is applied for prediction. In particular, a policy like the IVT may result in changes in subtle fishing strategies that are not directly measurable given the data currently collected by observers.

To test for this possibility, we trained a series of boosted regression trees using the xgboost package in R (Chen et al., 2024). xgboost is a tree-based algorithm similar to a random forest. However, unlike a random forest, the xgboost algorithm has mechanisms in place that actively update the model to address data points that the model is struggling to fit (though this does leave the model more prone to overfitting). Model parameters were tuned to prevent overfitting using a "rolling" validation grid in which years were sequentially added to the training split of a model which was then used to predict the held-out future years. See Elith et al. (2008) for a general introduction to boosted regression trees.

The base set of covariates used in this report were:

- Vessel flag fish-carrying capacity.
- Net depth and FAD depth. FAD depth represents the maximum length of the material hanging beneath the FAD (i.e. it does not represent actual in-water depth of this material, which will be affected by currents and other factors).
- Latitude, longitude, and their interaction (computed as the product of the two variables).
- Distance to coast.
- Month.
- Sea surface temperature.
- Vulnerable BET abundance index.

To try to identify changes in fishing strategies resulting from the implementation of the IVT, we adapted concepts introduced by Lennert-Cody & Berk (2007). We ran a series of experiments in which portions of the data were held out from the model training process, and then used the model to predict the outcome of interest in those held-out samples. Assuming the measured covariates and outcomes included in this analysis adequately capture the underlying processes, the performance of the model should not deteriorate substantially when predicting on held-out data.

If there is a decrease in model performance on held-out data, there may be several causes, which can occur simultaneously. First, the policy change may have affected fishing behavior in ways not adequately captured by covariates included in the model; in fact, such covariates may not have been known and were therefore not measured. This will lead to the model performing poorly on data from the post-policy change period, even when data from those years were included in the data used to train the model. And, second, the policy change may have affected the relationship between covariates included in the model, but this relationship cannot be estimated with data from the pre-policy change period. This will lead to a model trained on data prior to the policy change performing poorly on held-out data from the period after the policy change. We call this model a "residual change-point" model, as its purpose is to detect whether there are substantial changes in the residuals of the model associated with the implementation of the IVT.

We ran multiple versions of this analyses. For the "rolling" experiment, we ran a series of rolling one-step-ahead models, in which data for years *1:X* were used to train the model, which was then used to predict year *X+1*. If the dynamics of the system of not changed, we would expect the model to perform roughly equally as well in year *X+1* as it did in years *1:X*. As an alternative to this "rolling" experiment, we ran a "random" experiment in which for each year *x* a random subset of vessels were held out from the training set. We only include OBJ sets in this analysis due to the low probability of encounter of BET in NOA sets.

The analysis was treated as a two-class classification problem. The set-level response variable was the presence/absence of BET catch greater than 10 t. That is, 'presence' refers to a BET catch in the set greater than 10 t and 'absence' refers to a BET catch in the set less than or equal to 10 t. As a sensitivity, the analysis was also run with the response variable defined as the presence/absence of any BET in a set.

We then compared the presence or absence of BET in any given set for year *x* to the presence / absence prediction generated by the model. We can quantify the performance of the model using three different metrics:

1. Accuracy: The proportion of observations for which the model correctly predicted the BET catch for the set to be greater than 10 t (presence) or less than or equal to 10 t (absence).
2. "Surprise presence": The model predicted the BET catch was less than or equal to 10 t but the set actually had BET catch greater than 10 t.
3. "Surprise absence": The model predicted that a set had BET catch greater than 10 t but the set actually had BET catch less than or equal to 10 t.

Our hypothesis is that the IVT may have incentivized fishers to change their behaviors to avoid BET. If this is the case, and if these choices affect behaviors that are not directly measured in the data fed to the model, we would expect this to show up as decrease in accuracy in the IVT years, primarily associated with an increase in the rate of "surprise absences".

2.6. Forecasting Model

Attributes of tropical tuna catches (catch, catch per set, and number of sets) exhibit both longer-term (decadal and year-to-year) and shorter-term (seasonal) trends. We developed a trend-based forecasting model to examine whether attributes of tropical tuna catches changed substantially when the IVT went into effect. Changes before-and-after a policy interventions should be interpreted with caution, as in the absence of a valid control unit any observed effects could simply be a coincidence. However, when complemented by the other analyses in this report this type of simpler model can be a useful way of understanding exactly what processes appear to be changing in the system.

We fit a Bayesian generalized additive model (GAM) to the catch, number of sets, and catch per set for each of the tropical tuna species by year, month, and highliner group.

The general form of these models is:

$$y_{m,t} \sim \beta_0 + \beta_1 lag_{m,t} + \beta_2 month + s(year|highliner) + highliner + s(bet)$$

Where *y* is the outcome in question for metric *m* (e.g. catch per set or total catch) for tuna species *t*, The β terms are regression coefficients, lag is a 12-month lag of outcome *y* for species *t*, *highliner* denotes whether a given observation is from the BET highliner group, and *bet* is the estimated abundance of BET in a given time step. s(year |highliner) denotes a smooth term on numeric year for the data of highliner vessels and s(bet) denotes a smooth term on the estimated abundance of BET in a given time step.

We fit this GAM using data from the pre-IVT period, and then used the model to generate a posterior predictive distribution of the metric of question in the post-IVT period. The *lag* variable was constrained to contain no data from the IVT period (2022 and 2023). We then compared the observed and predicted values for the metrics in question during the post-IVT period. This allows us to identify which attributes for which species appear to break from their historic trends when the IVT went into effect.

2.7. Synthetic Controls

The DiD approach outlined above works by assuming that the average trend of a metric of interest in the non-highliner group would have applied to the highliner group in the absence of the IVT. The assumption of this method is that every non-highliner vessel is weighted equally (i.e. equally valid) as a control for the highliner vessels. However, this may not be the case; some non-highliner vessels may be more representative of the trends of the highliner vessels than others.

Synthetic controls (Abadie et al., 2010; Abadie, 2021) offer an alternative to this "equal weighting" approach of a conventional DiD. Synthetic controls adaptively weight the contributions of individual vessels in the non-highliner group to best approximate the pre-IVT trends in the highliner group (with steps in place to prevent over-fitting to the estimated trends of the individual vessels in the non-highliner group, the "synthetic control units"). This approach provides a custom synthetic "control" unit for every highliner vessel in the analysis, which we can then compare to the actual values of interest post-IVT to estimate the effect of the policy in question.

We used an implementation of synthetic controls here called the "generalized synthetic control" (GSC, Xu, 2017), implemented with the gsynth package in R. We utilized the "matrix completion" estimation method, as described in Athey et al. (2021) as we found it performed better in cross-validation testing. The basic structure of the GSC approach is as follows, with the dependent variable being annual catches of individual tropical tuna species on OBJ sets per vessel.

1. Assign a treatment and control group, in this case highliners and non-highliners. This defines the two groups that the model assumes are (highliner) and are not (non-highliners) affected by the IVT.
2. Separate the data into "before" and "after" IVT periods.
3. Train a model predicting OBJ catch using data from all time periods from the non-highliner group and only the pre-IVT period for the highliner group (only when using the matrix completion method). This step estimates latent time-varying and vessel-specific model coefficients based only on vessels not currently affected by the IVT.
4. Train a secondary model predicting the OBJ catch of highliner vessels using the predicted values of the non-highliner group from the pre-IVT period. This is the step that constructs the "synthetic control", i.e. the weighting of each individual non-highliner vessel in reproducing the pre-treatment trend in the OBJ catches of the highliner vessels.
5. Use this secondary model to predict the OBJ catch of the highliner vessels in the IVT period. This step provides our prediction of the catches of the synthetic control units in the treated period. In other words, the prediction of what highliner vessels would have caught in OBJ sets in the IVT period had the IVT not happened.
6. Subtract the observed OBJ highliner catches from the predicted OBJ highliner catches generated by step 5. This is the estimated causal effect of the policy.

The synthetic control approach is intended to match the average pre-IVT trends in OBJ catches of the highliner vessels almost perfectly, with a variety of numerical and analytical techniques used to prevent over-fitting, namely a series of one-step-ahead cross validation routines. Uncertainty estimates are calculated by bootstrapping.

We used this synthetic control approach to attempt to estimate the causal effect of the IVT on total annual catches by OBJ sets of tropical tuna species, with a particular focus on BET effects. We set the minimum number of pre-IVT years a vessel needed to occur in the database in order to be included in the model fitting at 12. The synthetic control included the following covariates:

- Pre-and-post IVT.
- Highliner status.
- Mean annual Oceanic Niño Index (ONI) value.
- The mean annual latitude, longitude, and latitude times longitude of OBJ sets per vessel.
- The estimated biomass of BET vulnerable to OBJ sets.
- The number of OBJ sets.

Note that by including these covariates we are assuming that they are exogenous to the IVT program itself. Results are almost completely insensitive to inclusion or exclusion of spatial covariates that conceivably could be endogenous, exogenous, or a mixture to the IVT program. By including OBJ sets in the synthetic control we are effectively modeling catch per OBJ set (CPUE). However, by fitting to catch and conditioning on effort, we are able to more easily provide estimates and uncertainty in the units of relevance to management (total catch). Along with these effects, the synthetic control method estimates a series of latent time and vessel specific effects that make up the core of the actual synthetic control unit.

Whether we control for effort or fit to CPUE, we are making the assumption that the IVT did not directly affect the total amount of OBJ sets, but rather the CPUE of those OBJ sets. We make this assumption because neither anecdotal or empirical evidence points to a change in the dynamics of the total amount of effort or OBJ sets by the highliner group caused by the IVT. We ran sensitivity analyses in which the model was fit to CPUE rather than catch and found similar but slightly more variable results.

3. RESULTS

3.1. Exploratory Analysis

We examined trends in the raw data prior to any formal statistical analyses to see what, if any, visual trends coincide with the implementation of the IVT. For the purposes of this section, we treat the IVT as going into effect in 2022 (acknowledging that there may have been some anticipatory effects).

3.1.1. Fishery Dynamics

BET catches continued a downward trend post IVT, and were lower in 2022 and 2023 than in any other pre-IVT year in the last decade. Conversely, the YFT catches in the post IVT years were at or near historic highs of the last decade (Figure 2, Figure 3). SKJ catches spiked dramatically in 2023.

The post-IVT cumulative catch curve appears to be in line with the distribution of cumulative catch curves observed in prior years, though it is flatter than in the immediate pre-IVT years. We do not see a visually-obvious flattening of the cumulative catch curve coinciding with the implementation of the IVT, but neither do we see an increase in the concentration of BET among the fleet’s vessels (Figure 4).That is, the historical tendency of a large percentage of the fleet-level BET catches to be generated by a relatively small percentage of vessels has not markedly changed.

We classified vessels into two groups: “highliners” and “non-highliners” (see Section 3.2). This process resulted in 25 highliner vessels and 81 non-highliner vessels (Figure 5). While highliner vessels had some low-BET catch years and vice versa, this procedure broadly separated the vessels at the inflection point between higher BET catch vessels and lower BET catch vessels. Of the 25 vessels in the highliner group, 87% were sampled by the Enhanced Monitoring Program established in Resolution C-21-04 as part of the IVT Program to, needed to provide the best scientific estimate of BET catch per trip.

The non-highliner group consistently had more sets and vessels than the highliner group, and both groups followed similar trends in these values over time (Figure 7). Both highliner and non-highliner vessels primarily set on OBJ schools, though the highliner group depended more on OBJ sets. Both groups saw general increasing trend in the number of OBJ sets. The most notable difference between the two groups occurred post 2021, when the non-highliner group experienced a large increase in OBJ sets, and a much larger decrease in the number of NOA sets compared to the trend in the highliner group (Figure 8).

While trends in YFT and SKJ catches of highliner and non-highliner vessels were generally similar over the 2009–2023 period, the trends in BET catches of the two vessel groups over the same time period were quite different (Figure 6). BET catches were actually higher in the non-highliner group prior to 2010, after which highliner catches of BET increased dramatically for several years before beginning a steep decline starting in 2020 (Figure 6).

SKJ and YFT had largely parallel trends in mean CPUE for the highliner and non-highliner groups during the study period. Mean CPUE of BET for the non-highliner group declined steadily over the study period. Mean CPUE of BET for the highliner group was largely stable from 2010 through 2020, but experienced a sharp decline in the following years, reaching historic lows for the highliner group in the post-IVT years of 2022 and 2023 (Figure 10).

The proportion of annual tropical tuna catch made up of BET declined steadily over time in the non-highliner group. For the highliner group, levels were largely stable from 2010 through 2020, after which the proportion of the catch of the highliner group made up of BET began to decline rapidly (Figure 11). We separated out CPUE of BET by OBJ and NOA sets.

One possible explanation for the differences in the trends of CPUE of OBJ sets between the highliner and non-highliner groups is spatial differences in BET abundance. If the non-highliner groups fish in areas with a different trend in BET abundance than the highliner groups, then we would expect to see differences in their CPUE trends. Alternatively, if the trends reflect differences in fishing practices rather than space, we would expect to see the same trend in CPUE within the highliner and non-highliner groups independent of fishing location.

To assess this, we examined the spatial distribution of sets between 2014 and 2023, separating out the IVT years of 2022 and 2023. Highliner vessel OBJ sets were concentrated in the north and west of the EPO, with hotspots in the southeast in some years. Non-highliner OBJ sets were concentrated in the east of the EPO. However, both groups fished some OBJ sets throughout the fishing grounds (Figure 12). CPUE of BET on OBJ sets for both highliners and non-highliners tended to be highest along the equator in the western parts of the EPO. Non-highliner vessels had lower CPUE of BET even within the same spatial areas as the highliner vessels (Figure 13).

To further explore whether spatial differences alone might explain the different BET CPUE trends between highliner and non-highliner vessels, we defined a cutoff point of 115 degrees west based on the rough longitude at which the predominance of sets by highliners relative to non-highliners shifts. We then compared the trends in the CPUE of the highliner and non-highliner vessels in the eastern and western portions of the EPO. If space alone was the cause of these differences, we would expect highliner and non-highliner vessels fishing the same area to have similar BET CPUE on OBJ sets. The CPUE trend was much better explained by the nature of the vessel (highliner vs. non-highliner) than the fishing location (Figure 14). In other words, non-highliners fishing in the east or west showed the same general downward trend, whereas highliners in the east or west had largely the same stable then declining trend. This result lends support to the hypothesis that the differences in CPUE trends between the highliner and non-highliner groups are driven more by fine-scale differences in fishing practices than large-scale fishing location choices.

3.1.2. Fishing Strategies

Exiting IATTC Area

One hypothesis is that vessels at risk of exceeding the IVT may have shifted operations west of the IATTC boundary of 150 degrees west. Examining the data, there was no clear shift in either the amount of BET catch or number of sets west of 150. That does not mean that individual vessels may not have made this move, but the amount does not appear to be enough to cause a large-scale shift in the spatial distribution of BET catch or sets (Figure 15).

Fishing Strategy Cluster

The IATTC has used forms of cluster analyses in the past to describe fishing strategies in the purse-seine fleet (Lennert-Cody & Berk, 2007). We built off of this work to evaluate whether there were any visually obvious changes in fishing strategies as defined by clusters of activity types coinciding with the IVT program. We classified each set by class 6 purse-seine vessels from 2010 to 2022 based on things like location, time of year, set type, net depth, and captain, using the methods described in Section 3.3. The clustering algorithm assigns individual sets to clusters defined by a tree-like structure. We examined whether the proportion of sets in each cluster changes meaningfully in a manner coinciding with the IVT program. Based on these methods we do not see any obvious and sudden changes in the distribution of sets per cluster coinciding with the implementation of the IVT (Figure 16).

3.1.3. Yellowfin Tuna Catches

One hypothesis behind the recent increases in YFT catches is that vessels affected by the IVT program may have changed their behavior in a way intended to reduce BET catch but that might have incidentally increased YFT catch (Figure 2). We examined whether recent increases in YFT catch are concentrated among BET "highliners" that might be particularly affected by the IVT program. Historically, roughly two thirds of the annual YFT catch has come from the non-highliner group. The highliner group accounted for roughly half of the increase YFT catches from 2021 to 2022, but most of the year-to-year increases in YFT catch have come from the non-highliner group. This does not mean then that the IVT may not have had some secondary impacts on YFT catches based on this analysis, but the catches from the highliner vessels on their own are not sufficient to explain the recent increases in YFT catches (Figure 17). See SAC-15 INF-L for an exploration of the potential role of ENSO events in explaining recent changes in YFT catches.

3.2. Statistical Effects of the IVT

We conducted a range of statistical procedures to evaluate empirical evidence for the effect of the IVT on various aspects of the tropical tuna purse seine fishery. We first examined whether the IVT appears to have caused a change in the probability of a "high" BET catch set, defined as a set catching 10 t or more of BET. We then ran a series of models examining the impacts of the IVT on absolute fishery metrics, primarily catch.

3.2.1. Probability of Catching BET

Examining first the before-and-after change in the odds of class 6 purse seine vessels catching $\geq$ 10 t of BET in OBJ sets, some vessels increased their odds of BET $\geq$ 10 t, more had lower odds, and many remained unchanged. Visually it appears as though maybe there are more highliners in the group that had lower odds of BET post IVT (Figure 18). We used the DiD model described in Section 3.4 to quantify whether highliners had meaningfully lower odds of a high BET set post-IVT relative to the pre-IVT trends.

The DiD model estimated a sudden drop in the probability of BET for the highliners in 2022 and 2023 relative to the recent pre-IVT values. However, the model does not support the parallel trends assumption; i.e. the $year \times highliner$ effects are meaningfully different than zero in the pre-IVT years, indicating that the trend in the non-highliner vessels of the probability of BET catch is not a valid control for the trend in the highliners. This means that while highliner vessels had lower probability of catching BET in 2022 and 2023, we lack a valid control to reliably separate out broader changes that could explain this shift other than the IVT. That being said the model estimated a dramatic decline in the probability of highliner vessels catching more than 10 t of BET in a set coinciding with the implementation of the IVT (Figure 19).

Residual Change-Point Model

We ran an analysis in the manner of Lennert-Cody & Berk (2007) to attempt to measure whether there have been changes in the probability of catching BET in OBJ sets resulting from either unobserved changes in fishing strategy, or changes in the relationship between observed covariates and the probability of BET catch. We call this approach a "Residual Change-Point" model (see Section 3.5 for methods), as it assesses whether there was a change in the residuals of the predictive model coinciding with the implementation of the IVT.

The highliner and non-highliner groups and "random" and "rolling" model structures all had similar levels and trends in mean accuracy (correct classification of presence or absence of high BET catch in a set). Both the "random" and "rolling" designs showed a sudden drop in mean accuracy coinciding with the IVT (Figure 20).

We quantified this change in model accuracy by running a DiD style analysis with the before and after periods defined as years less than 2022 (before) and 2022 and 2023 (after) and the control and treatment groups defined by non-highliner and highliner vessels, respectively, and the dependent variable being the accuracy, surprise absence rate, and surprise presence rate (controlling for vessel-specific and seasonal effects).

The DiD model estimated a drop in accuracy and increase in surprising absences for the average highliner vessel in the true IVT years relative to the trend in the placebo IVT years, consistent with our hypothesized IVT effects (Figure 21). The sample size for surprise presences is much lower than that of surprise absences, in part because presence of BET is much rarer than absence of BET in the underlying data. In order for there to be a surprise presence there needs to be a true presence, which is relatively rare in the data, which the model then miss-classifies as an absence, which further reduces the sample size. As such, the wider shifts in the surprise presence rate could be simply a sample size issue. The results shown in Figure 21 are consistent with the hypothesis that the IVT caused highliner vessels to shift behavior in some way that resulted in lower probability of encountering BET, particularly as the decrease in accuracy is largely driven by an increase in surprise absences, meaning instances in which based on past data the model would expect there to be BET catches, but no BET catches were recorded.

