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## Background analyses and data inputs for the 2022 skipjack tuna stock assessment in the Western and Central Pacific Ocean

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## 2 Executive Summary

This information paper provides details on the key supporting analyses and data sets used to inform the 2022 assessment model for the western and central Pacific Ocean (WCPO) skipjack stock. These include:

- The standardization procedure used for the catch per unit effort (CPUE) time-series to provide relative abundance indices for the index fisheries.
- The preparation of tagging data to construct the tag input files
- The development of mixing period assumptions.
- The adjustment of longline fishery length compositions.
- The reweighting approach of the length-composition data for extraction and index fisheries.

The Japanese pole and line (JPPL) fishery CPUE time-series was standardized to provide indices of relative abundance for six of the ten index fisheries. Similar to the 2019 skipjack stock assessment (SA), a spatiotemporal modeling approach was used with the primary differences being a uniform spatial knot configuration to account for historical fishery contraction, and the region 8 index was truncated to include 1975-1997 due to inadequate sampling coverage.

The CPUE time-series for the purse seine fisheries in regions 6-8 (PS.6-8) was standardized to provide indices of relative abundance for three of the ten index fisheries. Similar to previous work on the standardization of purse seine CPUE data for skipjack (Vidal et al., 2020), a spatiotemporal modeling approach was applied however, we defined effort as the cumulative daytime path length between sets, computed from VMS and logsheet rather than using the set as the unit of effort. Data was filtered to include only unassociated sets to remove the influence of advancements in fish aggregating device (FAD) technology. Vessels that were defined as FAD specialists ( $\geq 70 \%$ of sets on FADs during non-closure periods) were removed for that year to remove potential biases introduced as a result of differences in unassociated set fishing skill during closure periods.

Monthly catch and effort for the purse seine fishery in the Philippines (i.e., region 5, PS.5) fishery were estimated from port sampling data and the CPUE time-series was then standardized to provide an index of relative abundance for the final index fishery. Methodology for the standardization of the Philippines purse seine CPUE followed those applied in the 2019 skipjack SA (Bigelow et al., 2019) by applying generalized linear models (GLMs).

Compared to the 2019 tag file, an additional 59 release events were added to the tag file, which was the result of additional release events that were previously missing length at release or from additional release events that had not met the 2019 skipjack SA cut-off year to be included in the model. These changes to the tagging file contributed an extra 53,575 effective releases and 7,213 usable recaptures. The corrections of tag releases for usability,
tag shedding, and tag-induced mortality reduced the total number of effective releases to 383,387 and 63,305 usable recaptures in the 2022 tag file.

In the previous skipjack SA (Vincent et al., 2019a), assumptions of mixing period duration were influential to stock status. Simulations using an individual-based model of tagged release groups were performed to estimate release event-specific mixing periods and regionspecific mixing periods for events not simulated (Scutt Phillips et al., 2022).

The size composition data were reweighted prior to integration into the assessment model to remove potential bias due to uneven sampling of skipjack over space and time within model strata. This approach applies two reweighting schemes; one for extraction fisheries that uses catch as the weighting factor to promote length composition data that are representative of removals, and one for survey fisheries that uses CPUE as the weighting factor to promote length composition data that are representative of the population. The reweighting of size compositions was performed using the methods applied in previous assessments of albacore, bigeye, and yellowfin tuna (Peatman et al., 2020; Vidal et al., 2021) and are described in detail in Appendix 1 -Reweighting of size composition data.

## 3 Introduction

Stock assessments for tuna in the Western and Central Pacific Ocean (WCPO) conducted by the Pacific Community (SPC) generally utilize the statistical software MULTIFAN-CL (Fournier et al., 1998; Hampton and Fournier, 2001; Kleiber et al., 2019). These models have extensive data requirements and specific formats for input files. This paper describes the data and its pre-processing that were used in the 2022 stock assessment (SA) of skipjack tuna Katsuwonus pelamis in the WCPO where stand-alone manuscripts were not considered warranted in each case. This report should not be viewed as the only inputs used in the 2022 skipjack assessment. Instead, readers should also refer to the information papers on the estimation of reporting rate priors (Peatman, 2022) and the estimation of tagger effects (Peatman et al., 2022, Scutt Phillips et al., 2022).

## 4 Standardized catch per unit effort (CPUE)

Catch per unit effort (CPUE) data plays a vital role in the stock assessment of skipjack as it provides a measure of relative abundance to the assessment model. Variables affecting catchability and population density are accounted for in a spatiotemporal modeling approach (Thorson, 2015). The standardization of these data was performed using a spatiotemporal delta generalized linear mixed model (GLMM) when possible or generalized linear models (GLMs) otherwise. Data from the Japanese pole and line fishery (JPPL) and from the purse seine fishery in the WCPO were used to develop indices of relative abundance. For both the JPPL and the purse seine fishery in regions 6-8 (PS.6-8), the region-specific median of coefficient of variation was used as the basis for computing penalties for the CPUE indices in the 2022 skipjack SA.

### 4.1 Japanese pole and line

CPUE of skipjack caught by JPPL fishing vessels using an eight-region spatial structure
(Figure 1; as was used in the 2019 skipjack SA; Vincent et al. ,2019a) was estimated from logsheet data between 1972 and 2020. Data in 2018 was updated and two years of data from 2019 to 2020 were added since the 2019 skipjack SA. The spatiotemporal estimation method
and data screening procedures (SP) related to the model inputs were performed following methods employed in the 2019 SA (Kinoshita et al., 2019).

The CPUE standardization was calculated as delta-lognormal GLMM indices by multiplying the set of indices obtained from the proportion of non-zero catch (by a binomial model) and the value of non-zero catch (by a lognormal model; Kiyofuji, 2016; Kiyofuji et al., 2011; Kiyofuji and Okamoto, 2014; Langley et al., 2010; Lo et al., 1992). JPPL fleets were divided into offshore pole-and-line (OS) and distant water pole-and-line (DW) according to vessel size, which affects their fishing strategy. OS operations consist of short cruises of less than two weeks during a fishing season from April through December, and their main fishing ground is distributed offshore of Tohoku, Japan (north of $30^{\circ} \mathrm{N}$ ). In contrast, DW fishing cruises may be longer than a month and fish throughout the year with a wide fishing ground in the WCPO.

### 4.1.1 Fisheries data

The JPPL logsheet data utilized in the CPUE standardization covered the period from 1972 to 2020. Coverage data from 2021 was only about $50 \%$ due to delays in digitizing caused by covid19 and therefore, were not included in the standardization. The spatiotemporal resolution of the logsheet data is 1 arc-degree at noon position (equal to $1 \times 1^{\circ}$ grid cells) and daily. The following information was included for the CPUE calculation: date, skipjack catches in weight, number of poles, gross registered tonnage (GRT), and vessel identification. The JPPL data was categorized by vessel size with vessels between 20 and 199 GRT defined as OS and vessels greater than or equal to 200 GRT defined as DW.

Historical changes in catch and effort and decadal shifts in the fishery grounds are shown in Figure 2 and Figure 3, respectively. In the 1970s, the catch reached the highest (around $200,000 \mathrm{mt}$ ) in the recorded periods as well as the number of vessels and poles (Figure 2). Fishery grounds in the 1970s were widely spread in most regions except regions 5 and 6 , and there were hot spots (over 1000 metric ton per $1^{\circ}$ grid cell) in regions $1,2,3,7$, and 8 (Figure 3). However, the catch fell below 120,000 mt in the late 1980s with a drastic drop of effort (i.e., the number of vessels and poles), which was primarily due to the reduction of the catch in regions 7-8. The catch and the effort have gradually decreased since the 1990s until 2020 when the lowest catch was recorded ( $37,851 \mathrm{mt}$ ). The continuous decrease was associated with contractions of the fishery grounds, which was remarkable in regions 4 and 8 , and there are few hot spots in most regions in the 2010s (Figure 3).

The catch in each quarter and its fishery ground for the recent period (2008-2020) are shown in Figure 4. In general, the JPPL DW fishery operates throughout the year, whereas the JPPL OS fishery operates from late January (quarter 1) to late November (quarter 4). Thereby, the catch in quarters 1 and 4 are much lower than those in quarters 2 and 3 (Figure 4). In quarter 1 , most of the JPPL fishery operates in tropical-subtropical areas (regions 3, 4, 7, and 8). Subsequently, the spatial distributions of the JPPL spread toward the north in quarters 2-3 (mainly region 2; Figure 4), and then back southward in quarter 4.

