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CPUE analysis and data inputs for the 2023 bigeye and yellowfin tuna assessments in the WCPO

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Details of revisions to the original report

Plots were added (see Appendix 2: Fishery catch and size composition **plots**) for each species and fishery showing catch time series, catch record time series, and size composition (i.e., length or weight) time series. Includes regional structure diagram for each fishery, catch by flag, and quarterly aggregated size composition.

Executive summary

This information paper provides details on the key supporting analyses and data sets used to inform the 2023 assessment models for the western and central Pacific Ocean (WCPO) bigeye and yellowfin tuna stocks. These include the standardization procedure used for the catch per unit effort (CPUE) time-series to provide relative abundance indices for the index fisheries and the preparation of tagging data to construct the tag input files. Preparation of size composition data, analysis to inform tagger effects modeling, and tag reporting rate priors are covered in papers Peatman et al. (2023a) (SC19-SA-IP-03), Peatman et al. (2023b) (SC19-SA-IP-08), and Peatman and Nicol (2023) (SC19-SA-IP-07).

The operational longline (LL) fishery CPUE time-series was standardized to provide indices of relative abundance for the longline index fisheries assigned to each model region. Similar to the previous analysis (Ducharme-Barth et al., 2020b), a delta-gamma mixed-effects spatiotemporal modeling approach with two catchability covariates for FLAG and hooks-between-floats (HBF) was used. A random forest (RF) machine learning approach was used to predict HBF for records where it was not available. However, in response to suggestions from the independent yellowfin peer-review (Punt et al., 2023), changes to this approach were made to include:

- The application of the spatiotemporal modeling package "sdmTMB" instead of the previously applied "VAST" package.
- An increased resolution of spatial effects by increasing the number of spatial "knots" (from 154 to 371) in the spatiotemporal model mesh configuration.
- The investigation of a sub-basin scale model with "non-viable" (poorly sampled) 5° x 5° grid cells removed and compared to the results with globally modelled indices. Results indicated differences in spatial characterization however, these differences were in areas with comparatively low abundance.
- Additional abundance-based covariates including month (for the bigeye data only) and environmental covariates of depth of 15°C isotherm and the difference between the depth of the 12°C and 18°C isotherms were included. These covariates were included to create a biological envelope to inform relative abundance specifically in areas with low sampling coverage while allowing for changes in spatial distribution due to infrequent environmental events.
- A principal-fleet model was developed and compared to the multi-fleet results to assess the effects of combining fleets. Results to the indices derived from multiple fleets were very similar to the principal-fleet results.

The resulting indices for both bigeye and yellowfin tuna showed declines in many of the key stock assessment regions and were consistent with the trends seen in both the previous 2020 analyses (Ducharme-Barth et al., 2020b; McKechnie et al. 2017b; Tremblay-Boyer et al., 2017a; Tremblay-Boyer and Pilling, 2017) and the nominal catch-per-unit-of-effort.

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1 CPUE standardization

This section describes the processes and analyses used to generate indices of relative abundance from fisheries-dependent longline operational (set-level) catch and effort data. These indices were used as inputs in the 2023 Western and Central Pacific Fisheries Commission (WCPFC) bigeye and yellowfin tuna stock assessments (Figure 1). Given the spatial and temporal scale of the different longline fleets operating in the region, the resultant indices of abundance represent an important input to the stock assessments of both bigeye and yellowfin tuna. The operational longline dataset is a consolidation of operational level data from the distant-water fishing nations (DWFNs) and Pacific-Island countries and territories (PICTs) longline fleets operating in the Pacific basin. This dataset is the most complete spatiotemporal record of longline fishing activity in the Pacific, spanning from 1952 to the present and is the result of a tremendous collaborative; data sharing effort from the countries involved.

This dataset was first created in 2015 in support of the Pacific-wide bigeye tuna stock assessment (McKechnie et al., 2015a, 2015b), and was subsequently analysed to generate indices of relative abundance (McKechnie et al., 2017b; Tremblay-Boyer et al., 2017a; Tremblay-Boyer and Pilling, 2017) for the 2017 WCPFC bigeye and yellowfin tuna stock assessments (McKechnie et al., 2017a; Tremblay-Boyer et al., 2017b). The 2015 analysis describes in detail the process used to identify species targeting via catch composition clustering, analyses on the inclusion of gear and vessel covariates that are unavailable for the full time period of interest, and choice of model error structure (McKechnie et al., 2015b). In 2017, work was done to identify methods for generating vessel identifier "proxies" for those records where vessel identifier was unavailable (Tremblay-Boyer and Pilling, 2017). Additionally, 2017 saw the first application of spatiotemporal modeling approaches in support of WCPFC stock assessments (Tremblay-Boyer et al., 2017a). The current work builds off these previous efforts and analyses of the operational longline data, as well as the spatiotemporal modeling done in support of WCPFC bigeye and yellowfin tuna stock assessments in 2020 (Ducharme-Barth et al., 2020a; Vincent et al., 2020). For additional background and description of both the operational longline data-set and previous analyses please consult these earlier reports.

1.1 Data preparation

The operational dataset consisted of 12,793,288 longline set-level records from the commercial longline logbooks of 32 different fishing nations from a period of 1952 through the present day (Figure 2 and Figure 3). In the consolidated dataset, each record contained the vessel's flag, vessel's fleet, date, location (to the nearest 1° x 1° spatial cell), effort (number of hooks fished), and species catch (albacore tuna, bigeye tuna, striped marlin³, swordfish, and yellowfin tuna; Figure 4). Nominal catch-per-unit-of-effort (CPUE defined as catch per 100 hooks fished) indicated declines in catch rate over the model period in key regions for

³ Striped marlin catch was unavailable for Japanese records prior to 1967.

each species (Figure 5 and Figure 6). Hooks-between-floats (HBF) and unique vessel ID were also available although coverage was incomplete, particularly in the early years.

Prior to analysis, the data were filtered similarly to the method first described in McKechnie et al. (2015b). This data cleaning process occurred in the following steps:

1. Removed records with missing year: -2 records (negligible %)

2. Removed records from 2022 or 2023: -194,187 records (-1.52 %)

3. Removed records from outside of the Pacific basin: -21,992records (-0.17 %)

4. Removed records with more than 50 HBF outliers: -32,635 records (-0.26 %)

5. Removed records with number of hooks fished; per set, greater than 5,000 or less than 150: -8,256 records (-0.07 %)

6. Removed records with more fish caught than number of hooks fished: -19 records (negligible %)

7. Removed records with vessels that did not fish at least 10 quarters⁴ or made less than 30 sets: -847,102 records (-6.76%)

8. Removed records flagged under Belize (BZ), Panama (PA), or Spain (ES): -23,794 records (-0.20 %)

9. Remaining records: 11,665,301 records (91.18 %)

Catches without the presence of any of the five species included in the data set were retained as these zero catches were informative for establishing species distribution limits within the spatiotemporal modeling framework assuming that targeting and reporting remained relatively constant.

Records that were missing HBF were not excluded as these were imputed as was done previously (Ducharme-Barth et al., 2020b). Records missing vessel ID were retained since vessel ID was considered as a potential covariate however, the number of unique vessels was excessive (>6000), thereby preventing inclusion in the standardization due to the computational burden.

1.1.1 Missing data imputation

Given the limited number of catchability covariates that were available across fleets over the time-series of the assessment period, it was necessary to impute missing HBF values to maintain temporal continuity in the standardized indices. This imputation procedure was conducted to estimate missing observations of HBF (predominantly from Japanese records prior to 1967 and records from a variety of flags in assessment region 6; Figure 7), and missing fleet identifiers, OS or DW, for Japanese records prior to 1957.