That the 'rolling' and 'random' splits performed extremely similarly provides some evidence as to what might be driving this shift in the probability of BET catch. If the change in BET catch probability was due to a shift in the relationship between one of the model covariates and the probability of BET capture between the pre-and-post IVT periods, we would expect to see a drop in accuracy for the highliners in the 'rolling' setup but not the 'random'. This would be because the 'rolling' results were trained on no post-IVT data, where as the 'random' split had access to both pre-and-post IVT data. If the cause of the drop if performance was a change in say the effect of net depth from the pre- to the post-IVT period, the 'rolling' model would not be able to detect that, but the 'random' model would, since it has access to observations in every year. Instead, since both model configurations showed similar trends, this suggests that the change is related to some unmeasured covariate that increased the rate of surprise absences of BET in OBJ sets of highliner vessels post-IVT.

3.2.2. Forecasting Model

We examined whether any of the absolute metrics of BET exhibited any clear deviations from their pre-IVT trends upon implementation of the IVT, using the methods described in Section 3.6. BET CPUE of OBJ sets by non-highliner vessels has declined steadily since 2010, which no apparent change in the trend coinciding with the IVT. In contrast, OBJ CPUE of BET fluctuated around a relatively steady mean level from 2010 to 2020, but dropped substantially below the pre-IVT trend in the IVT years of 2022 and 2023 (Figure 22). Total number of OBJ sets showed no clear change coinciding with the IVT for either the highliner or non-highliner groups (Figure 23). OBJ associated BET catches did not deviate from the pre-IVT trend for the non-highliner group, but highliner catches declined somewhat relative to the trend (Figure 24).

These break-point analyses are useful, but must be interpreted with caution; a change before and after could be caused by some exogenous shock, and the lack of a change might also be misleading, as perhaps catches for example would have increased post IVT in the absence of the IVT, but instead the presence of the IVT causes the appearance of no change relative to the pre-IVT trends.

3.2.3. Synthetic Controls

The synthetic control approach (see Section 3.7 for methods) improves on the before and after comparisons shown in Section 4.2.2 by generating statistical predictions of how the outcome of interest would have evolved in the IVT period in the absence of the IVT. In other words, the synthetic control approach approximates an experimental application of the IVT. We focused our results on the catch of BET in OBJ sets, though we also ran synthetic control models for SKJ and YFT.

The synthetic control approach allows for the inclusion of covariates (e.g. sea surface temperature, biomass of vulnerable BET tuna) as well as optimization of the contribution of each of the non-highliner vessels to the creation of the synthetic control unit. The synthetic control estimates annual catch in the absence of the IVT, which can then be scaled up to total annual estimated highliner values as appropriate. Subtracting the estimated values from the observed values provides an estimate of the effect of the policy, which we would expect to be zero in the pre-policy years in a correctly specified and estimated model.

The synthetic control approach estimated that the IVT reduced highliner BET catches on OBJ sets by 8,638 t, equivalent to a -23% reduction relative to the expected purse-seine BET catch in 2022 and 2023 without the IVT (Figure 25). The synthetic control was able to match the pre-IVT trends (see Xu, 2017 for details on how the synthetic control method avoids overfitting). As a check of the performance of the model, we ran a placebo trial where we artificially assigned 2015 as the IVT year, and then evaluated the performance of the model under these placebo settings (Figure 26). The model should estimate no policy effect post placebo IVT, until the years in which the actual IVT occurred (acknowledging that performance also decreases since fewer pre-IVT years are available to fit the synthetic control) (Abadie, 2021). The placebo diagnostic performed relatively well, with the model mostly estimating no policy effect of the IVT until 2022 and 2023, with an exception of 2018. While the model did not estimate any effect sizes close to the levels seen in 2022 and 2023 in the placebo years, the model did estimate meaningfully non-zero effects in some years, meaning that some of the magnitude observed in 2022 and 2023 could be due to model errors.

We ran these same synthetic control analyses for catches of YFT and SKJ on OBJ sets. The model did not estimate significant effects of the IVT on YFT (Figure 27). The increases in YFT attributed to the IVT in the recent years are in line with the range of deviations of the observed catches from the synthetic control in the pre-IVT group, and the placebo test similarly indicates little support for the model identifying a reliable effect of the IVT on YFT catches (Figure 28). The model estimated a significant positive effect of the IVT on SKJ catches, but the model failed the placebo test, indicating that we should not treat the main model results for SKJ as being reliable (Figure 29,Figure 30). This poor performance for both YFT and SKJ is likely because the highliner / non-highliner distinction is not meaningful for these species.

3.3. Effects of the IVT on Species Composition

2022 and 2023 both had elevated levels of YFT catch relative to the recent past (Figure 3). We explored whether there is any evidence that the IVT might explain this increase, as a result of, for example, vessels adjusting their behavior in a way to avoid BET but as a result catching more YFT. We ran a DiD-style analysis (Section 3.4) examining evidence for a causal effect of the IVT on the vessel's annual balance of YFT and BET catch. Specifically, for each vessel in each year we calculate the total catch of YFT and BET, and then fit a DiD style model to the difference between YFT and BET catch. Positive values mean that that vessel caught more YFT than BET in that year, and vice versa. The model found no significant effect of the IVT on the volume of YFT to BET catch (Figure 31).

4. DISCUSSION

Many dynamics of the purse-seine tuna fishery in the EPO have changed in the 2000s. Between 2020 and 2023 catches of BET continued a downward trend to a local minimum, while catches of YFT and SKJ generally increased. The objective of this report was to describe the nature of these changes, and specifically explore the potential role that the IVT program implemented in Resolution C-21-04 may have had in any of these changes.

Policy evaluation in social-ecological systems is inherently challenging, particularly for systems of the geographic and temporal scale of the EPO tropical-tuna purse-seine fishery. Specifically, it can be extremely difficult to separate out the effects of a policy from the impacts of other concurrent changes in the fishery, such as environmental or economic shocks. In an effort to resolve this challenge, we evaluated the IVT using multiple lines of evidence, often leveraging the trends of the "non-highliner" vessels as a control unit for the "highliner" vessels, under the assumption that they were affected by the same broad changes in the EPO as the highliner vessels, but were unaffected by the IVT itself due to their low history of BET catches.

While all of the lines of evidence compiled here have shortcomings, together they provide strong evidence that the IVT resulted in a decrease in catches of BET among the highliner vessels, seemingly through a change in behavior that reduced the CPUE of BET in OBJ sets. Looking just at the trends in the data, catches of BET reached a local minimum in 2022 and 2023. CPUE of highliner vessels decreased dramatically in the years coinciding with the IVT in a way not seen in the non-highliner vessels. This drop in highliner OBJ CPUE occurred in both the eastern and western portions of the EPO. There also appears to have been a sharp reduction in the probability of highliner vessels catching more than 10 t of BET in an OBJ set that began in the IVT years, driven by an increase in the rate of "surprise absences" in 2021-2023, meaning sets that in the past would have been expected to produce 10 t or more of BET tuna did not. OBJ BET CPUE deviated sharply from the pre-IVT trend starting in the IVT years, even though the trend in the total number of OBJ sets remained stable. This resulted in a slight decrease in BET OBJ catch post-IVT relative to the pre-IVT trend.

We used the forecast model shown in Figure 24 to estimate the pre-IVT standard deviation of the residual BET catches that cannot be explained by the covariates included in that model, obtaining a standard deviation of 1,077. This means that in any given year, BET catches could vary by at least up to $\pm$ 2,111 away from the trends estimated in Figure 24. The mean effect size of roughly 8,638 t of BET per year estimated by the synthetic control is larger than this variation, but we should keep in mind that some of this effect size may be made up of background variation in BET catches attributed incorrectly to the IVT, as evidenced by the synthetic control placebo tests (Figure 26).

The synthetic control models estimated the difference between the observed highliner catch and the amount of highliner catch the model would have expected to see in the absence of the IVT. This synthetic control approach estimated an average reduction in annual BET catch by highliners of 8,638 t in 2022 and 2023, equivalent to a -23% reduction in BET catch in 2022 and 2023. Further research is needed to establish what changes exactly were made by the fleet to achieve this reduction.

We found no evidence that the IVT might explain some of the recent increases in YFT catch. Highliners did not account for a disproportionate amount of recent increases in YFT (Figure 17). The synthetic control approach found no consistent causal signal of the IVT on YFT catches (Figure 27). The species composition analysis found no significant shift in the ratio of YFT to BET catch among the highliner vessels (Figure 31).

In summary, this analysis explored evidence for an impact of the IVT program on various aspects of the tropical tuna fisheries in the EPO. While we found no evidence for clear changes in measured fishing behaviors, numerous lines of evidence suggest that the IVT resulted in a meaningful decrease of BET catch by historic BET highliner vessels. We found no evidence that the IVT alone can explain the recent increases in YFT catches. Alternative explanations for these results may exist, but would need to explain why highliner BET CPUE dropped at the same time as the IVT was implemented, why this drop in CPUE at the time of the IVT was not seen in the non-highliner vessels (Figure 10), and why these differences in CPUE trends between the highliner and non-highliner vessels persist even when these two groups of vessels fished the same general area (Figure 14). Further research is needed to determine what specific fishing practices the incentives provided by the IVT induced in the fishing fleet that resulted in the reductions in BET catch estimated by this report.

We conclude that the IVT program was likely successful in incentivizing a reduction in BET catches. The IVT program's tiered threshold system provided a direct incentive for vessels to reduce BET catches. However, the EMP sampling may have also played a role in the incentives generated by the IVT program, in addition to providing independent estimates of BET catches, with a corresponding measure of precision, and generating data for scientific research (SAC-15 INF-H).

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6. TABLES

TABLE 1. IVT program threshold levels as defined by C-21-04. BET threshold for 2022 refers to the average catch from 2017:2019. For 2023:2024 BET threshold is calculated as the catch from the prior year.

Annual BET Threshold	Additional Closure Days	Years Applied
>1,200 t	8	2022
>1,200 t	10	2023:2024
>1,500 t	13	2023:2024
>1,800 t	16	2023:2024
>2,100 t	19	2023:2024
>2,400 t	22	2023:2024

7. FIGURES

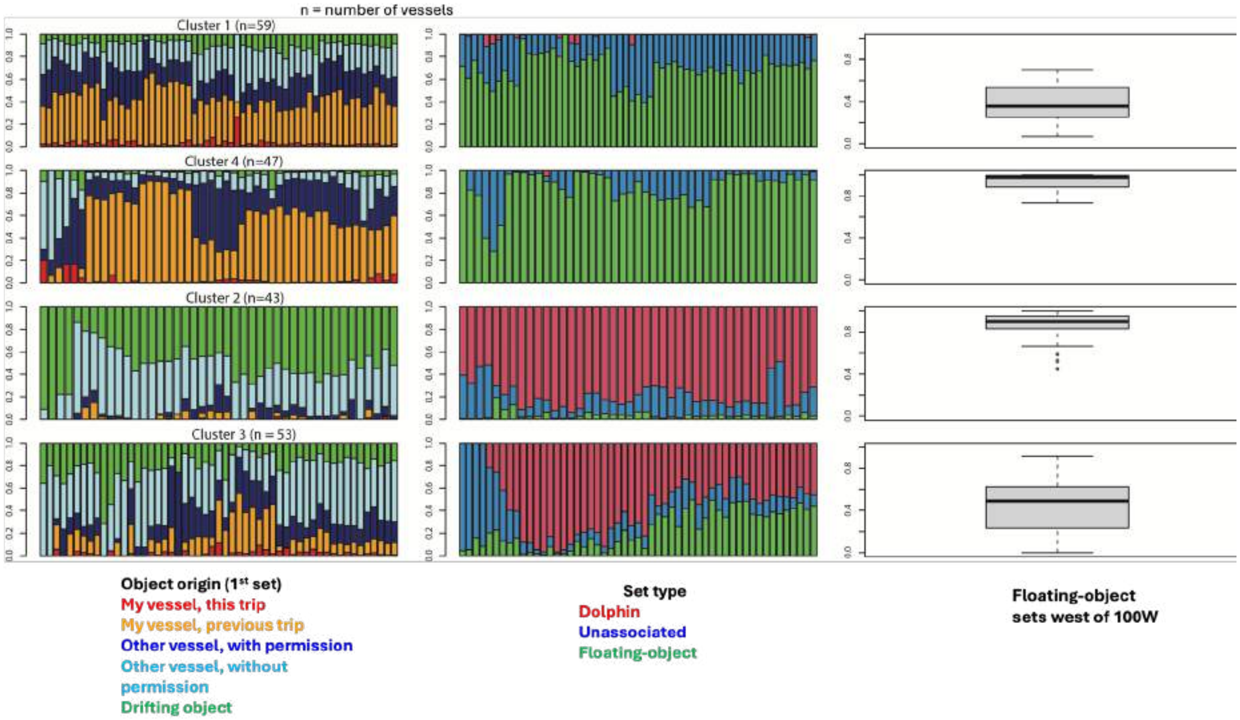

FIGURE 1. Visual summary of attributes of fishing strategy clusters using methods described in Lennert-Cody et al. (2018).

FIGURA 1. Resumen visual de los atributos de los conglomerados de estrategias de pesca utilizando los métodos descritos en Lennert-Cody *et al*. (2018).

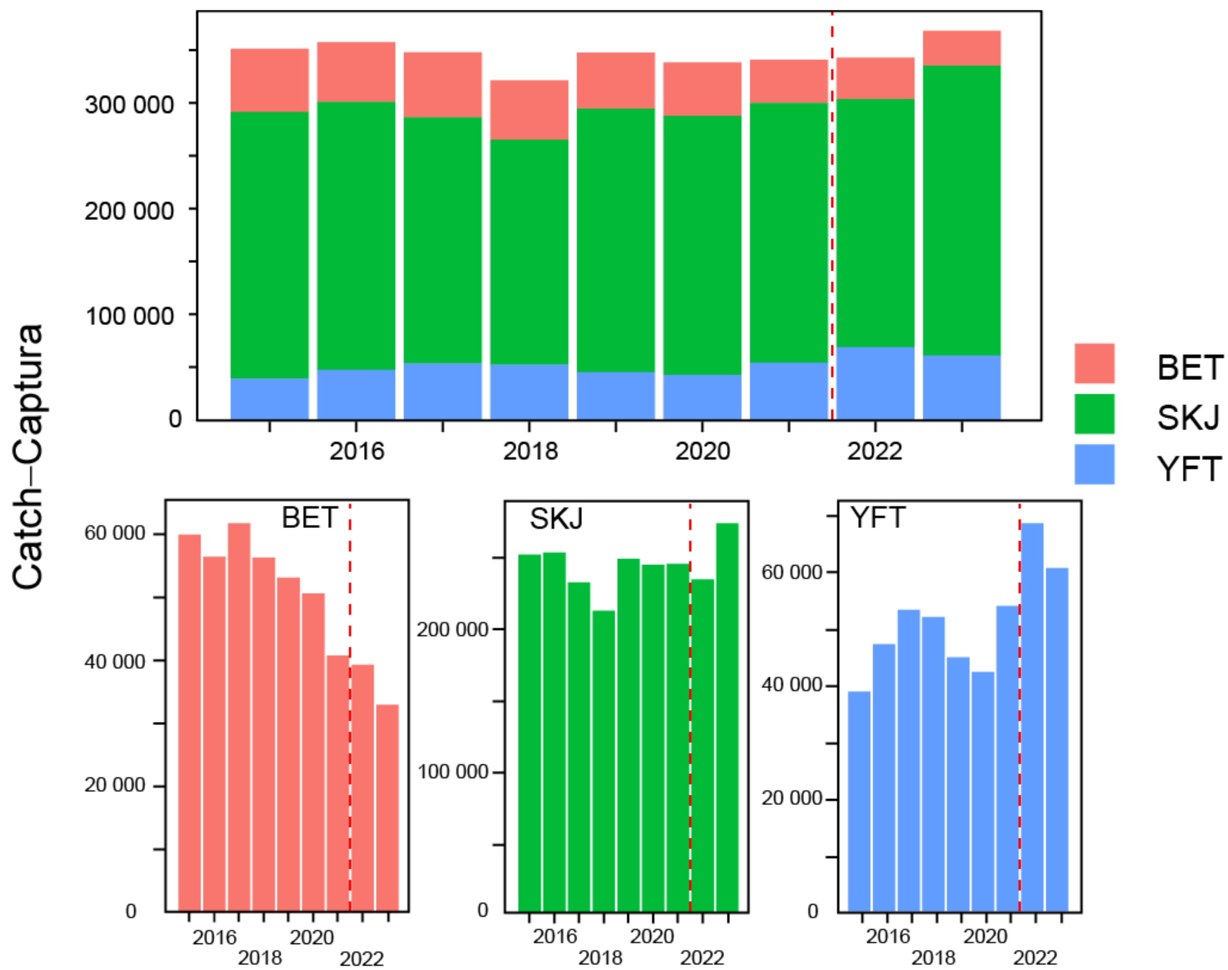

FIGURE 2. Total class 6 purse seine catch (t) from used in this analysis over time and by species. Red vertical line indicates official announcement of IVT program in (2022).
FIGURA 2. Captura total (t) de buques cerqueros de clase 6 utilizada en este análisis a lo largo del tiempo y por especie. La línea vertical roja indica el anuncio oficial del programa de UIB en 2022.

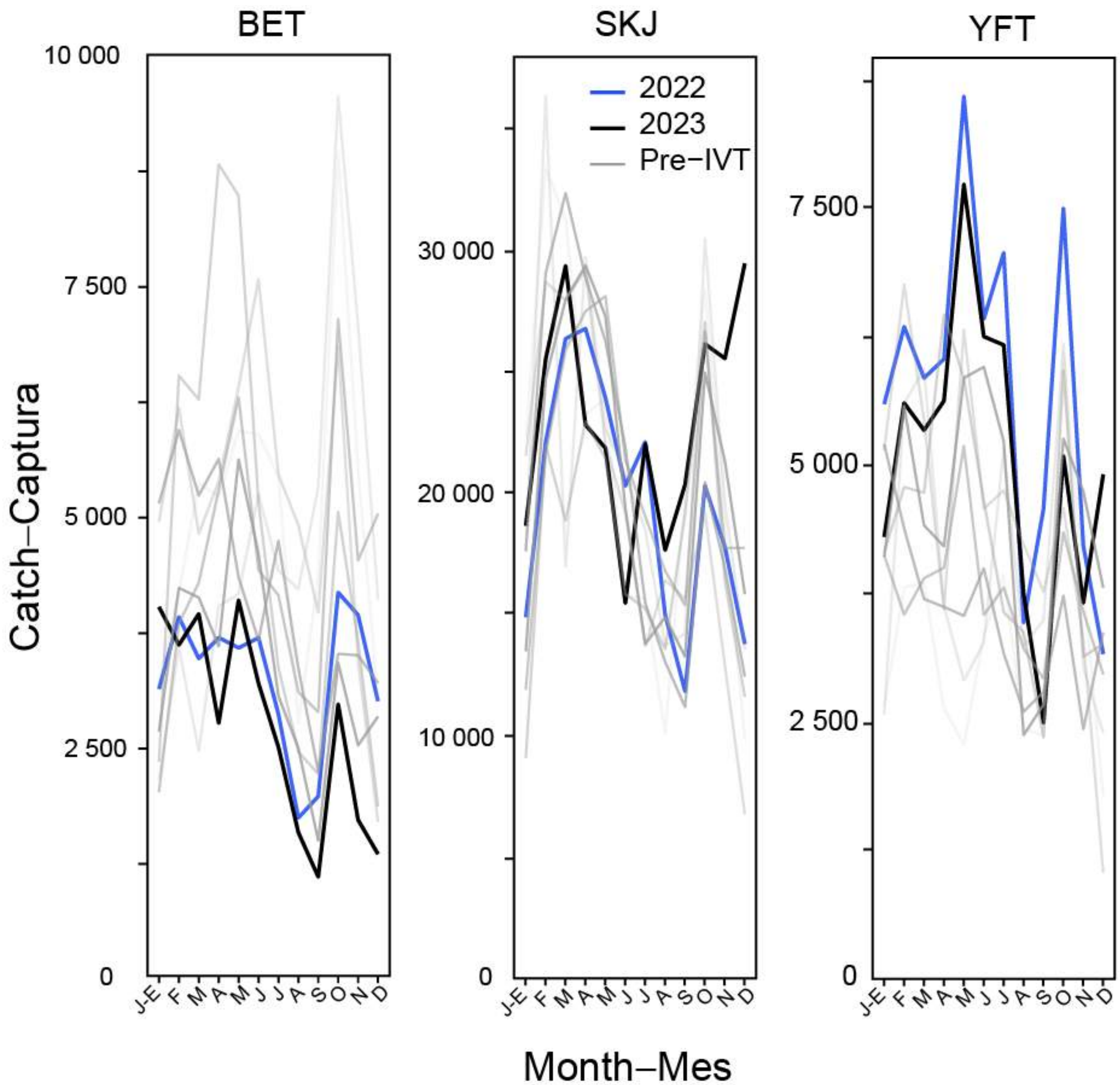

FIGURE 3. Class six purse-seine catch (t) by month by species. Each line represents a different year between 2015 and 2023, with transparency of the line indicating how many years in the past a given line represents. Pre-IVT years are shown in blue, post-IVT years in red and green.

