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EXPLORATION OF JOINT LONGLINE INDICES OF ABUNDANCE FOR BIGEYE AND YELLOWFIN TUNA IN THE EASTERN PACIFIC OCEAN

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SUMMARY

This document aims to develop joint longline indices of abundance for bigeye and yellowfin tuna in the EPO, with the goal of enhancing the accuracy and precision of the longline indices for future stock assessments. In addition to catch and effort data from Japan, catch and effort data were compiled from China, Chinese Taipei, and Korea to construct joint abundance indices for both species. An initial step involved a comprehensive analysis and comparison of data from the four CPCs to identify data subsets suitable for CPUE standardization for bigeye and yellowfin tuna in the EPO. Subsequently, we compared CPC-specific indices of abundance for each species separately to evaluate the consistency of index temporal variations across CPCs. Based on this comparison, we selected the group of CPCs to be included in the joint longline index of abundance for each species.

The selected joint longline index of abundance for yellowfin is based on CPUE data from Japan and Korea. This joint index is consistent with the Japanese index for yellowfin and has substantially lower uncertainty, indicating the joint index has higher precision. The selected joint longline index of abundance for bigeye is also based on CPUE data from Japan and Korea. This joint index shows notable differences from the Japanese index for bigeye. Analyses conducted in this study suggest that these differences are primarily due to divergent catchability trends for bigeye between the two fleets. As this document focuses on developing a joint longline index of abundance for use in the benchmark assessment of yellowfin tuna, the joint index of abundance for bigeye is considered preliminary and requires further investigation. Future improvements to the joint indices of abundance for both yellowfin and bigeye will also focus on incorporating CPUE data from China and Chinese Taipei. Preliminary analyses in this study suggest that index temporal variations from these two fleets may not be fully consistent with those from Japan and Korea. Further work is needed to better understand the sources of this inconsistency and evaluate whether CPUE data from these two fleets should also be incorporated into the joint indices.

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).

Since the last benchmark assessment, “survey” fleets have been treated independently from fishery 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 referring 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 previous stock assessments of bigeye and yellowfin tuna in the EPO, the longline index fleet was based on fishery-dependent CPUE and length composition data collected by Japanese commercial longline vessels that consistently target bigeye tuna. Among all distant-water longline fleets operating in the EPO, the Japanese fleet offers the most extensive spatial coverage and the longest time series of high-quality logbook data. These characteristics make it uniquely valuable for developing a reliable standardized index of abundance with a large contrast across time.

Our current approach to CPUE standardization for bigeye tuna and yellowfin tuna in the EPO involves the utilization of a spatiotemporal delta-generalized linear mixed model (GLMM). This type of model has gained prominence in recent years for standardizing fishery-dependent CPUE data, including for highly migratory species (Ducharme-Barth et al. 2022; Xu et al. 2019). Spatiotemporal GLMMs can account for time-area interaction by including a spatiotemporal term to both encounter probability and positive catch rate. In contrast to the traditional GLM, the spatiotemporal GLMMs explicitly consider spatial and temporal autocorrelation in spatial and spatiotemporal terms. An additional advantage of spatiotemporal GLMM is its capacity to impute fish abundance in unfished areas based on spatial and temporal autocorrelation. Moreover, it can compute an index of relative abundance that is area-weighted over the entire spatial domain of the population of interest. Specifically, we used the Vector Autoregressive Spatio-Temporal Model (VAST; Thorson and Barnett 2017) as the spatiotemporal GLMM to standardize the longline CPUE data for bigeye tuna in the EPO. VAST has been demonstrated to perform well in standardizing fishery-dependent CPUE data for highly migratory species based on various simulation studies (Ducharme-Barth et al. 2022; Grüss et al. 2019).

Despite the application of more advanced spatiotemporal GLMM, the standardization of longline CPUE data for bigeye tuna in the EPO remains notably challenging. In the tropical EPO, bigeye tuna has been the main target species of the Japanese longline fishery since the 1970s, driven by its high commercial value in the global sashimi market (Matsumoto 2008). The Japanese longline fishery, upon which the CPUE standardization relies, historically operated extensively across the tropical EPO until about 2000. Since then, it has gradually withdrawn from the eastern part of the tropical EPO, presenting a systematic large-scale contraction of the fishing ground. This significant contraction necessitates the imputation of fish abundance by the spatiotemporal model for a pronounced portion of the tropical EPO. Although the spatiotemporal model can perform imputation by using estimated spatial autocorrelation patterns, this process is susceptible to substantial bias due to a lack of neighboring data to inform the imputation for the large unfished area in the east. Adding to the complexity, the contraction of the fishing ground likely results from depletion-driven preferential sampling, a phenomenon the spatiotemporal GLMM cannot explicitly account for in the imputation of fish abundance. Both the CPUE trends from the longline and purse-seine fishery, catching respectively large and small bigeye, exhibit a more rapid decrease in the eastern than the western tropical EPO. The higher depletion rate of the target species (i.e., bigeye tuna) can explain why the Japanese longline fishery gradually moved out of the eastern side of the tropical EPO since 2000. Ignoring this preferential sampling process can lead the spatiotemporal model to overestimate fish abundance in unfished areas (Conn et al. 2017; Pennino et al. 2019).

This document aims to develop joint longline indices of abundance for bigeye and yellowfin tuna in the EPO, with the goal of enhancing the accuracy and precision of the longline indices for future stock assessments. In addition to catch and effort data from Japan, catch and effort data were compiled from China, Chinese Taipei, and Korea to construct joint abundance indices for both species. An initial step involved a comprehensive analysis and comparison of data from the four CPCs to identify data subsets suitable for CPUE standardization for bigeye and yellowfin tuna in the EPO. Subsequently, we compared CPC-specific indices of abundance for each species independently to evaluate the consistency of index trends across CPCs. Based on this comparison, we selected the group of CPCs to be included in the joint index of abundance for each species.

2. DATA

2.1. Comparison across Asian longline CPCs

2.1.1. Japan

The operational-level logbook data for the Japanese longline fishery have been recorded since 1952, providing a long-term dataset. Over this period, the logbook format has been updated seven times at irregular intervals, with new data fields added each time. For example, before 1993, fishing locations were recorded at a 1°×1° resolution. However, the 1994 format update introduced a minute field, enabling higher-resolution data. Details regarding these logbook format changes can be found in the previous workshop report.

The Japanese longline fishery rapidly expanded its fishing grounds after the abolition of the MacArthur Line in 1952, reaching the coast of Central America by 1960 (Suzuki 1988). The fishing area continued to expand, and by 1965, it had reached its widest geographical extent, with the period up to around 1970 being the peak of geographical expansion. Initially, yellowfin tuna and albacore were targeted mainly for canned and processed products. However, from the mid-1970s, increasing demand for sashimi and improvements in freezing technology led to a shift in the primary target species to bigeye tuna. Since 2000, fishing activity along the coasts of North and South America has declined, and the current main fishing grounds are concentrated within 15 degrees north and south of the equator in the EPO.

Before the mid-1970s, Japanese longliners operated at relatively shallow depths (25–170 m) by maintaining tension on the mainline and using a long distance between floats relative to the mainline length, typically using 4–6 HBF, targeting yellowfin and albacore tuna (SAKAGAWA et al. 1987). In the 1970s, deep-set longlines were developed, using 10 or more HBF, reaching depths of 25–300 m or deeper (Suzuki et al. 1978). This method remains widely used by Japanese longliners targeting bigeye tuna.

2.1.2. China

Since 2008, the Chinese government has issued relevant notices to standardize the reporting of fishing logbooks, ensuring compliance with the data submission and reporting requirements of regional fisheries management organizations and participation in analytical work. At present, the reporting rate of fishing logbooks among China's distant-water fishing enterprises has reached 100% with continuous improvements in data quality over the years. Building on this foundation, pilot programs for electronic fishing logbooks are being actively promoted to enhance the efficiency of data submission. The Secretariat of IATTC and Shanghai Ocean University have reached a consensus on collaborating to analyze longline fisheries' catch rates using Chinese fishing logbook data. In this context, China has submitted a portion of high-quality fishing logbook data for the EPO from 2015 to 2023. However, due to data quality issues, only a limited amount of data was available for 2017.

China's entry into fishing operations in the EPO occurred relatively late, with the Chinese tuna longline fleet commencing operations in the region since 2001. There are over 20 tuna longline vessels that operate seasonally in the EPO. In the same year, China began reporting tuna catch data to IATTC. Since 2010, IATTC has imposed a quota of 2,507 metric tons on China's bigeye tuna catch, thereby constraining the development of China's bigeye tuna fishery in the EPO. Since 2012, the number of Chinese longline vessels that target primarily albacore tuna in the EPO has increased rapidly.

The histogram of Hooks between Floats (HBF) for Chinese vessels in the Eastern Pacific Ocean (EPO) exhibits a strong bimodal pattern, reflecting distinct fishing strategies employed by Chinese fleets. A clustering analysis based on species compositions (bigeye, yellowfin, albacore, and swordfish) revealed three main groups of Chinese vessels operating in the EPO: bigeye-targeting vessels (HBF < 20), albacore-targeting vessels (HBF >= 20), and yellowfin-targeting vessels. These groups exhibit relatively homogeneous spatial distributions of HBF.

2.1.3. Korea

The Korean distant-water longline tuna fishery has operated in the Pacific Ocean since 1958. The data reporting and management of the Korean distant-water longline fishery are legally based on the Distant Water Fisheries Development Act. Until November 2012, fishers used paper logbooks to record their fishing information and submitted the logbooks within 30 (home-based) or 60 (foreign-based) days after their operations were completed. During that time, it was difficult to achieve a 100% data coverage. However, in December 2012, the government strengthened and revised the Act to require fishers to report data monthly using an electronic logbook format (e.g., Excel), and it was possible to achieve 100% coverage thereafter. In September 2015, Korea developed and changed the Electronic Reporting System. Since then, fishers have reported their fishing information daily, which is reviewed by the National Institute of Fisheries Science (NIFS) in real time.

