INTER-AMERICAN TROPICAL TUNA COMMISSION

1ST EXTERNAL REVIEW OF DATA USED OF STOCK ASSESSMENTS OF TROPICAL TUNA IN THE EASTERN PACIFIC OCEAN

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LONGLINE INDEX OF RELATIVE ABUNDANCE FOR BIGEYE TUNA IN THE EASTERN PACIFIC OCEAN

1. INTRODUCTION

Indices of relative abundance are a crucial input to stock assessment models as they directly inform the changes in population abundance over time (Francis 2011). Ideally, indices of abundance should be calculated using fishery-independent survey data, collected using the same fishing gear and operation across time to assure constant catchability and selectivity, and have a random or fixed sampling design in space. However, for most tuna species worldwide, including bigeye tuna in the EPO, survey data are not available. Therefore, indices of abundance are derived solely from fishery-dependent CPUE data. These data need to be standardized so that the abundance index is approximately proportional to population abundance (Maunder and Punt 2004). To achieve this, the standardization model needs to remove the part of the variation in the CPUE data that is not driven by changes in population abundance. Furthermore, the standardization model should impute fish abundance for unfished locations and use an area-weighting approach to compute the abundance index for the population for the entire spatial domain of the stock (Thorson *et al.* 2015).

We use a delta-generalized linear mixed spatiotemporal model VAST (Thorson and Barnett 2017) to standardize the Japanese longline CPUE data for bigeye tuna in the EPO. VAST is an open-source R package[1] that has recently gained increasing popularity in standardizing fishery-dependent CPUE data for tunas (Ducharme-Barth *et al.* 2022, Maunder *et al.* 2020b, Satoh *et al.* 2021, Xu *et al.* 2019). Fishery-dependent CPUE data, including those for tunas, are not randomly distributed in space. They tend to concentrate in areas with high fish abundance or easy-to-fish locations (a phenomenon referred to as preferential sampling) and do not cover the entire spatial domain of the stock within a quarter or even a year. VAST can estimate spatial and temporal correlations and use that information to impute fish abundance for unfished locations using neighboring CPUE data.

To standardize longline CPUE for the survey fleet, VAST separately models encounter probability and positive catch rate to account for zero-inflated catch rate observations. We specify VAST to use the logit and gamma link functions for the linear predictors of encounter probability and positive catch rate, respectively. Both linear predictors include an intercept (year-quarter) term, a time-invariant spatial term, a time-varying spatiotemporal term, a catchability covariate (using HBF as a 2-knot spline) term, and a vessel effects term. Of these five terms, the intercept term and the catchability covariate term are estimated as fixed effects and the other three terms are estimated as random effects. This VAST model treats the four quarters equally (no seasonal component), consistent with the "quarters-as-years"

[1] https://github.com/James-Thorson-NOAA/VAST

approach used in the stock assessment model. The coefficient of variation (CV) of the longline index of relative abundance is also estimated by VAST and is scaled to have a mean of 0.15 between 1979-2014 for use in the stock assessment.

Since the last benchmark assessment, “survey” fleets have been treated independently from the fisheries structure, total catch, and catch composition in the assessment models. In the EPO, there were no fishery-independent surveys of tuna abundance and size composition, with the term "survey" in the context of the assessment model refers to a fleet that has data (e.g., abundance index and size composition) but takes no catch (Methot and Wetzel 2013). For the “areas-as-fleets” approach on which the assessment is based, the abundance index and the associated composition data should reflect the conditions of the entire bigeye population in the EPO (Maunder *et al.* 2020a). Therefore, the abundance index for a survey fleet should be computed using an area-weighting approach for the entire spatial domain rather than for an area defined for the fishery. The composition data associated with the survey abundance index should be spatially weighted by catch rate and aggregated across the entire spatial domain as well.

In the assessment of bigeye tuna in the EPO, the survey fleet is based on fishery-dependent CPUE and length composition data collected by Japanese commercial longline vessels that persistently target bigeye tuna. Among all distant-water longline vessels operated in the EPO, Japanese longline vessels have the highest spatial coverage within the EPO and the longest history of high-quality logbook data, providing the information needed for the standardization of a reliable abundance index with a large contrast across time. In the exploratory assessment model, we revise the definition of longline survey fleet as well as the methodology used in the standardization of the abundance index and associated length compositions.

2. CHANGES IN THE LONGLINE INDEX SINCE THE LAST BENCHMARK ASSESSMENT

In the last benchmark assessment model, two longline survey fleets are defined based on the time of operation: ‘early’ (1979-1992) and ‘late’ (1995-2019). Catchability and selectivity are estimated separately for the two survey fleets and the coefficient of variation (CV) of the late index of abundance is fixed while that of the early index is estimated. The main reason for splitting the longline abundance index into two time periods is that gear configurations of Japanese longline vessels changed abruptly in 1993 and 1994. Specifically, both hooks-between-floats and mainline material, two key indicators of hooks’ depth distribution in the water column, changed rapidly in 1993-1994. As the depth distribution of bigeye tuna in the EPO is influenced by body size (Schaefer and Fuller 2010), these notable changes in gear configurations may lead to a temporal change in catchability and selectivity for the survey fleet.

The current good practices for CPUE modeling advise against splitting the abundance index by time into separate non-overlapping time blocks unless there is clear evidence against constant survey catchability and selectivity (Hoyle *et al. accepted*). Splitting the abundance index by time ignores a large amount of information in the CPUE data, particularly the continuous trend of population abundance over a long period. Hoyle *et al.* argue that if the assessment model is misspecified, splitting the abundance index can introduce bias as the model may not be able to reliably scale the split abundance indices. Thus, analysts should at least consider whether the estimated change in catchability at the split makes sense. Regarding this point, we revisit the survey definition in the exploratory assessment by checking the estimated change in catchability and selectivity at the split.

Indeed, the last benchmark assessment model estimates similar catchability and selectivity for the early and late survey fleets. The estimated catchability for the early period (1.58 ± 0.39) is slightly higher than that for the late period (1.34 ± 0.13). The selectivity curves estimated for the two time periods are also closely aligned (Figure 1). This result is contrary to expectations, as the catchability of the main target species (Japanese longline fishery in the EPO persistently targets bigeye tuna) is expected to increase over time due to continuous improvements in fishing technology and knowledge. This counterintuitive result suggests that the assessment model may be mis-specified and is unable to reliably scale the two abundance indices. Consequently, an analysis is conducted to evaluate the sensitivity of model results to the decision of whether to split the abundance index by time.