In both cases a formulation of the Random Forests (RF) machine learning approach (Breiman, 2001), Ensemble Random Forests (ERF; Siders et al., 2020), was applied to predict

⁴ Vessels that entered the fishery within the last 10 quarters of the model period were not subject to this exclusion.

the missing observations. RF is a computationally efficient machine learning algorithm capable of handling large quantities of "training" data, non-linear interactions between covariates, and can produce predictions either via regression or multiple-category classification.

As was done in the previous assessment, we developed flag-specific ERF models which predicted the HBF bin (bins of 5 HBF) from missing HBF (n=2,718,265) using fleet id, year, month, longitude, latitude, number of hooks fished, total catch in numbers, and proportion of species catch for albacore tuna, bigeye tuna, striped marlin, swordfish, and yellowfin tuna.

Japanese records with fleet (OS or DW) missing (n=251,139) were predicted using a similar classification approach. Missing fleet prior to 1957 was predicted as a function of month, longitude, latitude, number of hooks fished, total catch in numbers, and proportion of species catch for albacore tuna, bigeye tuna, swordfish, and yellowfin tuna. The training dataset was the Japanese records with fleet recorded from 1958-1967.

We refer readers to Ducharme-Barth et al. (2020b) for further information on methodology for developing flag-specific predictions of HBF and missing fleet identification for Japanese records.

1.1.2 Spatiotemporal trends in nominal CPUE

The spatial distribution of nominal CPUE for bigeye (Figure 5) and yellowfin tuna (Figure 6) indicated declines in the intensity of hot spots of nominal CPUE. For bigeye tuna, these hotspots were located along the equatorial counter-currents (particularly in the eastern Pacific Ocean), and around the Hawaiian islands. Yellowfin tuna indicated a hot-spot in the equatorial western and central Pacific Ocean.

1.2 Modeling approach

The volume of records in the operational longline dataset posed computational challenges. Modeling the data in a spatiotemporal framework such as the VAST package, as was used previously (Ducharme-Barth et al., 2020b), or the sdmTMB package, can be much slower compared to a traditional delta-lognormal generalized linear model (GLM) without interactions between the spatial and temporal terms. The run time for a spatiotemporal model is impacted by the selected software (e.g., VAST vs. sdmTMB), the resolution of the spatial effects (i.e., the number of "knots") in the model, the number of time steps estimated, and the volume of data. The length of the stock assessment time-series (1952-2021) and the corresponding quarterly time-step determined the number of time steps for the CPUE model leaving only software selection, resolution of spatial effects, and volume of data as factors for improved computational efficiency.

1.2.1 VAST to sdmTMB

One of the recommendations of the yellowfin independent peer review (Punt et al., 2023) was to consider an alternative spatiotemporal modelling framework, specifically, the sdmTMB package. The sdmTMB geostatistical software has been developed to be computationally efficient, flexible, and user-friendly with online community support (Anderson et al., 2022) and thus, a reasonable alternative for improving reproducibility and efficiency of CPUE analyses. The sdmTMB package has been demonstrated to produce comparable results to other spatiotemporal model software packages (including VAST; Anderson et al., 2022).

We initially modelled the bigeye and yellowfin longline data through 2018 using sdmTMB with identical model and spatial knot configurations (i.e., mesh parameterisation) to compare the results with the VAST model results from the previous analysis (Ducharme-Barth et al. 2020b). This comparison provided a demonstration of how similar the two software packages were at modeling the same longline dataset (Figure 8, Figure 9, Figure 10, and Figure 11). After demonstrating that these two software packages produced similar results, we selected sdmTMB to evaluate and select potential density covariates and to model the updated data through 2021.

1.2.2 Increased spatial resolution

Species distribution models have been demonstrated to be sensitive to mesh parameterisation with increasing coarseness of meshes resulting in a loss of accuracy (Dambly et al. 2023) however, meshes that were too fine suffered from overfitting. For WCPO bigeye and yellowfin CPUE, overfitting would be unlikely considering the computational challenges of modeling such a large spatial extent. In the previous analysis (Ducharme-Barth et al. 2020b), a mesh with 154 knots was implemented to create a balance between computational feasibility and an appropriate spatial resolution (Figure 12). However, we increased the resolution of spatial effects to produce more robust indices to 371 knots (Figure 13).

Comparison of the new mesh design with the VAST model results from the previous analysis (Ducharme-Barth et al., 2020) indicated similar results (Figure 14, Figure 15, Figure 16, and Figure 17).

1.2.3 Sub-sampling

Another approach to managing the computational challenge presented by the operational longline dataset was to randomly sub-sample the number of records to reduce the computational overhead of the model as was applied in previous analyses (Ducharme-Barth et al., 2020b; McKechnie et al. 2017b; Tremblay-Boyer et al., 2017a; Tremblay-Boyer and Pilling, 2017). In the current analysis, we randomly sub-sampled 5 observations within predefined strata of time step \times spatial cell \times flag-group. This post hoc stratification resulted in a more tractable, and more spatiotemporally balanced final dataset of 630,025 records (5.40% of total records). Even with the resampling, the dataset was still more heavily weighted towards the tropical model regions due to some spatial cells having a higher number of flag-groups operating within their boundaries (Figure 18).

1.2.4 Potential covariates

We chose to implement the spatiotemporal modeling framework with the inclusion of environmental covariates as abundance covariates. Seasonal patterns in nominal CPUE were indicated for both bigeye and yellowfin tuna (Figure 19 and Figure 20). Season was included as a potential covariate modelled by including month as a cyclic spline (with 12 knots). Oceanographic covariates were also evaluated and assumed to impact abundance in model runs and were included as a cubic regression polynomial spline (with 3 knots).

The vertical distribution of bigeye and yellowfin tuna has been demonstrated to be linked with thermal preference (Holland et al., 1992; Schaefer and Fuller, 2002) and the depth of thermocline can impact yellowfin habitat (Houssard et al., 2017). Abascal et al. (2018) demonstrated that thermocline depth has been shown to affect catch rates of bigeye by longline gears and can be used to predict spatiotemporal variability at a basin scale. Potential oceanographic covariates included sea-surface temperature (SST; Figure 21), depth of 15°C

isotherm, and the difference between the depth of the 12°C isotherm and the 18°C isotherm (Δ depth 12-18°C) and were derived from data (Gouretski and Cheng, 2020) downloaded at <u>https://www.metoffice.gov.uk/hadobs/en4/download-en4-2-2.html</u>. El Niño Southern Oscillation data were also included as a potential covariate but caused model instability and therefore, were not included in the analyses.

We continued the inclusion of catchability covariates within the spatiotemporal modelling framework. The Flag groupings used in the standardization models are defined in Table 1. The distant water fishing nation records for Japan, Chinese Taipei, and the United States were split by fleet group based on differences in operation and/or gear configuration. The Fiji charter vessels were also split apart from the domestic Fiji records. Records from PICTs and Indonesia were grouped into 3 categories, broadly corresponding to pelagic eco-regions in the WCPO (Longhurst,1999) and patterns in species catch composition: countries with exclusive economic zones (EEZs) overlapping with the northern extent of the western Pacific warm pool (NP), countries with EEZs mainly within the equatorial waters of 10°N and 10°S latitude (EQ), and countries with EEZs primarily south of 10°S latitude (SP).

Longline fishers are able to manipulate the characteristics of their gear in order to target depths associated with particular species, often on a set-by-set basis. This is done through a combination of adjustments to the line setting speed, float line length, branch line length and HBF. Even still, variability in current, surface winds, and water density can result in longlines with the same gear configuration fishing at effectively different depths. Additionally, the material of the mainline can also affect the position of hooks in the water column although, this is unlikely to change from set to set. Onboard observers commonly record this information however, it was largely unavailable (except for HBF) in the operational longline dataset consolidated across all flags. As a result, HBF was the only available covariate which could be used to model the effects of gear configuration on bigeye and yellowfin tuna catch rates.

