Longline CPUE indices for Indian Ocean yellowfin tuna: analysis methods and their implications for the indices.

A comparison of IOTC-2024-WPTT26(DP)-14 and previous analyses

20 November2024

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1. Executive summary

Longline CPUE indices are very important in determining the outcomes of tuna stock assessments. Their development is one of the most important parts of the stock assessment process. The 2024 joint longline indices for yellowfin tuna were considerably more optimistic than the 2021 indices, particularly in the northwestern area R1. The reasons for these differences were unclear to the 2024 WPTT.

Changes are appropriate if they provide better indices, based on better methods. However, each change to established methods should be clearly described, justified with evidence, and accepted by the IOTC. Indices based on unchanged methods should also be provided, so that the WPTT can observe how the changes affect assessment outcomes. Fishery management requires reliable, consistent, and evidence-based scientific advice.

I have identified several changes to methods in 2024 that the WPTT was not fully aware of. Most appear scientifically debatable, at best. Together these changes are likely to have caused the more optimistic index trends during the period up to 2020.

In analyses since 2020, some changes have been reported to the approaches used in 2015-2019. These need not be further discussed here, although I note that operational data access is now available again, which is likely to improve the indices. A few unreported changes have also occurred, which are mentioned below.

1. Confirmed changes
    a. Use of cluster analysis for tropical areas. This has previously been advised against by WPM and WPTT and has not been used before in a YFT assessment. It is likely to have significantly affected the tropical indices, increasing them in recent years.
    b. Combining data for R1a and R1b in the R1 dataset, instead of using R1b only. This is against good practice and has been advised against, because a) the 2 areas have different abundance trends, and the CPUE model used is not suitable for this situation, and b) there are data quality issues within R1a, which is why it has not been used in the past to develop an R1a index. This is likely a major cause of the increased indices in R1b.
    c. The delta component of the delta lognormal CPUE model omits the log(effort) term, which is an error. This will bias the indices, but it is not clear in which direction or how much.

   d. The 2024 indices used the delta lognormal approach, whereas the 2021 indices used the lognormal(CPUE + c) approach. The delta lognormal should be an improvement if set up correctly. However, see the point above.
   e. The data filtering process was probably different in 2021 and 2024. The 2021 analyses retained only the top 50% of vessels by effort, as long as they had fished in at least 20 strata. No filtering is mentioned in the 2024 paper, and all data may have been included.
2. The following issues may affect the reliability of both sets of indices. These methods were applied in 2015-2019, but not in 2021 or 2024.
   a. Spatial reweighting – this should be done to avoid bias. It usually makes a small difference to index trends, with the direction depending on how effort distribution has moved through time.
   b. Binomial rescaling – this should also be done to avoid bias, and sometimes makes a small difference to the index trends, in either direction.

I note the recommendation of the Independent Review of the 2021 YFT assessment of a cross-RFMO workshop to identify the best methods for developing longline CPUE indices. This was justified by the importance of the longline CPUE indices and the complexity of the analysis. Analysts in other RFMOs are dealing with similar problems, and there is much to learn by collaborating and sharing expertise. SPC has proposed a joint-RFMO workshop on this subject towards the end of 2025.

Citation: Hoyle, S.D. (2024). 'Longline CPUE indices for Indian Ocean yellowfin tuna: analysis methods and their implications for the indices. A comparison of IOTC-2024-WPTT26(DP)-14 and previous analyses.' IOTC-2024-SC27-INFO1. 14 pp.

2. Introduction

Longline CPUE indices are very important in determining the outcomes of tuna stock assessments, since they inform the model about the relative abundance of the stock through time. Stock assessments for bigeye and yellowfin tuna in the Indian Ocean have, since 2016, fitted to indices of abundance based on collaborative analyses of longline catch and effort data from multiple fleets, known as joint longline indices. For the Indian Ocean, these were initially developed during a collaborative workshop involving Japanese, Korean, and Taiwanese scientists, along with an independent consultant (Hoyle et al., 2015b).

The 2024 joint longline indices for yellowfin tuna (Matsumoto et al., 2024), which were used in the 2024 assessment of yellowfin tuna (Urtizberea et al., 2024), were considerably more optimistic than the 2021 indices (Kitakado et al., 2021) used in the 2021 assessment (Fu et al., 2021). Substantial differences between the two sets of indices are apparent during the period of overlap from 1975 to 2020 (Figure 1). This is particularly obvious for the northwestern index labelled LL1b, which is based on data from both R1a and R1b. It is also true for the northeastern LL 4 (R4) index, though this index is so low in 2010-2020 that the size of the difference is difficult to see. The two temperate indices (LL2and LL3, i.e., R2 and R3) are also more optimistic during the overlap period in 2024 than in 2021, but to a lesser degree than the tropical indices.

These changes could not have been caused by adding data to the end of the time series – this generally has only a small effect on earlier indices, due to changes in the estimates of shared parameters such as vessel effects and spatial effects.