2.1. Change No.1: spatial domain

The first change implemented in the standardization methodology for the survey fleet is about the spatial domain on which the standardizations of the abundance index and the associated length frequencies are based. In the last benchmark assessment, the spatial domain is restricted to the "core" longline fishing ground, which includes only the 1° x 1° cells with at least 80 quarters of CPUE data between 1979 and 2019 (Figure 2). This was done to address the concern that the marked westward contraction of the Japanese longline fishing ground in the past decade may result in a biased index for those years. By fitting the CPUE standardization model to data collected only from the core fishing ground, the potential impact of biased spatial imputation of fish abundance for unfished locations on the accuracy of the standardized abundance index was reduced.

Findings in recent studies (Xu *et al. in prep*) suggest that restricting the CPUE standardization to the core fishing ground, where the depletion rate is relatively slow, likely leads to a hyper-stable abundance index for bigeye tuna in the EPO. In the past two decades, an obvious local depletion of the bigeye tuna population has been observed in the eastern EPO. Catch rates of bigeye in both longline (Xu *et al. in prep*) and OBJ (FAD-05 INF-D) fisheries have decreased pronouncedly faster in the tropical fishing ground east of 110°W than west of 110°W. During the same period, Japanese longline vessels gradually retreated from the eastern fishing ground, which is relatively data-poor and excluded from the core fishing ground (Figure 2). Thus, the abundance index standardized for bigeye in the less-depleted core fishing ground does not reflect the population trend at the EPO-wide level. It likely underestimates the rate at which the bigeye population in the EPO decreased over time. In this exploratory assessment, we broaden the definition of the core fishing ground to include the 1° x 1° cells with at least 20 quarters of CPUE data between 1979 and 2022, allowing the eastern EPO to be included in the spatial domain for the CPUE standardization (Figure 2). As expected, the abundance index estimated based on the new spatial domain decreases faster between 1979 and 2022 (Figure 3). However, this approach requires imputing many more spatiotemporal cells (see below).

2.2. Change No.2: temporal structure of spatiotemporal random effects

The second change we make in the standardization methodology for the survey fleet is the assumption on which the imputation of fish abundance for unfished locations is based. Given that the spatial domain extends beyond the previous core fishing ground to encompass locations with relatively sparse CPUE data, the abundance index for this exploratory assessment is subject to greater influence by imputed fish densities for unfished locations. As such, it is crucial to address potential biases associated with the imputation process, particularly in this case where fishery-dependent CPUE data is preferentially sampled. Most CPUE standardization models, including the one we use in this exploratory assessment, cannot explicitly account for preferential sampling in the imputation process. Ignoring preferential sampling in fishery-dependent CPUE data results in positive bias in imputed fish density for unfished locations. As the extent of unfished locations expands over time due to the depletion-induced contraction of the Japanese longline fishery, the positively biased imputation plays an increasingly more important role in the area-weighted abundance index, leading to a hyper-stable abundance index.

The spatiotemporal term, which describes how the spatial pattern of fish density changes over time, needs to be interpolated for each location and time. In the CPUE standardization model developed for the last benchmark assessment, the spatiotemporal term is assumed to be temporally independent but spatially correlated according to the Matérn function. Thus, the spatiotemporal terms for the unfished eastern EPO are interpolated solely based on data collected from the fished western EPO during the same year-quarter. This approach ignores the concurrence of local depletion and preferential sampling, potentially leading to positively biased imputations of bigeye density in the eastern EPO. To achieve more realistic imputations of bigeye density for the eastern EPO, we modify the assumption for the spatiotemporal terms to be correlated in both space and time. Specifically, the spatiotemporal terms are now assumed to follow a random-walk process in time to capture the directional change in the spatial distribution of bigeye abundance over time (the pronounced local depletion pattern). Under this assumption, the spatiotemporal terms for the unfished eastern EPO are interpolated based on data collected not only from the fished western EPO in the same year-quarter but also from the eastern EPO in adjacent fished years. The spatiotemporal dynamics of bigeye density predicted by the improved CPUE standardization model demonstrate the evolution of bigeye depletion in the EPO (Figure 4). A recent simulation study conducted by the staff (Xu *et al. in prep*) shows that this assumption leads to a less-biased abundance index for bigeye tuna in the EPO than the previous assumption. As expected, the abundance index estimated based on this assumption indicates a more pessimistic population trend than the abundance index estimated based on the previous assumption (Figure 3).

3. RECENT RESEARCH USING OPERATIONAL DATA

The operational longline CPUE dataset was provided by Japan to the IATTC staff in the summer of 2023 for a 5-week period of collaborative research on the standardization of the Japanese longline index of abundance for bigeye and yellowfin tunas in the EPO. This research was focused on two main topics: 1) the impact of using aggregated vs. operational CPUE data on the standardized index of relative abundance; and 2) the sensitivity of the standardized index to the specification of HBF as a catchability covariate.

3.1. Aggregated vs. operational data

We compare four indices of relative abundance to investigate the impact of using operational vs. aggregated Japanese longline CPUE data on the standardized longline index for bigeye tuna in the EPO. The four indices of abundance are standardized by four spatiotemporal models with a factorial design: identical spatiotemporal models except for the source of input CPUE data (aggregated vs. operational) and the link function for the positive catch rate (gamma vs. log). The aggregated data has been used to compute the index of relative abundance for bigeye tuna in the EPO since 2019. It includes catch and effort information aggregated from the operational dataset by 1° x 1° grid, year, month, vessel, and HBF.

The same filter is applied to the aggregated and operational Japanese longline CPUE data to remove the vessels and grids with very limited samples. Specifically, the filter removes the vessels with less than 40 quarters of available CPUE data and the grids with less than 20 quarters of available CPUE data between 1979-2022. After the filter is applied, the data frame of aggregated CPUE remains 302,564 rows from 224 unique vessels; the data frame of operational CPUE remains 760,537 rows from 226 unique vessels. The ratio of the two numbers of rows indicates that a vessel makes, on average, 2.5 sets within a 1° x 1° x month stratum.