FIGURA 3. Captura (t) de buques cerqueros de clase 6 por mes y por especie. Cada línea representa un año diferente entre 2015 y 2023, y la transparencia de la línea indica cuántos años en el pasado representa una línea determinada. Los años previos al UIB se muestran en azul; los años posteriores al UIB se muestran en rojo y verde.

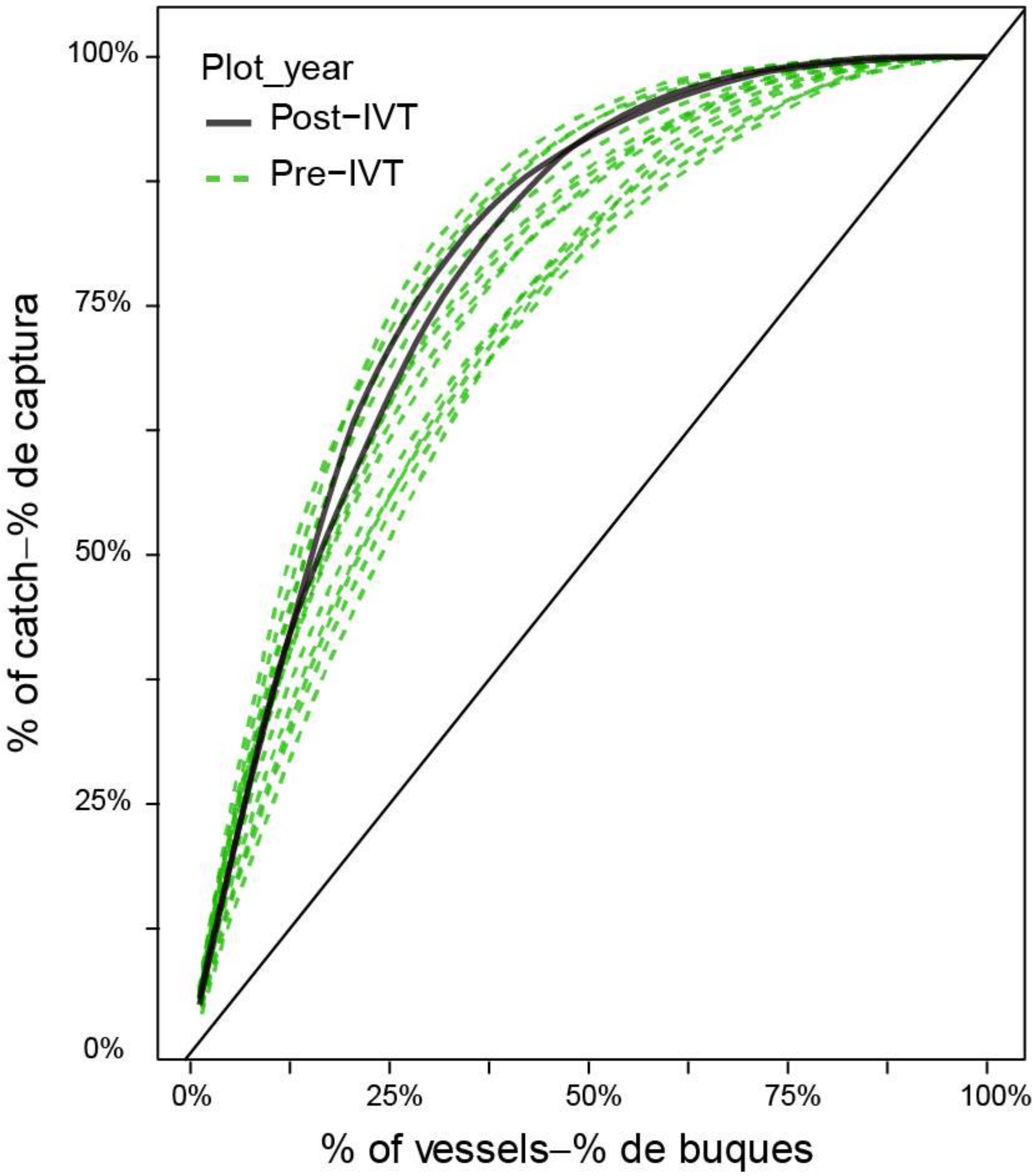

FIGURE 4. Cumulative class-6 purse-seine catch of BET by vessel by year. Lines closer to the one-to-one diagonal line indicate a more equal distribution of BET catch across all vessels fishing that year. Lines curved away from the one-to-one line indicate a greater concentration of BET catch among some vessels fishing that year.

FIGURA 4. Captura acumulativa de BET de buques cerqueros de clase 6 por buque y por año. Las líneas más cercanas a la línea diagonal individual indican una distribución más equitativa de la captura de BET entre todos los buques que pescaron ese año. Las líneas que se alejan de la línea indican una mayor concentración de la captura de BET entre algunos buques que pescaron ese año.

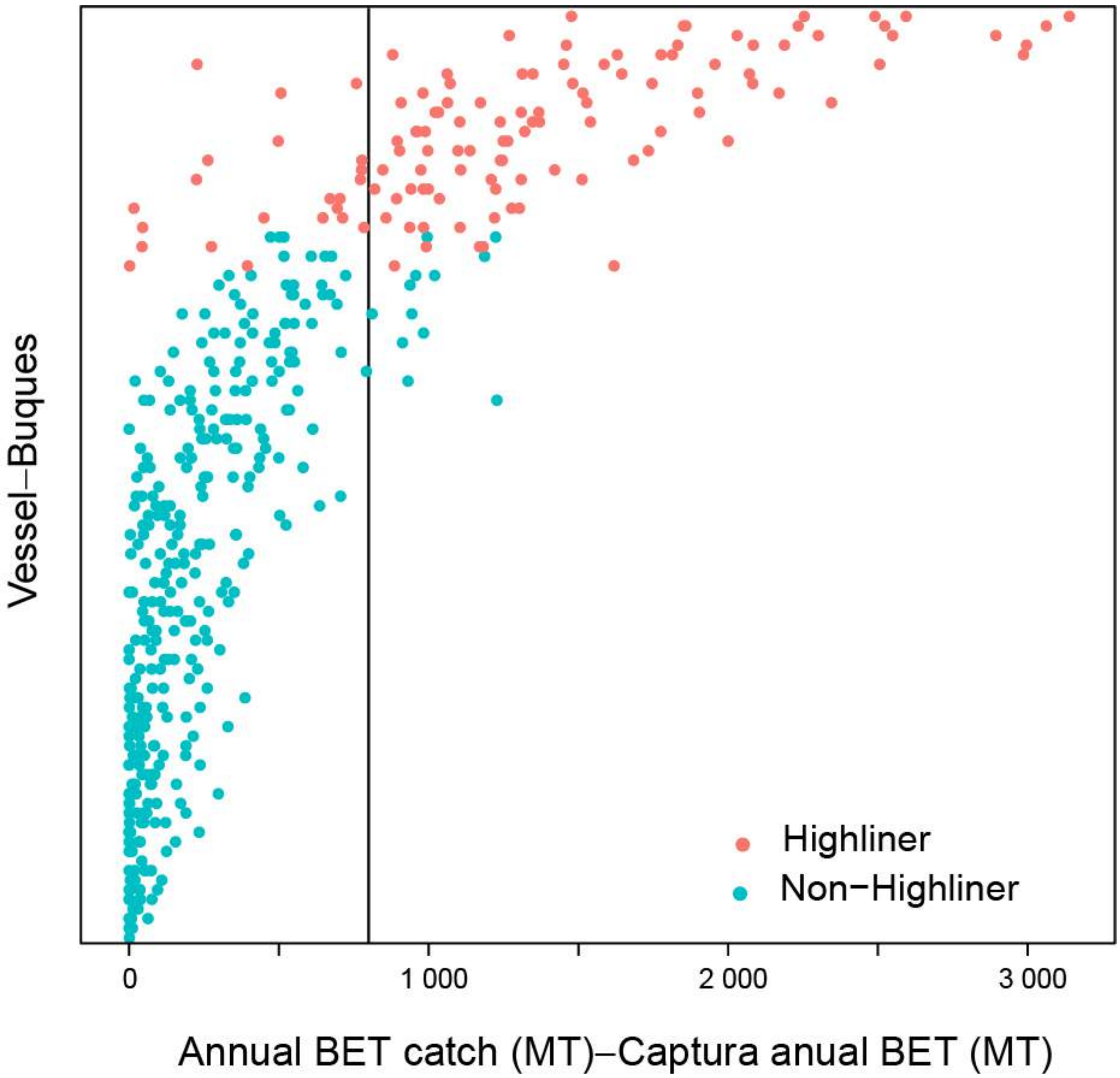

FIGURE 5. Distribution of annual class six purse-seine catches per vessel (rows) between 2017 and 2021. Color indicates whether a vessel is classified as a ‘highliner’, defined as annual catches greater than or equal to 800 in at least half of the included years.

FIGURA 5. Distribución de las capturas anuales de buques cerqueros de clase 6 por buque (filas) entre 2017 y 2021. El color indica si un buque está clasificado como “*highliner*”, definido como capturas anuales iguales o superiores a 800 en al menos la mitad de los años incluidos.

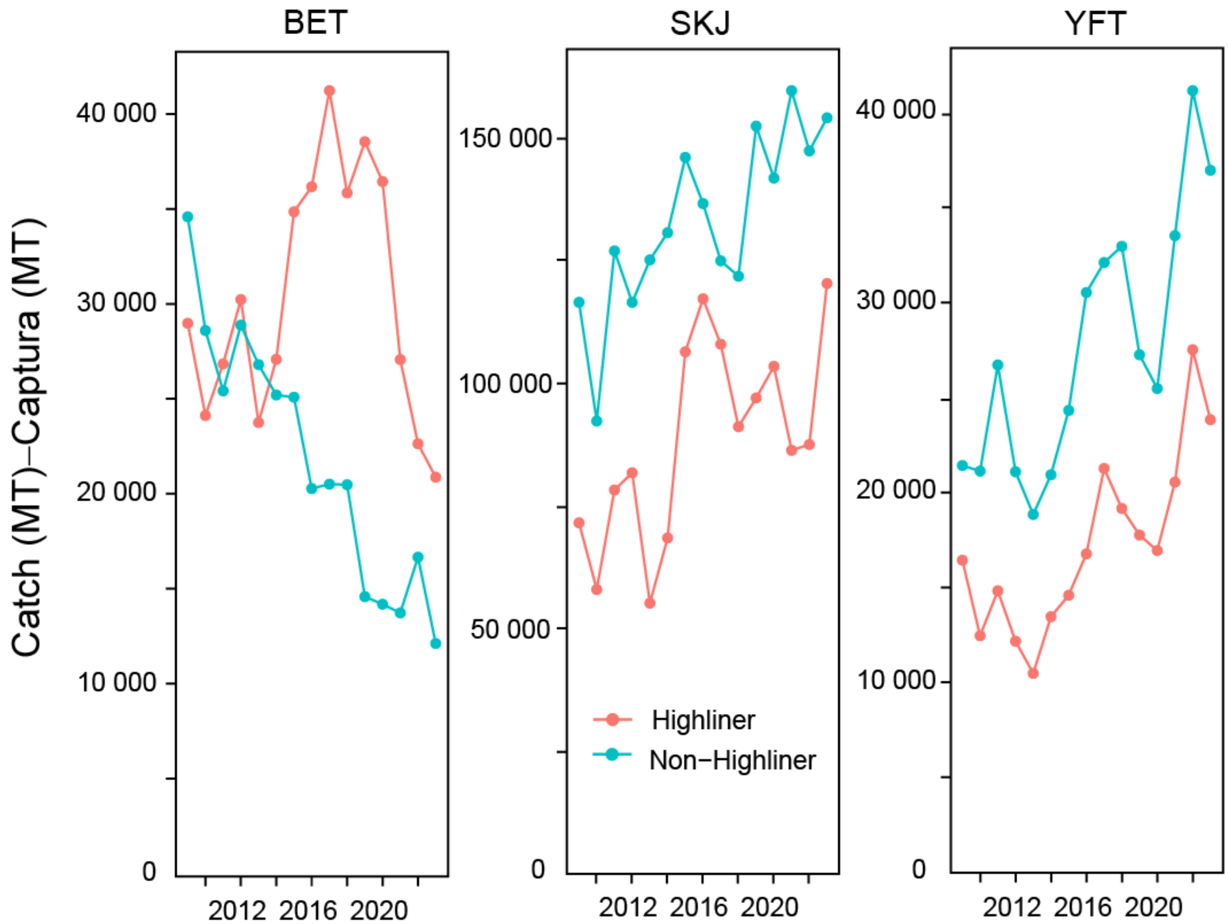

FIGURE 6. Class 6 purse-seine vessel catch (t) per year per species included in this analysis, broken out by BET highliner and non-highliner vessels.

FIGURA 6. Captura (t) de buques cerqueros de clase 6, por año y por especie, incluida en este análisis, desglosada por buques *highliner* y *non-highliner*.

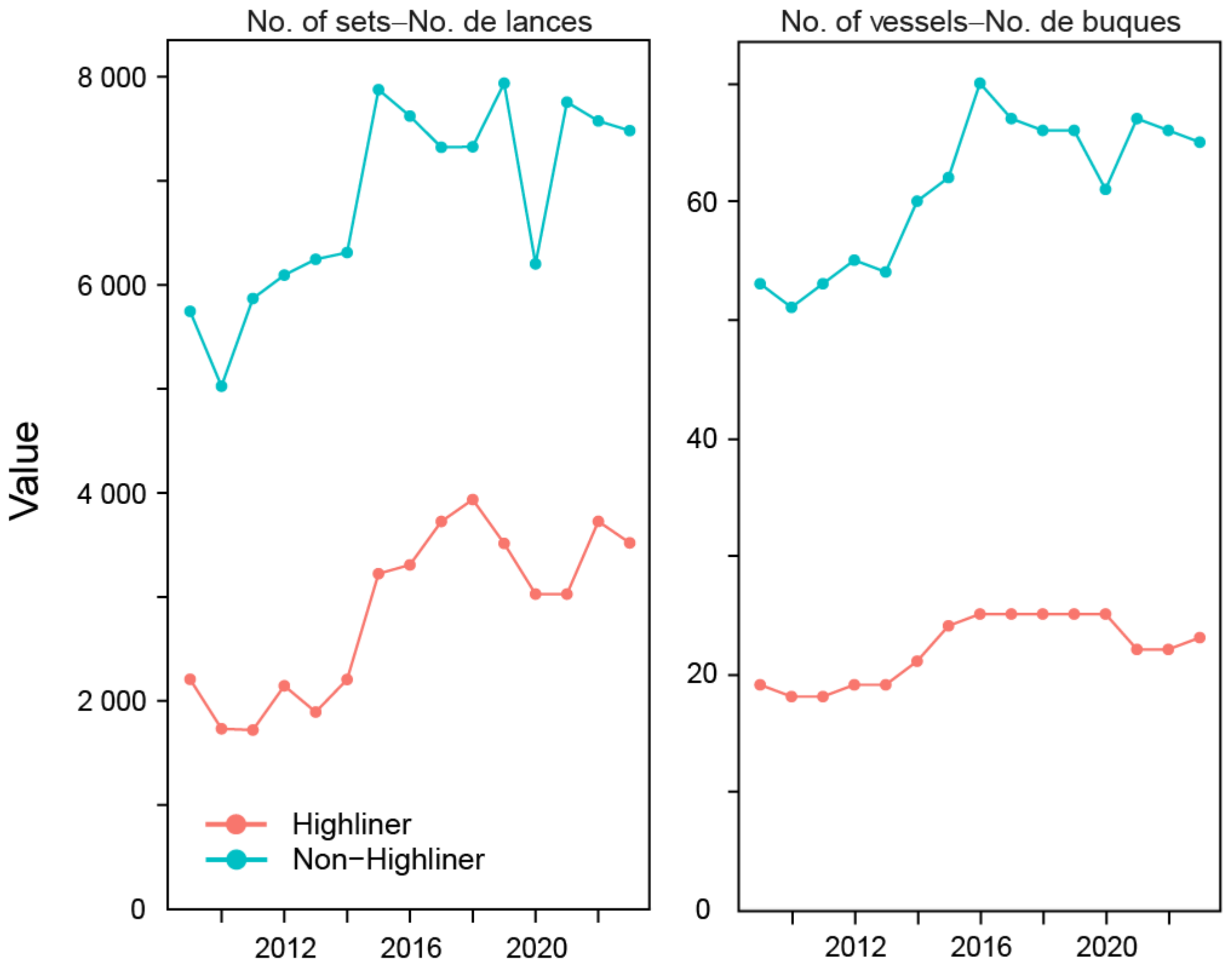

FIGURE 7. Number of class 6 purse-seine sets (OBJ and NOA) and vessels used for this analysis, broken out by BET highliners and non-highliners.
FIGURA 7. Número de lances de buques cerqueros de clase 6 (OBJ y NOA) y buques utilizados en este análisis, desglosados por buques *highliner* y *non-highliner*.

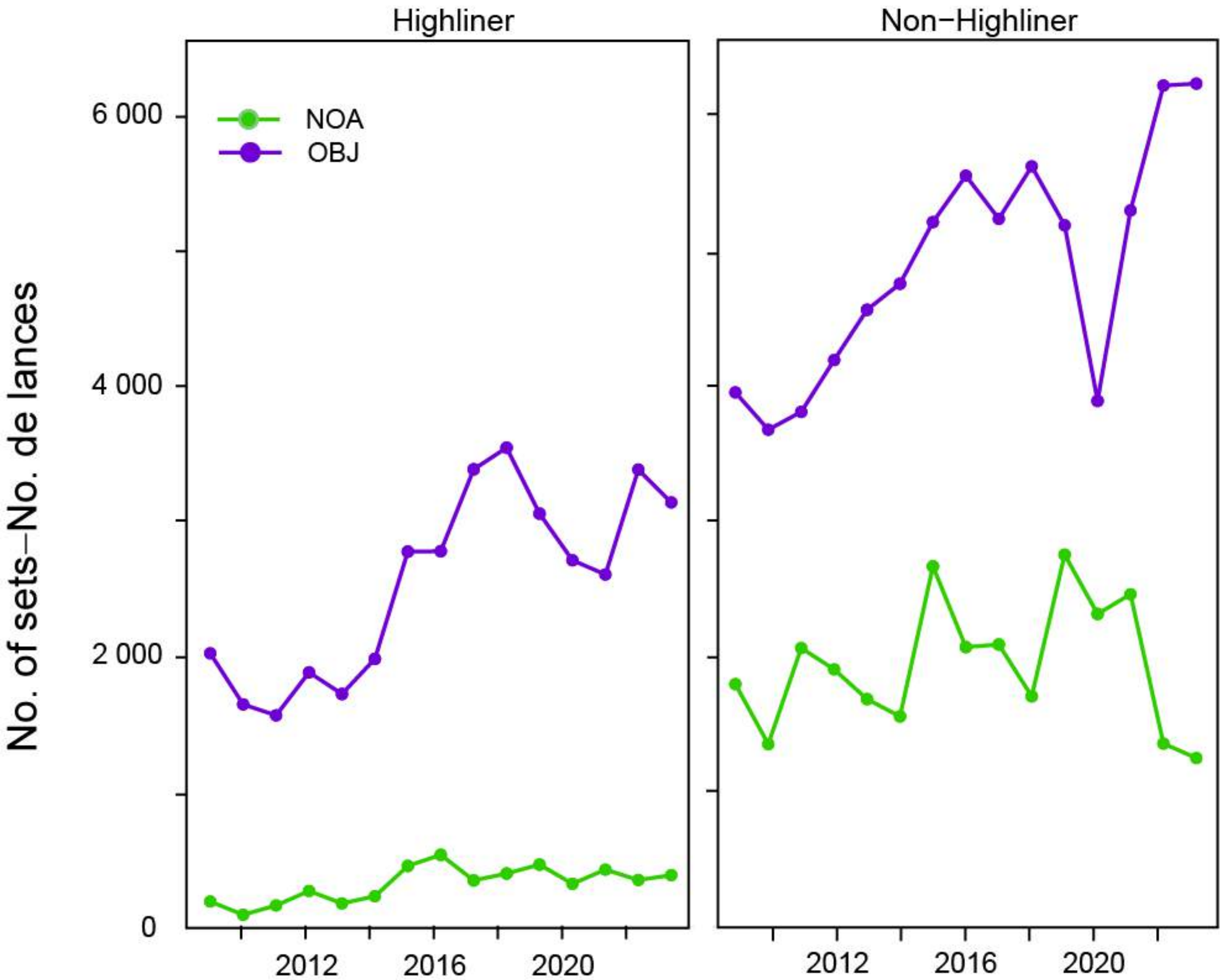

FIGURE 8. Number of class 6 purse-seine sets by set type used for this analysis, broken out by BET highliners and non-highliners.