As was done in the previous analysis (Ducharme-Barth et al., 2020b), HBF "bins" were modelled using a penalized "bs" spline with 3 degrees of freedom. This enforced a correlation structure on the data such that adjacent HBF bins were estimated to have a similar effect. Additionally, HBF and flag-group were again, modelled as additive effects.

Vessel identification (ID) represents an important variable that could explain changes in catchability over time as seen in the 2019 and 2022 CPUE analyses of Japanese pole-and-line skipjack tuna (Kinoshita et al., 2019; Teears et al., 2022). Feedback from members of the 2023 pre-assessment workshop (PAW) recommended exploration of including vessel ID as a catchability covariate in the CPUE analysis. Preliminary testing demonstrated that including vessel ID exacerbated the computational challenges as the sub-sampled dataset contained over 6000 unique vessel IDs. Therefore, vessel ID was not included in the analyses. However, this remains an area of future research to develop an index that efficiently incorporates vessel ID in the standardization model.

1.2.5 Covariate selection

The HBF and flag-group covariates provided a means for accounting for differences in catchability however, potential density covariates (i.e., environmental factors) were evaluated and selected by comparing the predictive performance (Geisser and Eddy, 1979; Sivula et al., 2022) of the candidate models thereby, ensuring that newly developed models were not

subject to overfitting of the data. This was done using k-fold cross-validation and the expected log pointwise predictive density (ELPD; Gelman et al., 2014) as a metric.

Cross-validation was implemented by first filtering the sub-sampled data to include the years 1995 through 2000 for computational efficiency of the cross-validation procedure. The data was then split into five, approximately equal sized datasets or "folds", by randomly sampling the data without replacement. Since these data were spatially explicit, spatial blocking was performed using the blockCV package (Valavi et al., 2018) to ensure that training and testing data sets were separated spatially to test the model performance in both nearby and distant locations (Figure 22). For each model run, one of the folds was withheld for testing the predictive capacity while the remaining four folds were used for training the model. Then, the trained model was used to predict the response variable (i.e., CPUE) on the testing fold. This process was repeated with a different fold being withheld each time until all five folds had been used for testing. The sum of the ELPD values for all the fold predictions was used for comparing performance among models.

Predictive performance evaluation was then applied in a reverse stepwise process by comparing the full model (i.e., the model with all potential covariates) to nested candidate models where each of the potential covariates was removed. All model combinations contained the additive effects for HBF, and flag group used in the previous analysis (Ducharme-Barth et al., 2020b) as these effects have been previously demonstrated as important catchability covariates. Comparisons were then performed between candidate models with the full model. The best performing candidate model was then adopted as the new "full" model and this process was repeated until removing covariates no longer improved the predictive performance.

The predictive performance for bigeye CPUE (Table 2) was best when the model included season, the depth of 15°C isotherm, and Δ depth 12-18°C however, for yellowfin CPUE (Table 3), the predictive performance was best when the model only included the depth of 15°C isotherm and Δ depth 12-18°. As such, these covariates were incorporated into the model configuration to inform density by providing a biological envelope to characterize the spatiotemporal distribution.

1.3 Model configuration

Spatiotemporal models have been shown to be more accurate and less biased than equivalently structured delta-GLMs when fit to fisheries dependent data (Grüss et al., 2019; Zhou et al., 2019). Additionally, explicitly modeling the spatiotemporal structure of the data allows these models to cope with non-stationary effort distributions like the ones exhibited in the operational longline dataset (Ducharme-Barth et al., 2019). In the previous analysis (Ducharme-Barth et al., 2020b), the VAST spatiotemporal modeling approach (Thorson et al., 2015; Thorson, 2019) was used to generate regionally weighted, relative abundance indices as the spatial average of predicted abundance once catchability effects have been "standardized" out. As stated previously, we developed a spatiotemporal model using sdmTMB (Anderson et al., 2022) that modelled the longline data similarly to VAST. The sdmTMB software was selected for updating the CPUE analysis through 2021.

The models implemented in the VAST package (version 3.3.0) and the sdmTMB package (version 0.3.0), were spatiotemporal delta generalized linear mixed models (GLMMs). These models accounted for an interactive relationship between space and time and were specified

using Gaussian random fields to define the spatial and spatiotemporal components of the model (Thorson et al., 2015, Anderson et al., 2022). These Gaussian random fields are defined with a Matern covariance function. Using the estimated correlation structure of the data, spatiotemporal delta-GLMMs can simultaneously interpolate abundance of unobserved strata. The addition of environmental covariates can further inform areas of poor sampling by creating a biological envelope of relative density while allowing the model to detect spatial changes in the distribution due to infrequent environmental events.

The delta-GLMM structure implemented in R using the sdmTMB package (Anderson et al., 2022) to update the CPUE analysis is defined below by species.

Bigeye binomial component⁵

 $y_i \sim Bernoulli(p_i)$

$$log \frac{p_i}{1-p_i} \sim YearQtr_i + \omega_1(x_i) + \phi_1(x,t_i) + s(HBF_i) + Flag_i + s(season_i) + s(iso. 15) + s(\Delta iso. 12_18) + \epsilon_1$$

Bigeye positive component

$$c_i \sim Gamma(log\mu_i, \sigma^{-2}, \lambda\sigma^2)$$

$$log\mu_i \sim YearQtr_i + \omega_2(x_i) + \phi_2(x_i, t_i) + s(HBF_i) + Flag_i + s(season_i) + s(iso. 15) + s(\Delta iso. 12_18) + \epsilon_2$$

Yellowfin binomial component

$$\begin{aligned} y_i \sim Bernoulli(p_i) \\ log \frac{p_i}{1-p_i} \sim YearQtr_i + \omega_1(x_i) + \phi_1(x,t_i) + s(HBF_i) + Flag_i + s(iso.\,15) \\ &+ s(\Delta iso.\,12_18) + \epsilon_1 \end{aligned}$$

Yellowfin positive component

$$c_i \sim Gamma(log\mu_i, \sigma^{-2}, \lambda\sigma^2)$$

$$log\mu_i \sim YearQtr_i + \omega_2(x_i) + \phi_2(x_i, t_i) + s(HBF_i) + Flag_i + s(iso. 15) + s(\Delta iso. 12_18) + \epsilon_2$$

where *i* is the record number, ω is the spatial random effect at location *x*, φ is the spatiotemporal random effect at location *x* and time *t*, *s*(*HBF*) is the spline on HBF, *Flag* is the additive effect of flag-group, *s*(*season*) is the cyclic spline on month, *s*(*iso*. 15) is the spline on the depth of the 15°C isotherm, *s*(Δiso . 12_18) is the spline on Δ depth 12-18°C, and \in is the associated error.

⁵ The version of sdmTMB (version 0.3.0) used in these analyses does not allow for covariates to be defined separately for each component of the delta model. Given that a continuous error distribution is used for the positive component and HooksFished is already included in the response variable, we were unable to use it as an offset in the binomial component of the model.

Relative abundance indices were developed as area-weighted indices with catchability covariates (i.e., HBF and flag) held constant to remove their effects on estimates of relative abundance and density covariates (i.e., depth of 15°C isotherm, Δ depth 12-18°C, and season (only included for bigeye) were allowed to vary over space and time.

1.4 Results

Nominal CPUE of bigeye and yellowfin tuna showed similar levels of decline across the assessment regions (Figure 23 and Figure 24) with the exception being the northern regions (1 & 2) for yellowfin tuna which; were relatively flat throughout the time-series.