According to the QQ plot, the gamma link is more appropriate than the log link for bigeye tuna regardless of which CPUE dataset is used (Figure 5). Model residuals appear to follow closely to the normal distribution only when the gamma link function is assumed in the spatiotemporal model for the positive catch rate. Moreover, the comparison of the QQ plot suggests that the spatiotemporal model fits noticeably better to the operational dataset than the aggregated dataset (Figure 5).

For the two standardized indices based on the gamma link function for the positive catch rate, we compare the ratio of the two to evaluate the impact of the data source on CPUE standardization. Overall, the two indices are very similar without a noticeable difference in the long-term trend (Figure 6). The relative difference between the two indices is generally within ±5% before 2005 and within ±10% after 2005. The increased difference between the two indices is likely due to the reduced sample size in the last two decades - the aggregation has a larger impact on the standardized index when the sample size is small. The CV of the two indices have very minor differences in both scale and trend (Figure 6). The reduced sample size in recent years has resulted in a rapid increase in the uncertainty associated with the index.

3.2. HBF as a catchability covariate

It is still unclear how HBF should be parameterized in the spatiotemporal model as a catchability covariate. HBF is currently parameterized as a 2-knot spline for both the encounter probability and positive catch rate in the spatiotemporal model (a 3-knot spline was explored initially but the spatiotemporal model did not converge). Data suggests that HBF increased persistently over time from 1979, including a rapid rise in 1993-1994 (Figure 7) due to the concurring change of mainline material. The density of the mainline material changed in 1993-1994 so did the interpretation of a given HBF with respect to catchability. The current spatiotemporal model, however, does not account for the adjustment of HBF caused by the change of mainline material.

There was a rapid change in the mainline material between 1993 and 1995, during which the type of mainline changed from predominantly type 2 to predominantly type 1 (Figure 8). This rapid change concurred with a rapid increase in HBF from a mean of 13 in 1993 to a mean of 16 in 1995. The target species of the fishery was unchanged (bigeye tuna) before and after that period, so the increase of HBF is likely used to compensate for the change in mainline material. It is hypothesized that the 3-unit increase in HBF is to compensate for the reduction in mainline weight. Accordingly, the effect of HBF as a catchability in the CPUE standardization model needs to be adjusted according to the type of mainline. We compare four CPUE standardization models to investigate the effect of adjusting HBF on the index of abundance for bigeye tuna. The first model (adjusted1) was adjusted by using the type of mainline information provided by the operational data. Specifically, the HBF associated with type 1 mainline is subtracted by 3 (Figure 9). The effect of adjusted HBF on encounter probability and positive catch rate is estimated by the spatiotemporal model to be dome-shaped and persistently positive, respectively (Figure 9). The second model (adjusted2) uses the year of operation as an approximation to adjust. Specifically, the HBF since 1995 is subtracted by 3 and the CPUE data in 1994 is removed because the mainline in 1994 is a mixture of the two types. The third model (unadjusted) includes HBF as a catchability covariate without any adjustment. The fourth model (ignored) does not include HBF as a catchability covariate. The comparison of standardized indices from the four models suggests that the index for bigeye tuna is not very sensitive to how HBF is specified in the spatiotemporal model (Figure 10). Only the index associated with ignoring HBF's effect on catchability is obviously different from the others.

3.3. Joint longline index of abudance

Due mainly to the increased uncertainty associated with the Japanese longline index of abundance for bigeye tuna in the EPO, it has been recommended to explore developing a joint longline index of abundance by basing the standardization on CPUE data from multiple CPCs. We briefly explore it by comparing the selectivity of the two currently most important longline fleets for bigeye tuna in the EPO: Japan and Korea. The comparison shows that the two longline fleets have apparent differences in fishery selectivity within the same spatiotemporal windows. Therefore, more research is needed to develop a length-specific spatiotemporal model where the different selectivity patterns between Japan and Korea can be accounted for in the standardization of the joint longline index of abundance.

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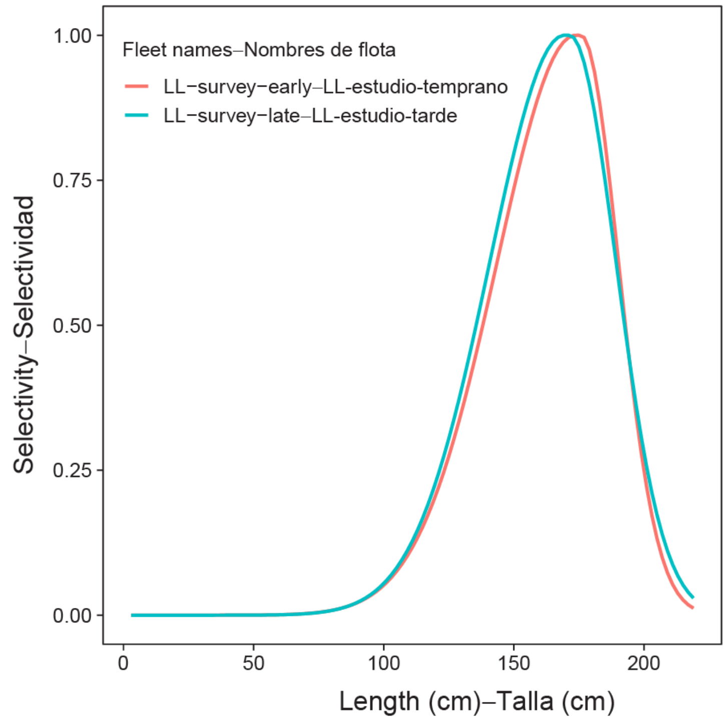

FIGURE 1. Estimated selectivity curves for the early and late longline survey fleets in the last benchmark assessment model.