The Korean longline tuna fishery in the EPO operated mainly in the tropical area between 20° N and 20°S. Before the 1990s, the Korean longline tuna fishery operated in temperate as well as tropical waters, primarily catching bigeye tuna, yellowfin tuna, and albacore tuna. After that, the Korean longline tuna fishery has concentrated in tropical regions, mainly targeting bigeye and yellowfin tuna. Furthermore, over the past five years, there has been a trend of increasing catches in the EPO where bigeye tuna are the main species caught. Before the mid-1980s, the Korean longline tuna fishery operated at relatively shallow depths. Thereafter, the number of HBF showed an increasing trend, and recently it has been maintained at a consistent level.

2.1.4. Chinese Taipei

The Taiwanese tuna longline fishery in the Pacific Ocean began in the early 1960s, primarily operating in the southern and western-central regions to target albacore. There was little fishing activity in the EPO until the mid-1980s when operations began in the southern EPO. Shortly thereafter, some vessels expanded into the northern EPO, where high catch rates of the northern stock of albacore were recorded.

In the late 1990s, fishing efforts gradually shifted toward the tropical regions of the EPO, with increased targeting of bigeye and yellowfin tuna. Between 1999 and 2001, a marked change was observed in gear configuration, particularly in the HBF, indicating a strategic shift toward deeper longline sets aimed at bigeye tuna. This change in fishing strategy resulted in a notable decrease in the proportion of albacore and a corresponding increase in the proportion of bigeye tuna in the species composition of the catch.

In accordance with regulations, the use of electronic logbooks (E-logbooks) has been mandatory in Taiwan since 2017. As a result, longline vessel data have become more complete from that year onward.

2.2. Vessel classification

It is important to emphasize that the catch and effort data presented in this document are incomplete and are intended solely to standardize CPUE for bigeye and yellowfin in the EPO. One CPC excluded a small portion of its logbook data due to issues such as problematic location and catch recordings. We excluded the portion of another CPC’s logbook data corresponding to small vessels, as these records were not consistently reported over time. Additionally, early data from all CPCs were removed, as CPUE data from the initial phase of longline fishery development is unlikely to be representative. In summary, this section presents filtered catch and effort data tailored specifically for CPUE standardization.

Some CPCs' longline fisheries are known to include multiple targeting strategies. Among the gear characteristics available in the catch and effort dataset, hooks-between-floats (HBF) is the only one that may provide insight into targeting strategies. The histogram of HBF for China reveals a clear bimodal distribution, with modes at 16 and 27. To investigate the strategies associated with these modes, a clustering analysis was performed using aggregated species composition data (bigeye, yellowfin, albacore, and swordfish). The analysis identified three main primary groups of Chinese vessels operating in the EPO: those targeting bigeye (HBF < 20), those targeting albacore (HBF >=20), and those targeting yellowfin (all of which are associated with a single company group) (Figure 1). These three groups exhibit relatively homogeneous spatial distributions of HBF (Figure 3). For Chinese Taipei, the histogram of HBF shows a primary mode at 16–17, a secondary mode at 10, and a tertiary mode at 25 (Figure 1). The primary mode corresponds to activity in the tropical fishing ground, while the other two are associated with the temperate fishing ground in early and later periods, respectively (Figure 3). It is important to note that all vessels of Chinese Taipei included in this analysis are larger than 100 metric tons.

The HBF distributions for Japan and Korea exhibit similar bimodal patterns, with modes at 13 and 17 (Figure 1). These two modes are separated by time (around 1995) instead of by fishing strategy (Figure 2). Both Japan and Korea have reported employing only a bigeye-targeting strategy in the EPO since 1979 and 1990, respectively. Spatial patterns of HBF for these two CPCs have remained consistent over time, with larger HBF values observed in the tropical fishing ground and smaller values observed in coastal regions of Mexico and Peru (Figure 3). This spatial variation is likely related to differences in thermocline depth, which is shallower in the coastal zones than in the high seas.

Based on the HBF-based classification described above, vessels in the compiled catch and effort dataset used for constructing joint abundance indices are categorized into six groups (hereafter referred to as "flags"): CHN-BET, CHN-YFT, CHN-ALB, JPN, KOR, and TWN.

2.3. Data availability

The Chinese catch and effort data represent the shortest time series among the four CPCs, reflecting their relatively recent entry into the EPO longline fishery (Figure 4). The earliest available data are from 2015, and only a limited amount of data was provided for 2017 due to concerns regarding data quality. Consequently, all the Chinese data for 2017 were removed from this study. Spatially, CHN-ALB vessels primarily operate in temperate waters south of 15°S, CHN-BET vessels are concentrated in tropical waters between the equator and 15°S, and CHN-YFT vessels mainly operate in the core yellowfin area north of the equator.

In contrast, the Japanese dataset provides the longest temporal coverage, spanning from 1979 to 2024 (Figure 4; earlier data were excluded due to the absence of vessel identification). By the 1980s, the Japanese longline fishery had expanded widely across the EPO, with longitudinal coverage stretching from the 150°W management boundary to the western coast of the Americas. This extensive spatial coverage persisted into the 2000s. However, since then, the Japanese fleet has contracted significantly, now operating mainly in the western portion of the EPO. Since no other CPCs operated in the eastern portion of the EPO during the same period, this systematic shift in the spatial distribution of the Japanese fishing ground presents a major challenge for standardizing CPUE for both bigeye and yellowfin tuna in the EPO.

The Korean fishery experienced significant expansion across the tropical EPO in the 1990s (Figure 4). However, it has undergone a pronounced contraction towards the western portion of the tropical EPO since the early 2000s. Chinese Taipei's fishery has been fully developed since 2000, covering both tropical and temperate waters of the EPO (Figure 4). However, since 2010, the fishing ground has also shifted westward within the EPO.

2.4. Spatial distribution of CPUE

For albacore, CPUE is generally higher south of 15°S and lower north of 15°S (Figure 5, top row). An exception to this pattern is observed for the albacore-targeting flag (CHN-ALB), which also shows high CPUE for albacore between 10°S and 15°S. In contrast, the spatial pattern for bigeye is reversed: CPUE is generally higher in fishing grounds north of 15°S than south of 15°S (Figure 5, middle row). For Yellowfin, CPUE exhibits greater spatial variability across flags (Figure 5, bottom row). As expected, the highest CPUE values are associated with the yellowfin-targeting flag (CHN-YFT). Similar to bigeye, yellowfin also shows higher CPUE in fishing grounds north of 15°S than south of 15°S. In summary, both CPUE and species composition exhibit a pronounced latitudinal gradient. Across all flags, vessels tend to catch more bigeye than albacore north of 15°S, and more albacore than bigeye south of 15°S (Figure 6).

2.5. Data selection for CPUE standardization

This document focuses on the standardization of longline CPUE for bigeye and yellowfin tuna. To ensure consistency in targeting strategies, we selected catch and effort data exclusively from vessels associated with bigeye-targeting flags: CHN-BET, JPN, KOR, and TWN. Given the substantial differences in species composition on either side of 15°S, only data from vessels operating within the tropical fishing grounds (10°N-15°S) were considered for further analysis. Two additional filtering criteria were applied to the tropical data subset:

1. HBF must fall within the range of 10 to 20 (Figure 7)
2. Grid cells must contain at least 25 years of data across the time series (Figure 8)

In the previous CPUE standardization for bigeye tuna, a threshold of 20 quarters was used to select grid cells to be included in the model. However, the uncertainty of predicted fish abundance is high in the easternmost portion of tropical EPO and within the EEZ of French Polynesia. To address this, a stricter threshold of 25 years was applied in this study to the CPUE standardization for both bigeye and yellowfin tuna.

In the final dataset selected for CPUE standardization, the spatial domains for JPN, KOR, and TWN span both the western and eastern sides of the EPO, while that for CHN-BET includes only the western EPO (Figure 8). Notably, none of the selected flags operate in the easternmost portion of the tropical EPO or within the EEZ of French Polynesia. Regarding spatial coverage, the areas covered by JPN, KOR, and TWN are about twice that covered by CHN-BET (Figure 9, top). Since 2020, KOR and TWN have contributed the majority of fishing effort in terms of the number of hooks deployed (Figure 9, middle). Among the four flags, KOR and CHN-BET have the largest and smallest number of vessels, respectively (Figure 9, bottom).

2.6. Nominal CPUE

Nominal CPUE by year was calculated for both bigeye and yellowfin tuna within the tropical fishing ground, using the filtered dataset for CPUE standardization (Figure 10). For bigeye, KOR and CHN-BET record, respectively, the highest and lowest nominal CPUE in recent years. The nominal CPUE levels for JPN and TWN have remained relatively similar in recent years. For yellowfin, the temporal patterns in nominal CPUE are less clear, with different flags exhibiting divergent trends, including some that move in opposite directions. To enable more robust comparisons of CPUE trends across flags, spatiotemporal models were developed to provide standardized indices of abundance for bigeye and yellowfin tuna.

2.7. CPUE standardization Model

VAST (Thorson and Barnett 2017) is chosen as the platform to standardize the longline CPUE for yellowfin and bigeye, which is computed as the number of fish caught per 1,000 hooks. VAST is an open-source R package (https://github.com/James-Thorson-NOAA/VAST) and 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). As a delta-generalized linear mixed model, VAST separately models encounter probability and positive catch rate to account for zero-inflated catch rate observations. We specify VAST to use the logit link for the linear predictors of encounter probability for both species and the lognormal and gamma links for the positive catch rate for bigeye and yellowfin tuna, respectively. The four quarters are treated equally in VAST.