However, this contrasts with the trends in nominal CPUE, specifically in regions 1-6 which, indicated lower CPUE at the beginning of the time-series and higher CPUE than the standardized CPUE at the end of the time-series. Furthermore, the nominal CPUE exhibited higher seasonal variability for both bigeye and yellowfin as evidenced by the larger spikes occurring periodically. The addition of environmental covariates and season (for bigeye) provided additional information on changes in density to help stabilize the model estimation.

1.4.1 Diagnostics

Residual analysis was performed using probability-integrated-transform (PIT) residuals (Warton et al., 2017), evaluated using the DHARMa R package (Hartig and Lohse, 2017). Standardization of bigeye and yellowfin tuna CPUE coding scripts available at SPC GitHub repository <u>https://github.com/PacificCommunity/ofp-sam-2023-YFT-BET-cpue</u> (login required). All analyses performed in 'R' (Team, 2020).

The diagnostic plots of the PIT residuals, aggregated across the time series at the level of the $5^{\circ} \times 5^{\circ}$ grid cell, from the bigeye and yellowfin tuna spatiotemporal CPUE standardization model are shown in Figure 25 and Figure 26, respectively, and exhibited a normal distribution centred around 0.5, indicating an overall reasonable fit to the data. The spatial pattern of the residuals revealed higher residuals around the peripheral areas of the spatial domain, most notably, in the eastern Pacific Ocean.

The encounter probabilities (Figure 27) declined over the time-series for bigeye and yellowfin tuna with regions 3 and 4 (and 8 for yellowfin) remaining high throughout the time series. Regions 1 and 9 for bigeye and 1 and 2 for yellowfin were lower throughout the time-series. The positive component of the standardization model (Figure 28) declined throughout the time-series for both bigeye and yellowfin tuna for all regions. Regions 1 and 2 for bigeye and regions 5 and 6 for yellowfin were lower than the other regions throughout the time-series.

The fixed effects for density covariates indicated that for Δ depth 12-18°C and for the depth of the 15°C isotherm (Figure 29) for both bigeye and yellowfin tuna, values at or slightly below the mean resulted in higher predictions of CPUE. The seasonal fixed effect (i.e., month) for bigeye tuna (Figure 30) indicated that the predicted CPUE was slightly lower from approximately April through August.

The fixed effects for catchability covariates (Figure 31) demonstrated the importance of flag group in predicting CPUE and that there were differences in flag effects among species. Similarly, HBF also indicated differences among HBF bins and among species.

1.5 Alternative configurations

In addition to exploring the use of environmental covariates to further inform density we explored several other suggestions from the independent yellowfin peer-review (Punt et al., 2023) regarding the CPUE data.

1.5.1 Sub-basin scale

The independent yellowfin peer-review (Punt.et al., 2023) recommended modelling regions independently and comparing the decorrelation distances among regions with the global model (i.e., global refers to the entire 9-region stock assessment spatial extent). It was also recommended that we compare the within region trends with those of the global trends. We aggregated the regions into 3 "sub-basins" defined as regions 1 and 2 in the "north", regions 3, 4, 7, and 8 in the equatorial sub-basin ("equator"), and regions 5, 6, and 9 in the "south" (Figure 32). This exploratory modeling was done using the model configuration and mesh from the previous analysis (Ducharme-Barth et al., 2020b) with covariates for HBF and flag group but modelled using sdmTMB.

Often, the use of CPUE data suffer from edge effects due to preferential sampling whereby observations are sparse in some time steps of the analysis around the periphery of the fishery and therefore, relative abundance is poorly informed. This results in the standardization model to be informed solely by neighbouring cells. Xu and Lennert (2022) spatially constrained the standardization analysis to $1^{\circ} \times 1^{\circ}$ cells with a threshold of years of CPUE data over a specified period. Similarly, we modified the sub-basin scale mesh to remove cells that might be considered not "viable" by removing any 5° x 5° cells with \leq 500 observations prior to creation of the mesh used for fitting the spatiotemporal model.

The results for bigeye tuna indicated high correlations (Figure 34 and Figure 35) for the north and equatorial sub-basins (r > 0.8, p < 0.01) and a moderate correlation in the south (r = 0.43, p < 0.01). The decorrelation distances for the north, equator, and south were 1700, 1280, and 1210 km, respectively. The global decorrelation distance was 1680 km which, was more similar to the north than the equator and south decorrelation distances.

The results for yellowfin tuna indicated a high correlation (Figure 36 and Figure 37) for the equatorial sub-basin (r = 0.9, p < 0.01) and moderate correlations in the north (r = 0.69, p < 0.01) and south (r = 0.68, p < 0.01). The decorrelation distances for the north, equator, and south were 2050, 2000, and 1450 km, respectively. The global decorrelation distance was 1990 km which, was more similar to the north and the equator than the south decorrelation.

These results provide evidence that some regions are more accurately characterized by the global model than others as it was apparent that some regions had a higher influence over the decorrelation distance parameter. However, these influences seem to be driven by differences in scaling as the lower correlation for bigeye tuna is in the south where standardized CPUE is much lower than the north and equator (Figure 35) for both the independent sub-basin models and the global model. Similarly for yellowfin, the lower correlations were in the south and north sub-basin areas where the standardized CPUE is much lower than the equator for both the independent sub-basin models and the global model. Furthermore, these results are consistent with the spatial distribution of nominal CPUE (Figure 5) as the higher nominal CPUE for bigeye tuna has historically been above 10°S (the boundary of the south sub-

basin). Likewise for yellowfin tuna, the higher nominal CPUE (Figure 6) has historically been between 10°N and 10°S (the approximate boundary of the equatorial sub-basin).

The removal of viable cells from the mesh configuration ignores the changes in spatial distribution due to infrequent environmental events (Punt et al., 2023). For this reason, the removal of viable cells was not adopted for use in the standardization of the longline data for bigeye and yellowfin and instead, the incorporation of environmental covariates was implemented to create a biological envelope that has the flexibility to model infrequent environmental events that could cause changes in spatial distribution.

1.5.2 Single fleet indices

An important concern communicated from the independent yellowfin peer-review (Punt et al., 2023) was the combining of data from multiple fleets into a single analysis. It was recommended that an analysis be conducted using only a principal fleet for comparison to assess the effects of combining data from multiple fleets.

As a principal fleet, we chose to model the Japanese fleet data (sub-sampled following methods in *Sub-sampling* to n=600,561) as it extends back to the beginning of the time series and operates in all regions of the 9-region structure. However, there have been decadal shifts in spatial patterns associated with the historical decline in effort (Figure 38) specifically, in the southern regions 6 and 9 of the Japanese fleet since the 1970s. This shift in effort has the potential to cause biases in the derived standardized abundance indices as has been shown in previous research (Carruthers et al., 2010; Ducharme-Barth et al., 2022; Maunder et al., 2020). Sampling coverage of at least 20-40% of the intended spatial domain has been shown to perform comparably to random sampling patterns in simulations for the skipjack Japanese pole-and-line fishery if the sampling patterns are not excessively variable and non-random (Ducharme-Barth et al., 2022).

Sampling coverage in the Japanese fleet over time (Figure 39) indicated that regions 6 and 9 were sampled at a very low proportion (< 20%) for the majority of the time series. In the other regions, the locally weighted smoothing function approximated the sampling coverage above 20% for the entire time series except for the eastern regions 2 and 4 where the coverage drops below 20% in the last few years. For the regions with inadequate coverage during parts of the time-series, it would be appropriate to truncate them temporally if they were to be included as indices for stock assessment to ensure they are representative of relative abundance throughout the time-series. For the purposes of comparing single fleet indices to indices derived from multiple fleets, the resulting indices were very similar (Figure 23 and Figure 24) however, the estimates of uncertainty for the Japanese fleet data were much higher overall and especially, in the south and parts of the eastern area of the spatial extent (Figure 40 and Figure 41).