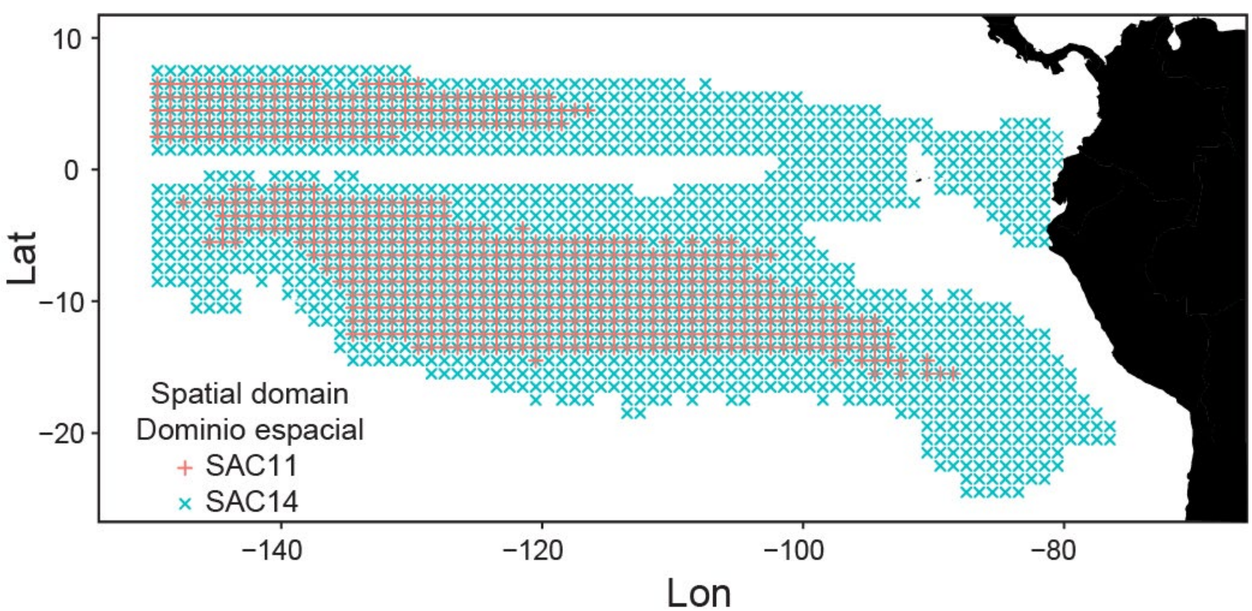

FIGURE 2. Comparison of the spatial domain on which the CPUE standardization for the last benchmark assessment (SAC11) and this exploratory assessment (SAC14) is based.

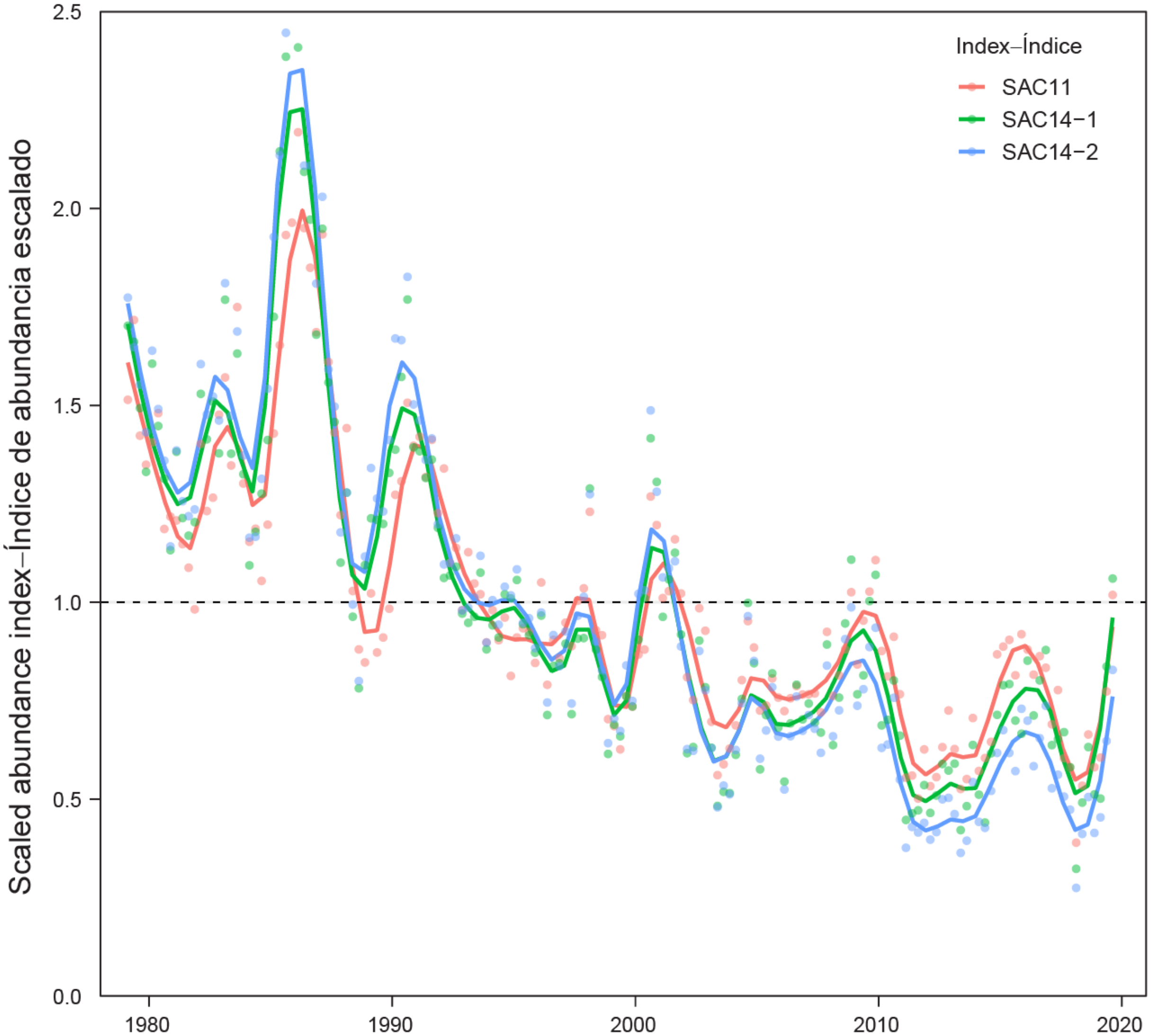

FIGURE 3. Comparison of the longline abundance indices standardized for bigeye tuna in the EPO. SAC11 represents the abundance index estimated for the last benchmark assessment; SAC14-1 represents the abundance index estimated for this exploratory assessment based on the assumption that spatiotemporal terms are independent in time but correlated in space; and SAC14-2 represents the abundance index estimated for this exploratory assessment based on the assumption that spatiotemporal terms are correlated in space and follow a random-walk process in time. The color dots and lines are the quarterly estimates and smoothed values, respectively. All three indices are scaled to have a mean of 1 for easy comparison.