Both the linear predictors of encounter probability and positive catch rate include an intercept (year-quarter) term, a time-invariant spatial term, a time-varying spatiotemporal term, and a vessel effect term. For the models in which more than one flag's data are used, the two linear predictors include an additional flag effect term to account for the difference in catchability among flags. By using Template Model Builder (Kristensen et al. 2016), the intercept term and the catchability term are estimated as fixed effects; the spatial term, the spatiotemporal term, and the vessel effect term are estimated as random effects. Given that values at nearby locations are usually more similar than those at remote sites, the spatial and spatiotemporal random effects are both assumed to be autocorrelated in space.

VAST uses the area-weighting approach to compute the index of abundance. It first predicts fish density for each spatial knot and time and then sums the product of fish density and area of the knot over space to derive the abundance index. Choosing the number of spatial knots needs to consider the trade-off between model accuracy and model efficiency. A total of 100 spatial knots is used in this spatiotemporal model to balance the two components. Considering that the CV of predicted fish density increases over time due to reduced sample size and spatial coverage, a bias-correction algorithm (Thorson and Kristensen 2016) is applied to remove the re-transformation biases in VAST-derived quantities.

In the CPUE standardization model developed for this document, spatiotemporal terms are assumed to be correlated in both space and time. Specifically, the spatiotemporal terms are assumed to be spatially correlated according to the Matérn function and to follow a random-walk process in time. Under this assumption, the spatiotemporal terms for unfished locations are interpolated based on data collected not only from nearby fished locations in the same year but also from the same location in adjacent fished years.

2.8. Joint indices of abundance

For each species, we first applied spatiotemporal models to the catch and effort data of each flag independently, to evaluate the consistency of the indices of abundance across flags. This comparison provides valuable insight into which flags' CPUE data are consistent with Japanese CPUE data, which historically served as the sole source for standardizing longline CPUE for both bigeye and yellowfin tuna. It is important to note, however, that some differences among flag-specific indices are expected, as each index is spatially weighted over a distinct geographic domain (Figure 8).

Following the comparison of flag-specific abundance indices, we developed several candidate joint indices for each species. These joint indices were then compared with the corresponding Japanese index to assess the influence of incorporating additional flags' CPUE data on the accuracy and precision of longline indices of abundance for bigeye and yellowfin tuna.

3. RESULTS

3.1. Bigeye

3.1.1. Flag-specific index of abundance

In terms of interannual variation, the index for KOR closely mirrors that for JPN, except in recent years when the index for JPN has become highly uncertain due to limited sample size and reduced sample coverage (Figure 11). The index for TWN exhibits significantly greater seasonal fluctuation compared to other flags, suggesting that at least part of the TWN fleet may have a seasonal fishing strategy. The index for CHN-BET only provides a continuous time series since 2018, during which the index for JPN is highly uncertain due to the contraction of its longline fishery. Consequently, assessing the degree of consistency between the two indices is not feasible yet.

In terms of long-term trend, the index for KOR does not show an overall decline since 1990, while JPN does (Figure 11). Over the past three decades, the index for JPN shows that the abundance of large bigeye declined over time, whereas that for KOR shows no noticeable sign of decline. The index for TWN also reflects a modest decline over the last two decades. However, the presence of pronounced seasonal variation obscures a clear interpretation of the trend. The index for CHN-BET remains too limited in temporal scope to provide insights into long-term trends.

3.1.2. Joint index of abundance

Given that the index for KOR is consistent with that for JPN with respect to interannual variation, we developed two joint indices of abundance and compared them with the Japanese index. The first joint index incorporates CPUE data from both JPN and KOR, while the second incorporates CPUE data from all four flags. Both joint indices exhibit nearly identical interannual variation compared to the Japanese index (Figure 12, top panel). However, they show a slightly lower rate of depletion in the abundance of large bigeye tuna. The difference between the two joint indices is minor and is primarily noticeable during the last decade of the time series.

The coefficient of variation (CV) for the Japanese index begins to increase markedly after 2015, reflecting the contraction of the Japanese longline fishery (Figure 12, bottom panel). As expected, incorporating data from KOR into the CPUE standardization model significantly improves the precision of the abundance index for the period in which Korean data are available. In particular, the CV of the joint (JPN + KOR) index is approximately half of the CV of the Japanese index after 2015, indicating a substantial reduction in the uncertainty of the abundance index in recent years. Across the entire time series, however, the joint index that includes all four flags is less precise than the joint index that includes only JPN and KOR.

A key unresolved question regarding the abundance index for bigeye tuna is why the Japanese and joint (JPN + KOR) indices have noticeably different long-term trends. It could be due to differences between JPN and KOR in long-term catchability trend or spatiotemporal distribution of fishing effort. To investigate this, we constructed an additional joint index using Japanese CPUE data and only the subset of Korean CPUE data that matched the spatiotemporal distribution of Japanese fishing activity. In other words, the Korean CPUE data from spatiotemporal strata without corresponding Japanese CPUE data were excluded. In terms of long-term trend, this joint index more closely resembles the joint index based on the full Korean CPUE dataset than the Japanese index (Figure 13). This finding suggests that the divergence in long-term trends between the joint (JPN + KOR) index and the Japanese index is primarily driven by differences in catchability trends over time, rather than by differences in the spatiotemporal distribution of fishing activity.

3.2. Yellowfin

3.2.1. Flag-specific index

In terms of interannual variation, the index for KOR closely mirrors that for JPN, except in recent years when the index for JPN has become highly uncertain due to limited sample size and reduced sample coverage (Figure 14). The index for TWN displays similar timing in interannual fluctuations compared to the index of JPN, but its magnitude of variation is substantially greater. Although the index for CHN-BET covers a short period, it has shown general consistency with the index for KOR since 2018, the year from which the index for CHN-BET became continuously available.

In terms of long-term trend, the index for KOR is highly consistent with the index for JPN. Both indices show a decline from 2001 to 2005, followed by a relatively stable period until 2018, and then a notable increase to much higher levels thereafter (Figure 14). The index for TWN exhibits a slightly different trend. However, the presence of pronounced seasonal variation obscures a clear interpretation of the trend. The index for CHN-BET remains too limited in temporal scope to provide insights into long-term trends.

3.2.2. Joint index

Given the high consistency between the indices for KOR and JPN, we developed two joint indices of abundance and compared them with the Japanese index. The first joint index incorporates CPUE data from both JPN and KOR, while the second incorporates CPUE data from all four flags. Both joint indices exhibit interannual variability and long-term trend that closely resemble those of the Japanese index. The difference between the two joint indices is minimal and primarily noticeable during the last decade of the time series.

The CV for the Japanese index begins to increase markedly after 2015, reflecting the contraction of the Japanese longline fishery (Fig. 15, bottom panel). As expected, incorporating data from KOR into the CPUE standardization model significantly improves the precision of the abundance index for the period in which Korean data are available. In particular, the CV of the joint (JPN + KOR) index is approximately half of the CV of the Japanese index after 2015, indicating a substantial reduction in the uncertainty of the abundance index in recent years. Across the entire time series, however, the joint index that includes all four flags is less precise than the joint index that includes only JPN and KOR.

4. DISCUSSION

There is a critical need to develop joint longline indices of abundance for bigeye and yellowfin tuna in the EPO. The current indices, which rely solely on Japanese CPUE data, have shown an accelerating increase in uncertainty since 2015, undermining the precision of stock assessments with respect to estimating current management quantities. This study represents the first attempt to develop joint longline indices of abundance for bigeye and yellowfin in the EPO. Our analyses demonstrate that, for both species, the joint index of abundance based on Japanese and Korean CPUE data closely follows the Japanese index in terms of interannual variation while exhibiting significantly reduced uncertainty. Therefore, using the joint (JPN + KOR) index rather than the Japanese index would likely improve the stock assessments of both bigeye and yellowfin in the EPO.

For this year’s benchmark assessment for yellowfin tuna (SAC-16-03) and stock status indicators for both species (SAC-16-02), we recommend using the joint indices of abundance based on the CPUE data from both JPN and KOR. Several factors support this recommendation: 1) the interannual variation of the Korean index is generally consistent with the Japanese index; 2) the length frequency data provided by longline observers from both fleets are similar, suggesting comparable longline selectivity; 3) the Korean fleet has maintained a single bigeye-targeting strategy since 1990 (SAC11-INF-K); 4) Korea has replaced Japan as the most important longline fleet for both species in terms of catch amount.

To ensure timely updates to the joint indices used in stock assessments and stock status indicators for the Scientific Advisory Committee meetings, we recommend that both Japan and Korea continue submitting their most recent CPUE datasets to the IATTC staff by the end of March each year. While the CPUE trends for yellowfin tuna are notably consistent between the two fleets, the trends for bigeye tuna diverge noticeably. This discrepancy warrants further investigation, particularly about differences in long-term catchability trends for bigeye. We also recommend ongoing collaboration between scientists from Japan, Korea, and IATTC staff to investigate the underlying causes of the observed differences in the CPUE trends for bigeye tuna between the two fleets and participation by all nations in the upcoming Tuna Longline CPUE Workshop.

Future improvements to the joint indices of abundance will likely also focus on incorporating CPUE data from China and Chinese Taipei. While joint indices of abundance that include all CPCs' CPUE datasets were developed during this exploration, they were not selected for use in this year's benchmark assessment for yellowfin tuna or stock status indicators. Specifically, these joint indices exhibited even larger CVs than the joint indices that include CPUE data from JPN and KOR, indicating a lack of consistency between the CPUE data from CHN/TWN and those from JPN/KOR.

For both species, the Chinese index shows potential for future inclusion into the joint indices, as its interannual variation generally aligns with the Korean index since 2018. However, due to the short duration of the continuous time series since 2018, it is currently difficult to assess consistency with sufficient confidence. We recommend that China continue submitting high-resolution CPUE data to the staff so that the consistency in the index can be reassessed as the time series lengthens.

For both species, the index for Chinese Taipei displays markedly higher seasonal variability than those for other CPCs. This suggests that at least part of the fleet may have a fishing strategy that varies seasonally. We recommend continued collaboration between scientists from Chinese Taipei and IATTC staff to better understand the CPUE data, associated length composition data, and fleet dynamics, in order to investigate the causes of the observed large seasonal fluctuations in the index.