2 Tagging data preparation

Mark-recapture tagging data can provide valuable information to an assessment if it is representative of the entire population and can influence the estimation of fishing mortality, natural mortality, and movement among regions within an integrated assessment model. The creation of the tag files used in MULTIFAN-CL (MFCL; Fournier et al., 1990, 1998) for the 2023 assessment of bigeye and yellowfin follow the general methods previously outlined in Berger et al. (2014), McKechnie et al. (2016, 2017), Vincent and Ducharme-Barth (2020),

and Teears et al. (2022). Preparation of input files coding scripts are available at SPC GitHub repository <u>https://github.com/PacificCommunity/ofp-sam-bet-2023-data-prep</u> for bigeye and <u>https://github.com/PacificCommunity/ofp-sam-yft-2023-data-prep</u> for yellowfin tuna. All analyses performed in 'R' (Team, 2020).

2.1 Tagging data

Mark-recapture information from four tagging programs included in these assessments: the Regional Tuna Tagging Programme (RTTP; 1989-1992), Coral Sea Tagging Program (CSTP, intermittently over 1991-2001), Pacific Tuna Tagging Program (PTTP; 2006-present) and the Japanese Tagging Program (JPTP 2000-present). For model simplicity, the CSTP tag events were modelled assuming the same reporting rates as the RTTP because some of the tagging events that were assigned as CSTP in the previous assessments were part of the RTTP. Indeed the CSTP cruises were actually targeted cruises of the RTTP to tag bigeye and yellowfin tuna in a specific aggregation area in the Coral Sea. This also reduced the number of reporting rate parameters that needed to be estimated within MFCL.

The tag displacements for bigeye tuna (Figure 42) indicated substantial southerly movements within and from region 1 to region 7 from the JPTP program. The PTTP program demonstrated extensive longitudinal movements within and from the regions 3, 4, and 8 to outside of the 9-region structure into the eastern Pacific Ocean (EPO) and, to a lesser extent, to region 7. The RTTP program displacements indicated more localized movements within the equatorial regions with the exception of releases from region 9 which, showed more northerly movements to regions 3, 4, and 8, and a surprising high number of recaptures within region 9 even after more than 183 days at liberty.

The tag displacements for yellowfin tuna (Figure 43) indicated similarities to the bigeye tuna displacements with considerable southerly movements within and from region 1 to region 7 from the JPTP program. The PTTP program also exhibited substantial longitudinal movements within and from regions 3,4, and 8 to region 7 and to the EPO. However, unlike the bigeye tuna displacements, there was far more movement to region 7 and much less to the EPO for yellowfin tuna. The RTTP program displacements indicated moderate movements within and from regions 3 and 8 to regions 7 and 4 with the exception of releases from region 9 which, similar to bigeye tuna, showed more northerly movements to regions 3, 4, and 8, and a number of recaptures within region 9 after more than 183 days at liberty.

2.2 Tag preparation file overview

Many of the tags are unusable in the assessment due to inadequate information such as missing data (e.g., time, location or fishery of recapture), outside of assessment spatial extent, or cannot be attributed to a fishery because they are captured by a gear that is not included in the assessment. The ratio of releases to recaptures can impact estimates of mortality in the assessment model and to preserve this ratio, the number of releases need to be corrected based on the number of recaptures that can be used in the model. Additionally, tagging induced mortality and tag shedding (Vincent and Ducharme-Barth, 2020) can impact overall survival that is not related to either natural or fishing mortality as well as the differential effects of individual taggers on tagging-induced mortality (i.e., tagger effects; Berger et al., 2014; Peatman et al. 2023b; Vincent and Ducharme-Barth, 2020). Tag seeding studies provide some information on the magnitude of tag reporting rates for some of the purse seine fisheries in the assessment (see Peatman and Nicol, 2023 for further details). These factors

need to be accounted for to ensure parameters of interest in MFCL are accurately estimated. The observed proportion of tag returns were corrected to reflect the actual recapture rate and this process was conducted using the same methods as the previous bigeye and yellowfin tuna assessments (Ducharme-Barth et al., 2020a; Vincent et al., 2020). The formulae and methods used are presented in detail in McKechnie et al., 2016) and we refer the readers to that report. A summary is provided below.

The creation of the tagging data files for use in MFCL were:

- 1. Extraction and filtering of release/recapture data from the database.
- 2. Correction of releases for base tagging-induced mortality (7% assumed) and mortality from tagger effects (Peatman et al. 2023b).
- 3. Correction for instantaneous tag shedding (6.97%; Vincent and Ducharme-Barth, 2020).
- 4. Correction of usability ratio calculated as the ratio of usable to total recaptures at the scale of the length bin within a tagging release event.
- 5. Consideration of grouping of fisheries/tagging programs for tag recaptures and reporting rates.
- 6. Construction of tag reporting rate priors from tag seeding experiments (Peatman and Nicol, 2023).

Tags that are recaptured within the same quarter as the release event but do not have a recapture location are assigned to the PS fishery in the release region. To reduce computational time for MFCL and improve model stability, all release events with less than 10 effective tag releases were excluded. All release events that occurred after the end of 2019 were excluded from the assessment to prevent biases from not including recaptured fish that were not reported or entered into the database at the time of the assessment (there is often a substantial lag between recapture and reporting). Tagger effects and reporting rates were updated with additional data as available, and are described in detail in (Peatman et al., 2023b; Peatman and Nicol, 2023, respectively).

2.3 Japanese tagging data

The same procedures for preparing the tag file as outlined above were conducted for preparation of the Japanese tag data. The tag shedding and base tagging mortality rate were assumed to be the same as those estimated from the SPC tagging studies. For the purposes of correction for tagger effects, the median correction factor for all release groups was assumed. It should be noted that there are a moderate number of recaptures from this tagging program by small-scale fisheries that are not included in the assessment model. However, these were accounted for by the usability correction factor that was applied in the same manner as tags from the SPC databases.

2.4 Forced mixing period

Previous assessments of bigeye and yellowfin tuna (prior to 2020), the tag file was created based on the best estimate of release and recapture dates to assign the release and recapture period (quarter) within the model. However, this could result in tags that are released the day before the end of a quarter and recaptured a few days later in the next quarter being assigned to have a mixing period of 1 quarter. To ensure that a comparable mixing period was applied to every tag released, tag recapture periods in the tag file were adjusted. Individual tag

recaptures were assigned to a recapture quarter based on the time at liberty (TAL). A separate tag file was created for the 1, 2, and 3 mixing period assumptions. Any recapture that did not meet the required TAL according to the tag file being created (i.e., 1 quarter mixing period TAL \geq 92 days, 2 quarter mixing period TAL \geq 183 days, and 3 quarter mixing period TAL \geq 274 days) had the recapture quarter reduced by one quarter to ensure the recapture would not be considered mixed by MFCL. The need to ensure a uniform mixing period across all tag releases was noted in Vincent et al. (2019) and was applied in the 2020 bigeye and yellowfin tuna assessments (Ducharme-Barth et al., 2020a; Vincent et al., 2020, respectively). This method was also supported by the independent yellowfin peer-review (Punt et al., 2023) to be continued in future assessments.

2.5 Summary and comparison to 2020 tag file

After updating the tagger effects and applying the various correction factors to the raw data, the resulting tagging data corrections for the 2023 bigeye and yellowfin tuna stock assessments were similar to the tagging data from the 2020 bigeye and yellowfin tuna stock assessments as shown in (Figure 44, Figure 45, Figure 46, and Figure 47).

3 Tag mixing

Depending on the distribution of fishing effort in relation to tag release sites, the probability of capture of tagged fish soon after release may be different to that for the untagged fish. It is therefore desirable to designate a time period following tag releases as "pre-mixed" and compute fishing mortality for the tagged fish during this period based on the actual recaptures, corrected for tag reporting and tagging effects, rather than use fishing mortalities based on the general population parameters. This, in effect, desensitizes the likelihood function to tag recaptures in the specified "pre-mixed" periods while correctly removing fish from the tagged population that is present after the "pre-mixed" period. We refer to the "pre-mixed" period as the "mixing period" (as described in the Forced mixing period section).