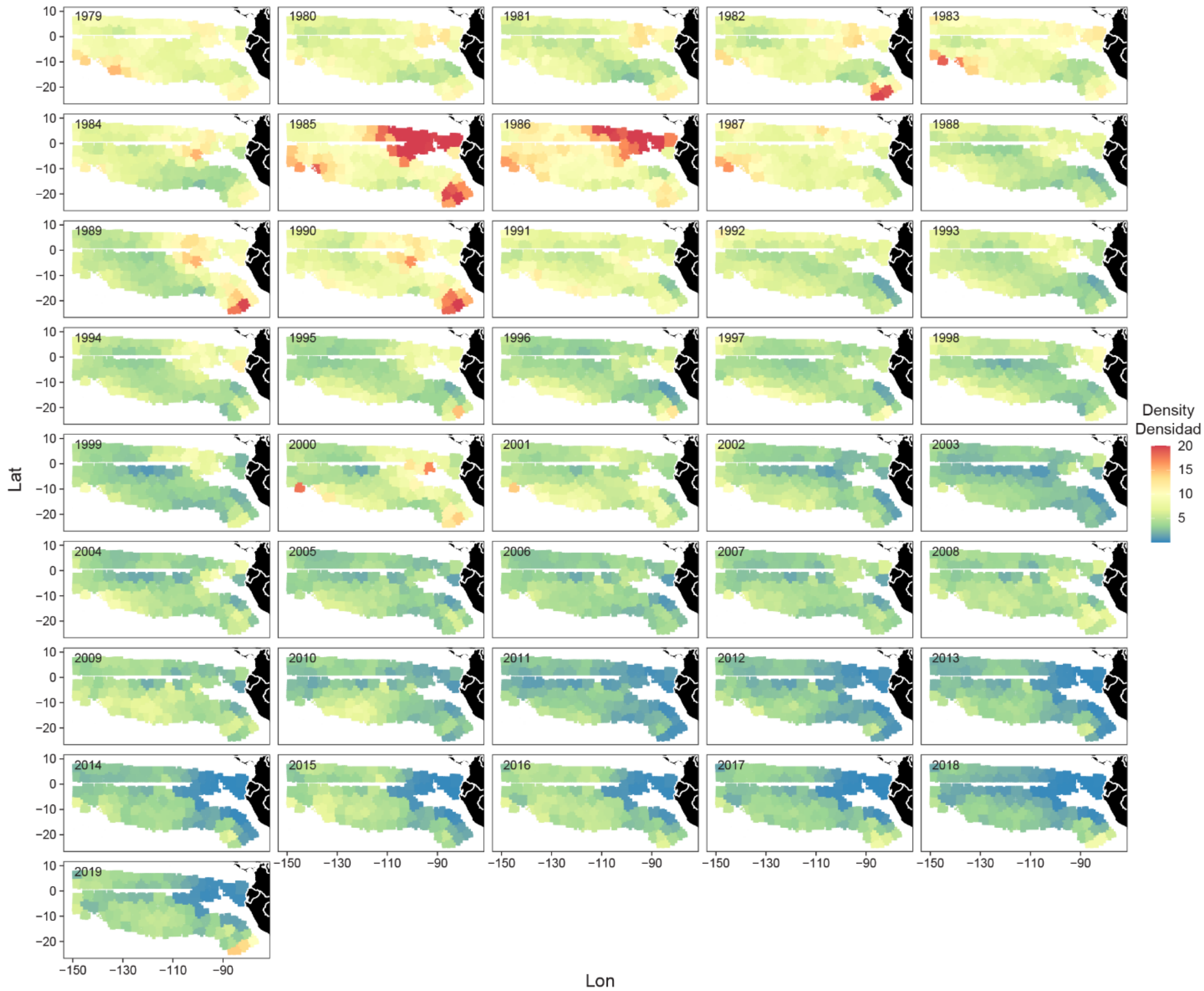

FIGURE 4. Maps of predicted bigeye density by year from the CPUE standardization model developed based on Japanese longline data.