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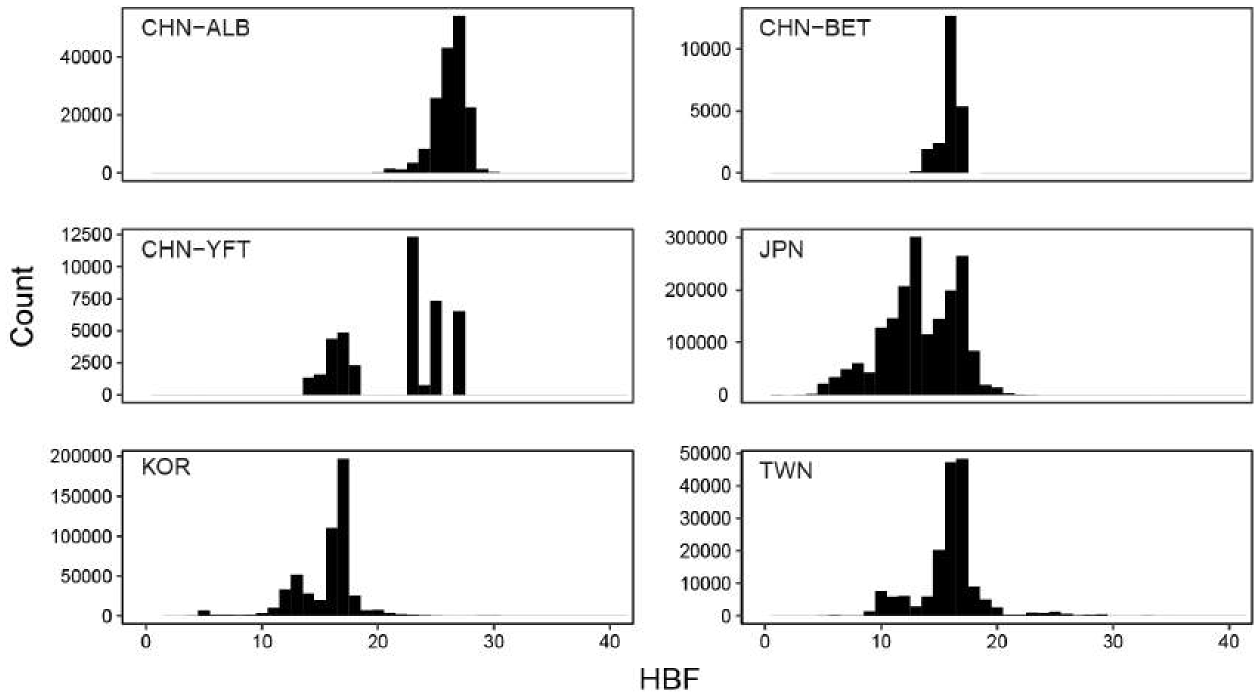

FIGURE 1. The histogram of hooks-between-floats (HBF) for the six flags defined in this study.

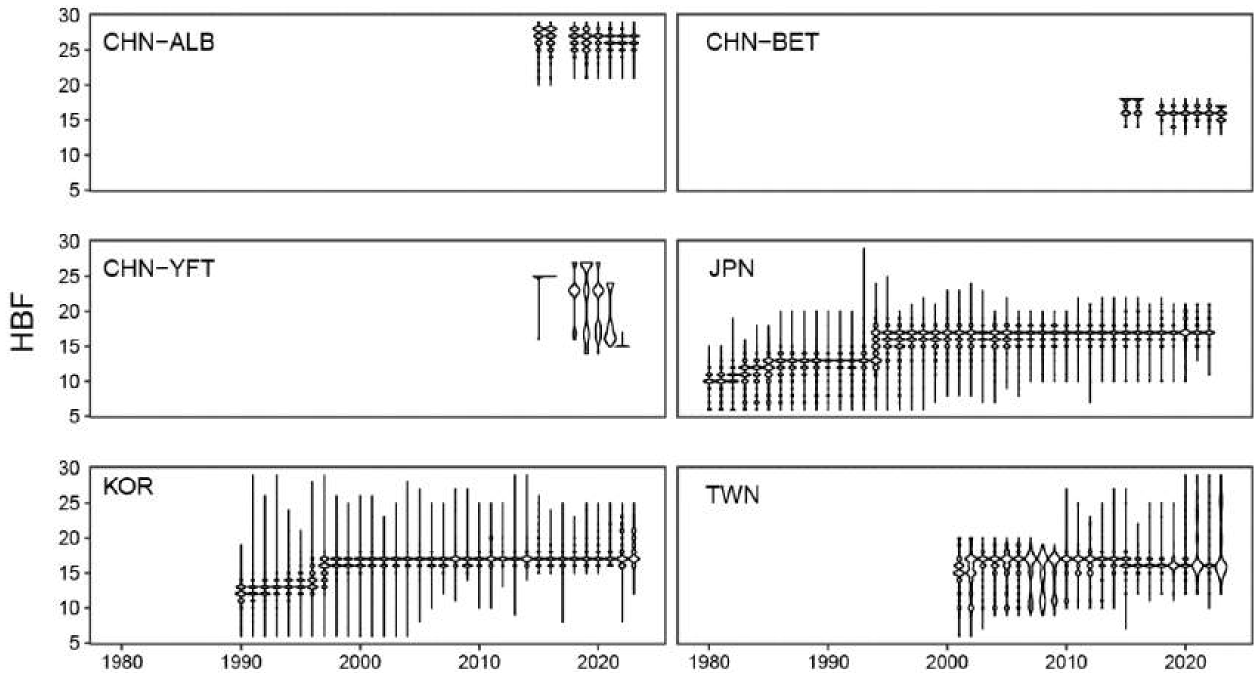

FIGURE 2. The violin plot of hooks-between-floats (HBF) by year for the six flags defined in this study.

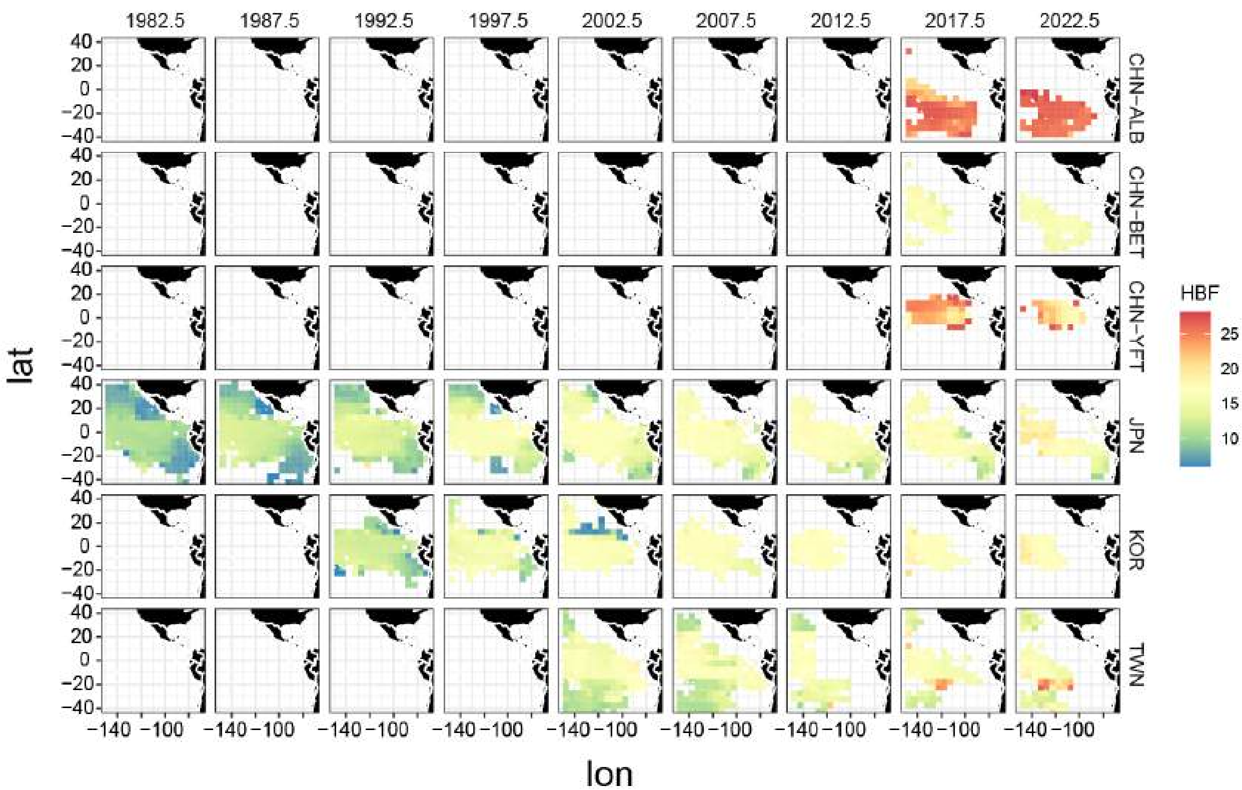

FIGURE 3. The spatiotemporal distribution of average hooks-between-floats (HBF) for the six flags defined in this study.