FIGURA 8. Número de lances de buques cerqueros de clase 6, por tipo de lance, utilizados en este análisis, desglosados por buques *highliner* y *non-highliner*.

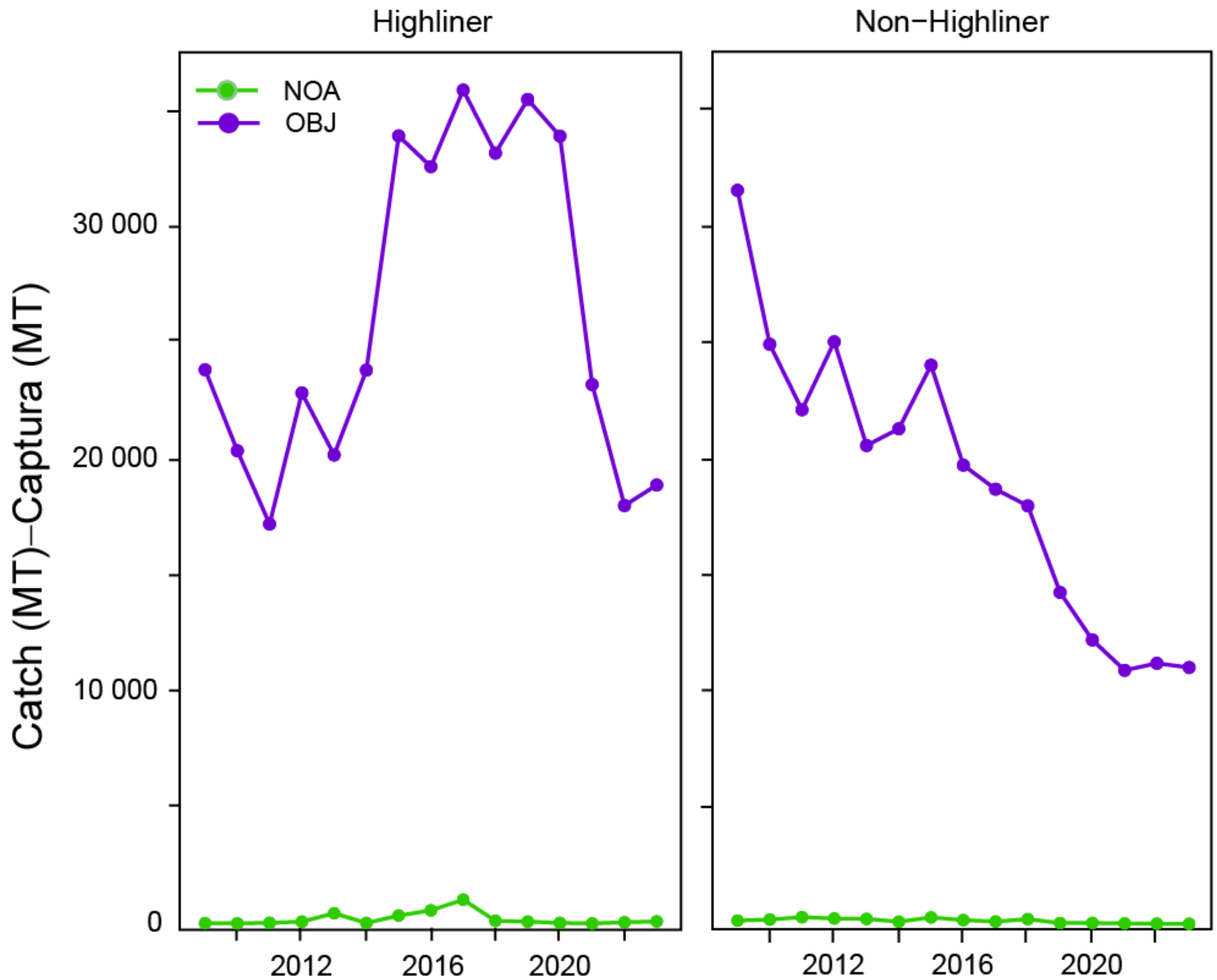

FIGURE 9. Class 6 purse-seine BET catch (MT) by set type and highliner group.
FIGURA 9. Captura (t) de BET de buques cerqueros de clase 6 por tipo de lance y grupo *highliner*.

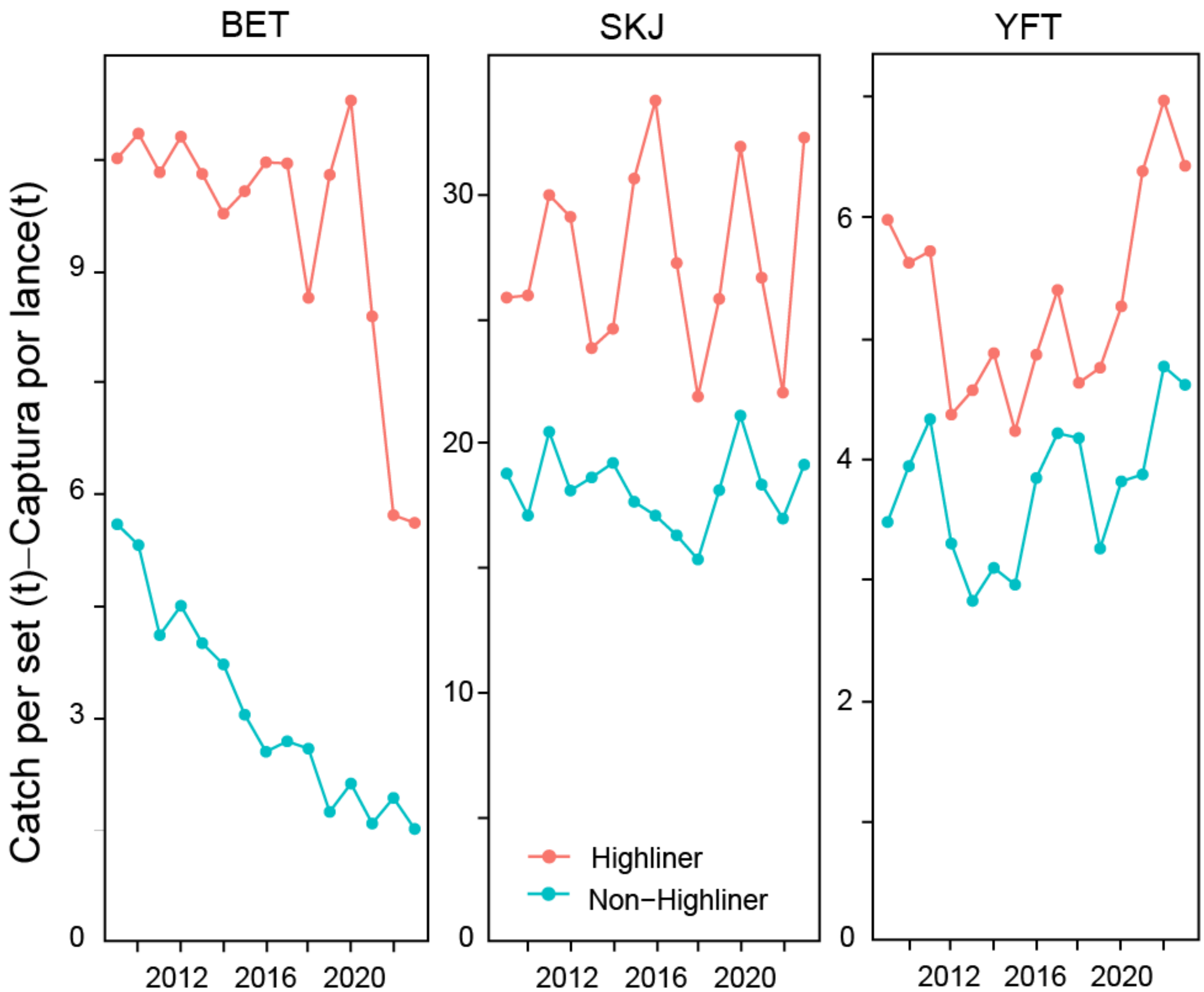

FIGURE 10. Class six purse-seine vessel catch (t) per set per year per species, broken out by BET highliner and non-highliner vessels.

FIGURA 10. Captura (t) de buques cerqueros de clase 6, por año y por especie, desglosada por buques *highliner* y *non-highliner*.

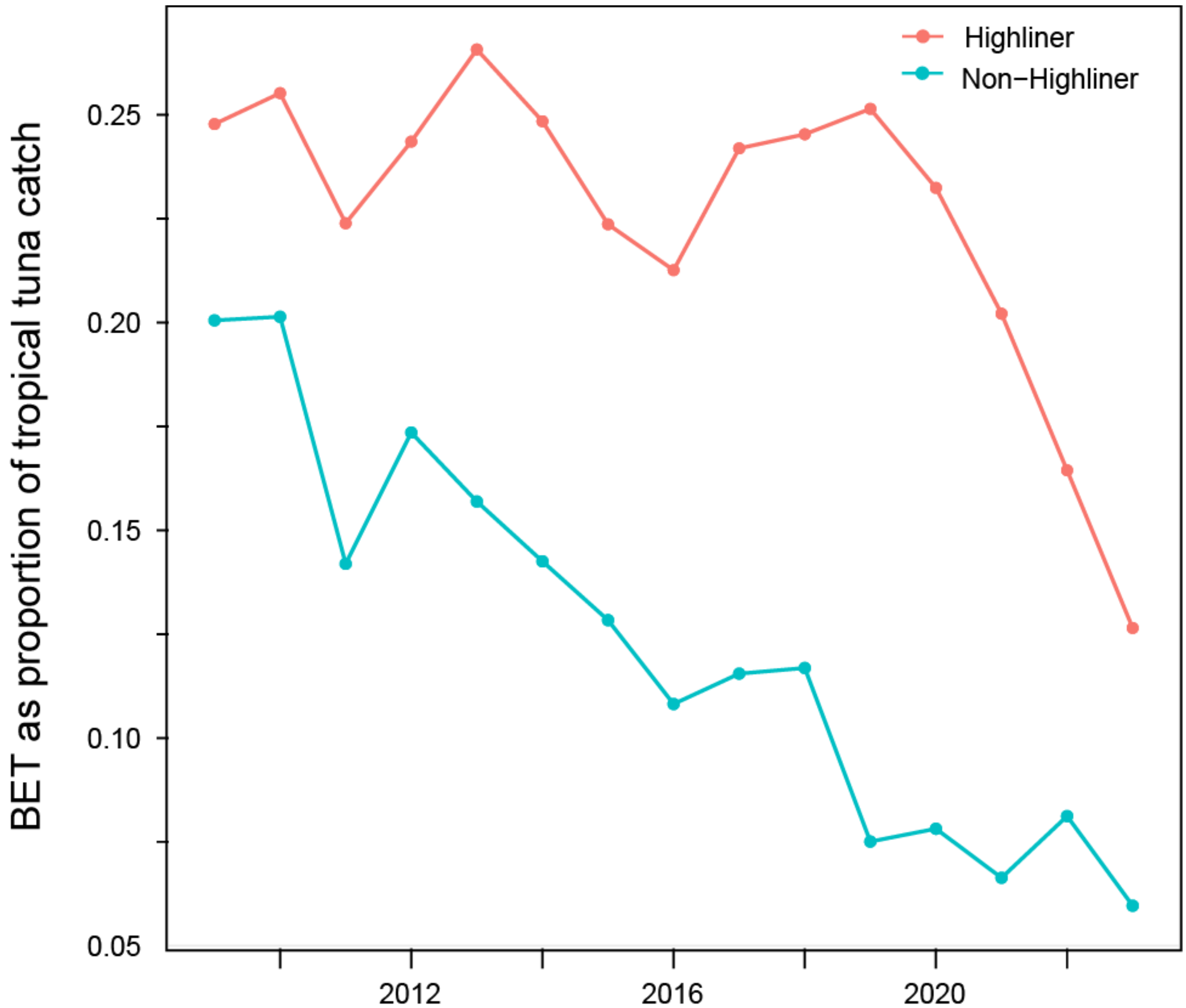

FIGURE 11. Class 6 purse-seine BET catch as a proportion of all tropical tuna catch over time, by highliner status.

FIGURA 11. Captura de BET de buques cerqueros de clase 6 como proporción de toda la captura de atunes tropicales a lo largo del tiempo, por estado de *highliner*.

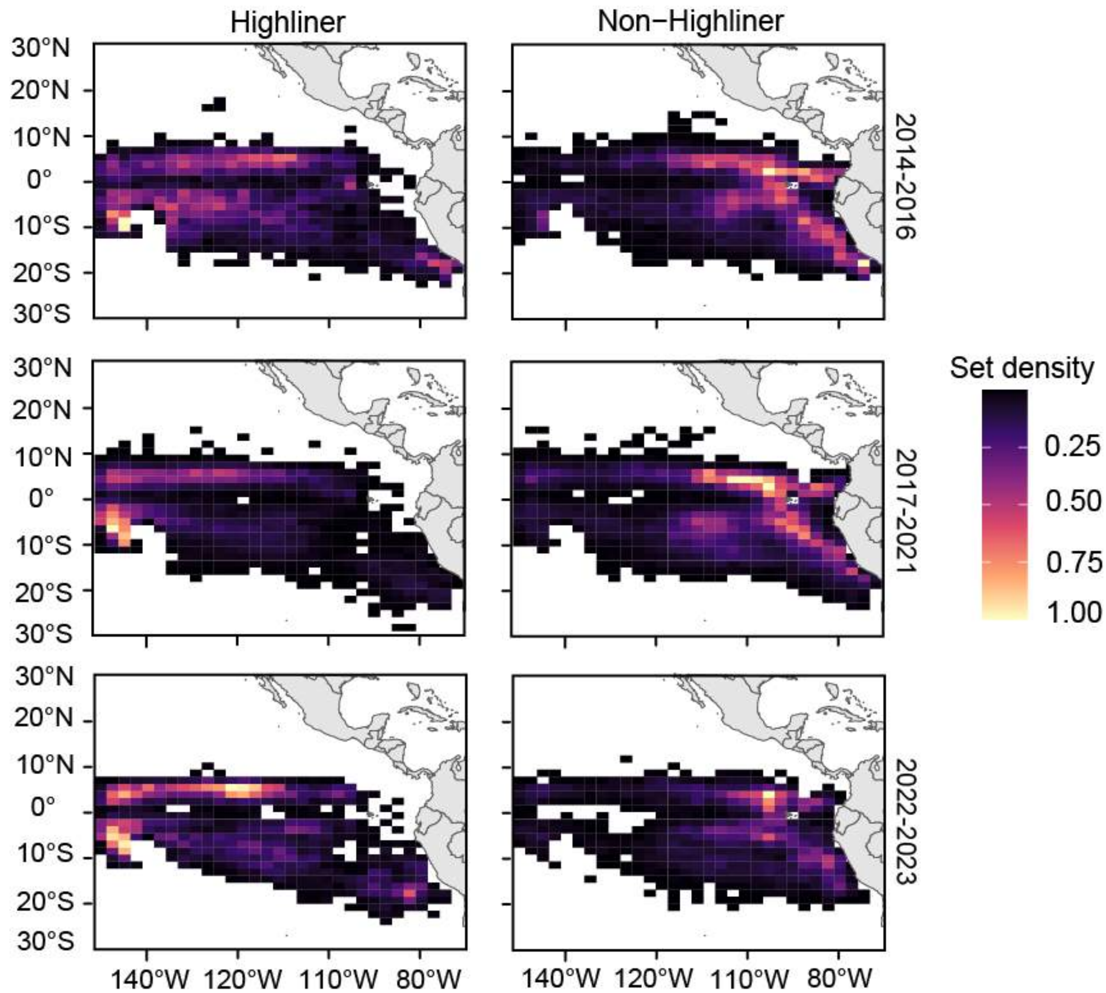

FIGURE 12. Spatial density of OBJ sets between 2014 and 2023 by BET highliners and non-highliners.
FIGURA 12. Densidad espacial de lances OBJ entre 2014 y 2023, por buques *highliner* y *non-highliner*.

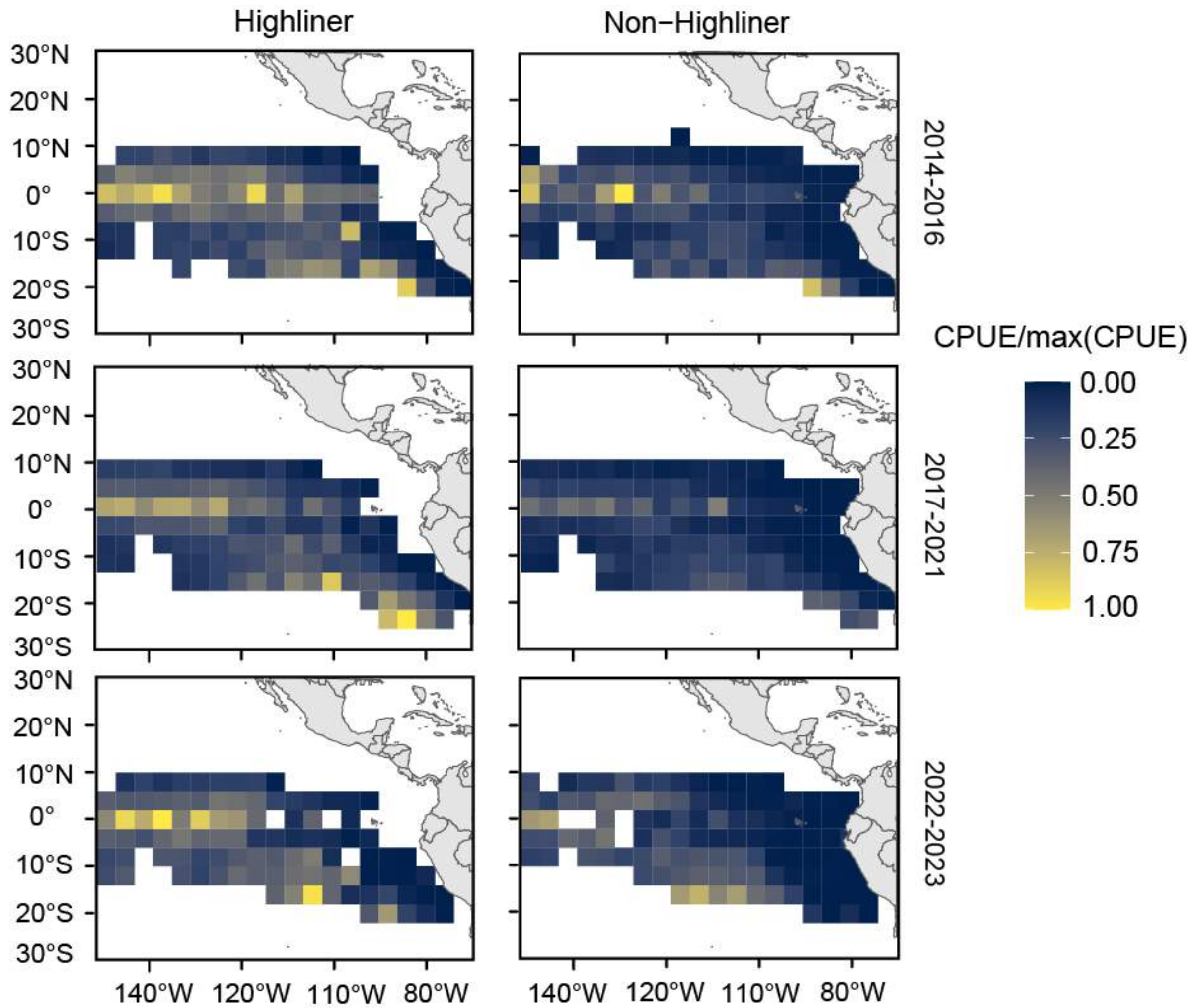

FIGURE 13. Spatial max scaled CPUE of OBJ sets between 2014 and 2023 by BET highliners and non-highliners. Scaling performed across highliner and non-highliner but within time blocks.