The seasonal trend of the JPPL fishery is directly related to the seasonal migration of skipjack, which is driven by their thermal physiology and reproduction biology. Comparing the physiological tolerance of the lower thermal limit for young skipjack of $18^{\circ} \mathrm{C}$ (Barkley et al., 1978; Kiyofuji et al., 2019) with the sea surface temperature (SST) revealed that there were few areas where skipjack can survive in region 2 in quarter 1 (Figure 5). Gradually, the
areas spread toward the north due to the elevation of the SST from quarter 2 to quarter 3 . The northern limit of the habitat is up around $42^{\circ} \mathrm{N}$ in quarter 3 (Figure 5), which is roughly consistent with the northern limit of the fishery grounds in regions 2 and 3 (Figure 4; Matsumoto et al., 1984). In quarter 4, the northern limit retracts back southward. In addition, rough index of spawning temperature $24^{\circ} \mathrm{C}$ shows that it is not suitable for skipjack to spawn in regions 1 and 2 (Figure 5), leading to further migration southward for spawning and resulting in seasonally available fishery grounds in region 2 . These annual patterns of migration and the shifting fishery grounds are a consequence of the behavioural response of skipjack to the temperature via their thermal physiology and reproduction biology.

Information on the fishing technology (i.e., fishing devices) used in JPPL collected via interview are available only in the DW fleets (Shono and Ogura, 2000). In order to have more complete spatiotemporal coverage within the assessment model time period and region, DW and OS trips were combined in a joint analysis following methods in Kinoshita et al. (2019). To account for potential differences in catchability between the two vessel classes, the fixed effect of Class was added along with the polynomial spline of vessel size in GRT. Kinoshita et al. (2019), in preliminary analyses of the nominal CPUE in spatiotemporal strata that were fished by both DW and OS vessels showed similarities in the magnitude and trend of mean catch rates between the classes. Given the joint modeling approach of the DW and OS trips and the fact that device information was unavailable for OS vessels, device covariates were not included in the spatiotemporal model following the methods of Kinoshita et al. (2019).

The vessel information was necessary to include vessel effects in the CPUE standardization. Since the JPPL logsheet data did not contain any information to identify vessels, the unique ID was assigned to each vessel in the last assessment by using license number (changeable every 5 years), a ship's register prefecture, and GRT (Kinoshita et al., 2019). In this assessment, A new lookup table of year, license number, and unique ID was created from the 2019 ID data, and then applied to the 2022 JPPL data with some updates for newly registered vessels.

Updated data were filtered out by using the following procedures to prepare the data for CPUE standardization. The screening process here was the same as used in the 2019 assessment for spatiotemporal modeling.

Filter 1: Remove the data outside the stock assessment boundaries
Filter 2: Remove the data with number of poles $<2$ and number of crew $<5$
Filter 3: Remove the data of vessels with no vessel IDs assigned in and after 1987, when fishing license numbers changed substantially

Filter 4: Remove extremely high skipjack catch records of over 200 tons per day
Filter 5: Remove the data of vessels that had operated for less than 5 years and less than 10 days per year

### 4.1.2 Model configuration

The initial phase of the analysis was to replicate as close as possible the indices applied in the 2019 assessment, using the same data. This was not a straightforward process for this assessment due to several challenges presented to the SPC assessment team with data being inaccessible to the new SPC analysts tasked with performing the analysis. Consequently, we
worked closely with Japan scientists from the Japan Fisheries Research and Education Agency (FRA) to accomplish the CPUE standardization. Additional problems were encountered utilizing scripts from the 2019 skipjack SA with customized functions that were incompatible with updated R packages and consequently, the model scripts were modified/ simplified and evaluated on the 2019 data set to ensure the model could produce similar results to those produced in the 2019 skipjack SA.

We fit a spatiotemporal delta lognormal generalized linear mixed model (delta-GLMM; Thorson et al., 2015), using the VAST package in R. Spatiotemporal models implicitly account for spatial and spatiotemporal autocorrelation in catch rates using Gaussian Markov random fields assuming geometric anisotropy, which allows for spatial autocorrelation to vary in magnitude based on the direction of neighbouring knot locations. This provides a means of predicting the density relative to the aggregated environmental and biological factors that influence both the distribution and catchability (Thorson, 2019). Spatial locations at which the effects were estimated (i.e. the knots; $\mathrm{n}=280$ ) were uniformly distributed across the spatial domain (Figure 6) as recommended by Ducharme-Barth et al. (2022) to improve estimation using spatially imbalanced data such as the contracting fishery of the JPPL skipjack data.

Using this framework allowed for a joint analysis of the DW and OS data and allowed for the simultaneous estimation of all the regional abundance indices using a single model. The basic equations applied are as follows for each model part (binomial and lognormal):

$$
\begin{aligned}
p_{i} \sim \text { YearQtr } & + \text { VesselID }+\omega_{1}\left(x_{i}\right)+\phi_{1}\left(x_{i}, t_{i}\right)+\text { Class }+s(\text { NumPoles })+s(\text { grt }) \\
& +\xi_{1}\left(x_{i}, t_{i}\right) \\
c_{i} \sim \text { YearQtr } & + \text { VesselID }+\omega_{1}\left(x_{i}\right)+\phi_{1}\left(x_{i}, t_{i}\right)+\text { Class }+s(\text { NumPoles })+s(\text { grt }) \\
& +\xi_{1}\left(x_{i}, t_{i}\right)
\end{aligned}
$$

where $p_{i}$ was the encounter probability, $c_{i}$ was the positive catch rate (CPUE defined as catch in kilograms per daily logsheet record), YearQtr was a fixed effect, VessellD was a normally distributed random effect for vessel identification, $\omega_{1}\left(x_{i}\right)$ was the spatial random effect at knot $x$ associated with the $\log$ sheet record $i, \phi_{1}\left(x_{i}, t_{i}\right)$ was the spatiotemporal random effect at YearQtr $t$ and knot $x$, Class was a fixed effect denoting a vessel as either OS or DW, $s$ (NumPoles) was a polynomial of degree 5 for the number of poles fished, $s(g r t)$ was a polynomial spline of degree 5 for the vessel size, and $\xi_{1}\left(x_{i}, t_{i}\right)$ was the linear effect of sea surface temperature (SST; Smith and Reynolds, 1981) at YearQtr $t$ and knot $x$. Both $\omega$ and $\phi$ are described by multivariate normal spatial random fields $\operatorname{MVN}(0, R)$ where $R$ was a Matérn correlation function. For the variable $\phi$, temporal independence was assumed across YearQtr.

Model selection with Akaike Information Criteria (AIC) was performed progressively in the following order: by comparing the density-based spatial knot configuration with a uniform configuration, removing random effects for vessel identification, removing catchability covariates, and then removing density covariates. 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 JPPL CPUE coding scripts available at SPC GitHub repository https://github.com/PacificCommunity/ofp-sam-Pole-and-Line-CPUE-Standardization and https://github.com/PacificCommunity/ofp-sam-sst (login required). All analyses performed in ' $R$ ' (Team, 2020).

The standardized CPUE indices used as inputs into the 2022 skipjack SA were calculated as area-weighted indices. The model produces estimates of skipjack density by $1^{\circ}$ grid cells. Grid cell densities were adjusted for differences in grid cell area at varying latitudes (Budic et al., 2015) using the grid cell calculator at:
https://www.engr.scu.edu/~emaurer/tools/calc_cell_area_cgi.pl and these grid cell-specific densities were then summed for each region by year-quarter to create the final relative abundance index.

### 4.1.3 Results and discussion

The results from the model selection (Table 1) indicated that models with catchability covariates, density covariates, and random effects for vessel identification were preferred over models missing one or more of these covariates and the spatial knot configuration had little impact on the AIC or the maximum gradient. Since the uniform spatial knot configuration was suggested as the preferred configuration for estimating a relative abundance index for a contracting fishery based on simulation work by Ducharme-Barth et al. (2022), the model selected for estimating the JPPL relative abundance index included all potential covariates and utilized the uniform spatial knot configuration.

The decadal shifts in spatial patterns associated with the historical decline in catch and effort (Figure 2 and Figure 3) of the JPPL fishery since the 1970s 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 JPPL fishery if the sampling patterns are not excessively variable and non-random (Ducharme-Barth et al., 2022). Sampling coverage in the JPPL over time (Figure 7) indicated that regions 5 and 6 were sampled at a very low proportion ( $<20 \%$ ) for the majority of the time series and were not included as input indices in the assessment model. For regions 1, 3, 4 and 7, the locally weighted smoothing function approximated the sampling coverage above $20 \%$ for the entire time series. The region 2 smoothing function approximated the sampling coverage below $20 \%$ for the last five years of the time series; however, the sampling coverage in some quarters during those years were above $30 \%$. The region 8 smoothing function approximated the sampling coverage below $20 \%$ for the years before 1975 and after 1997 and the index for region 8 was truncated to exclude these years with inadequate sampling coverage.