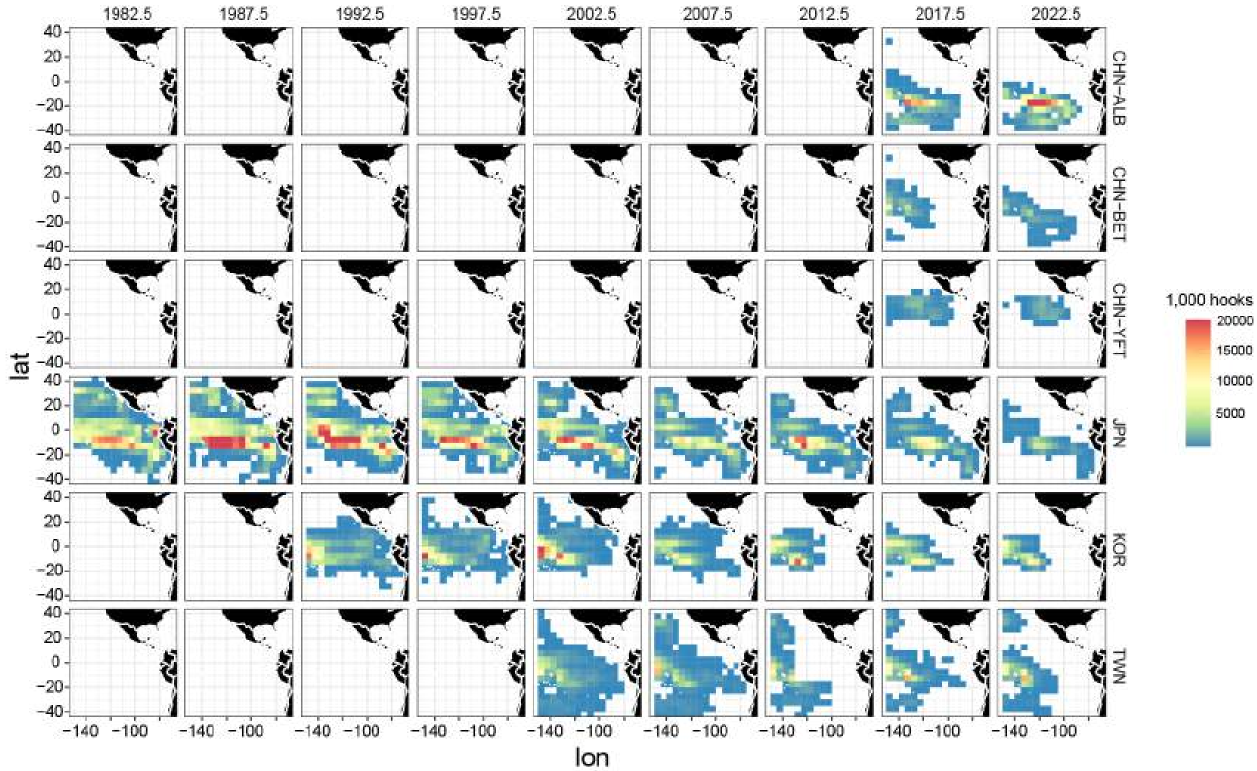

FIGURE 4. The spatiotemporal distribution of fishing effort (in number of hooks) for the six flags defined in this study.

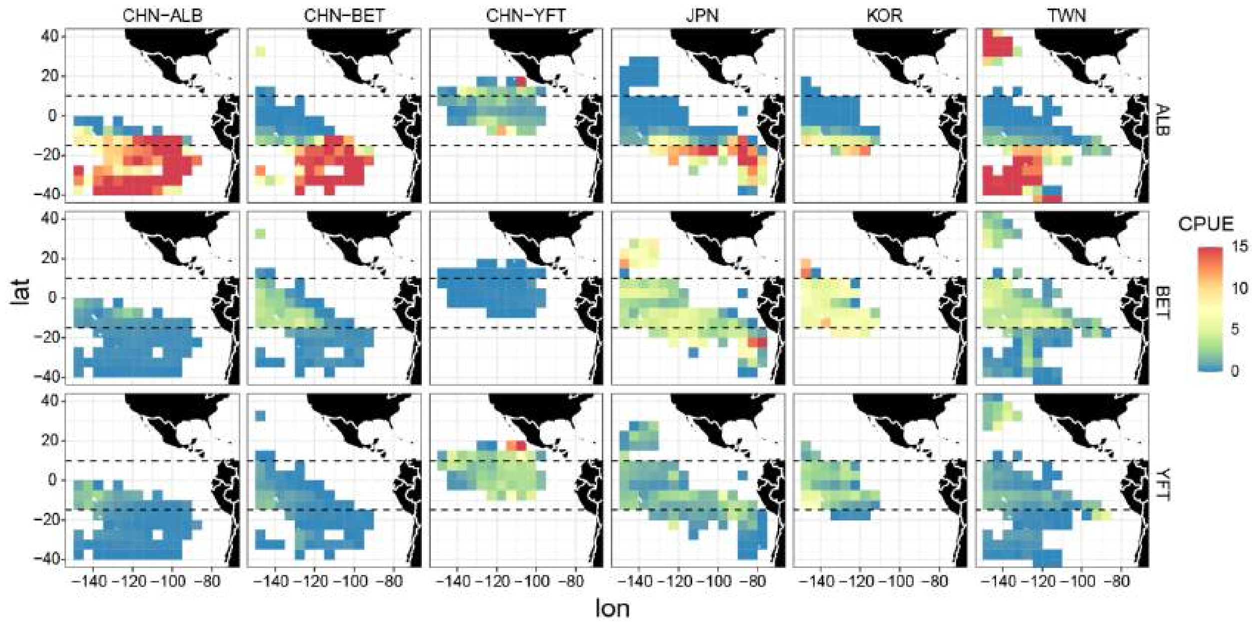

FIGURE 5. The spatiotemporal distribution of CPUE (in number of fish per 1,000 hooks) for the six flags between 2018 and 2022.

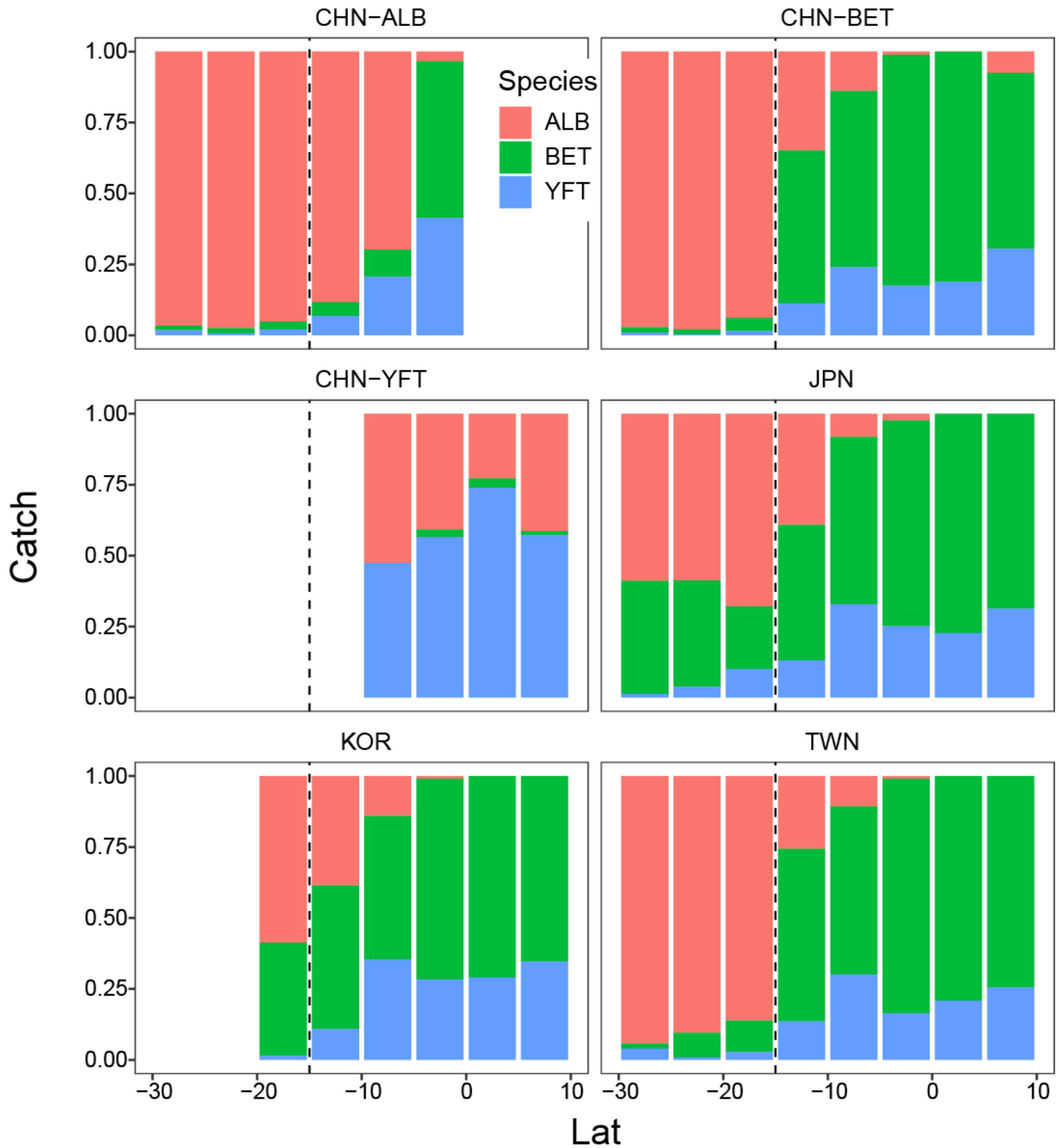

FIGURE 6. The species composition of catch (in number of fish) by latitude for the six flags between 2018 and 2022.