The allocation of appropriate "mixing periods" for tag release groups is problematic, and mixing rates may vary depending on release locations and contexts (i.e., releases on FADs versus free schools, releases in archipelagic waters versus releases in open ocean), fishing effort distribution and environmental/food conditions that influence movements. The yellowfin peer review considered mixing period assumptions and endorsed an approach applied to the 2022 skipjack assessment (Castillo Jordan et al., 2022; Scutt Phillips et al., 2022) whereby an external, individual based model was used to estimate mixing periods specifically for each release group, taking into account the unique locational and temporal (environmental, fishing effort) contexts of each release event, constituting the group, that may result in different rates of mixing of released fish. It applied the individual based Lagrangian model (Ikamoana) (Scutt Phillips et al., 2018) to track movement of individual fish (particles) and quantify the fishing pressure that individuals experienced across their dispersal trajectories in comparison to a population of simulated untagged particles. It was not possible to develop this approach for the current assessment, and it remains to be seen if this approach can be developed in future for bigeye or yellowfin.

Mixing period assumptions received considerable discussion at the Pre-assessment Workshop (Hamer, 2023) where it was suggested that some external analysis of tag-recapture patterns would be useful to support a range of tag mixing assumptions for sensitivity analyses. We

currently do not have a robust, easy, and practical to apply methodology for estimating tag mixing periods that is readily adaptable to changes in model spatial structure, and that accounts for the changes in spatiotemporal fishing effort that have occurred over the duration of available tagging data. Previous analytical approaches have been applied to this problem for skipjack in the WCPO to determine if mixing had likely occurred by certain periods after releases (Kolody and Hoyle, 2014) and qualitive approaches, similar to described below, for considering tag mixing periods for yellowfin tuna in the Indian Ocean (Langley and Million, 2012). Each method has pro and cons, and further work is required to develop analyses to guide tag mixing assumptions in future WCPFC tuna assessments.

To support assumptions of tag mixing for the current yellowfin and bigeye assessments, we conducted a qualitative review of the main PTTP tag release events for yellowfin and bigeye using mapping of tag release and recapture distributions. The approach is similar to that of Langley and Million (2012) and could be considered as a qualitative version of the TART analysis in Kolody and Hoyle (2014). The maps involve plotting at 1° x 1° resolution the distributions of year/quarter tag releases and associated recaptures at intervals of 0, 1, 2, 3 and 4 quarters after release (0 quarter meaning recapture during the assigned quarter of release, 1 quarter meaning recapture during the first quarter after the quarter of release, etc.). The recaptures are scaled to the catches and plotted per tagging cruise as numbers of tags recaptured per 100 mt of catch in 1° x 1° grids cells. The catches used are for the purse seine fishery which accounts for 90% of bigeye tag returns and 94% of yellowfin tag returns. This scale to catch provides a better indication of relative tag recapture rate across the model region compared to using absolute recapture numbers. We considered that when recaptures are observed in 1° x 1° cells spread throughout the model regions of their release (noting recaptures outside the model region of release do not factor into the fishing mortality estimates) in relation to the catch distribution and with roughly similar rates of recapture that this was a reasonable indication that tagged fish had mixed to a satisfactory degree for the assumptions of the assessment model.

The 'tag mixing' plots provided a diagnostic for considering tag mixing assumptions. We used these plots to assign mixing periods to the region-specific tag releases for each PTTP tagging cruise. This assignment based on an expert qualitative judgement is not ideal but is a step forward, provides increased transparency, and people can make their own judgements based on the plots. The assigned mixing periods were summarised to provide a general indication of likely mixing periods to apply in sensitivity analyses. These assessments were conducted for the 9 region and a simpler model structure whereby the equatorial regions 3 and 4 of the 9-region model are merged into one region.

As further support for this qualitative assessment we plotted the distributions of displacement distances of tag recaptures for recaptures grouped according to times at liberty of 1, 2, 3, 4, 5, and 6 quarters (i.e., 1 quarter after release in this analysis corresponds to 0-3 months' time at liberty, 2 quarter is 3-6 months' time at liberty etc.) for releases from tropical model regions 3, 4, 7 and 8 of the 9-region model.

Example tag mixing plots are provided below, and all plots for yellowfin and bigeye are provided in Appendix 1: Tag mixing plots. Figure 48 is an example where there are a good number of tag releases and recaptures, and improved mixing can be clearly observed at 1 quarter (i.e., 3-6 months after release).

In contrast many of the plots have quite low numbers of tag releases and recaptures, and some have release locations not well centred in the model regions and close to region boundaries. In these cases, tagged fish often moved outside the release regions soon after release and so therefore were no longer used in the analysis for the release region. Because of these issues, for quite a few of the plots it was problematic to make judgments on whether the tagged fish appeared well mixed or not by a certain quarter after release. Some plots could suggest that mixing was unlikely by 1 quarter, but there were too few recaptures in the release region after 1 quarter to judge if improved mixing had occurred by 2 quarter or 3 quarters (Figure 49).

Tag displacement distances tended to stabilise from 2 to 3 quarters at liberty (Figure 50), which is similar to the assignments of tag mixing period of 1 quarter and 2 quarter for the majority of tag mixing plots that could be assessed for both yellowfin and bigeye (Table 4).

Overall, the qualitative analyses indicated that tag mixing periods of 1 and 2 quarters are a reasonable assumption for sensitives, however, there is considerable uncertainty on mixing periods for many of the tag release cruises. Some tag release groups showed more obvious evidence for mixing than others depending on how many tags were released (i.e., the qualitative assessments were more reliable for larger tag releases), so the results mostly reflect those cases. Perhaps, encouragingly for the tag releases with high numbers of release (1,000s) and recaptures (100s) tag mixing seemed to be occurring, and these releases will have more influence on the stock assessment. Because it is not possible to even qualitatively assign mixing periods to each tag release cruise, we suggest continuing with the approach of applying the same fixed mixing periods for each release cruise and maintaining 1 and 2 quarter mixing periods in the uncertainty grid as per the previous assessment. While these qualitative assessments of mixing period assumption could no doubt be improved with more time, we suggest they provide a stronger basis for mixing period assumptions than in the previous assessment.

4 Adjustment to fisheries length composition data

Fisheries dependent bigeye and yellowfin tuna length composition data were adjusted for several fisheries as there were anomalies that were suspected to not be representative of the compositions for bigeye and yellowfin tuna. Specifically, the miscellaneous gears fisheries length compositions in region 7 in the Philippines and Indonesia were filtered to include only fish below 96 cm. Also, the handline fishery length compositions in region 7 in the Philippines and Indonesia were filtered to include only fish above 68 cm. Preparation and treatment (including re-weighting) of size composition data for the assessments is described in detail in Peatman et al., (2023a) (SC19-SA-IP-03).

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6 Tables

Table 1: Representation of flag-groups in the final dataset used for the CPUE standardization model.