The diagnostic plots of the PIT residuals, aggregated across the time series at the level of the spatial knot and $1^{\circ}$ grid cell, from the spatiotemporal CPUE standardization model are shown in Figure 8 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 (Figure 8), most notably, on the eastern edges where sample sizes have progressively declined throughout the time-series. This emphasizes the importance of utilizing the uniform spatial knot configuration as recommended by Ducharme-Barth et al. (2022) to better inform the CPUE throughout the spatial extent.

The resulting indices developed from the simplified 2022 CPUE model applied to the 2019 data set (Figure 9) were almost identical to the 2019 skipjack SA indices for region 3-4, 7 \& 8 however, the region 1 and 2 indices differed slightly primarily in the first quarter where the 2022 indices estimated lower CPUE as compared to the 2019 indices. Similar to the 2019 SA,
the updated standardized CPUE mean-centred indices with the 2022 data for the JPPL
(Figure 10) showed a stable trend in relative abundance over the time-series for regions 1-4, 7 , and 8 , however, the estimates in regions 1 and, more notably, in region 2 showed differences in CPUE for quarters 1 and 3. The area-weighted CPUE standardized indices for the JPPL (Figure 11) indicated that regions 1 and 3 had much lower relative abundance of skipjack as compared to regions $2,4,7$, and 8 . Regions 2,4 , and 8 (located on the eastern margin of the eight-region spatial extent) demonstrated higher temporal variability as compared to the other regions demonstrating that skipjack may be more temporally transient in these regions as compared to the central and western margins of the spatial extent. The area-weighted standardized CPUE indices were utilized as inputs to the stock assessment in conjunction with shared catchability among these fisheries, model to preserve the regional scaling differences in relative abundance of skipjack. This demonstrates the importance of the JPPL fishery data for developing relative abundance indices and, as such, they are a key input to the stock assessment model as they span the largest proportion of the total spatial extent.

### 4.2 Regions 6-8 purse seine

Operational (set-level) purse seine fishing catch and effort data were obtained for the tuna purse seine fleets within the WCPO. As of 2010, $100 \%$ of tuna purse seine trips in the region were required to carry a fisheries observer, and therefore, the time series used for this analysis extended from 2010 through 2021. The skipjack stock assessment region extends roughly from $50^{\circ} \mathrm{N}$ to $20^{\circ} \mathrm{S}$ and from $110^{\circ} \mathrm{E}$ to $150^{\circ} \mathrm{W}$; however, the tropical purse seine sector of the skipjack fishery primarily operates within the 2022 stock assessment Regions 68 (Figure 12 and Figure 13); and therefore, those were the focal regions for this analysis.

### 4.2.1 Fisheries data

Different fishing strategies are employed within the purse seine fleet, with the most notable difference distinguishing between associated and unassociated sets. Associated sets are those made in association with floating objects, either natural (e.g., logs, debris, whale sharks), or man-made (i.e., fish aggregating devices; FADs) whereas unassociated sets (UNA) are those made on free-schooling tuna unassociated with floating objects. In previous analyses (Vidal et al., 2020, 2019) of CPUE standardization of the skipjack purse seine observer data for regions 6-8, both set types were modelled jointly with set type as a factor.

However, advancements in FAD technology can impact the catchability of skipjack over time for fishers that frequently perform sets on FADs. This can be particularly influential on the catch and effort relationship, with the adoption of satellite tracked and sonar-equipped FADs that allow fishers to target more productive FADs with high biomass of tuna. Consequently, there has been an increase in the reliance on drifting FADs and a corresponding increase of the deployment of manufactured drifting FADs (Escalle et al., 2021). Furthermore, fishers who fish primarily on FADs during quarters when FAD fishing is allowed (i.e., 'FAD specialists') are less likely to be proficient in free-school fishing during the FAD closure period, resulting in lower catch rates than those less reliant on FAD fishing. This could lead to artificially lower overall catch rates for the purse seine fishery during closure periods.

To remove the influence of these effects from FAD fishing, data was filtered to only include unassociated sets and any vessel in a given year with a median of $\geq 70 \%$ of sets on FADs per quarter was removed for that year. This value was chosen to remove as much influence from

FAD specialists while preserving as much data as possible. Therefore, the derived indices were essentially free-school only without FAD specialists.

In previous analyses (Vidal et al., 2020, 2019), effort has been defined at the set level. This unit of effort may be biased by not accounting for searching effort as purse seine fishers perform sets only after they have positively identified a substantial school of tuna. Thus, to better quantify effort, we used the Vessel Monitoring System (VMS) data to define effort as the cumulative daytime path length between unassociated sets calculated as the sum of the hourly distances travelled (recorded by VMS) between sets during daytime hours with a buffer of 30 minutes prior to sunrise and after sunset. The effort for the first set was assigned the trip-specific median value. The change in the effort definition did not have a large impact on the region and year-quarter aggregated effort time-series (Figure 14).

The full data set ( $\mathrm{n}=1,003,901$ sets) was also filtered to only include vessels between 50 and 80 m in length which were active in the fishery for approximately $20 \%$ of the time series of interest (observed fishing activity in at least 10 quarters between 2010 and 2021). To avoid a full exclusion of the vessels that had only recently entered the fishery, we included vessels that entered the fishery in 2018 or later if they had been active for at least seven quarters ( $\sim 44 \%$ of the most recent four years of the time series). The vessel length criteria was imposed (as previously implemented by Vidal et al., 2020) to align with the Vessel Day Scheme (Dunn et al., 2006) that resulted in a fleet with predominately $50-80 \mathrm{~m}$ vessels.

Sets were identified as 'failed' sets if the total tuna catch was less than five mt and removed from the data set as they were not expected to be representative of local density. In addition, extreme outlier catches (total tuna catch $\geq 99$ th quantile) were also removed. Lastly, records were removed if any data values were missing. The resulting filtered data set ( $\mathrm{n}=93,649$ ) was used for the CPUE standardization.

In previous research on CPUE standardization of purse seine data in regions 6-8 (Vidal et al., 2020), a suite of vessel, gear, and strategy-based covariates were considered in order to account for variability associated with factors affecting catchability. For factors that were highly correlated, one factor was chosen that was considered to be the most representative for each group of correlated factors. These potential covariates were vessel length, gross registered tonnage, well capacity, skiff horsepower, net length, net depth, and a species composition cluster variable to account for impacts to catch rates from catches dominated by yellowfin tuna. The cluster variable was defined using a k-means clustering algorithm based on the proportion of skipjack and yellowfin in each catch record (Figure 15). Environmental factors that could influence catchability were also evaluated and these were lunar phase and thermocline depth. Additionally, a suite of oceanographic condition variables affecting density and distribution of skipjack were considered and the variable chosen as a potential covariate was the El Niño-Southern Oscillation (ENSO) data. The model selection process identified three variables as significantly influencing catch rates and these were species cluster, vessel length, and ENSO (a spatially varying covariate). Building on this previous research, we adopted these covariates as potential covariates in the CPUE standardization of the purse seine data in regions 6-8.

### 4.2.2 Model configuration

For the purse seine in regions 6-8 (PS.6-8), we fit a spatiotemporal delta gamma generalized linear mixed model using the VAST package in R. For a general description of the VAST
spatiotemporal model see Model configuration. Spatial locations at which the effects were estimated (i.e., the knots; $\mathrm{n}=210$ ) were uniformly distributed across the spatial domain (Figure 16) to reduce the risk of bias caused by any spatial contractions in the fishery (Ducharme-Barth et al., 2022). The catch data were positively skewed with a high proportion of zeros ( $13.8 \%$ ), owing to sets composed of yellowfin and/or bigeye tuna, as failed sets were removed from the data set. The probability of a positive catch was assumed to have a binomial error distribution, while we assumed a gamma error distribution for the magnitude of positive catches. The basic equations applied are as follows for each model part (binomial and lognormal):

$$
\begin{aligned}
& p_{i} \sim \text { YearQtr }+ \text { VesselID }+\omega_{1}\left(x_{i}\right)+\phi_{1}\left(x_{i}, t_{i}\right)+\text { Cluster }+ \text { VesselLength }+\xi_{1}\left(x_{i}, t_{i}\right) \\
& c_{i} \sim \text { YearQtr }+ \text { VesselID }+\omega_{1}\left(x_{i}\right)+\phi_{1}\left(x_{i}, t_{i}\right)+\text { Cluster }+ \text { VesselLength }+\xi_{1}\left(x_{i}, t_{i}\right)
\end{aligned}
$$

where $p_{i}$ was the encounter probability, $c_{i}$ was the positive catch rate (CPUE defined as catch in metric tons per kilometre daytime path length or set depending on the effort metric being applied), YearQtr was a fixed effect, VesselID was a normally distributed random effect for vessel identification, $\omega_{1}\left(x_{i}\right)$ was the spatial random effect at knot $x$ associated with the observer data record $i, \phi_{1}\left(x_{i}, t_{i}\right)$ was the spatiotemporal random effect at YearQtr $t$ and knot $x$, Cluster was a fixed effect denoting a record as dominated by either skipjack or yellowfin, VesselLength was a fixed effect for vessel length, and $\xi_{1}\left(x_{i}, t_{i}\right)$ was the linear effect of ENSO at YearQtr $t$ and knot $x$. Both $\omega$ and $\phi$ are described by multivariate normal spatial random fields $M V N(0, R)$ where $R$ was a Matérn correlation function. For the variable $\phi$, temporal independence was assumed across YearQtr.