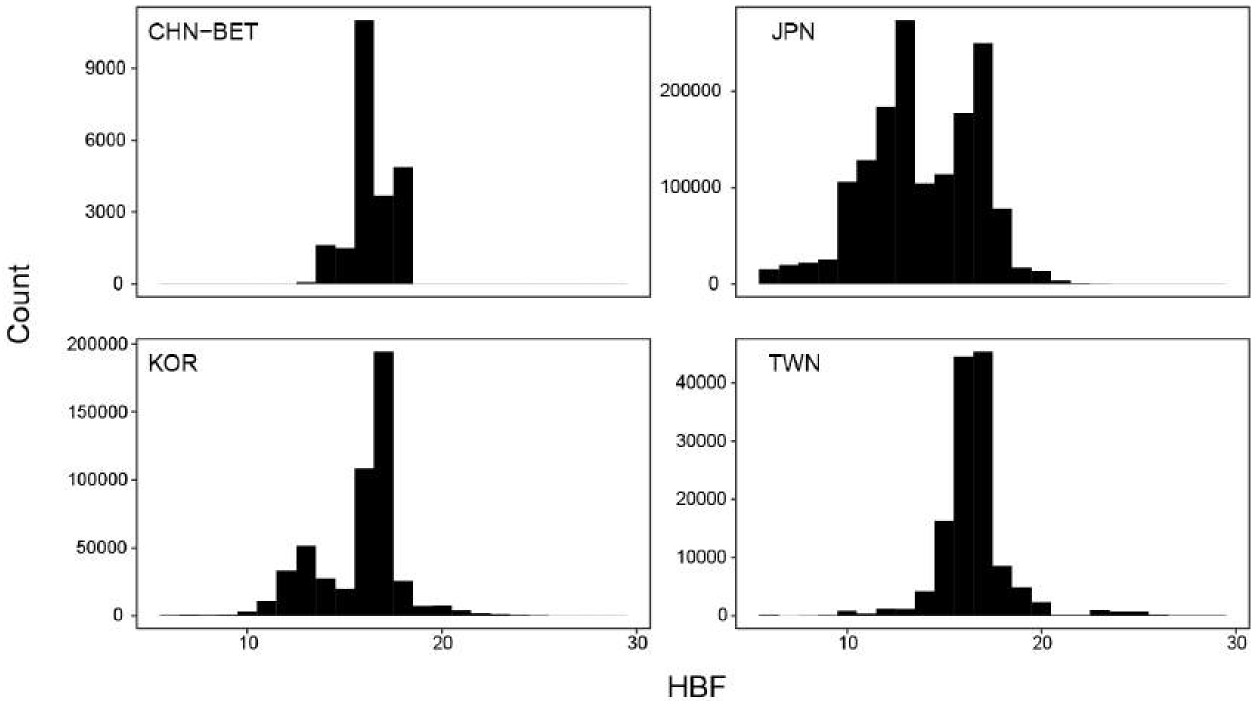

FIGURE 7. The histogram of hooks-between-floats (HBF) for the four flags included in the CPUE standardization for yellowfin and bigeye in the tropical fishing ground (15°S-10°N).

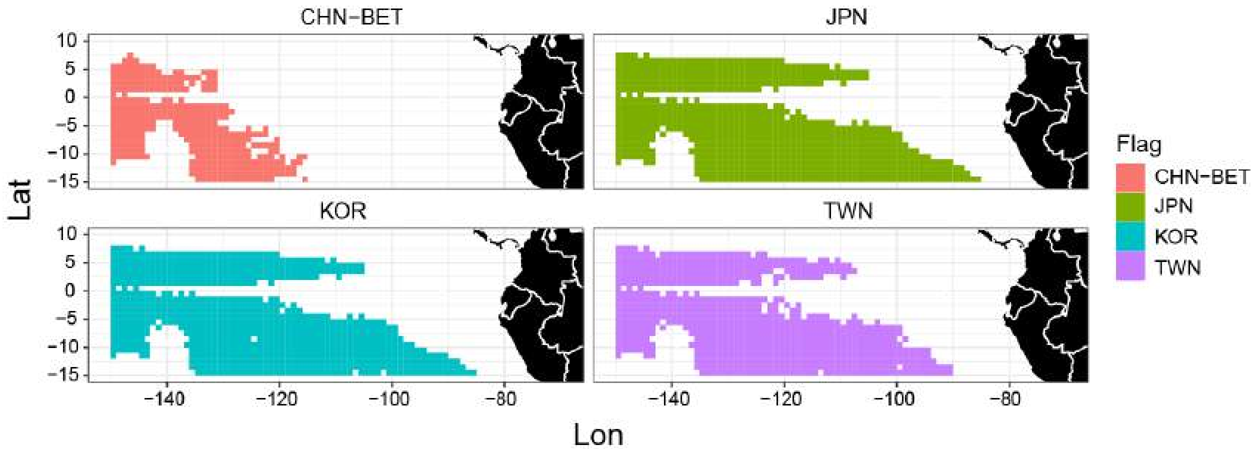

FIGURE 8. The spatial domain for the four flags included in the CPUE standardization for yellowfin and bigeye in the tropical fishing ground (15°S-10°N).

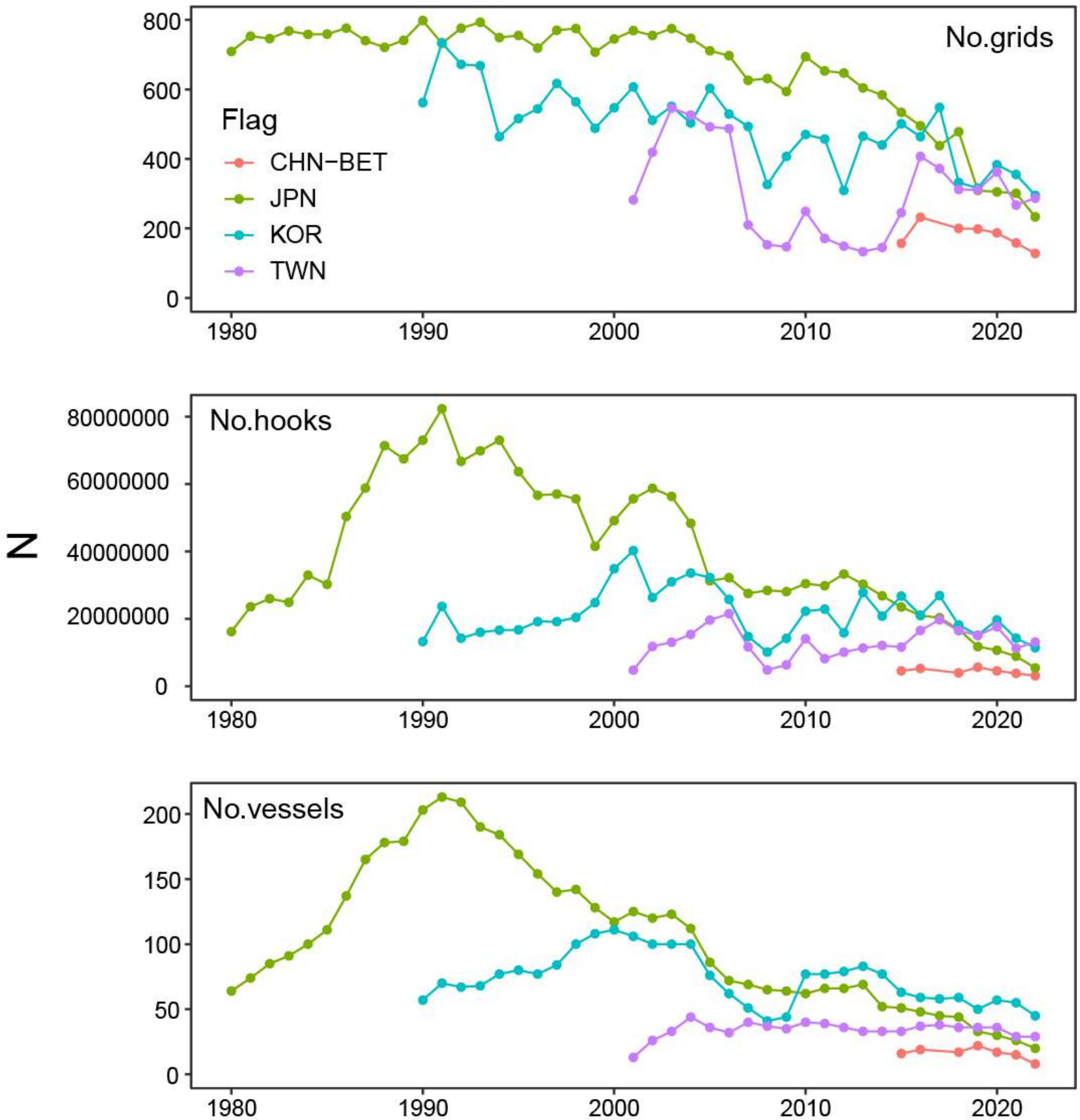

FIGURE 9. The spatial coverage (in number of $1° \times 1°$ grids), fishing effort (in number of hooks), and fleet size (in number of vessels) for the four flags included in the CPUE standardization for yellowfin and bigeye in the tropical fishing ground (15°S-10°N).