Flag.group ⁶	Flag.fleet	Ν	Percent
JP.DW	JP.DW	221,499	35.16%
JP.OS	JP.OS	107,545	17.07%
KR	KR	75,542	11.99%
TW.DW	TW.DW	61,776	9.81%
PICT.SP	CK, FJ.FJ, NC, NU, PF.PF, TO, TV, US.AS, VU, WS	52,048	8.26%
TW.OS	TW.OS	29,367	4.66%
CN	CN, CN.CN, CN.DW	24,356	3.87%
US.HW.D	US.HW (Hawaii deep set, >15 HBF)	15,599	2.48%
PICT.EQ	ID, KI, PG, PG.DW, SB, SB.DW	10,491	1.67%
US.HW.S	US.HW (Hawaii shallow set, <15 HBF)	5,372	0.85%
AU	AU.AU, AU.CV	8,097	1.29%
PICT.NP	FM, GU, MH, PW	7,728	1.23%
FJ.charter	FL.AU, FJ.CK, FJ.CN, FJ.KR, FJ.NZ, FJ.TW, FJ.US	6,231	0.99%
NZ	NZ.JP, NZ.NZ	4,374	0.69%

Table 2: Results from covariate selection process with k-fold cross-validation using expected log predictive density (ELPD; Gelman et al., 2013) as a comparative metric for bigeye tuna CPUE model. ELPD is expressed as the absolute value of the negative log-likelihood.

Covariates Added to Base Model (Flag + HBF)	ELPD
season + depth of 15° C isotherm + Δ depth (12-18°C)	35,197
season + depth of 15°C isotherm	35,200
depth of 15°C isotherm + Δ depth (12-18°C)	35,207
season + Δ depth (12-18°C)	35,350
SST + season + depth of 15°C isotherm + Δ depth (12-18°C)	35,648
SST + depth of 15° C isotherm + Δ depth (12-18°C)	35,653
SST + season + Δ depth (12-18°C)	35,681
$SST + season + depth of 15^{\circ}C isotherm$	35,757

⁶ ISO 3166 alpha-2 country codes are used to refer to the flags of individual nations.

Table 3: Results from covariate selection process with k-fold cross-validation using expected log predictive density (ELPD; Gelman et al., 2013) as a comparative metric for yellowfin tuna CPUE model. ELPD is expressed as the absolute value of the negative log-likelihood.

Covariates Added to Base Model (Flag + HBF)	ELPD
depth of 15°C isotherm + Δ depth 12-18°C	36,822
Δ depth 12-18°C	36,852
season + depth of 15° C isotherm + Δ depth 12-18°C	36,864
SST + depth of 15° C isotherm + Δ depth 12-18°C	36,883
season + Δ depth 12-18°C	36,898
SST + season + depth of 15° C isotherm + Δ depth 12-18°C	36,919
depth of 15°C isotherm	36,944
$SST + season + depth of 15^{\circ}C isotherm$	36,950
season + depth of 15° C isotherm	37,009
$SST + season + \Delta depth 12-18^{\circ}C$	37,072

Table 4: Summary of results of classification of mixing periods for tag release cruises for the 9-region model structure from the tag mixing plots (Appendix 1: Tag mixing plots), including analyses with equatorial regions 3 and 4 combined into a single region.

Model region (R) of release	Number	Numbers of tag release cruises classified to each					
cruise	of release	of the mixing period categories from $0-4$					
	cruises	quarters, $N = no$ classification possible					
		N	0	1	2	3	4
R7	2	0	1	0	1	0	0
R8	9	1	0	2	4	2	0
R3	7	4	2	1	0	0	0
R4	7	3	1	3	0	0	0
R5	1	1	-	-	-	-	-
Total	26	9					
Region 3 and 4 as single	13	9	0	4	0	0	0
region							

a) Yellowfin

b) Bigeye

Model region (R) of release	Number	Number of tag release cruises classified to each of					
cruise	of	the mixing period categories from $0-4$ quarters,					
	release	N = no classification possible					
	cruises	N	0	1	2	3	4
R7	2	1	0	1	0	0	0
R8	7	4	2	1	0	0	0
R3	5	5	-	-	-	-	-
R4	15	3	1	7	3	1	0
Total	29	13					
Region 3 and 4 as single	18	8	1	6	2	1	0
region							

7 Figures



Figure 1: Spatial structure by region number for the bigeye and yellowfin tuna stock assessments 9-region structure.



Figure 2: The number of operational longline records within each assessment region over time.



Figure 3: The decadal distribution of longline fishing effort (defined as hooks fished) across all fishing fleets in the operational longline data set.

Decadal species proportion catch - All fleets



Figure 4: The decadal distribution of proportion of species caught across all fishing fleets by 15° x 15° spatial cell in the operational longline data set. Includes albacore (ALB), bigeye (BET), striped marlin (MLS), swordfish (SWO), and yellowfin (YFT).





Figure 5: The decadal distribution of bigeye tuna nominal CPUE (numbers per 100 hooks fished) across all fishing fleets in the operational longline data set.



Figure 6: The decadal distribution of yellowfin tuna nominal CPUE (numbers per 100 hooks fished) across all fishing fleets in the operational longline data set.



Figure 7: The number of records with and without HBF by assessment region. The colour of the bar indicates the bin of HBF that each record was assigned to.



Figure 8: Mean centered standardized indices from 1952 to 2018 using VAST and sdmTMB spatiotemporal models from bigeye tuna CPUE longline data.



Figure 9: Standardized indices from 1952 to 2018 using VAST and sdmTMB spatiotemporal models from bigeye tuna CPUE longline data.



Figure 10: Mean centered standardized indices from 1952 to 2018 using VAST and sdmTMB spatiotemporal models from yellowfin tuna CPUE longline data.



Figure 11: Standardized indices from 1952 to 2018 using VAST and sdmTMB spatiotemporal models from yellowfin tuna CPUE longline data.



Figure 12: The distribution of 154 spatial knots used to define the mesh for the spatiotemporal standardization model used in the 2020 assessments of yellowfin and bigeye with the 9-region stock assessment structure (black rectangles) included. Extrapolation grid cells are colour coded to show the knot that they are associated with.



Figure 13: Equidistant projection showing the distribution of 371 spatial knots used to define the mesh for the spatiotemporal standardization model used in the 2023 assessments of yellowfin and bigeye. The 9-region stock assessment structure (blue) and the mesh boundaries (pink line) included.



Figure 14: Mean centered standardized indices from 1990 to 2010 using VAST ("mesh.2020") and sdmTMB with a higher resolution mesh ("mesh.2023") spatiotemporal models from bigeye tuna CPUE longline data.



Figure 15: Standardized indices from 1990 to 2010 using VAST ("mesh.2020") and sdmTMB with a higher resolution mesh ("mesh.2023") spatiotemporal models from bigeye tuna CPUE longline data.


Figure 16: Mean centered standardized indices from 1990 to 2010 using VAST ("mesh.2020") and sdmTMB with a higher resolution mesh ("mesh.2023") spatiotemporal models from yellowfin tuna CPUE longline data.



Figure 17: Standardized indices from 1990 to 2010 using VAST ("mesh.2020") and sdmTMB with a higher resolution mesh ("mesh.2023") spatiotemporal models from yellowfin tuna CPUE longline data.



Figure 18: The spatiotemporal distribution of aggregated observations by $5^{\circ} \times 5^{\circ}$ cell and decade from the final sub-sampled data set used to estimate the indices with 9-region model structure overlaid (red lines).



Figure 19: Bigeye tuna nominal (Nom.) CPUE (numbers per 100 hooks fished) by quarter (Qtr) over the spatial extent of the operational longline dataset.



Figure 20: Yellowfin tuna nominal (Nom.) CPUE (numbers per 100 hooks fished) by quarter (Qtr) over the spatial extent of the operational longline dataset.



Figure 21: Potential environmental covariates evaluated to inform density in standardization of CPUE for bigeye and yellowfin tuna. Covariates scaled (mean=0, sd=1) and include difference in depth of 12°C and 18°C isotherms (A), depth of 15°C isotherm (B), and seasurface temperature (C).



Figure 22: Spatial blocking of operational longline dataset over the spatial extent for k-fold (k=5) cross validation used in testing the predictive performance of candidate models with various environmental covariates. The colour in each block corresponds to the fold assignment (1-5).