FIGURA 13. CPUE máxima escalada espacial de lances OBJ entre 2014 y 2023 por buques *highliner* y *non-highliner*. Escalado realizado entre buques *highliner* y *non-highliner* pero dentro de bloques de tiempo.

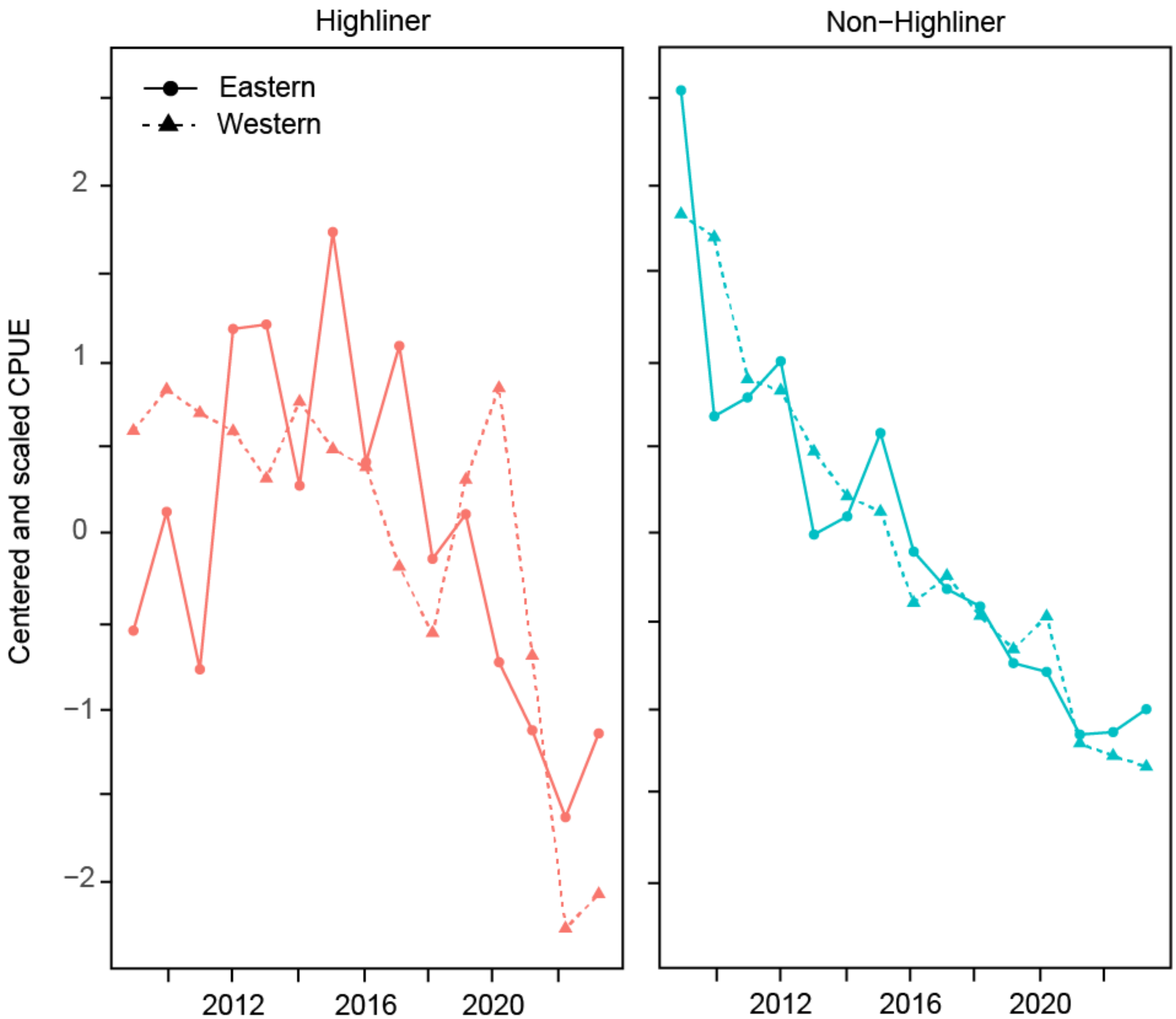

FIGURE 14. Centered and scaled OBJ catch per set broken out by Eastern and Western fishing ground. Western defined as fishing west of -115W, East as east of -115W.

FIGURA 14. Captura por lance OBJ centrada y escalada, desglosada por caladero oriental y occidental (occidental se define como la pesca al oeste de -115°O, oriental como al este de -115°O).

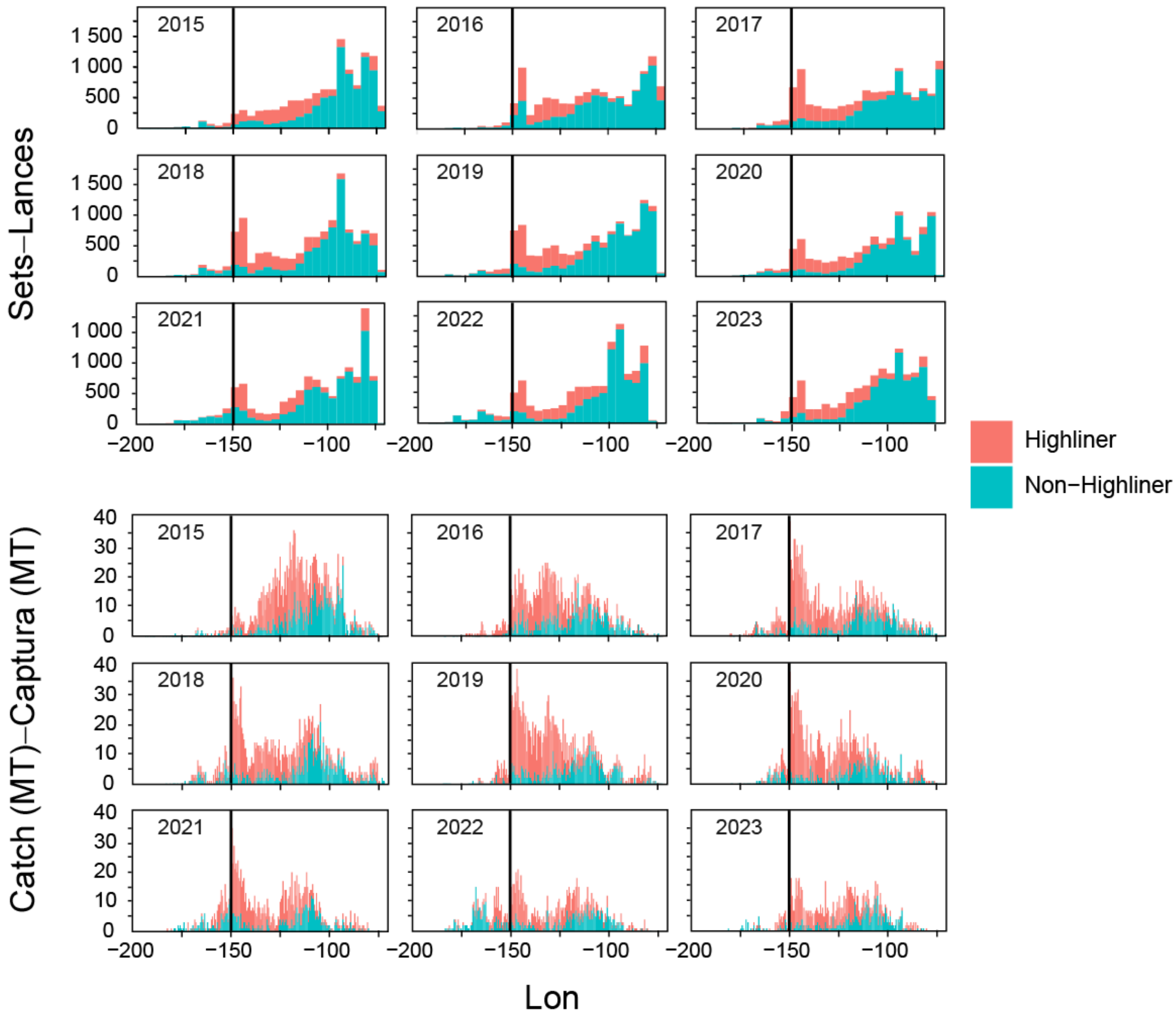

FIGURE 15. Number of sets (A) and catch of BET (t) by class 6 purse-seine vessels as a function of longitiude and year.

FIGURA 15. Número de lances (A) y captura de BET (t) por buques cerqueros de clase 6 en función de la longitud y el año.

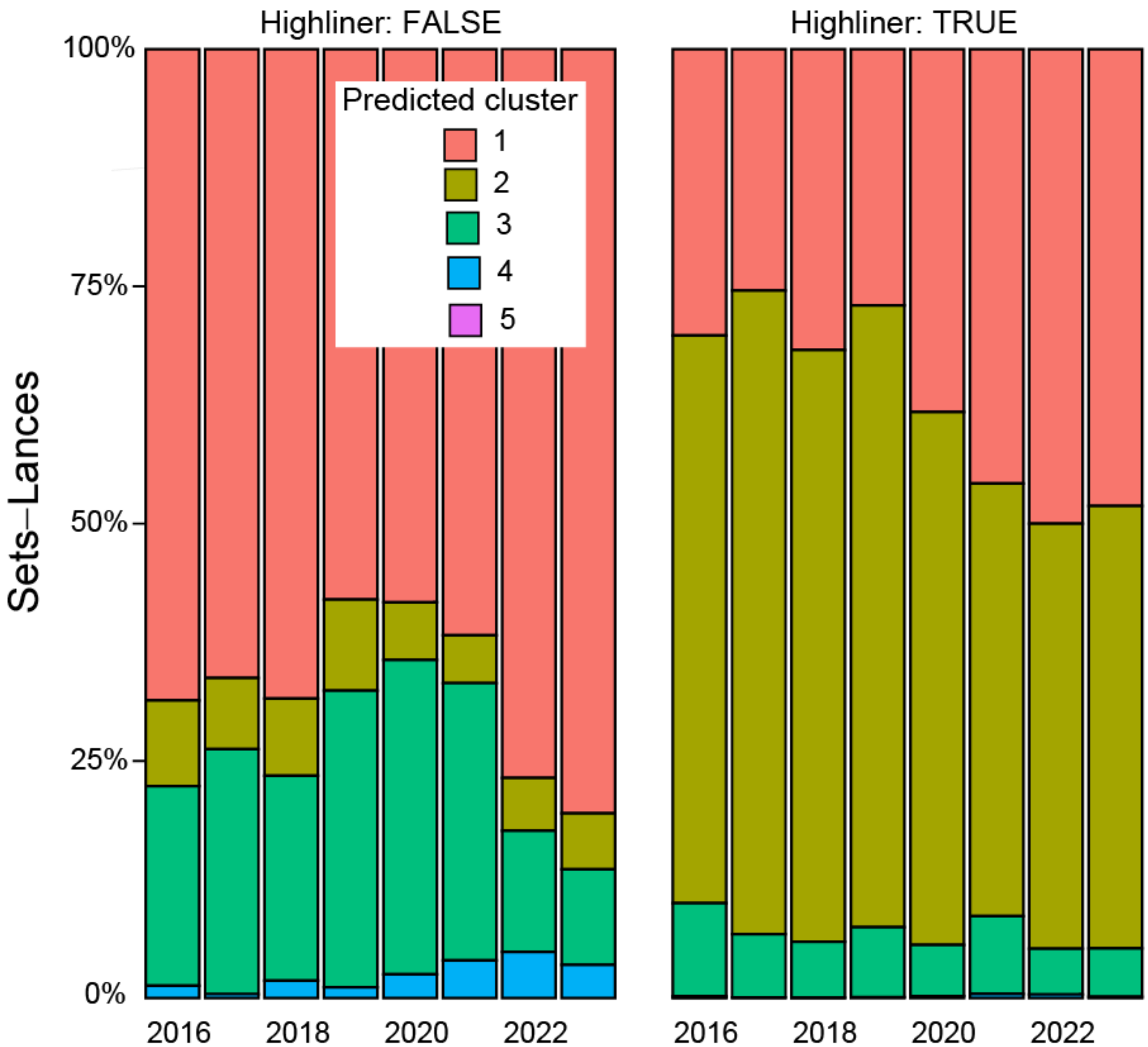

FIGURE 16. Percent of Class 6 purse-seine sets assigned to each estimated fishing strategy cluster over time.

FIGURA 16. Porcentaje de lances de buques cerqueros de clase 6 asignados a cada conglomerado de estrategias de pesca estimadas a lo largo del tiempo.

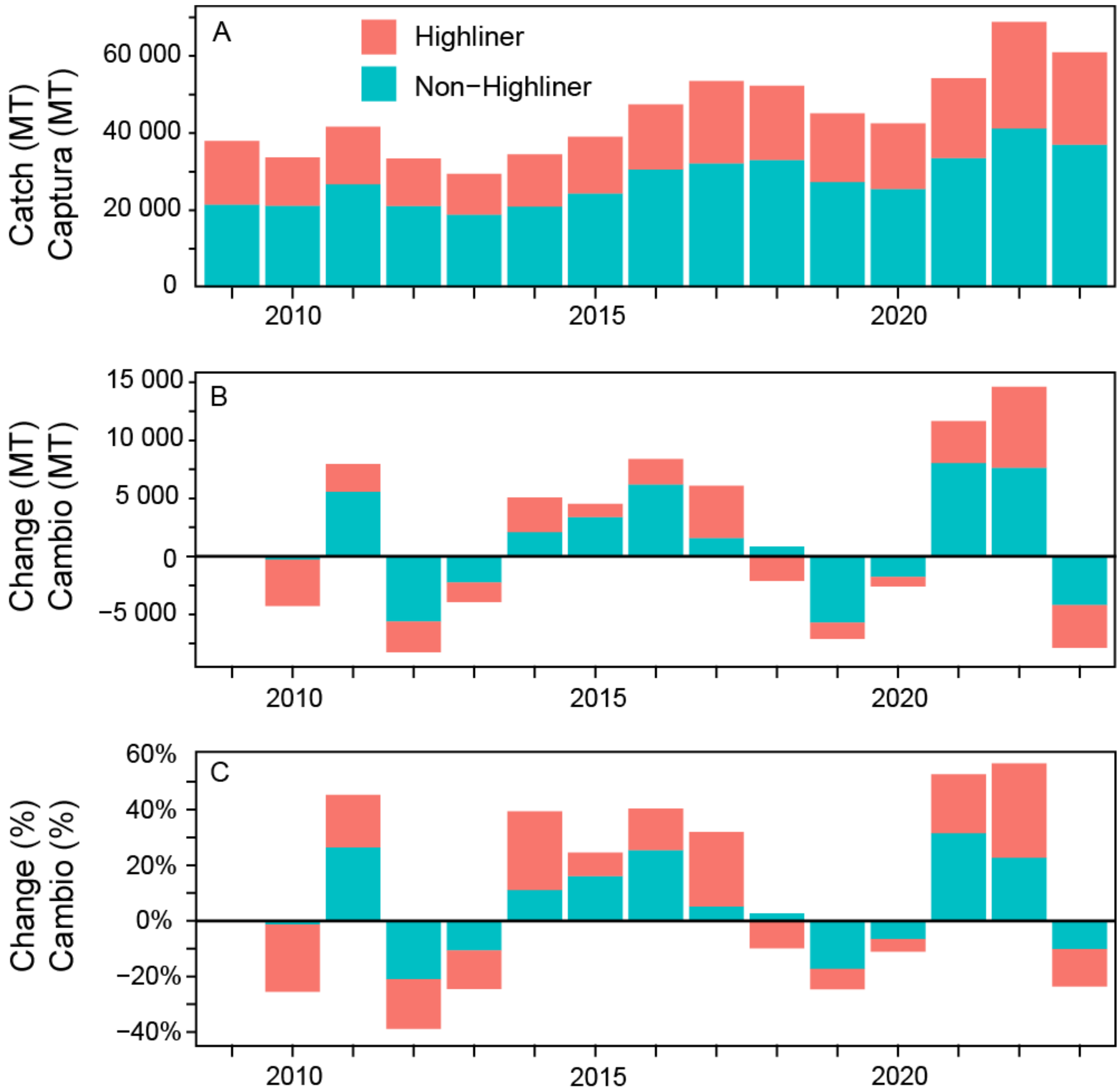

FIGURE 17. Breakdown of total (A), year-to-year absolute change (B), and year-to-year percent change (D) YFT class six purse-seine catch by BET highliner groups.

FIGURA 17. Desglose de la captura total (A), la variación absoluta interanual (B), y la variación porcentual interanual (C) de YFT por buques cerqueros de clase 6, por grupos de buques *highliner*.

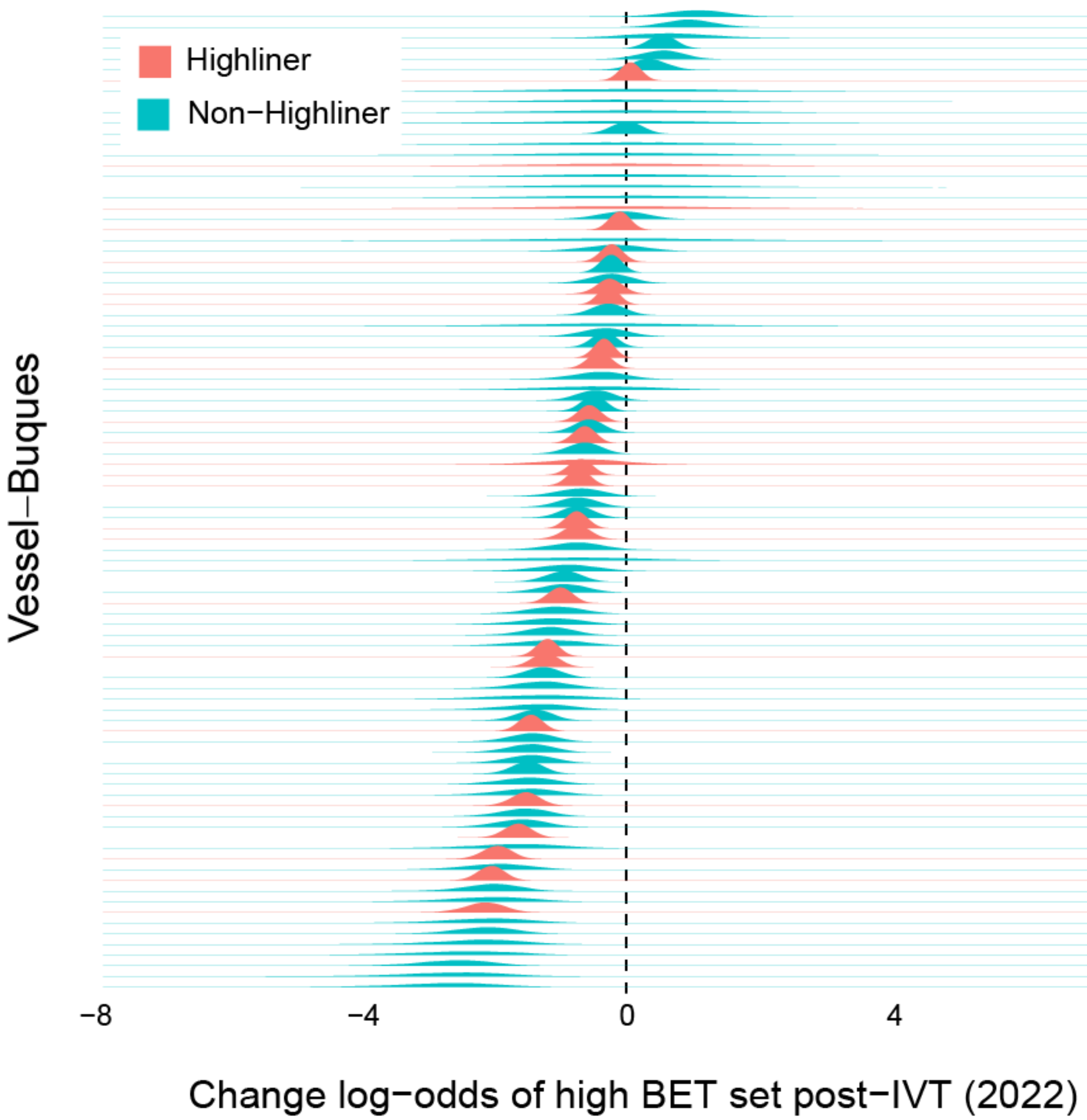

FIGURE 18. Estimated change in log-odds of class six purse-seine vessels catching >= to 10 t of BET in a set. Positive values mean higher odds of BET>=10 set, negative lower, post IVT year.
FIGURA 18. Cambio estimado en las probabilidades logarítmicas de que los buques cerqueros de clase 6 capturen >= 10 t de BET en un lance. Los valores positivos significan mayores probabilidades de lance de BET >=10, negativo inferior, año posterior al UIB.