Model selection was performed with AIC by removing one covariate and comparing nested models with the full model, selecting the candidate model with the best AIC, and then repeating the process until reducing the model ceased to improve the model AIC. Modelling was performed using effort as defined by the set and defined by daytime path length for comparison. Comparison of effort type metrics was done with AIC and confirmed using 10fold root mean square error (RMSE) cross-validation. A sensitivity analysis was performed to test the choice of the $70 \%$ threshold to filter FAD specialists by fitting the model filtered at $70 \%, 80 \%, 90 \%$, and $100 \%$ and then comparing the results.

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 PS.6-8 CPUE coding scripts available at SPC GitHub repository https://github.com/PacificCommunity/ofp-sam-Geostat_CPUE_standardization (login required). All analyses performed in ' $R$ ' (Team, 2020).

### 4.2.3 Results and discussion

Using AIC-based selection criteria, convergence statistics, and 10-fold RMSE crossvalidation, the results (Table 2) suggested that the nested models were not an improvement in model performance to the full model and the use of daytime path length as the effort metric had a notable improvement on model performance as compared to the use of the set level as the unit of effort. For these reasons, we selected the full model that included all the potential covariates with the daytime path length as the effort metric as the preferred model to be used for developing the standardized CPUE relative abundance indices for PS.6-8.

The diagnostic plots of the PIT residuals, aggregated across the time series at the level of the spatial knot and $1^{\circ}$ grid cell, from the spatiotemporal CPUE standardization model are shown in Figure 17 and exhibited a normal distribution centred around 0.5, indicating an overall reasonable fit to the data. The spatial pattern of the residuals indicated higher residuals around the peripheral areas of the spatial domain (Figure 17) and in region 7 in the high seas area outside of any exclusive economic zones (Figure 1). These spatial patterns are more severe where sample sizes have decreased in some years and underscore the need for utilizing the uniform spatial knot configuration as recommended by (Ducharme-Barth et al., 2022) to better inform the CPUE throughout the spatial extent.

The resulting indices developed from the standardization of CPUE data for PS.6-8 (Figure 18) suggested a declining overall trend from 2010 to 2021 . The area-weighted standardized CPUE indices (Figure 19) indicated progressively increasing total regional abundance moving westward from region 6 to region 8. Similar to the JPPL, the area-weighted PS.6-8 were utilized as inputs to the stock assessment model to preserve the regional scaling differences in relative abundance of skipjack. The scaling ratios between the indices calculated for regions 6, 7 and 8 in the JPPL and PS.6-8 were very similar between data types with 1:1.9:4.4 and 1:1.6:3.1, respectively.

The covariate influence plots (Figure 20) revealed that the influence of cluster type has a relatively stable trend throughout the time-series however, the influence of vessel length suggested a declining trend until the second quarter of 2020 when influence of vessel length increased sharply and varied thereafter. The influence of vessel identification showed a declining trend over the time-series. The spatial effects plots (Figure 21) indicated higher encounter probability in and around the Coral Sea, Tuvalu, Tokelau, and north-eastward from the Solomon Islands towards Micronesia whereas the spatial pattern characterizing the probability of positive catch rates was more variable and patchier throughout the spatial extent.

The sensitivity analysis to evaluate the 70\% threshold revealed (Figure 23) the 80\% threshold was very similar to a $100 \%$ threshold (the $90 \%$ model failed to converge) however there was a more distinct difference in the $70 \%$ threshold as compared to the $80 \%$ and $100 \%$ threshold indices, specifically, in 2010 and 2018. These results suggest that a threshold of $70 \%$ may be appropriate to remove the influence of FAD specialists on the free-school only PS.6-8 indices. Further research in this area may be warranted to provide more insight on the impacts of FAD specialists on free-school only indices.

Correlations between the JPPL and the PS.6-8 after smoothing with a simple moving average function (smoothing window $=5$; Figure 22) suggested that the JPPL correlated considerably better with the PS.6-8 when effort was defined as daytime path length ( $\mathrm{r} \geq 0.49$ ) as compared to when effort was defined at the set level ( $\mathrm{r} \leq 0.16$ ). This difference is rather surprising in view of the very high similarity of the two PS.6-8 effort metrics as seen in Figure 14. Consistent correlations between indices derived from different data sources provides evidence that the CPUE in regions 7 and 8 are indicative of the regional population abundance trends from 2010 to the last quarter of 2020. Furthermore, the low correlation of the JPPL with the PS.6-8 with effort defined at the set level indicated that the set may not be the most appropriate unit of effort for purse seine free-school only indices.

### 4.3 Philippines purse seine

The relative abundance index for the Philippines purse seine fishery located in region 5 (PS.5; Figure 1) was developed following the methods applied in the 2019 skipjack SA and for detailed methods we refer the reader to Bigelow et al. (2019). Port sampling data were used to estimate effort, catch, and standardized CPUE from the purse seine fishery operating in the southern Philippines EEZ and High Seas Pocket \#1 from 2005 to 2021. A relative abundance index was produced as a quarterly standardized CPUE index from 2005 to 2021 for use in the 2022 WCPFC skipjack tuna assessment. Effort, catch, and standardized CPUE was estimated using generalized linear models (GLMs) and model selection was performed using Bayesian Information Criteria (BIC). Potential covariates for the CPUE standardization included year-quarter (YR: QTR), area, and vessel identification. Effort by many vessels consisted of only a few trips and data were filtered for active vessels which had conducted 20 or more trips.

Results from the estimation of effort indicated an overall declining trend from 2005 to 2010 and then an increasing overall trend throughout the remaining time-series with high annual variability (Figure 25). The increase in purse seine effort was more pronounced from 2013 to 2021 due to the re-opening of High Seas Pocket \#1 for many Philippines flagged purse seine vessels. Results from the estimation of catch demonstrated an overall declining trend from 2005 to 2010 and then a stable trend thereafter with higher catches in some years after 2013 (Figure 24). There were 18 area designations in the database; however, area was relatively non-informative in the CPUE standardization model as fishing trips were dominated by 4 areas. Standardized CPUE trends for the potential models are illustrated in Figure 26. Trends were consistent among the models throughout the time-series. The preferred model provided an index that predicted quarterly CPUE with year-quarter (YR: QTR) and vessel effects. The standardized CPUE index indicated an overall declining trend in relative abundance throughout the time-series with higher variability prior to 2013.

## 5 Construction of tagging data files

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 MFCL for the 2022 assessment of skipjack follow the general methods previously outlined in Berger et al. (2014), McKechnie et al. (2017, 2016), and Vincent et al. (2019b). Preparation of input files coding scripts available at SPC GitHub repository https://github.com/PacificCommunity/ofp-sam-SKJ-data-prep-2022 (login required). All analyses performed in ' R ' (Team, 2020).

### 5.1 Tag file preparation 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 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 et al., 2019b) 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., 2022; Vincent et al., 2019b). 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, 2022 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 skipjack SA (Vincent et al., 2019b). 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., 2022; Scutt Phillips et al., 2020).
3. Correction for tag shedding (6.97\%; Vincent et al., 2019b).
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 (Peatman, 2022).
6. Construction of tag reporting rate priors from tag seeding experiments.

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 30 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 re-captured 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., 2022 \& Peatman, 2022, respectively).

### 5.2 Tagging data

Tagging data for the skipjack assessment were acquired from multiple tagging programs implemented by SPC (Figure 27 and Figure 28) and these include the Skipjack Survey and Assessment Program (SSAP; 1977-1982), the Regional Tuna Tagging Program (RTTP; 1989-1992) and the Pacific Tuna Tagging Program PTTP (2006-ongoing). Additional data are available for the ongoing Japanese tagging program (JPTP; Figure 27 and Figure 28), but these data are not held by SPC and updated datasets are provided just prior to each stock assessment. Due to numerous differences between these data and those from programs held by SPC, they are processed separately, and the methods used for the JPTP are presented in Aoki et al. (2022). The data obtained through the program are particularly valuable for skipjack tuna stock assessments in the WCPO due to wide temporal and spatial coverage and numerous recaptured tags reported (Figure 29). Additional mortality caused by tagger effects were not estimated for JPTP and SSAP tagging data due to lack of available data to inform these estimates thus, the median correction factor for all release groups was assumed.