Figure 23: Mean centered nominal, standardized ("sdmTMB"), and Japanese fleet ("JP") standardized indices from 1952 to 2021 for bigeye tuna CPUE longline data.



Figure 24: Mean centered nominal, standardized ("sdmTMB"), and Japanese fleet ("JP") standardized indices from 1952 to 2021 for yellowfin tuna CPUE longline data.



Figure 25: Spatial distribution of probability-integrated-transform (PIT) residuals aggregated across the full time series for bigeye tuna standardized CPUE at the level of the 5° grid cell (A) and histogram of aggregated PIT residuals (B).



Figure 26: Spatial distribution of probability-integrated-transform (PIT) residuals aggregated across the full time series for yellowfin tuna standardized CPUE at the level of the 5° grid cell (A) and histogram of aggregated PIT residuals (B).



Figure 27: Time-series of encounter probability by region for bigeye tuna (A) and yellowfin (B) with loess smooth line (blue) with error (grey shading).



Figure 28: Time-series of positive model component by region for bigeye tuna (A) and yellowfin (B) with loess smooth line (blue) with error (grey shading).



Figure 29: Density fixed effects from longline CPUE standardization for difference in depth of 12°C and 18°C isotherms for bigeye (A) and yellowfin (B) tuna and for depth of 15°C isotherm for bigeye (C) and yellowfin (D) tuna. Predicted CPUE coloured by flag group with loess smooth line (blue).



Figure 30: Density fixed effect from bigeye tuna longline CPUE standardization for month. Predicted CPUE coloured by flag group with loess smooth line (blue).



Figure 31: Catchability fixed effects from longline CPUE standardization for flag group for bigeye (A) and yellowfin (B) tuna and for hooks-between-floats (HBF) for bigeye (C) and yellowfin (D) tuna. Predicted CPUE coloured by flag group with loess smooth line for HBF (blue).



Figure 32: Aggregation of regions from the 9-region structure for exploratory sub-basin scale analyses.



Figure 33: Map of "viable" 5° x 5° cells (shown with centered black dots) over the standardization spatial extent for the sub-basin scale analyses. Cells with \leq 500 observations were removed (shown as empty cells) prior to creation of mesh configuration.



Figure 34: Mean-centered standardized CPUE for bigeye tuna from the independently modelled sub-basins ("basin") compared to the same sub-basin areas (i.e., north, equator, and south) derived from the global model ("global"). Correlation (r) and *p*-values included.



Figure 35: Standardized CPUE ("CPUE") and triangular moving average with a filter size 5 ("TMA_5") for bigeye tuna from the independently modelled sub-basins ("basin") compared to the same sub-basin areas (i.e., north, equator, and south) derived from the global model ("global").



Figure 36: Mean-centered standardized CPUE for yellowfin tuna from the independently modelled sub-basins ("basin") compared to the same sub-basin areas (i.e., north, equator, and south) derived from the global model ("global"). Correlation (r) and *p*-values included.



Figure 37: Standardized CPUE ("CPUE") and triangular moving average with a filter size 5 ("TMA_5") for yellowfin tuna from the independently modelled sub-basins ("basin") compared to the same sub-basin areas (i.e., north, equator, and south) derived from the global model ("global").



Figure 38: The decadal distribution of longline fishing effort (defined as hooks fished) for the Japanese fleet in the operational longline data set. The 2020 decade was removed as it would not be representative of the entire decade.



Figure 39: Proportion of spatial knots sampled over time by region for operational longline Japanese fleet. Region-specific coloured lines with confidence intervals approximated by locally weighted smoothing function. Light grey lines at 0.2 and 0.4.



Figure 40: Estimates of uncertainty derived by bootstrapping from the joint precision matrix plotted at 5° x 5° grid cell resolution and aggregated by decade for bigeye tuna standardized CPUE derived from multiple fleets (A) and Japanese fleet data (B).



Figure 41: Estimates of uncertainty derived by bootstrapping from the joint precision matrix plotted at 5° x 5° grid cell resolution and aggregated by decade for yellowfin tuna standardized CPUE derived from multiple fleets (A) and Japanese fleet data (B). Note the difference in scale between plots.



Figure 42: Mark-recapture displacements (grey lines, points indicate recapture locations) of bigeye tuna that have been at liberty for at least 183 days (~2 quarters) for the Pacific Tuna Tagging Program (PTTP), the Regional Tuna Tagging Program (RTTP), and Japanese Tagging Program (JPTP). Recapture locations identified with points (blue) with the exception of those released in region 9; emphasizing that many releases from region 9 are recaptured in region 9 after 183 days at liberty. Red points in RTTP plot indicate the Coral Sea tags.



Figure 43: Mark-recapture displacements (grey lines, points indicate recapture locations) of yellowfin tuna that have been at liberty for at least 183 days (~2 quarters) for the Pacific Tuna Tagging Program (PTTP), the Regional Tuna Tagging Program (RTTP), and Japanese Tagging Program (JPTP). Recapture locations identified with points (blue) with the exception of those released in region 9; emphasizing that many releases from region 9 are recaptured in region 9 after 183 days at liberty. Red points in RTTP plot indicate the Coral Sea tags.



Figure 44: Mark-recapture histograms of effective releases, recaptures, probability of recapture ("Recapt. Rate"), and releases by region for bigeye tuna by program for the Pacific Tuna Tagging Program (PTTP), the Regional Tuna Tagging Program (RTTP), and Japanese Tagging Program (JPTP).



Figure 45: Number of effective releases, recaptures, and the probability of recapture by year for tagged bigeye tuna from the Pacific Tuna Tagging Program (PTTP), Regional Tuna Tagging Program (RTTP), and the Japanese Tagging Program (JPTP) for the various mixing periods (1, 2, or 3 quarters) tag files for the 2023 SA compared to the 2020 Diagnostic ("Diag.") SA tag file.



Figure 46: Mark-recapture histograms of effective releases, recaptures, probability of recapture ("Recapt. Rate"), and releases by region for yellowfin tuna by program for the Pacific Tuna Tagging Program (PTTP), the Regional Tuna Tagging Program (RTTP), and Japanese Tagging Program (JPTP).



Figure 47: Number of effective releases, recaptures, and the probability of recapture by year for tagged yellowfin tuna from the Pacific Tuna Tagging Program (PTTP), Regional Tuna Tagging Program (RTTP), and the Japanese Tagging Program (JPTP) for the various mixing periods (1, 2, or 3 quarters) tag files for the 2023 SA compared to the 2020 Diagnostic ("Diag.") SA tag file.



Figure 48: Example tag mixing plots for bigeye tuna released on the CPF5 cruise in 2010 in model region 4, with 6090 tagged bigeye released and 535 total recaptures within region 4. This example shows that tag recapture rates and distributions in respect of the catches (faint yellow cells) indicate the tagged fish were well mixed at 1 quarter. Italics numbers indicate model region numbers from the 9-region model structure.



Figure 49: Example tag mixing plot for yellowfin tuna released on the CPF5 cruise in 2010 in model region 4, with 228 tagged yellowfin released and only 21 total recaptures within region 4. This example shows that although recaptures at 1 quarter were distributed though the region of release, the low recapture numbers mean low confidence in assigning a mixing period. Italics numbers indicate model region numbers from the 9-region model structure.





Figure 50: Box plots of distributions of displacement distances (y-axis) as a function of actual times at liberty grouped by quarters (x-axis) for yellowfin (left) and bigeye (right) tag releases in model regions 3, 4, 7, and 8. Note that 1 quarter at liberty here refers to 0-3 months, which is more aligned with the 0 quarter category in the tag mixing plots, 2 quarter here is more aligned with 1 quarter in the tag mixing plots etc.

Appendix 1: Tag mixing plots 8

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9 Appendix 2: Fishery catch and size composition plots































































































