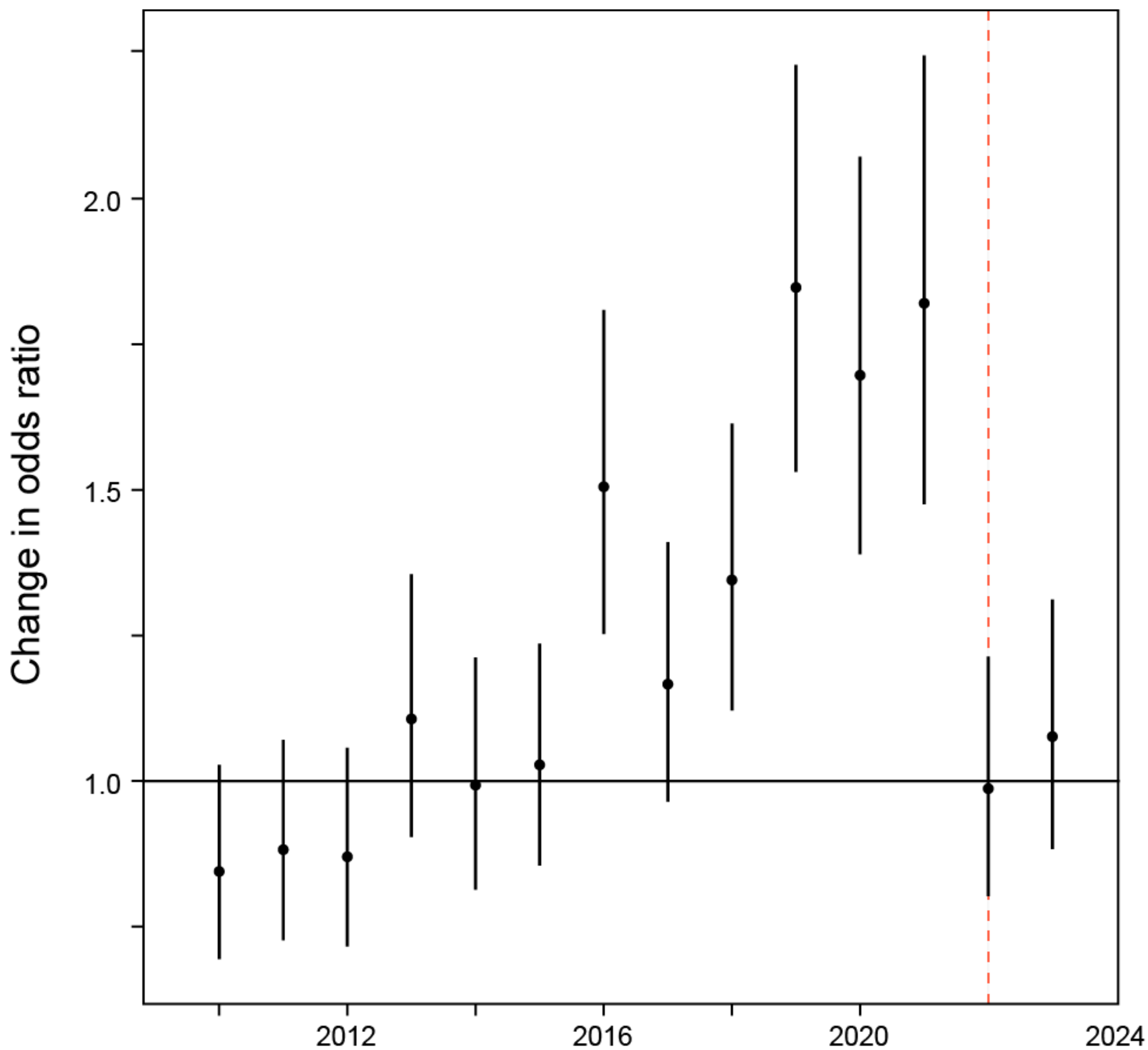

FIGURE 19. Marginal effect of being a highliner in each year conditional on control variables on the probability of a set having >= 10 t of BET.
FIGURA 19. Efecto marginal de ser *highliner* en cada año condicionado a las variables de control sobre la probabilidad de que un lance tenga >= 10 t de BET.

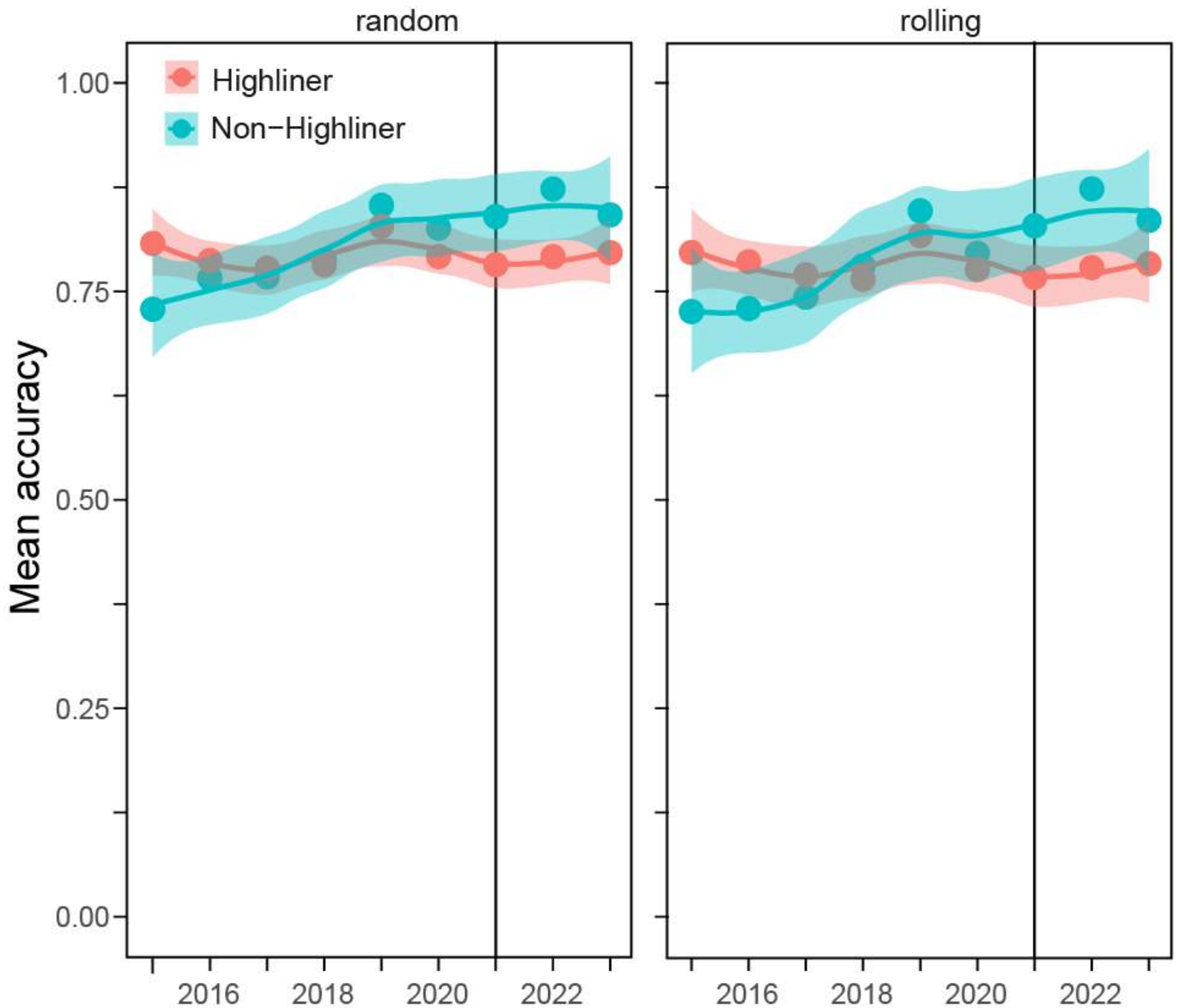

FIGURE 20. Mean testing split classification accuracy of BET catch detection models. For any given point, 'random' indicates that the testing split is made up of a randomly sampled subset of vessels in that year, rolling indicates that all data points in that year were held out from the training set.

FIGURA 20. Exactitud promedio de clasificación de la división de prueba de los modelos de detección de captura de BET. Para cualquier punto dado, "aleatorio" indica que la división de prueba se compone de un subconjunto de buques muestreados aleatoriamente en ese año; "progresivo" indica que todos los puntos de datos de ese año se retuvieron del conjunto de entrenamiento.

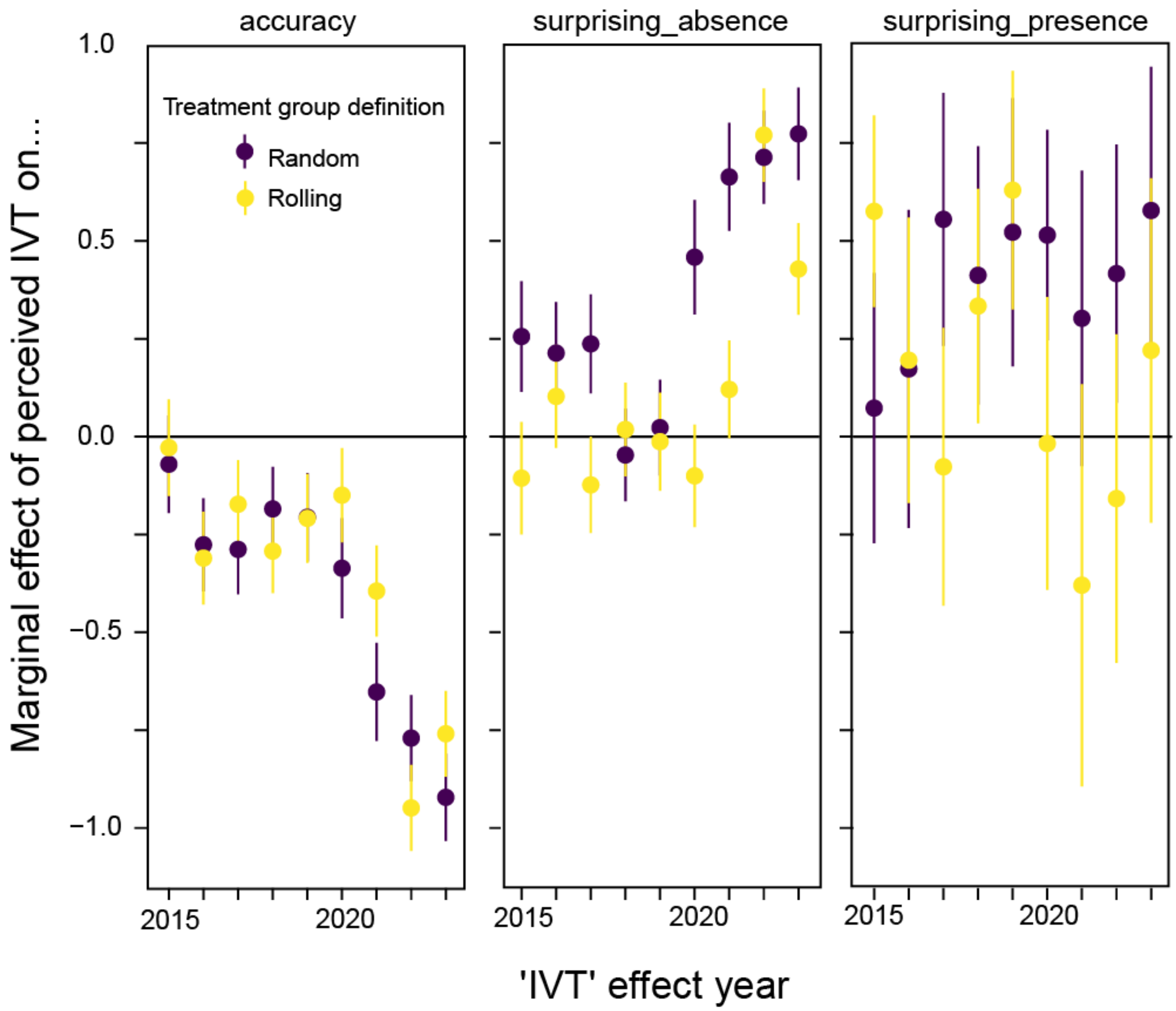

FIGURE 21. Results of DiD-style analysis on residuals of probability that a given set caught greater than or equal to 10 t of BET. Accuracy reflects the change in the overall accuracy of the model. Surprising Presence shows the change in the probability of a surprising presence, Surprising Absence the change in the probability of a surprising absence. All changes are conditional on the expected changed change in the metric in question based on the non-highliners. For any given point, 'random' indicates that the testing split is made up of a randomly sampled subset of vessels in that year, rolling indicates that all data points in that year were held out from the training set.

FIGURA 21. Resultados del análisis tipo DD sobre los residuales de la probabilidad de que un lance determinado capture 10 t o más de BET. La exactitud refleja el cambio en la exactitud general del modelo. Presencia sorpresa muestra el cambio en la probabilidad de una presencia sorpresa. Ausencia sorpresa muestra el cambio en la probabilidad de una ausencia sorpresa. Todos los cambios están condicionados por el cambio esperado en la métrica en cuestión con base en los valores de los buques *non-highliner*. Para cualquier punto dado, "aleatorio" indica que la división de prueba se compone de un subconjunto de buques muestreados aleatoriamente en ese año; "progresivo" indica que todos los puntos de datos de ese año se retuvieron del conjunto de entrenamiento.

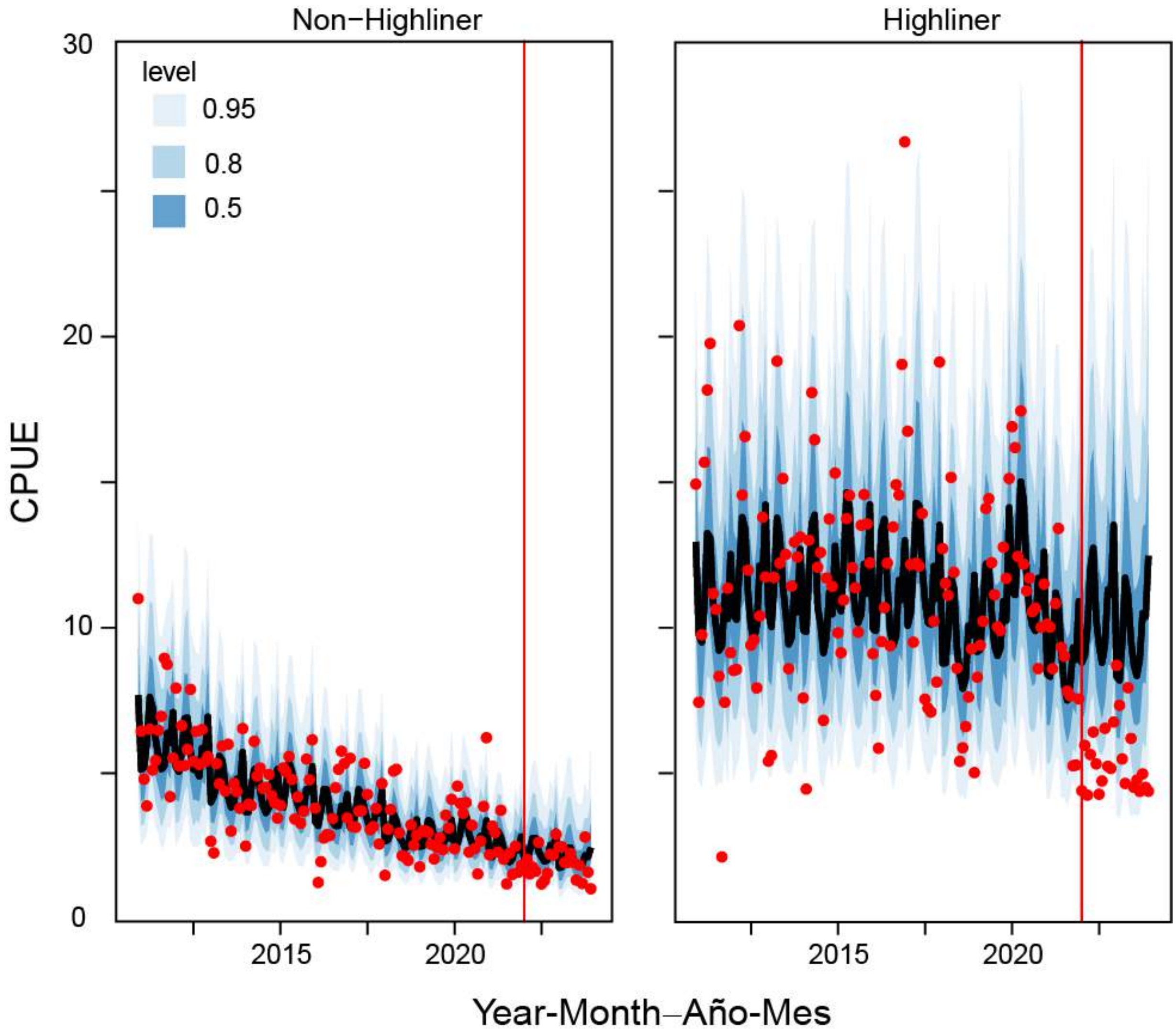

FIGURE 22. Observed (red points) and Bayesian GAM predicted (black line and blue distribution) catch per set (CPUE) of BET in OBJ sets. Trends are broken out by highliner status. Black line and blue distributions show mean and distribution of posterior predictive CPUE values. GAMs were fit using only data from before 2022.

FIGURA 22. Captura por lance (CPUE) observada (puntos rojos) y predicha por el MAG bayesiano (línea negra y distribución color azul) de BET en lances OBJ. Las tendencias se desglosan por estado de *highliner*. La línea negra y las distribuciones azules muestran el promedio y la distribución de la predicción posterior de los valores de la CPUE. Los MAG se ajustaron solo con datos previos a 2022.