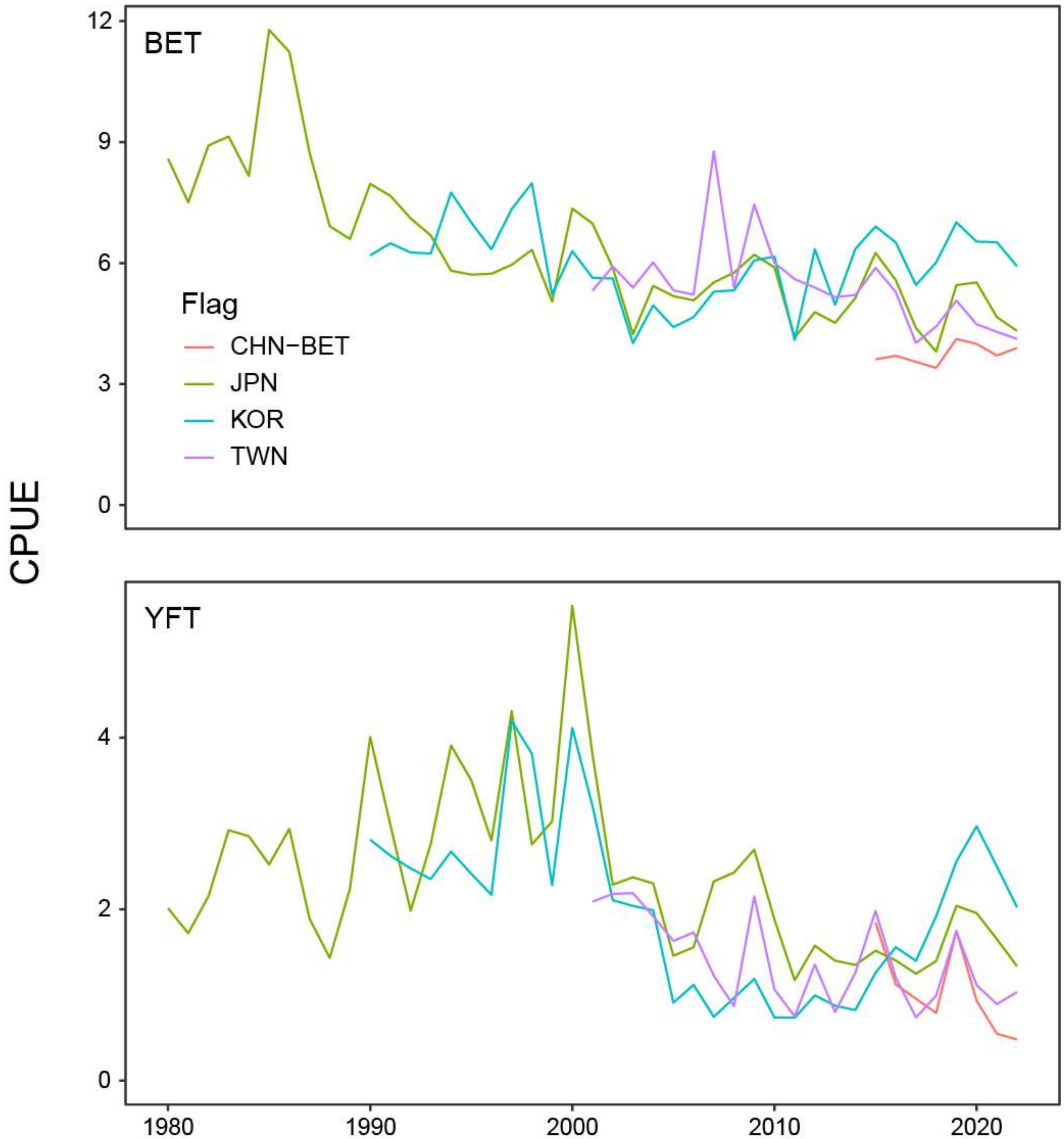

FIGURE 10. The nominal CPUE (in number of fish per 1,000 hooks) for the four flags included in the CPUE standardization for yellowfin and bigeye in the tropical fishing ground (15°S-10°N).

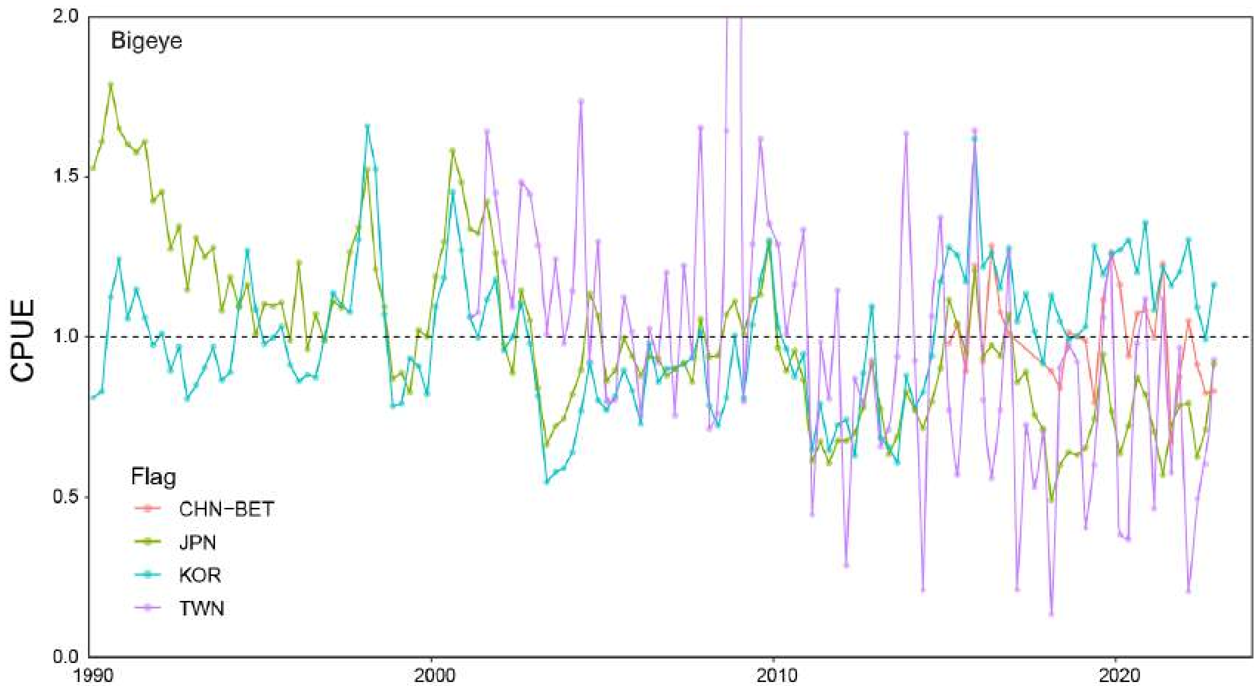

FIGURE 11. Comparison of flag-specific standardized indices of abundance for bigeye in the eastern Pacific Ocean.

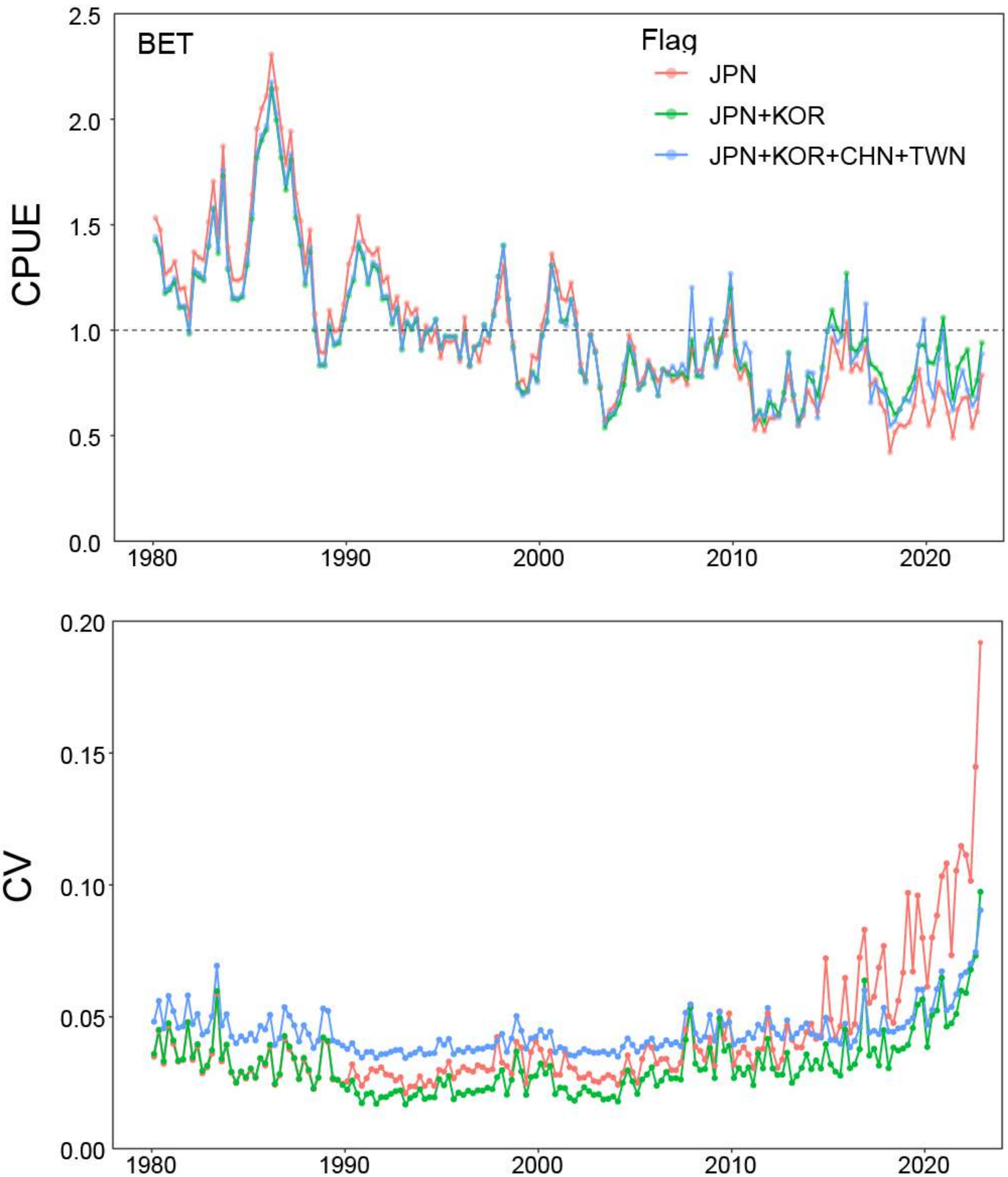

FIGURE 12. Comparison of the two joint indices of abundance (top) and the associated coefficients of variation (bottom) with the Japanese index of abundance for bigeye tuna in the eastern Pacific Ocean.