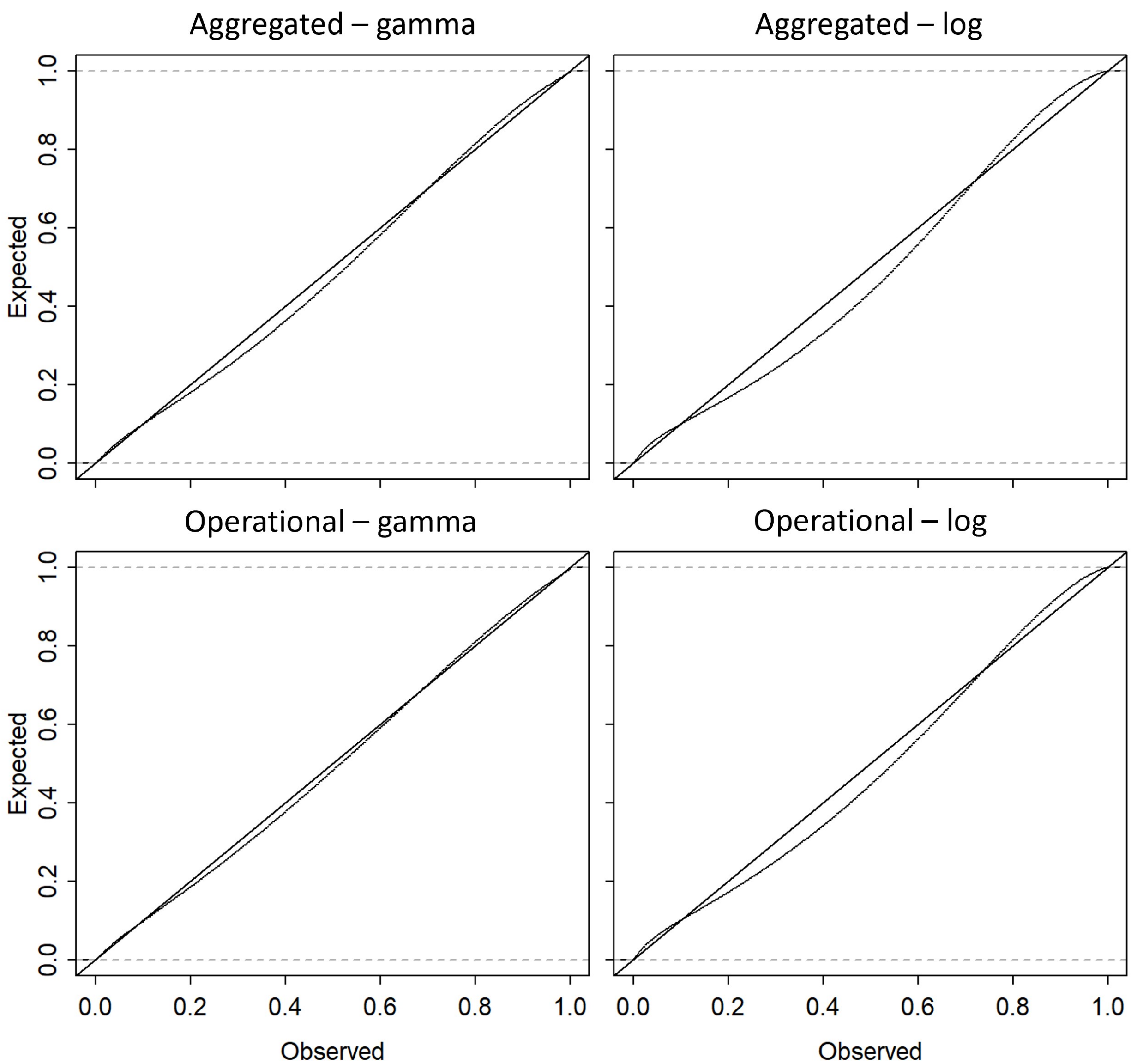

FIGURE 5. Comparison of the QQ plot for the four spatiotemporal models that are built to standardize the longline index of relative abundance for bigeye tuna in the EPO.

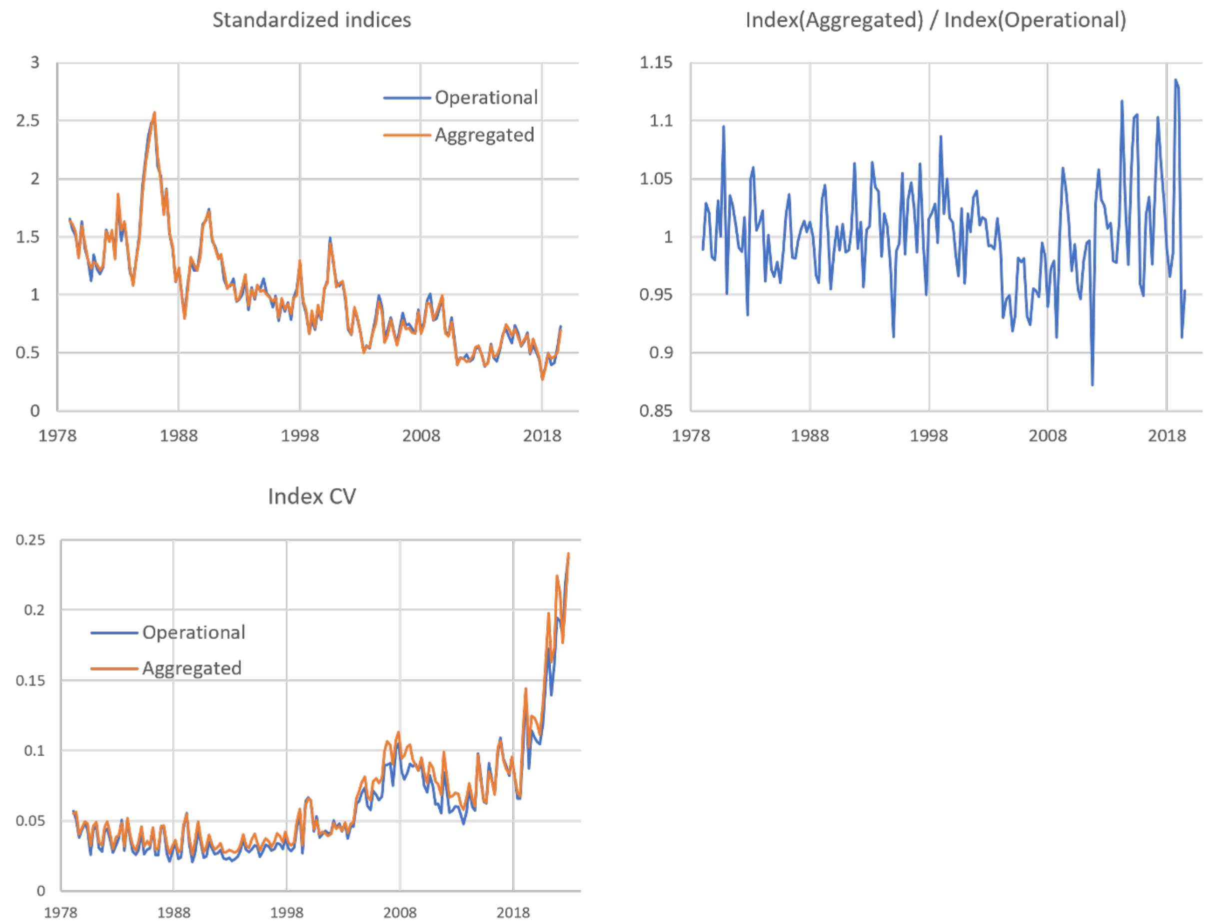

FIGURE 6. The longline indices of abundance estimated by the spatiotemporal models that are fit to the aggregated or operational dataset (top left); the ratio of the two indices (top right); and the coefficient of variation of the two indices.