### 5.2.1 Comparison to 2019 SA tag file

After updating the tagger effects and applying the various correction factors to the raw data, the resulting tagging data corrections for the 2022 skipjack SA were similar to the tagging data from the 2019 skipjack SA as shown in Figure 30.

## 6 Mixing periods

Mark-recapture tagging data can be very informative in stock assessments if they are representative of the overall population and hinges on the assumption the tagged fish have had adequate time to mix with the untagged population. Tagged fish that are captured shortly after release may not be representative of the population, but instead may be an indicator that the fish were tagged in an area with high fishing pressure. Consequently, a mixing period is implemented within MFCL where the tag release groups are modelled separately and do not influence the overall population mortality rates until after the appropriate period of mixing has transpired. In the previous skipjack SA (Vincent et al., 2019a), assumptions of mixing period duration were influential to stock status and a mixing period of 2 quarters indicated a more optimistic stock status as compared to a mixing period of 1 quarter.

The process of mixing tagged fish with the untagged population has been shown to exhibit spatiotemporal heterogeneity (Kolody and Hoyle, 2014; Sippel et al., 2015) and assumptions of spatially constant mixing periods may not be appropriate when estimating stock status. MFCL has the capacity to assume variable, individual mixing periods for each release group and for the 2022 skipjack SA, research was performed to quantify spatially-heterogenous mixing by applying an Individual-based Kinesis, Advection, and Movement of Ocean ANimAls simulator (Scutt Phillips et al., 2018) which accounts for movement behaviour and mortality within the WCPO and is based on the fine resolution modeling framework known as SEAPODYM (Lehodey et al., 2008; Senina et al., 2020). The methods used are presented in detail in (Scutt Philips et al., 2022) and we refer the readers to that report.

Within the simulation framework, the distribution of recapture probabilities of each tagged release group within a given region are compared to the distribution of recapture probabilities of the untagged population within the region at each time step (i.e., each quarter after release). When the two distributions are very similar, the distributions are assumed to be equivalent, and the tagged release group is considered mixed. The non-parametric test selected to indicate the level of dissimilarity was the two-sample Kolmogorov-Smirnoff test (Kolmogorov, 1933; Smirnoff, 1939). For each release group and quarter since release, the D statistic was calculated and compared to a selected threshold value to determine if mixing had occurred by the end of that quarter (Figure 31). The selection of the D statistic threshold (i.e., $0.1,0.2$, or 0.3 ) can have significant impacts on the assignment of appropriate mixing periods to each simulated release group. A more conservative D statistic of 0.1 results in only $12.2 \%$ of the total recaptures to be considered mixed and subsequently, included in the MFCL likelihood function (Figure 32) whereas a much less conservative D statistic of 0.3 results in $84.1 \%$ of the total recaptures to be considered mixed. An intermediate D statistic of 0.2 would result in $54.7 \%$ of the total recaptures to be considered mixed and thus, permitted to inform the MFCL model parameters.

The simulations were computationally demanding and, as such, not all release groups could be simulated from the four tagging program data sets. Thus, various release groups from the PTTP program and the JPTP program were selected to be simulated to maximize the spatial
coverage and the number of releases simulated. However, release groups varied considerably by number of effective releases. As shown in Figure 33, more release groups were simulated for the JPTP, yet the number of effective releases simulated was much higher for the PTTP as these release groups typically have a much higher number of effective releases per release group (Figure 28) than the JPTP. Release groups with higher numbers of releases were preferred over release groups with few releases if adequate spatial coverage could be maintained among the selection of release groups simulated. The resulting proportion of total recaptures by region considered mixed and not mixed for each $D$ statistic are shown in
Figure 34. Release groups that were not simulated were assigned the region-specific median mixing period calculated from simulated release groups (Table 3).

## 7 Adjustment to longline length compositions

In the last two previous skipjack SAs (i.e., 2016 and 2019), the length compositions in the longline fishery from the Japanese fleet from 2007-2010 in regions 1-4 were removed from the length compositions due to anomalies in the size distributions (McKechnie, 2016). Specifically, there was evidence of a prominent bimodal distribution during this period and a notable reduction in median length. The specific reason for these differences (i.e., changes in fishing practices) has not been determined nevertheless, for the 2022 skipjack SA, these anomalous longline length compositions from the Japanese fleet in regions 1-4 from 20072010 were removed. We refer the readers to McKechnie (2016) for further details regarding this adjustment to the input data.

## 8 Tables

Table 1: Model selection results for JPPL skipjack spatiotemporal model from the 2019 SA and 2022 SA including AIC, maximum gradient, and number of fixed parameters. Candidate models included potential covariates for knot spatial configuration (density or uniform), random effects for vessel identification (vessel), catchability covariates (q), and density covariates (sst). The model in bold was the selected model for developing the JPPL relative abundance index.

| Data | Model Configuration | AIC | Max <br> Gradient | \# of Fixed <br> Parameters |
| :---: | :---: | :---: | :---: | :---: |
| 2019 | density-based knots, vessel, q, sst | $16,119,095$ | 0.41 | 417 |
| 2022 | density-based knots, vessel, q, sst | $16,410,122$ | 0.58 | 433 |
|  | uniform knots, vessel, q, sst | $\mathbf{1 6 , 4 1 0 , 1 2 3}$ | $\mathbf{0 . 9 4}$ | $\mathbf{4 3 3}$ |
|  | density-based knots, q, sst | $16,471,799$ | 0.30 | 431 |
|  | density-based knots, sst | $16,471,831$ | 37.41 | 431 |
|  | density-based knots | $16,472,637$ | 2036.83 | 431 |

Table 2: Model selection results for PS.6-8 skipjack spatiotemporal model including AIC, maximum gradient, number of fixed parameters, and RMSE (from 10-fold cross validation). Candidate models included potential covariates for species cluster (skipjack or yellowfin), vessel length, El-Niño Southern Oscillation (ENSO), and random effects for vessel identification. Candidate effort metric types were also modelled for comparison. The model in bold was the selected model for developing the PS.6-8 relative abundance index.

| Effort <br> Metric | Model Configuration | AIC | Max <br> Gradient | \# Fixed of <br> Parameters | RMSE <br> $(\mathbf{1 0 - C V})$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Path <br> Length | cluster, length, ENSO, vessel | $\mathbf{3 5 7 , 2 9 6}$ | $\mathbf{3 . 2 5 E - 0 3}$ | $\mathbf{1 1 3}$ | $\mathbf{1 8 1 , 8 0 9}$ |
|  | cluster, ENSO, vessel | 357,311 | $6.44 \mathrm{E}-04$ | 111 |  |
|  | cluster, length, vessel | 357,313 | $2.47 \mathrm{E}-03$ | 111 |  |
|  | cluster, length, ENSO | 360,214 | $6.06 \mathrm{E}-04$ | 111 |  |
|  | length, ENSO, vessel | 375,216 | $2.83 \mathrm{E}+02$ | 111 |  |
|  |  |  |  |  |  |
| Set | cluster, length, ENSO, vessel | 790,270 | $1.72 \mathrm{E}-04$ | 113 | 394,282 |
|  | cluster, length, vessel | 790,276 | $4.37 \mathrm{E}-05$ | 111 |  |
|  | cluster, ENSO, vessel | 790,322 | $4.95 \mathrm{E}-06$ | 111 |  |
|  | cluster, length, ENSO | 791,618 | $3.53 \mathrm{E}-04$ | 111 |  |
|  | length, ENSO, vessel | 810,606 | $2.28 \mathrm{E}-05$ | 111 |  |

Table 3: Resulting region-specific D statistics by mixing quarter ( Qtr ) and corresponding mixing periods at various selected $D$ statistics (i.e., $0.1,0.2$, and 0.3 ) from tag mixing simulations. Proportion of release groups that were not simulated (NS) included.

| Region | D Statistic by Mixing Qtr |  |  |  | Mixing Period by D Stat. |  |  | Proportion NS |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0 Qtr | 1 Qtr | 2 Qtr | 3 Qtr | D = 0.1 | $\mathrm{D}=0.2$ | $\mathrm{D}=0.3$ |  |
| 1 | 0.21 | 0.13 | 0.12 | 0.12 | 4 | 1 | 0 | 0.59 |
| 2 | 0.32 | 0.15 | 0.11 | 0.10 | 3 | 1 | 1 | 0.48 |
| 3 | 0.20 | 0.14 | 0.06 | 0.06 | 2 | 0 | 0 | 0.51 |
| 4 | 0.32 | 0.27 | 0.25 | 0.25 | 4 | 4 | 1 | 0.49 |
| 5 | 0.12 | 0.11 | 0.17 | 0.15 | 4 | 0 | 0 | 0.79 |
| 6 | 0.31 | 0.20 | 0.16 | 0.13 | 4 | 1 | 1 | 0.42 |
| 7 | 0.25 | 0.19 | 0.13 | 0.09 | 3 | 1 | 0 | 0.69 |
| 8 | 0.24 | 0.19 | 0.15 | 0.11 | 4 | 1 | 0 | 0.93 |

## 9 Figures



Figure 1: The geographical area covered by the skipjack stock assessment and the boundaries for the eight-region assessment model.