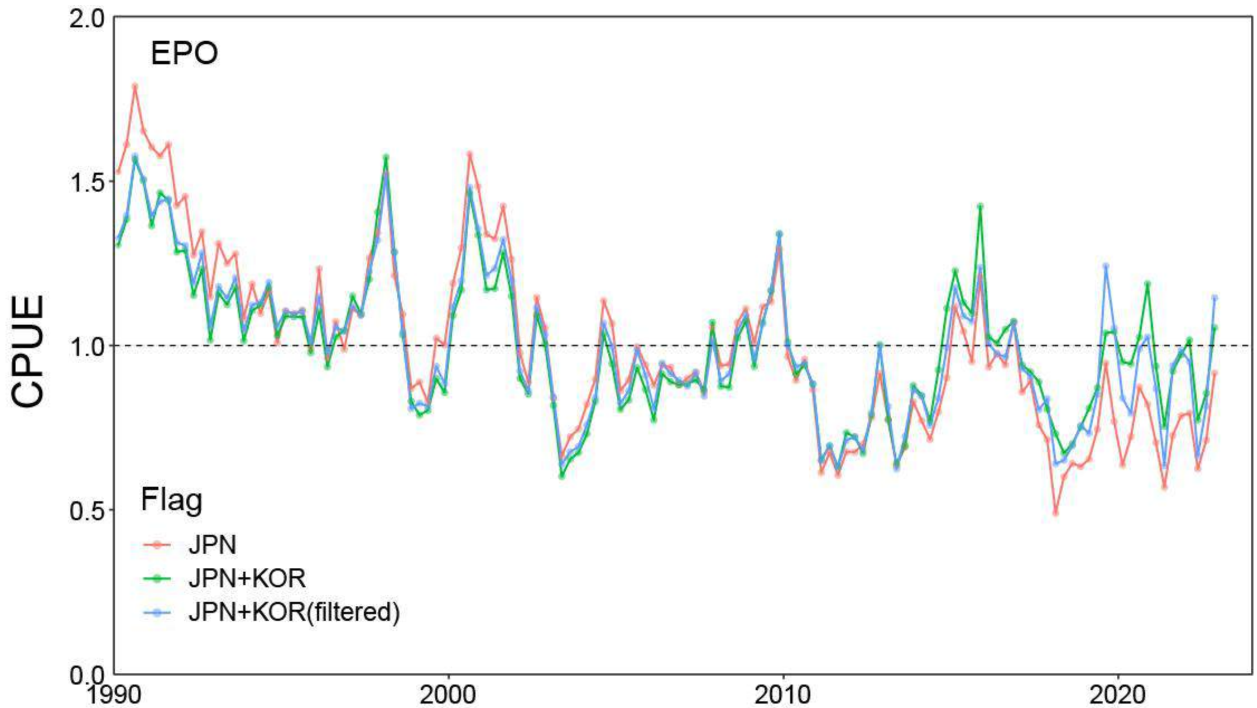

FIGURE 13. Comparison of joint (Japanese + Korean) indices of abundance with the Japanese longline index of abundance for bigeye tuna in the eastern Pacific Ocean. The green line shows the joint index of abundance based on all CPUE data from Japan and Korea and the blue line shows the joint index of abundance based on all CPUE data from Japan and filtered CPUE data from Korea.

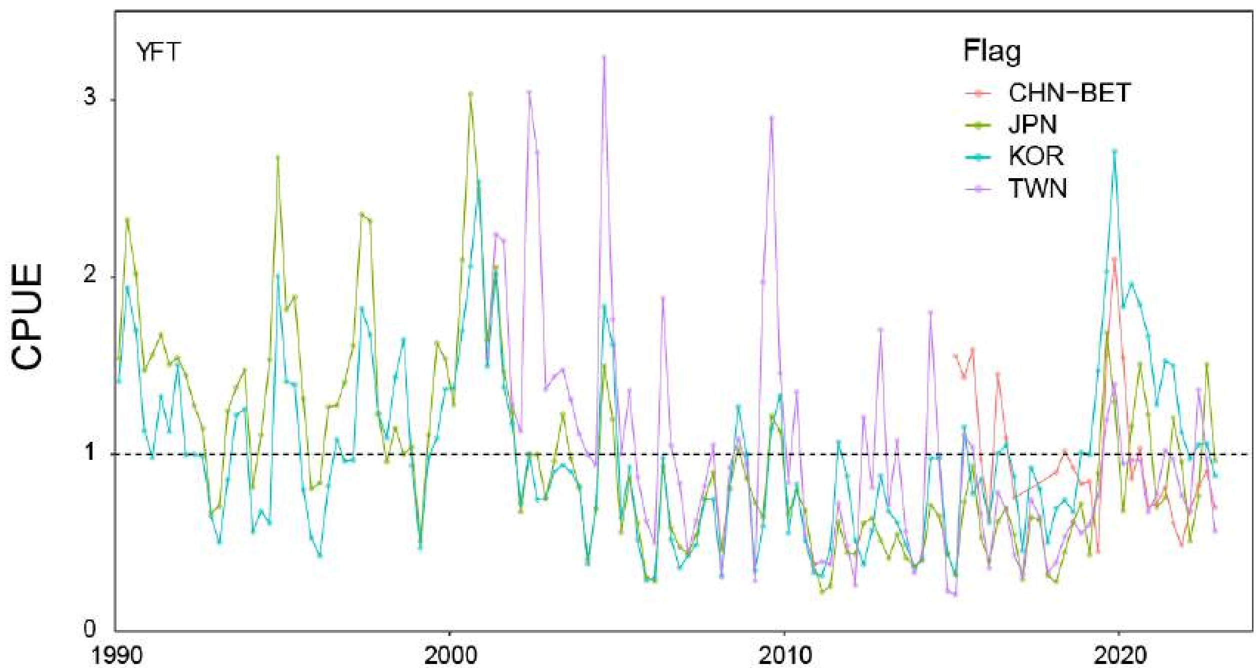

FIGURE 14. Comparison of flag-specific standardized indices of abundance for yellowfin in in the eastern Pacific Ocean.

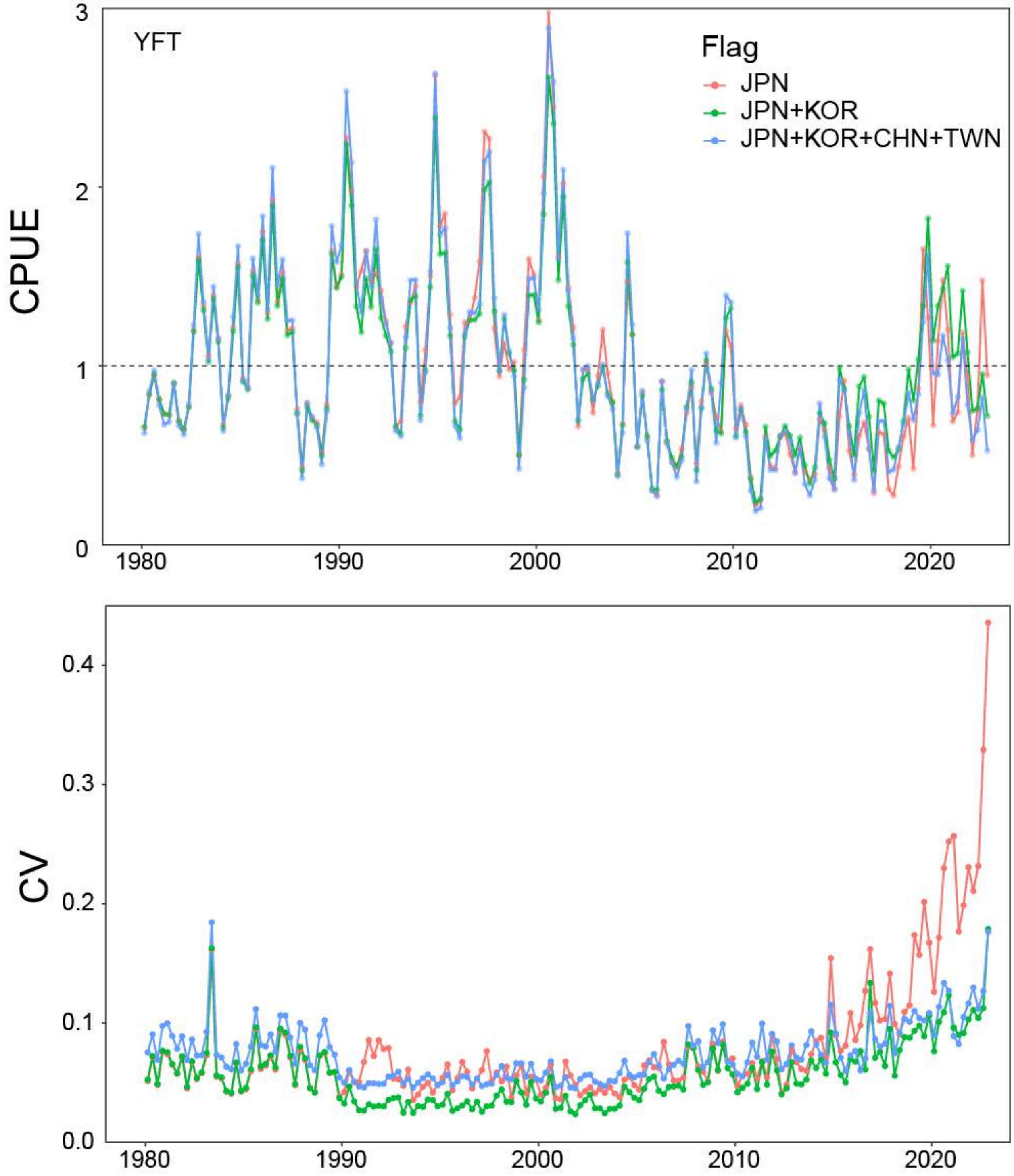

FIGURE 15. Comparison of the two joint indices of abundance (top) and the associated coefficients of variation (bottom) with the Japanese index of abundance for yellowfin in the eastern Pacific Ocean.