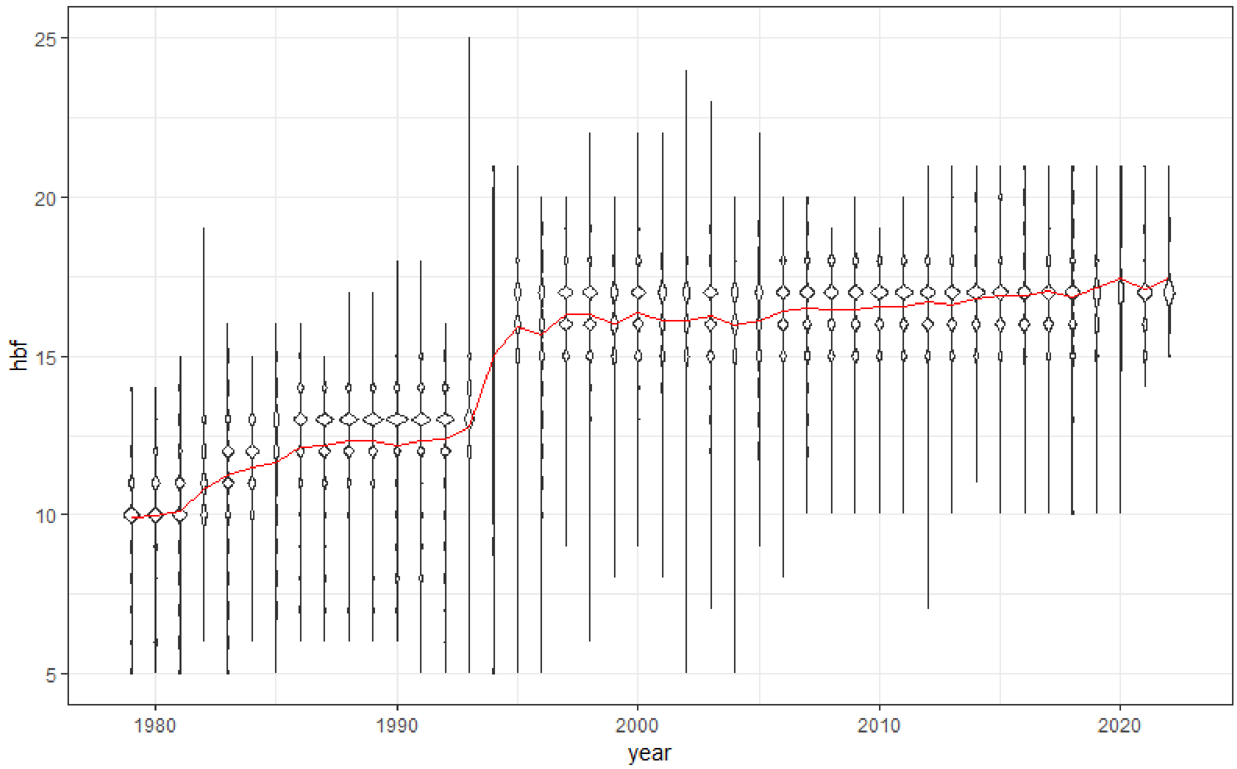

FIGURE 7. The distribution of HBF by year. The read line shows the trend of effort-weighted mean HBF in each year.

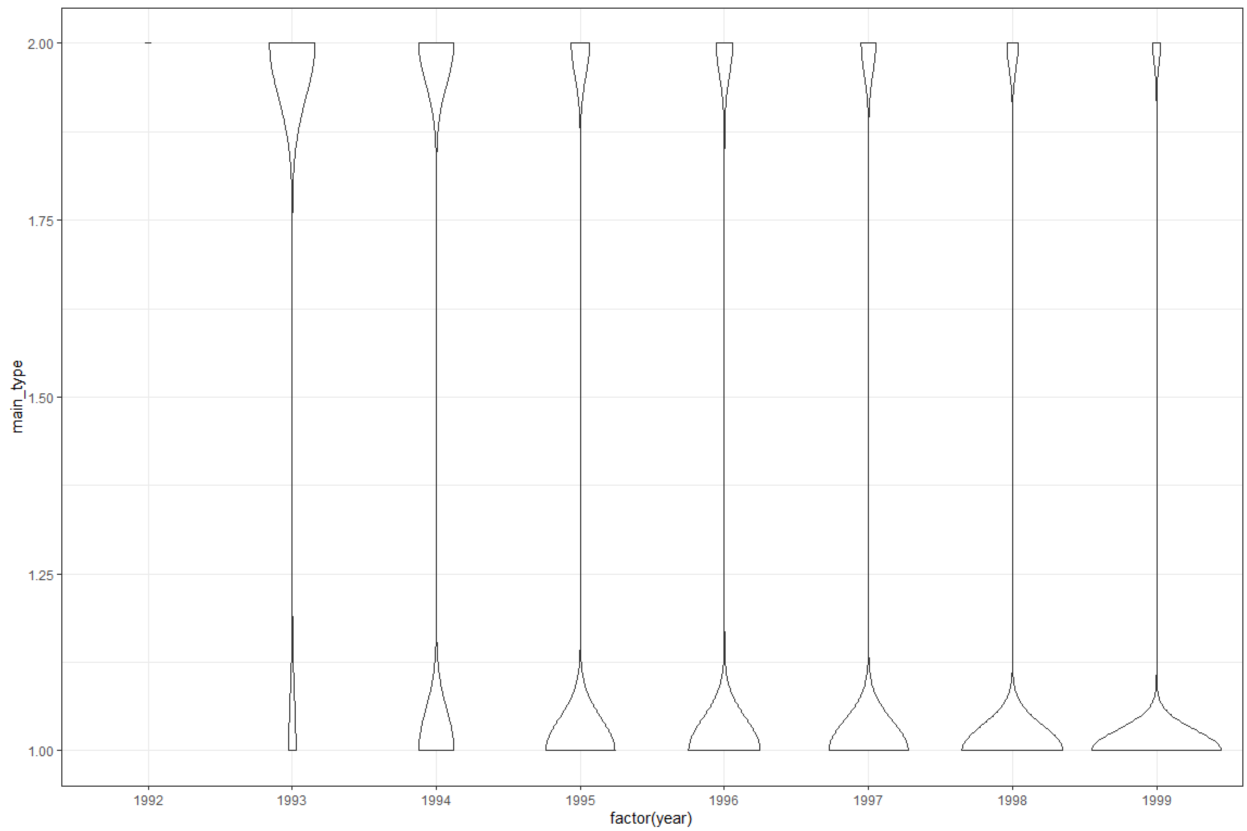

FIGURE 8. The distribution of mainline material of the Japanese longline fishery in the EPO.