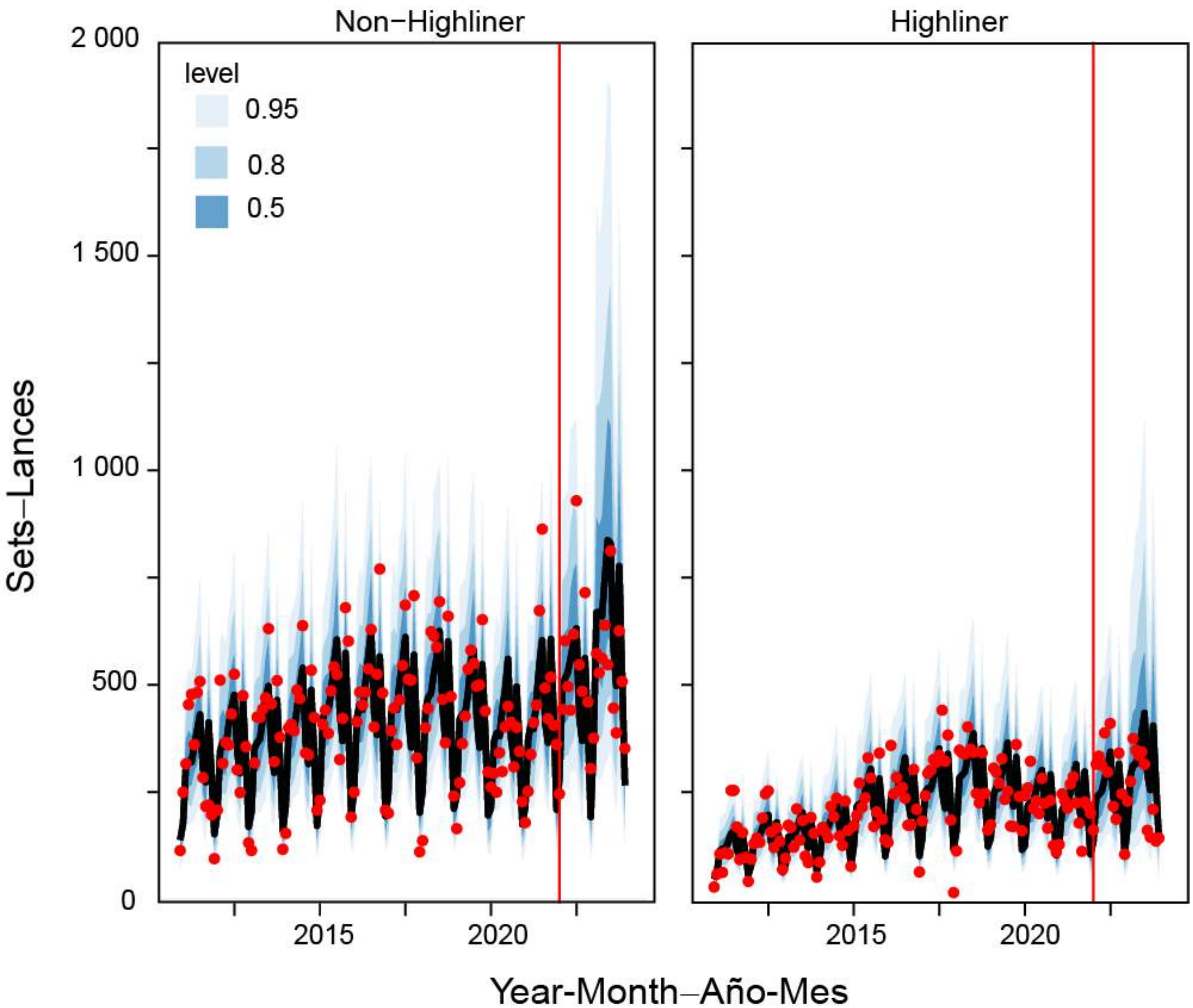

FIGURE 23. Observed (red points) and Bayesian GAM predicted (black line and blue distribution) OBJ sets. Trends are broken out by highliner status. Black line and blue distributions show mean and distribution of posterior predictive number of sets. GAMs were fit using only data from before 2022.
FIGURA 23. Lances OBJ observados (puntos rojos) y predichos por el MAG bayesiano (línea negra y distribución color azul). Las tendencias se desglosan por estado de *highliner.* La línea negra y las distribuciones azules muestran el promedio y la distribución de la predicción posterior del número de lances. Los MAG se ajustaron solo con datos previos a 2022.

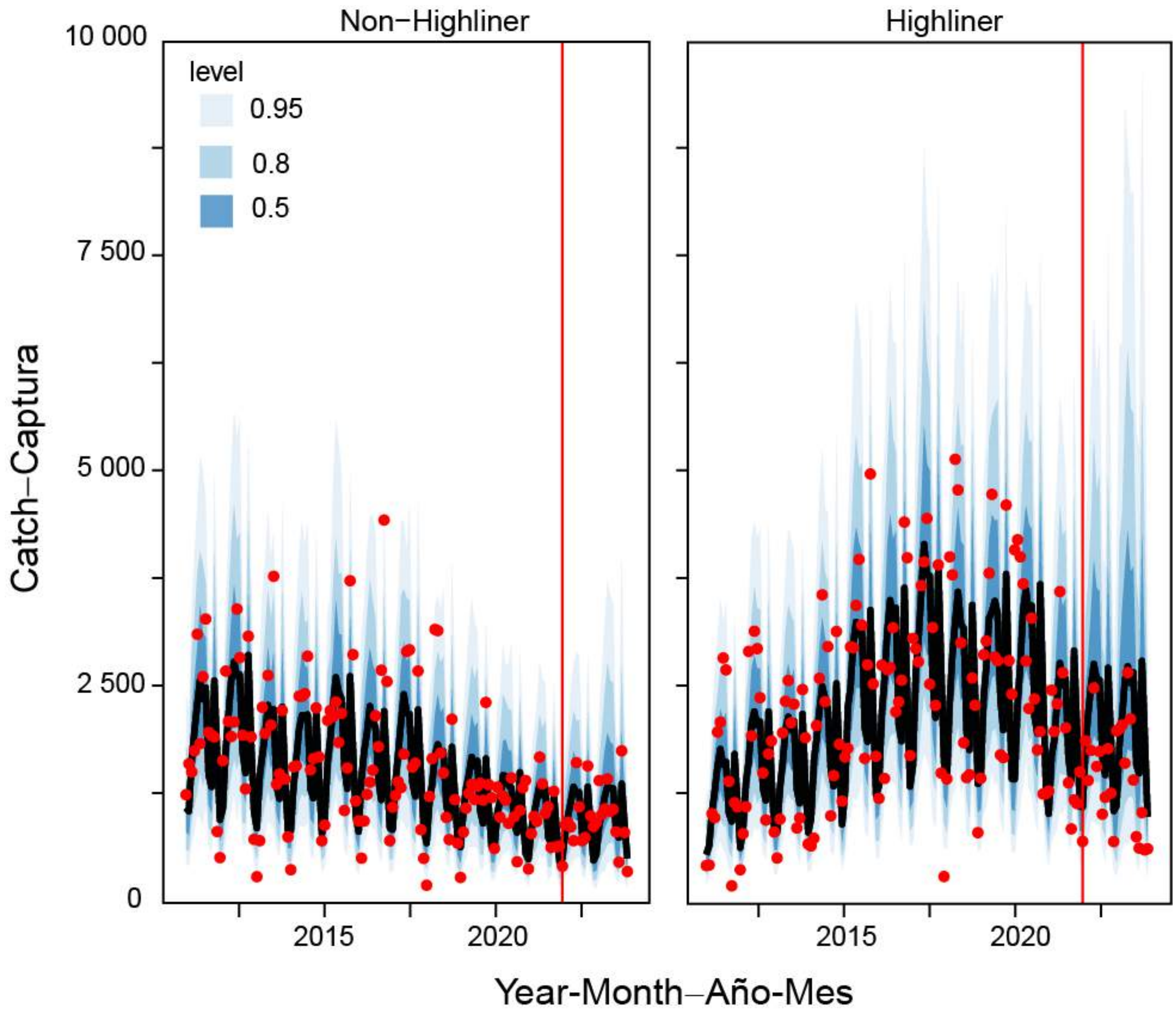

FIGURE 24. Observed (red points) and Bayesian GAM predicted (black line and blue distribution) BET catch from OBJ sets. Trends are broken out by highliner status. Black line and blue distributions show mean and distribution of posterior predictive BET catch. GAMs were fit using only data from before 2022.

FIGURA 24. Captura BET observada (puntos rojos) y predicha por el MAG bayesiano (línea negra y distribución color azul) de lances OBJ. Las tendencias se desglosan por estado de *highliner*. La línea negra y las distribuciones azules muestran el promedio y la distribución de la predicción posterior de la captura BET. Los MAG se ajustaron solo con datos previos a 2022.

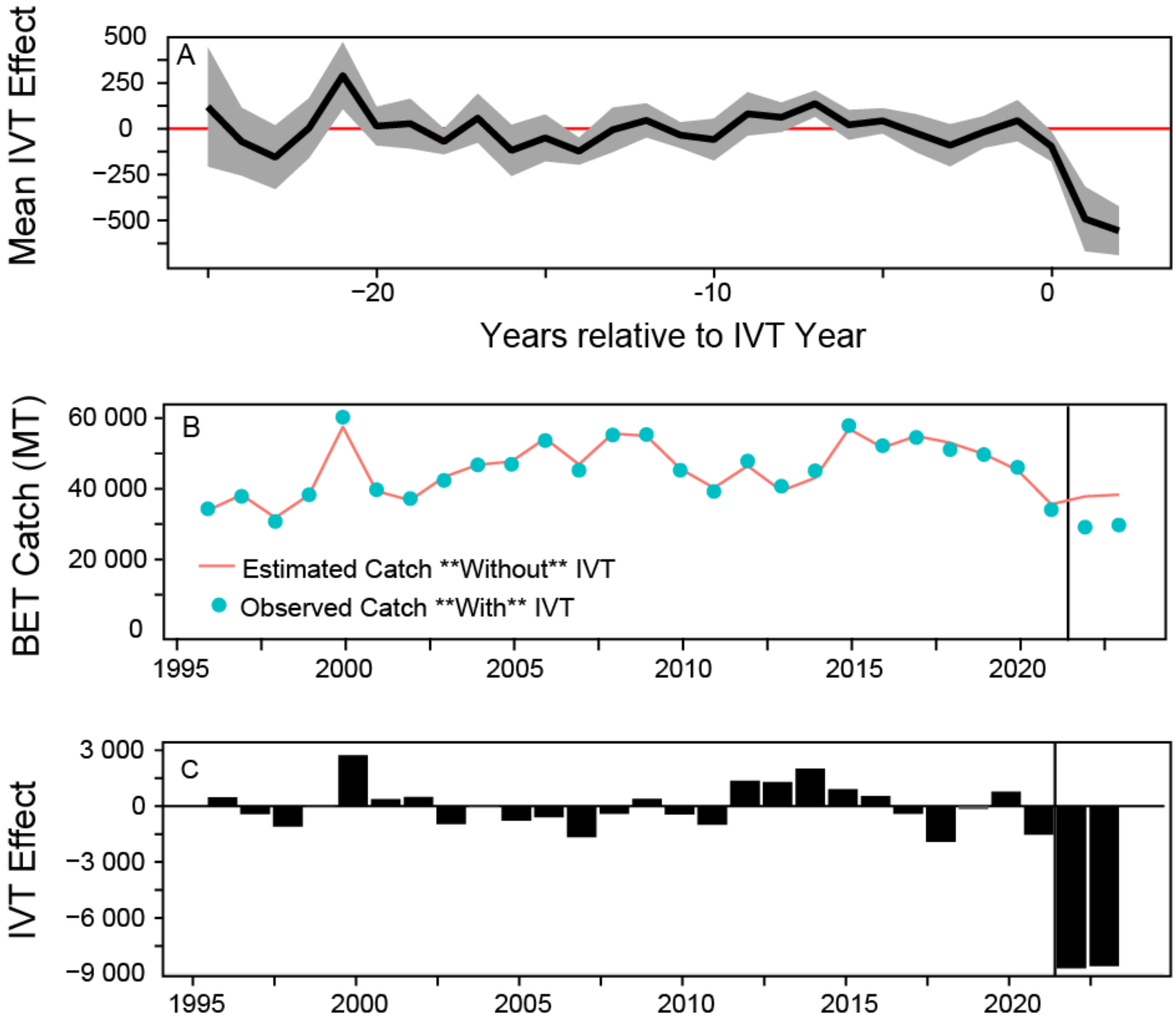

FIGURE 25. Impacts of IVT on BET catches estimated by synthetic control approach. A) Estimated effect of IVT on average highliner vessel as a function of number of years since IVT. Ribbon shows 95% confidence interval. B) Total observed with IVT and estimated without IVT class 6 purse-seine BET catches over time. C) Estimated difference in class 6 purse-seine BET catches over time. Vertical dashed lines show IVT year.

FIGURA 25. Impactos del UIB sobre las capturas de BET estimados por un enfoque de control sintético. A) Efecto estimado del UIB en un buque *highliner* promedio en función del número de años transcurridos desde el UIB. La franja muestra el intervalo de confianza del 95%. B) Total observado con el UIB y estimado sin el UIB de capturas de BET de buques cerqueros de clase 6 a lo largo del tiempo. C) Diferencia estimada en las capturas de BET de buques cerqueros de clase 6 a lo largo del tiempo Las líneas verticales discontinuas muestran el año del UIB.

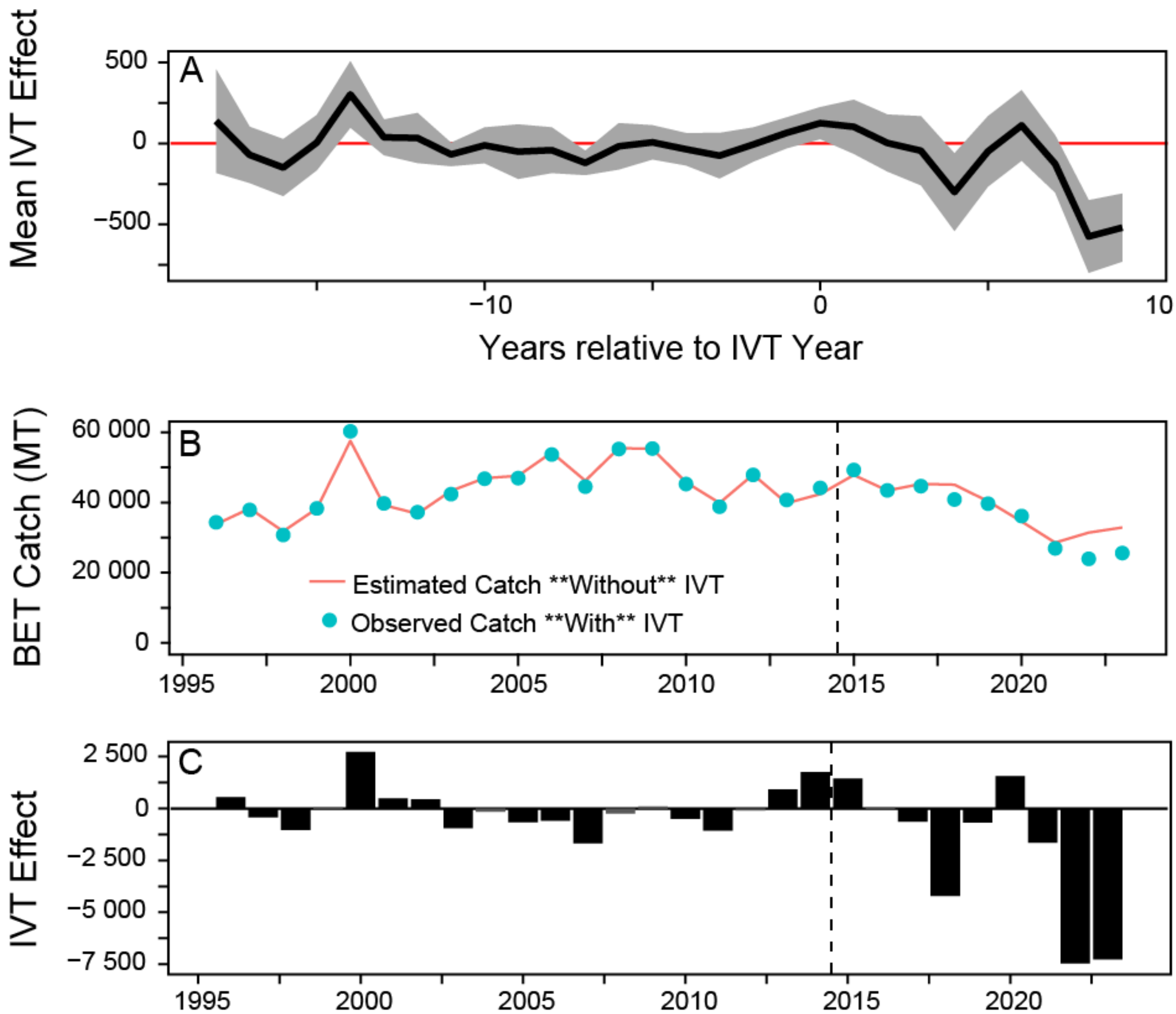

FIGURE 26. Placebo diagnostics of BET synthetic control. A) Estimated effect of IVT on average highliner vessel as a function of number of years since IVT. Ribbon shows 95% confidence interval. B) Total observed with IVT and estimated without IVT class 6 purse-seine BET catches over time. C) Estimated difference in class 6 purse-seine BET catches over time. Vertical dashed lines show placebo IVT year.

FIGURA 26. Diagnóstico placebo del control sintético de BET. A) Efecto estimado del UIB en un buque *highliner* promedio en función del número de años transcurridos desde el UIB. La franja muestra el intervalo de confianza del 95%. B) Total observado con el UIB y estimado sin el UIB de capturas de BET de buques cerqueros de clase 6 a lo largo del tiempo. C) Diferencia estimada en las capturas de BET de buques cerqueros de clase 6 a lo largo del tiempo Las líneas verticales discontinuas muestran el año placebo del UIB.

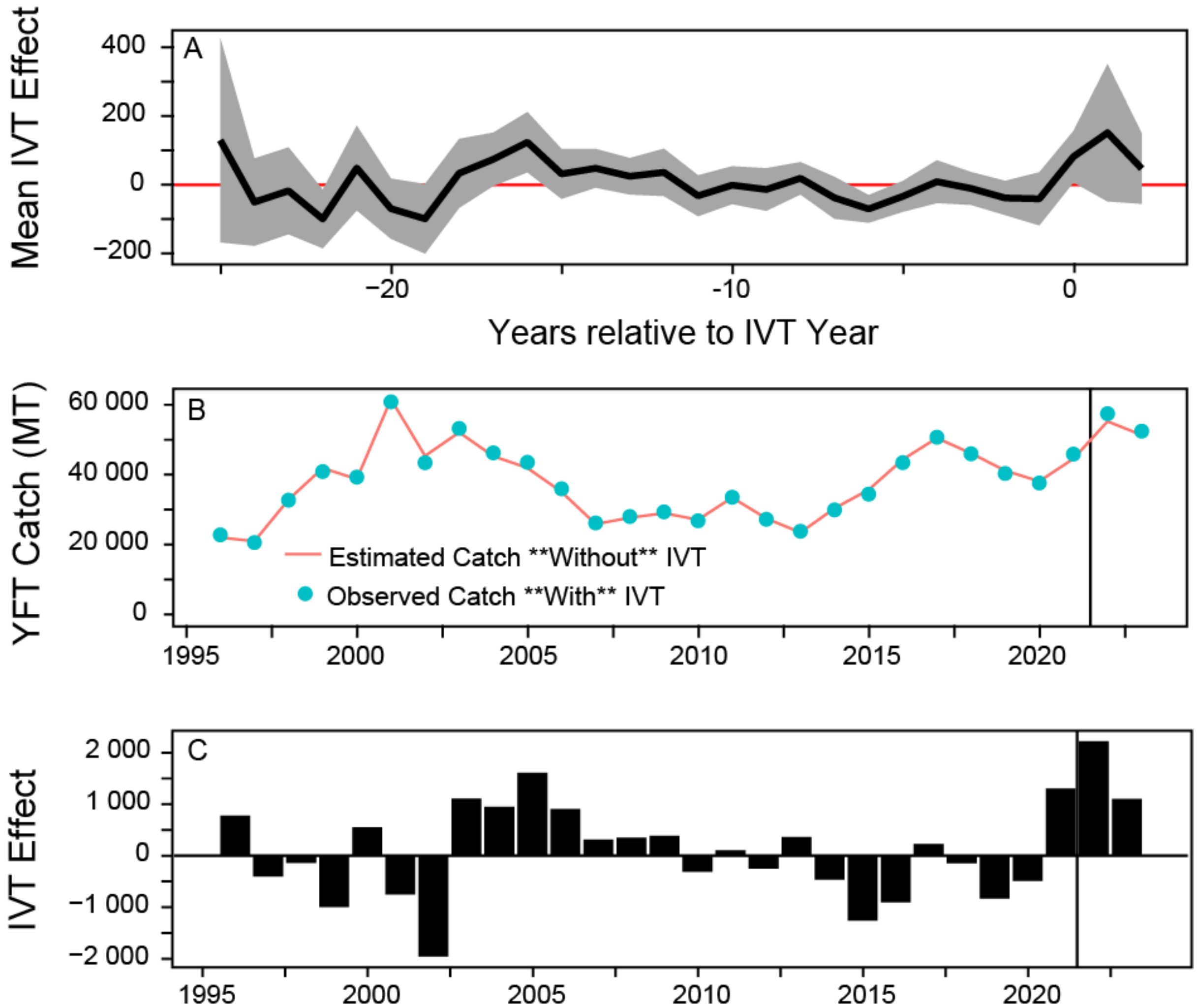

FIGURE 27. Impacts of IVT on YFT catches estimated by synthetic control approach A) Estimated effect of IVT on average highliner vessel as a function of number of years since IVT. Ribbon shows 95% confidence interval. B) Total observed with IVT and estimated without IVT class 6 purse-seine YFT catches over time. C) Estimated difference in class 6 purse-seine YFT catches over time. Vertical dashed lines show IVT year.