Figure 2: Historical change in skipjack catch by area ( $a$ ) and effort ( $b$ and $c$ ) of the Japanese pole and line fishery (JPPL) from 1972 to 2020. Vessels include distant water (DW) and offshore (OS) fleets.


Figure 3: Decadal shifts in spatial distribution of Japanese pole-and-line (JPPL) fishery skipjack catch (metric tons) from 1972 to 2020.


Figure 4: Skipjack catch ( 1,000 s metric tons) time series by quarter ( $a$ ) and seasonal spatial distribution (b) for the Japanese pole-and-line fishery.


Figure 5: Thermal habitats based on sea-surface temperature (SST, ${ }^{\circ} \mathrm{C}$ ) for skipjack by quarter in the Western and Central Pacific Ocean (WCPO).


Figure 6: Uniformly distributed spatial knot configuration (black dots) in the eight-region spatial structure (red lines) in the Western and Central Pacific Ocean (WCPO) for the skipjack Japanese pole-and-line (JPPL) spatiotemporal model. Sampling locations included in faded colours by region.


Figure 7: Proportion of uniformly configured spatial knots sampled over time by region for Japanese pole-and-line (JPPL) fishery. Region-specific coloured lines with confidence intervals approximated by locally weighted smoothing function. Light grey lines at 0.2 and 0.4.


Figure 8: Spatial distribution of probability-integrated-transform (PIT) residuals aggregated across the full time series, at the level of the knot (a) and the cell (b). Histogram of aggregated PIT residuals (c).


Figure 9: Mean-centred standardized abundance indices for regions 1-4, 7, and 8 for skipjack Japanese pole-and-line (JPPL) for the 2019 stock assessment (SA) CPUE model and the 2022 SA CPUE model applied to the 2019 data set (1972-2018). Data points are coloured by quarter.


Figure 10: Mean-centred standardized CPUE abundance indices from the 2019 SA model and the 2022 SA model for regions 1-4, 7, and 8 for skipjack Japanese pole-and-line (JPPL; 1972-2020). Data points are coloured by quarter.


Figure 11: Area-weighted CPUE standardized abundance indices for regions 1-4, 7 , and 8 for skipjack Japanese pole-and-line (JPPL) fishery from 1972 to 2020. Triangular moving average smoothing function applied to demonstrate overall trend (dark grey line; smoothing window $=5$ ).


Figure 12: Regional stock assessment structure for skipjack. The regions highlighted in blue indicate the regions where the spatiotemporal CPUE standardization was performed on purse seine data.


Figure 13: Observer reported unassociated purse seine effort (number of sets) in regions 6-8 (boundary lines in red and in ascending order from left to right), from 2010-2021. Does not include unassociated effort from vessels defined as FAD specialists for a given year.


Figure 14: Aggregated effort by region (6-8) and year-quarter for purse seine effort defined as daytime path length and by the set level.


Figure 15: Species composition clusters defined by k-means clustering of catch for skipjack (SKJ), bigeye (BET), and yellowfin tuna (YFT) in the purse seine in region 6-8. Cluster type 1 was dominated by skipjack and cluster 2 by yellowfin tuna.


Figure 16: Uniformly distributed spatial knot configuration (black dots) in the eight-region spatial structure (boundary lines in red) in the WCPO for the purse seine regions 6-8. Temporally aggregated sampling locations included in faded colours by region.


Figure 17: Probability-integrated-transform (PIT) residuals by knot ( $a$ ), by cell (b), and as histograms (c) of CPUE standardization of purse seine regions 6-8 for effort defined as daytime path length.


Figure 18: Standardized (solid line with points) and Nominal (dashed line) CPUE for purse seine regions 6-8 with effort defined as daytime distance (2010-2021).


Figure 19: Area-weighted standardized CPUE with standard error intervals for purse seine regions 6-8 with effort defined as daytime distance (2010-2021).


Figure 20: Influence plots for cluster type, vessel length, and random effects for vessel identification for PS.6-8 CPUE with effort defined as daytime distance.


Figure 21: Spatial effects plots for encounter probability and positive catch rates for PS.6-8 CPUE with effort defined as daytime distance


Figure 23: Sensitivity analysis results for purse seine CPUE in regions 6-8 (PS.6-8) with vessels filtered in a given year with a median of $\geq 70 \%, 80 \%$, and $100 \%$ FAD sets per quarter.


Figure 22: Standardized skipjack CPUE for Japanese pole-and-line (JPPL; black line) and purse seine fisheries using effort defined by set (PS.6-8; blue line) and by daytime path length (PS.6-8; red line) in regions 7 and 8 smoothed with a simple moving average function (smoothing window $=5$ ). Correlations between data types in each region included in top-right corner of each plot.


Figure 24: Estimated monthly catch time-series (in metric tons) for the Philippines purse seine (PS.5) fishery in region 5.


Figure 25: Estimated monthly effort time-series (in days) for the Philippines purse seine (PS.5) fishery in region 5.


Figure 26: Results from the CPUE standardization generalized linear model (GLM) for the Philippines purse seine (PS.5) fishery in region 5. The selected model included year-quarter (YR:QTR) and vessel effects (blue line).


Figure 27: Mark-recapture tagging displacements for the Pacific Tuna Tagging Program (PTTP), the Regional Tuna Tagging Program (RTTP), Japanese Tagging Program (JPTP), and Skipjack Survey and Assessment Program (SSAP).


Figure 28: Number of effective releases, recaptures, and the probability of recapture by year for tagged skipjack from the Pacific Tuna Tagging Program (PTTP), Regional Tuna Tagging Program (RTTP), Skipjack Survey and Assessment Program (SSAP), and the Japanese Tagging Program (JPTP).


Figure 29: Number of releases by region and program for tagged skipjack from the Pacific Tuna Tagging Program (PTTP), Regional Tuna Tagging Program (RTTP), Skipjack Survey and Assessment Program (SSAP), and the Japanese Tagging Program (JPTP).


Figure 30: Number of effective releases, recaptures, and the probability of recapture by year for tagged skipjack from the Pacific Tuna Tagging Program (PTTP), Regional Tuna Tagging Program (RTTP), Skipjack Survey and Assessment Program (SSAP), and the Japanese Tagging Program (JPTP) from the 2019 skipjack SA and the 2022 SA skipjack SA.


Figure 31: Recapture probability distributions for a simulated tagged release group (yellow) and the corresponding untagged population (blue) within a region including estimated dissimilarity statistic (D) calculated for quarters 0-3 since release. Median (black dots) and standard deviation (black lines) included.


Figure 32: Proportion of total recaptures by mixing assignment for dissimilarity statistic (D) at $0.1,0.2$, and 0.3 for skipjack tagging data.


Figure 33: Proportion of total number of effective releases and total number of release groups by mixing period for dissimilarity statistic (D) at $0.1,0.2$, and 0.3 for Pacific Tuna Tagging Program (PTTP) and Japanese Tagging Program (JPTP). Tagging data that was not simulated (NS) also included.


Figure 34: Proportion of recaptures by region and mixing assignment for dissimilarity statistic (D) at $0.1,0.2$, and 0.3 for skipjack tagging data in regions 1-8. Total recaptures by region are indicated at the top of each plot.

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## 12 Appendix 1 - Reweighting of size composition data

## 13 Introduction

This Appendix describes the pre-processing of size composition data prior to integration into the 2022 stock assessment model for skipjack tuna. Statistical correction of size composition data is required as size samples are often collected unevenly in space and time such that the samples require reweighting spatially using either catch, to be representative of the size of fish being removed from the population in the case of extraction fisheries, or estimated relative abundance (CPUE), to be representative of the size of fish in the population in the case of index fisheries. Corrections are also applied for any known measurement bias.

## 14 Methods

The reweighting procedure for purse seine fisheries was developed from the approach of Peatman et al. (2020). The reweighting approach for pole and line fisheries was developed from that used to reweight size compositions for longline fisheries in the 2020 yellowfin and bigeye (Peatman et al., 2020) and 2021 South Pacific albacore assessments (Vidal et al., 2021). Fifty 2 cm length classes were used, covering $10-12 \mathrm{~cm}$ through to $108-110 \mathrm{~cm}$. The reweighted sample sizes were generated for use with MFCL's self-scaling multinomial likelihood component for compositional data.