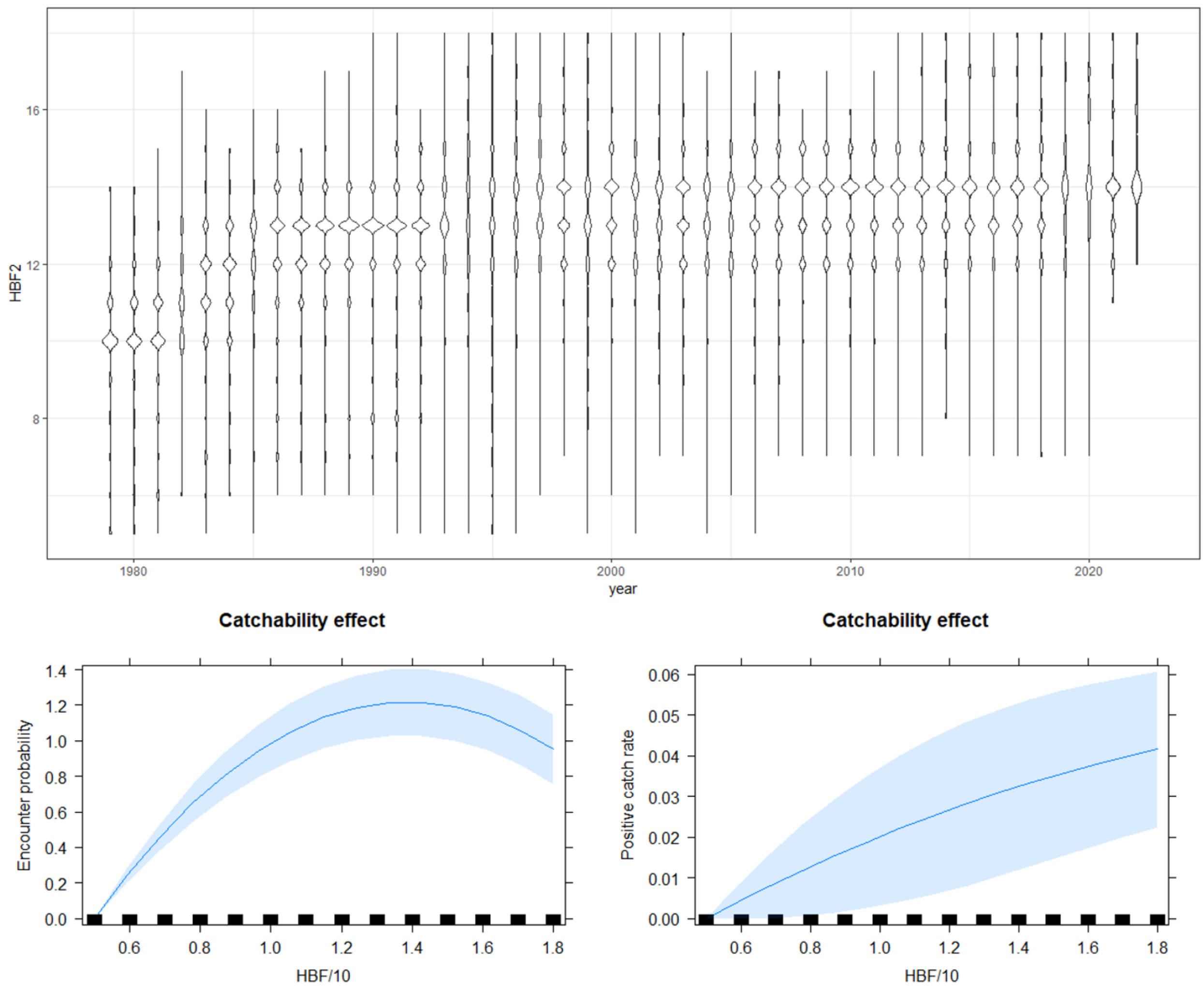

FIGURE 9. Effects of mainline type adjusted HBF (top) on the encounter probability (bottom left) and positive catch rate (bottom right) for bigeye tuna in the EPO. The effects are estimated by model adjusted1.

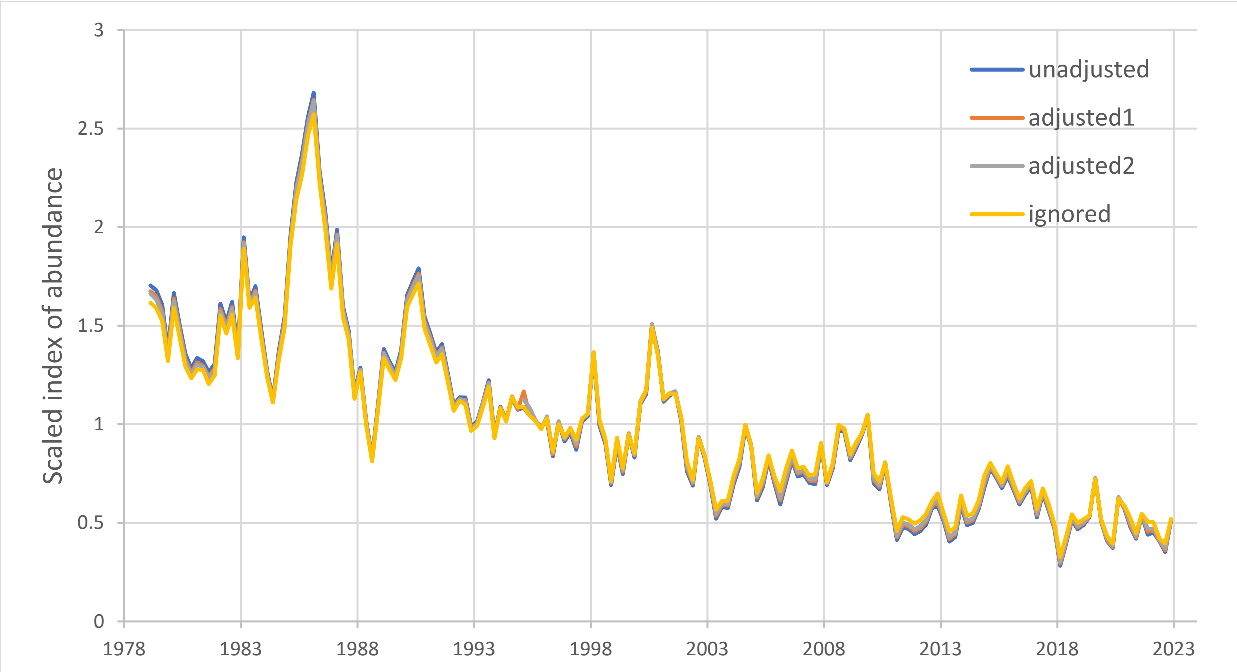

FIGURE 10. Comparison of the indices of relative abundance from four spatiotemporal models with different speciation of HBF as a catchability covariate.