FIGURA 27. Impactos del UIB sobre las capturas de YFT estimados por un enfoque de control sintético. A) Efecto estimado del UIB en un buque *highliner* promedio en función del número de años transcurridos desde el UIB. La franja muestra el intervalo de confianza del 95%. B) Total observado con el UIB y estimado sin el UIB de capturas de YFT de buques cerqueros de clase 6 a lo largo del tiempo. C) Diferencia estimada en las capturas de YFT de buques cerqueros de clase 6 a lo largo del tiempo. Las líneas verticales discontinuas muestran el año del UIB.

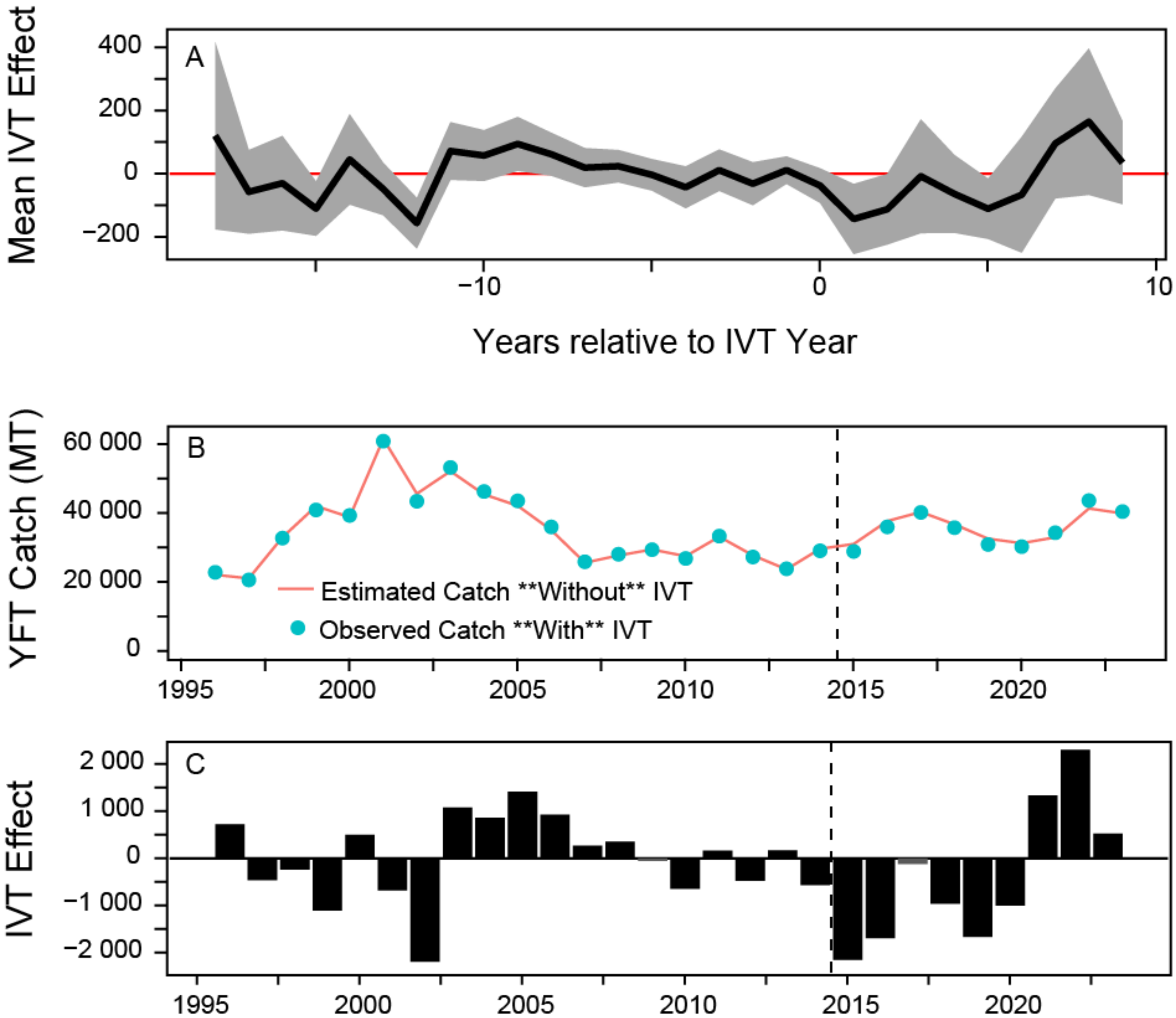

FIGURE 28. Placebo diagnostics of YFT synthetic control. A) Estimated effect of IVT on average highliner vessel as a function of number of years since IVT. Ribbon shows 95% confidence interval. B) Total observed with IVT and estimated without IVT class 6 purse-seine YFT catches over time. C) Estimated difference in class 6 purse-seine YFT catches over time. Vertical dashed lines show placebo IVT year.

FIGURA 28. Diagnóstico placebo del control sintético de YFT. A) Efecto estimado del UIB en un buque *highliner* promedio en función del número de años transcurridos desde el UIB. La franja muestra el intervalo de confianza del 95%. B) Total observado con el UIB y estimado sin el UIB de capturas de YFT de buques cerqueros de clase 6 a lo largo del tiempo. C) Diferencia estimada en las capturas de YFT de buques cerqueros de clase 6 a lo largo del tiempo. Las líneas verticales discontinuas muestran el año placebo del UIB.

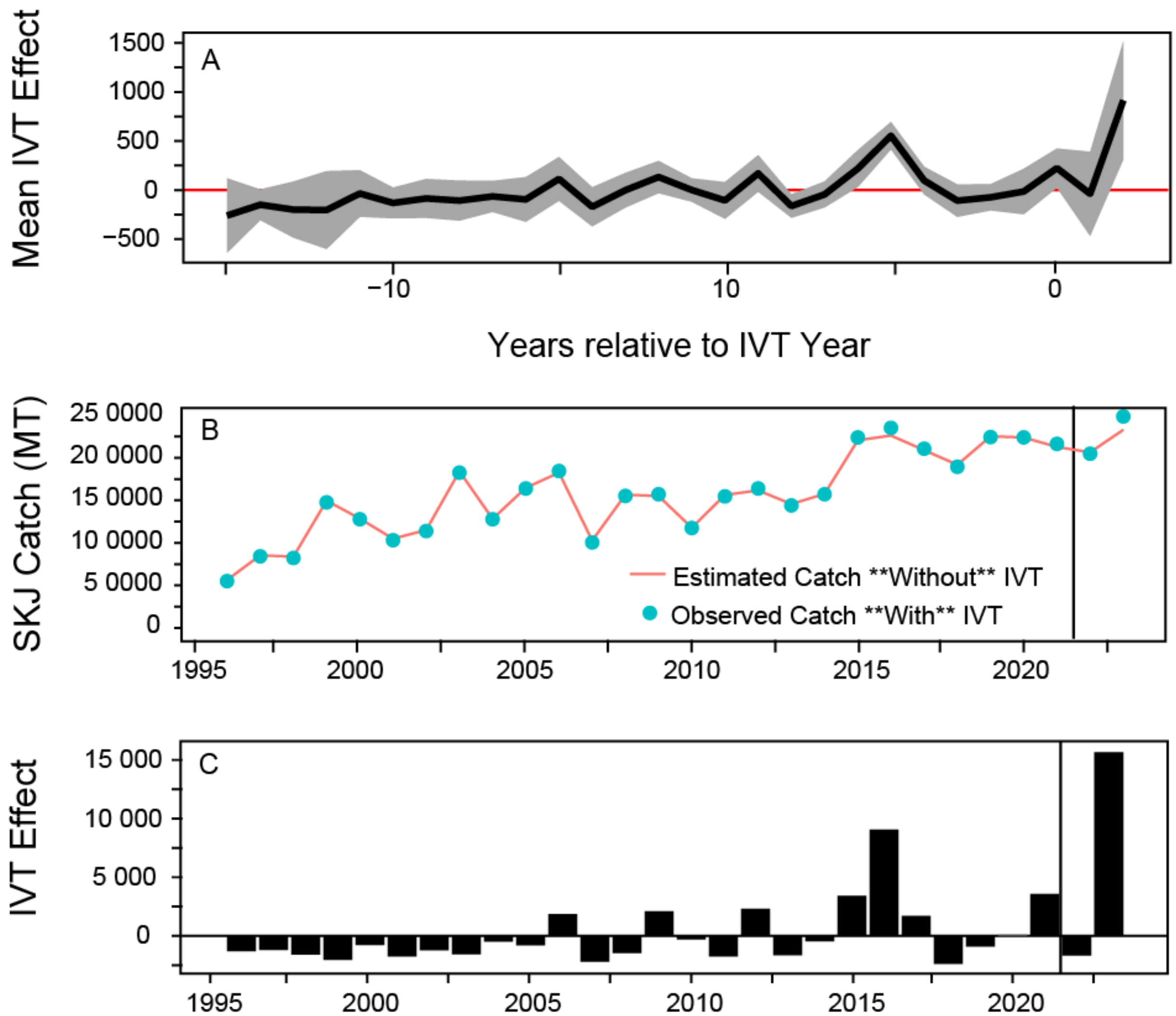

FIGURE 29. Impacts of IVT on SKJ catches estimated by synthetic control approach. A) Estimated effect of IVT on average highliner vessel as a function of number of years since IVT. Ribbon shows 95% confidence interval. B) Total observed with IVT and estimated without IVT class 6 purse-seine SKJ catches over time. C) Estimated difference in class 6 purse-seine SKJ catches over time. Vertical dashed lines show IVT year.

FIGURA 29. Impactos del UIB sobre las capturas de SKJ estimados por un enfoque de control sintético. A) Efecto estimado del UIB en un buque *highliner* promedio en función del número de años transcurridos desde el UIB. La franja muestra el intervalo de confianza del 95%. B) Total observado con el UIB y estimado sin el UIB de capturas de SKJ de buques cerqueros de clase 6 a lo largo del tiempo. C) Diferencia estimada en las capturas de SKJ de buques cerqueros de clase 6 a lo largo del tiempo. Las líneas verticales discontinuas muestran el año del UIB.

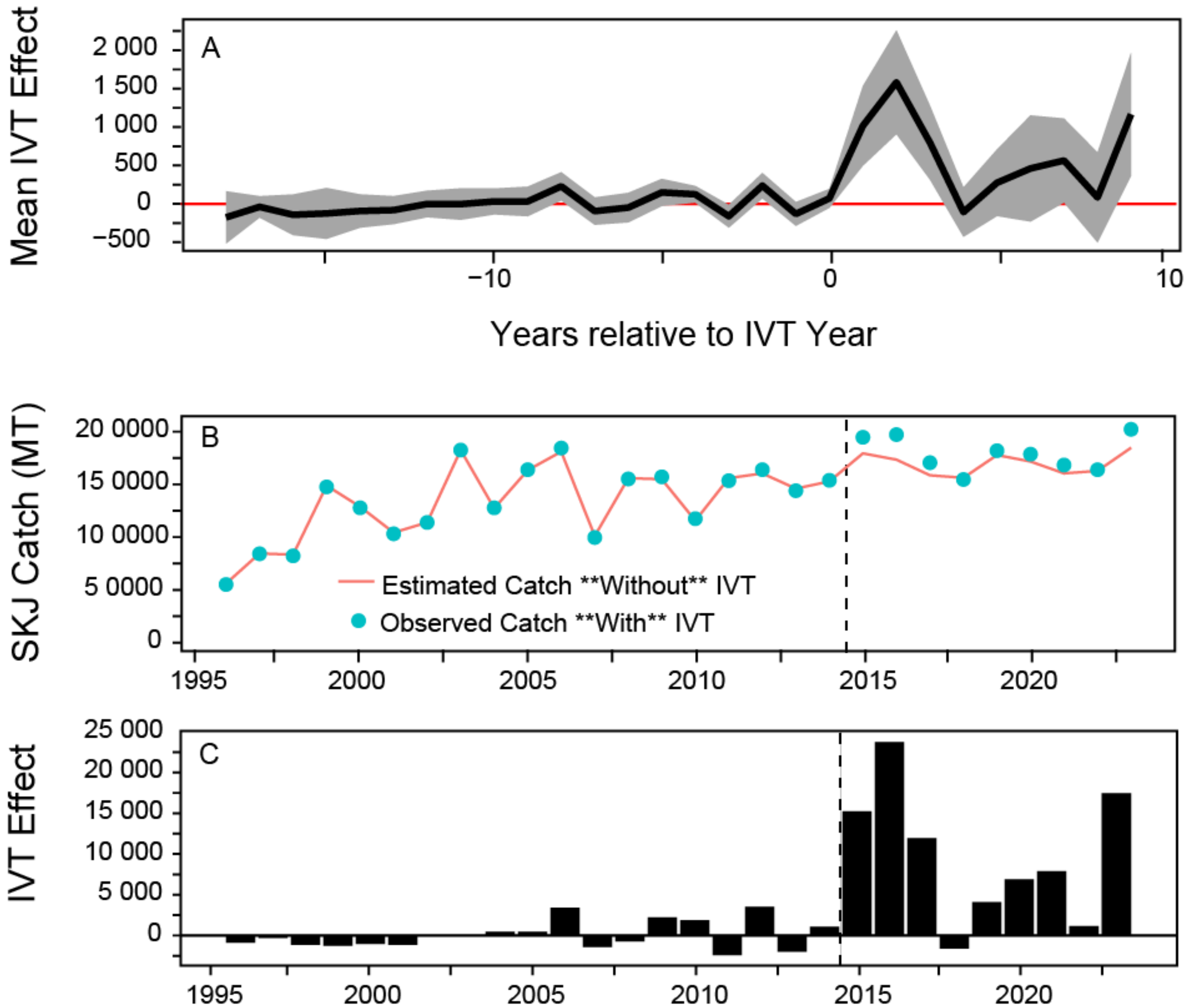

FIGURE 30. Placebo diagnostics of SKJ synthetic control. A) Estimated effect of IVT on average highliner vessel as a function of number of years since IVT. Ribbon shows 95% confidence interval. B) Total observed with IVT and estimated without IVT class 6 purse-seine SKJ catches over time. C) Estimated difference in class 6 purse-seine SKJ catches over time. Vertical dashed lines show placebo IVT year.

FIGURA 30. Diagnóstico placebo del control sintético de SKJ. A) Efecto estimado del UIB en un buque *highliner* promedio en función del número de años transcurridos desde el UIB. La franja muestra el intervalo de confianza del 95%. B) Total observado con el UIB y estimado sin el UIB de capturas de SKJ de buques cerqueros de clase 6 a lo largo del tiempo. C) Diferencia estimada en las capturas de SKJ de buques cerqueros de clase 6 a lo largo del tiempo. Las líneas verticales discontinuas muestran el año placebo del UIB.

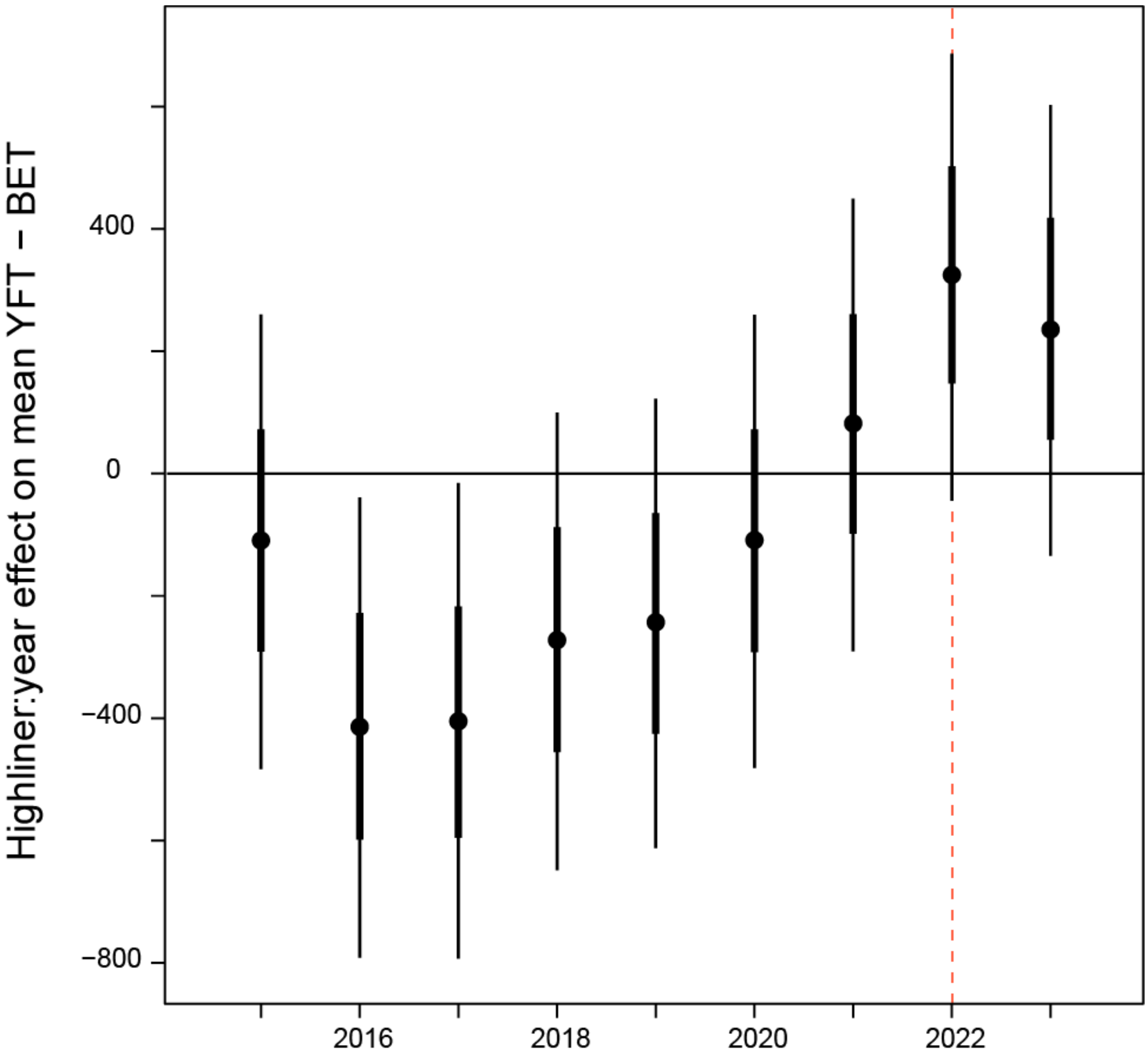

FIGURE 31. Estimated effect of the IVT on the average absolute difference in YFT catch to BET catch per year for class 6 purse seine vessels.
FIGURA 31. Efectos estimados del UIB sobre la diferencia absoluta promedio entre la captura de YFT y la captura de BET por año para los buques cerqueros de clase 6.