### 14.1 Purse seine size compositions

### 14.1.1 Purse seine data preparation

Length samples from the US Multilateral Treaty Port Sampling (i.e., origin ID = TTPS) and Japanese Skipjack Length Data (origin ID = JPSJ) datasets were extracted from SPC's LF MASTER database. Data from 2010 onwards were excluded due to the high observer coverage during this period. Samples that could not be attributed to assessment fisheries were excluded, e.g., samples with unknown school association in regions where fisheries are specific to set type. Samples provided at a 10 (latitude) x $20^{\circ}$ (longitude) or $5 \times 10^{\circ}$ spatial resolution were split to $5^{\circ}$ cells, using the proportion of reported US (TTPS data) or Japanese catch (JPSJ) in each $5^{\circ}$ cell, for the year-quarter and set type in question (i.e., associated vs unassociated). We note that the majority of TTPS ( $83 \%$ ) and JPSJ ( $78 \%$ ) samples were available at a $5^{\circ}$ resolution.

Observer grab and spill samples were extracted from SPC's master observer database, along with the association type and total catch of each set recorded by observers. Data from an observer's first purse seine trip were excluded. Spill samples were used where available, including both paired grab / spill trips and observer data from the Philippines observer programme, otherwise grab samples were used. Grab samples were corrected for grab sample bias using correction factors (Peatman et al., 2019).
The resolution of strata used in the reweighting process was year, quarter, $5^{\circ}$ cell, and fishery. Fisheries were specific to set type, i.e., free-school vs associated, in regions 5 to 8 . First, we implemented a set-level lower limit for observer sampling intensity, i.e., total samples per tonne of catch. This ensures that high volume sets with low levels of sampling do not have excessive influence on reweighted length compositions in years with relatively limited sampling
coverage. The lower limit was set at approximately $20 \%$ of the target grab sampling rate, i.e., 0.33 grab samples per tonne ${ }^{4}$.

Observer length samples of all tropical tunas were raised from set-level to strata-level by first converting set-level numbers by species and 1 cm length bin to proportions by species and 1 cm length bin. These proportions were then raised to estimated numbers caught by species and 1 cm length bin, so that the estimated set catch across all species summed to the observer's estimate of catch weight for the set. Length weight parameters used in this process are provided in Table A1-1. We then aggregated from set-level to strata-level by summing estimated numbers caught by species and 1 cm length bin across sets, and then rescaling the strata-level numbers so that the total number of fish in each stratum was equal to the original sample size. We then filtered the length frequencies for skipjack.

Separately, US Multilateral Treaty Port Sampling data and Japanese Skipjack Length Data were raised to a strata-level by summing the numbers of samples in each 1 cm length bin across records. These samples were then combined with the strata-level observer samples, giving skipjack length frequencies at a resolution of year, quarter, $5^{\circ}$ cell, and fishery. At this stage, skipjack size samples were filtered for strata with a minimum of 30 samples, to attempt to reduce noise in size compositions due to low sample sizes. The length samples were then aggregated to the 2 cm size classes.

### 14.1.2 Purse seine extraction fisheries

For extraction fisheries, strata-level length frequencies were raised to an MFCL fishery resolution, i.e., year, quarter and fishery as follows:

1. Strata-level numbers by size class were converted to catch-weight proportions by size class, using the length weight parameters in Table A1-1.
2. Strata-level catch weight proportions by size class were then converted to total skipjack catch by size class by multiplying by strata-level skipjack catch taken from S BEST data.
3. These were then aggregated across strata to obtain MFCL fishery resolution catch weights by size class.
4. Catch weights by size class were then converted to numbers caught by size class, by calculating the average weight of each size class using the length-weight relationships in Table A1-1.
5. Numbers caught by size class were then converted to proportions by size class, and rescaled so that the frequency in each year-quarter for a given fishery equalled the original number of samples in step 1.
6. The MFCL fishery resolution length compositions were then filtered for year-quarters where sampled strata accounted for a minimum proportion of the total catch of the fishery. This limit is referred to as the 'minimum sampled weighting'.
[^1]Finally, a $50 \%$ reduction in sample sizes was implemented for unassociated purse seine extraction fisheries in regions 6 to 8 , as the same samples were used to generate length compositions for both extraction and index fisheries (see below).

We note that the inclusion of 'JPSJ' samples required a slight modification to the reweighting procedure, relative to that used for the 2020 yellowfin and bigeye assessments (Peatman et al., 2020). Previously in step 1, size samples from all tropical tuna were included to generate species and size class proportions by weight, which were then applied to the total catch of tropical tuna in a stratum in step 2 to obtain species and size class specific catch weights. This assumes that the samples are representative of both the species compositions and size compositions of catches. The first assumption is not appropriate given the inclusion of the 'JPSJ’ samples, which are all skipjack. Instead, we used skipjack length samples and skipjack catches, to estimate the proportions of skipjack catch weight by size class within a stratum. This assumes that the skipjack samples are representative of the size compositions of skipjack catches.

### 14.1.3 Purse seine index fisheries

Purse seine CPUE indices were generated for regions 6 to 8 using data from free-school sets. Reweighted size compositions were generated for the purse seine index fisheries in these regions, using size samples from free-school sets for consistency with the data used to generate the CPUE indices.
'Strata weights' were defined as the proportion of estimated relative abundance in a region over a time-window of $2 k+1$ quarters accounted for by each stratum, i.e.

$$
W_{s, t}=\frac{\sum_{\tau=t-k}^{t+k} v_{s, \tau}}{\sum_{s} \sum_{t=t-k}^{t+k} v_{s, \tau}}
$$

where $W_{s, t}$ is the strata weight for stratum $s$ in year-quarter $t$, and $v_{s, t}$ is the estimated relative abundance from the CPUE standardisation model. A time window of 1 quarter was used to calculate the strata weights, i.e., $k=0$.

Strata-level length frequencies were raised to MFCL fishery resolution, i.e., year, quarter, and fishery, by:

1. Converting from strata-level numbers by size-class to proportions by size class.
2. The strata-level proportions by size class were then multiplied by the strata weight, $W_{s, t}$, and summed across strata to obtain MFCL fishery resolution proportions by size class.
3. These MFCL fishery resolution proportions by size class were then rescaled to sum to one and multiplied by the total samples for the fishery and year-quarter to obtain numbers by size class.
4. The MFCL fishery resolution length compositions were then filtered for year-quarters where sampled strata accounted for a minimum proportion of the total estimated relative abundance in the MFCL region, i.e., where the sum of strata weights $W_{s, t}$ from sampled strata exceeded a specified proportion (i.e., the 'minimum sampled weighting').

A 50\% reduction in sample sizes was then applied for the purse seine index fisheries, as the same size samples were also used to generate length compositions for extraction fisheries.

### 14.2 Pole and line size compositions

### 14.2.1 Pole and line data preparation

Available length samples from SPC's LF MASTER database were extracted. Length samples, and aggregate pole and line catch data, were aggregated to consistent flag-fleet groupings, using lookup tables held by SPC's Data Management team. For consistency with the purse seine compositions, we used a $5^{\circ}$ spatial resolution to reweight the pole and line size compositions. This was possible due to the high proportion of samples available at a $5^{\circ}$ resolution ( $85 \%$ ). Samples provided at a coarser spatial resolution, e.g., $10 \times 20^{\circ}$, were disaggregated to a $5^{\circ}$ resolution using the proportion of reported catch in each $5^{\circ}$ cell, for the year-quarter and flag-fleet in question. The resolution of strata used in the reweighting process was year, quarter, $5^{\circ}$ cell, and fishery. Available length samples were aggregated to a strata level, by summing frequencies by length class across records.

As with the 2019 assessment, only Indonesian size samples were used to generate size compositions for the pole and line fishery in region 5, given that the Indonesian fleet accounted for the majority of the reported catches from the fishery (Vincent et al., 2019b). This excluded 70,000 samples, representing c. $20 \%$ of the total samples available for the fishery, which were mainly samples from Japanese vessels collected pre-1980 when reported catches from the region were relatively low.

### 14.2.2 Pole and line reweighting methodology

Strata weights for extraction fisheries were defined as the proportion of fishery catch over a time-window of $2 k+1$ quarters accounted for by each stratum

$$
W_{s, t}=\frac{\sum_{\tau=t-k}^{t+k} C_{s, \tau}}{\sum_{s} \sum_{\tau=t-k}^{t+k} C_{s, \tau}}
$$

where $W_{s, t}$ is the strata weight for strata $s$ in year-quarter $t$, and $C$ is the reported catch. Strata weights for index fisheries were equivalent but weighted by estimated relative abundance from the pole and line CPUE standardisation models. A time window of one quarter was used for both extraction and index fisheries, i.e., $k=0$.

Strata-level size compositions were raised to MFCL fishery resolution, i.e., year, quarter, and fishery, by:

1. Converting from strata-level numbers by size-class to proportions by size class.
2. The strata-level proportions by size class were then multiplied by the strata weight, $W_{s, t}$, and summed across strata to obtain MFCL fishery resolution proportions by size class.
3. These MFCL fishery resolution proportions by size class were then rescaled to sum to one and multiplied by the total samples for the fishery and year-quarter to obtain numbers by size class.
4. The MFCL fishery resolution length compositions were then filtered for year-quarters where sampled strata accounted for a minimum proportion of the total catch of the fishery (extraction fisheries) or the total estimated abundance in the MFCL region (index fisheries), i.e., where the sum of strata weights $W_{s, t}$ from sampled strata exceeded a specified proportion.

A $50 \%$ reduction in sample sizes was then applied to the pole and line index fishery compositions, as well as to pole and line extraction fisheries in regions with index fisheries (i.e., regions 1 to 4,7 and 8 ), to reflect the use of the same size samples to generate both index and extraction fishery compositions.

## 15 Results and discussion

In the 2019 skipjack assessment, size compositions for purse seine extraction fisheries were reweighted, and raw (unweighted) size compositions used for pole and line extraction fisheries (Vincent et al., 2019b). For the 2022 assessment, we have reweighted size compositions for pole and line extraction and index fisheries. The use of raw size compositions for pole and line extraction fisheries is appropriate if the size samples have been collected such that they are representative of the catch. However, this does not necessarily imply that size samples are also representative of the underlying population. Reweighting of pole and line compositions for both types of fisheries relaxes assumptions regarding the extent to which the raw samples represent the size compositions of catches and the population, and ensures a consistent treatment of compositional data in the assessment model for all pole and line fisheries.

Reweighted size compositions for purse seine extraction fisheries are provided in Figure A1-1 to Figure A1-4, with purse seine index fishery compositions provided in Figure A1-5. Reweighted size compositions for pole and line extraction fisheries are provided in Figure A1 - 6 to Figure A1-8, with pole and line index fishery compositions provided in Figure A1-9 to Figure A1-11. The sample sizes of the compositional data are provided in Figure A1-12 and Figure A1-13. The reweighting process reduced apparent noise in compositions. Some apparent noise remained, which was commonly associated with year quarters with relatively low sample sizes, e.g., the associated purse seine extraction fishery in region 6 in 1999 and 2000 (Figure A1-3, Figure A1-12). There was apparent cohort progression in reweighted size compositions for a number of fisheries, most clearly seen in the pole and line extraction fishery in region 2 (Figure A1-6) and purse seine fisheries in regions 6 to 8 (Figure A1-3 to Figure A1-5).

The number of available samples varies between fisheries, with the most samples available for purse seine fisheries in regions 6 to 8 from 2010 to 2019 when observer coverage rates were comparatively high (Figure A1-12 and Figure A1-13). Observer coverage rates decreased in the second half of 2020 and 2021 due to Covid-19, leading to lower numbers of samples for purse seine fisheries, particularly those in regions 7 and 8 . There was also a corresponding reduction in the spatial coverage of samples for the purse seine fisheries in regions 7 and 8 .

Reweighted size compositions for pole and line fisheries in region 3 of the eight-region structure demonstrated strong temporal variation, particularly in the 1970s and 2000 (e.g., Figure A1-9). This led to similar patterns in the compositions for pole and line fisheries in region 1 of the five-region structure (e.g., Figure A1-10). The observed variation in sizes in this region has been suggested to reflect the periodic occurrence of large spawning fish and smaller recruits (Hamer, 2022).

The choice of minimum sampled weighting is a compromise between attempting to remove temporal variation in size compositions as a result of unrepresentative sampling, whilst avoiding excessive filtering (McKechnie, 2014). We recommend that a minimum sampled weighting of 0.3 be used for both purse seine and pole and line extraction fisheries. This
requires sampled strata in a given year-quarter to account for a minimum of $30 \%$ of the catch from the fishery, otherwise the reweighted size compositions for that year-quarter are excluded. Additionally, we recommend that a minimum sampled weighting of 0.1 be used for both purse seine and pole and line index fisheries with the eight-region structure. A minimum sampled weighting of 0.1 led to excessive filtering of size compositions for the pole and line index fishery in region 1 of the five-region structure, leaving data for relatively few year-quarters with comparatively high levels of apparent noise. As such, with the five-region structure we recommend a minimum sampled weighting of 0.1 for purse seine index fisheries, and 0 for pole and line index fisheries. These minimum sampled weightings are broadly consistent with those used in the most recent assessments of tropical tunas (Peatman et al., 2020).

Strata weights are calculated across time-windows. A longer time window 'smooths' out temporal variation in the weighting for a given strata through time, whereas shorter time windows allow the influence of a given strata to vary more strongly through time. A time window of 11 quarters was used for pole and line extraction fisheries, following the approach of McKechnie (2014) and Vidal et al. (2021) for longline fisheries in tropical tuna assessments. A time window of 1 quarter was used for all index fisheries, to avoid excessive smoothing of skipjack distributions within regions when calculating strata weights. A time window of 1 quarter is implicitly used to generate purse seine extraction fishery compositions. However, we note that reweighted compositions were insensitive to the length of the time window, and so the choice of time window length does not appear to be critical.

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## 17 Tables

Table A1-1: Length weight parameters by species.

| Species | $\mathbf{a}$ | b |
| :--- | ---: | ---: |
| Skipjack | $1.14 \mathrm{E}-05$ | 3.1483 |
| Yellowfin | $2.01 \mathrm{E}-05$ | 2.9860 |
| Bigeye | $6.48 \mathrm{E}-05$ | 2.7810 |

## 18 Figures



Figure A1-1: Reweighted length compositions for the purse seine extraction fisheries in regions 1, 2 and 3 with the eight-region structure, with a minimum sampled weighting of 0.3. The median length class is provided as a solid white line.


Figure A1-2: Reweighted length compositions for the purse seine extraction fisheries in region 1 with the five-region structure, with a minimum sampled weighting of 0.3 . The median length class is provided as a solid white line.


Figure A1-3: Reweighted length compositions for the associated purse seine extraction fisheries in regions 5 (distant water), 6,7 and 8 with a minimum sampled weighting of 0.3. The median length class is provided as a solid white line.


Figure A1-4: Reweighted length compositions for the unassociated purse seine extraction fisheries in regions 5 (distant water), 6,7 and 8 with a minimum sampled weighting of 0.3. The median length class is provided as a solid white line.


Figure A1-5: Reweighted length compositions for the purse seine index fisheries in regions 6,7 and 8 with a minimum sampled weighting of 0.1 . The median length class is provided as a solid white line.


Figure A1-6: Reweighted length compositions for the pole and line extraction fisheries in regions $1,2,3$ and 4 of the eight-region structure, with a minimum sampled weighting of 0.3. The median length class is provided as a solid white line.


Figure A1-7: Reweighted length compositions for the pole and line extraction fishery in region 1 of the five-region structure, with a minimum sampled weighting of 0.3. The median length class is provided as a solid white line.


Figure A1-8: Reweighted length compositions for the pole and line extraction fisheries in regions $5,6,7$ and 8 , with a minimum sampled weighting of 0.3 . The median length class is provided as a solid white line.


Figure A1-9: Reweighted length compositions for the pole and line index fisheries in regions $1,2,3$ and 4 of the eight-region structure, with a minimum sampled weighting of 0.1. The median length class is provided as a solid white line.


Figure A1-10: Reweighted length compositions for the pole and line index fishery in region 1 of the five-region structure, with a minimum sampled weighting of 0.0 . The median length class is provided as a solid white line.


Figure A1-11: Reweighted length compositions for the pole and line index fisheries in regions 7 and 8 , with a minimum sampled weighting of 0.1 . The median length class is provided as a solid white line.


Figure A1-12: Samples by year-quarter for reweighted compositions of extraction fisheries. Samples were capped at 15,000 .


Figure A1-13: Samples by year-quarter for reweighted compositions of index fisheries. Samples were capped at 15,000 .


[^0]:    ${ }^{1}$ Oceanic Fisheries Programme, The Pacific Community, Nouméa, New Caledonia
    ${ }^{2}$ National Research Institute of Far Seas Fisheries, Japan Fisheries Research and Education Agency
    ${ }^{3}$ NOAA Fisheries Pacific Islands Fisheries Science Centre, Honolulu, Hawaii, USA

[^1]:    ${ }^{4}$ The target grab sampling rate is 5 fish per brail. This equates to 5 fish per 3 tonnes of catch assuming a 5 metric tonne capacity brail which is c. $60 \%$ fill on average.