The reasons for these differences are unclear. Changes may be appropriate if based on methodological improvements, but any changes to established methods should be clearly described and justified with evidence. The effects on the indices of each individual change should be demonstrated. Similarly, changes to data filtering and data preparation should be justified, and their effects demonstrated. Fishery management requires reliable, consistent, and evidence-based scientific advice.

This working paper attempts to identify what has caused the large differences between the joint longline indices for yellowfin tuna provided by IOTC-2024-WPTT26(DP)-14 (Matsumoto et al., 2024) and those used for the 2021 yellowfin tuna stock assessment (Kitakado et al., 2021) (IOTC–2021-WPM12-18 & WPTT23(AS)-11). It also considers methods used in earlier joint analyses of Indian Ocean CPUE of yellowfin tuna (Hoyle et al., 2016; Hoyle et al., 2017; Hoyle et al., 2019a; Hoyle et al., 2018; Hoyle et al., 2015b).

This paper considers the methods employed, including data collection, processing, and analysis.

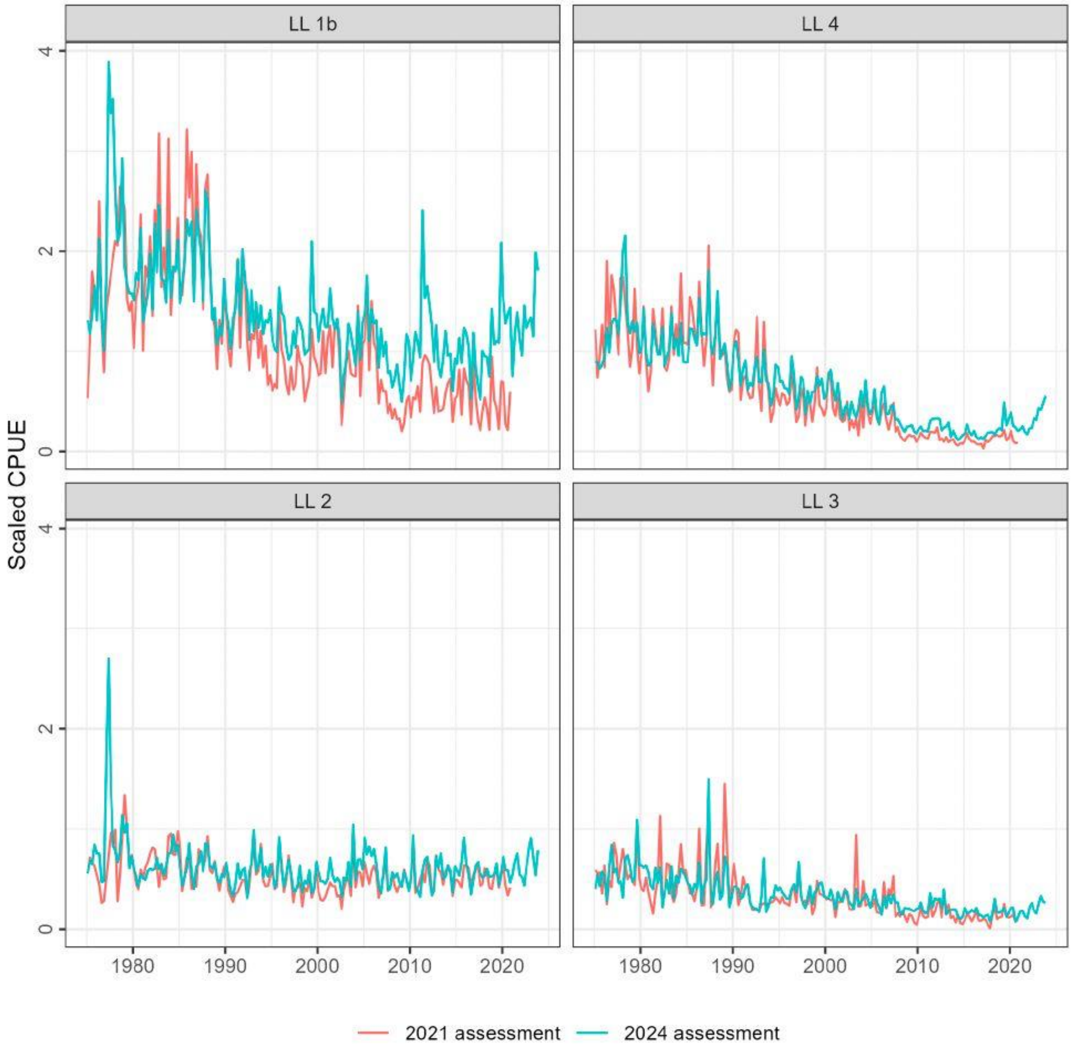

Figure 1: Comparison of the indices of abundance used in the 2021 and 2024 assessments – copied from Figure 16 in the 2024 SS stock assessment report (Urtizberea et al., 2024).

3. Materials and Methods

Note that the yellowfin tuna regions have been labelled in various ways through time. Throughout this working paper I have used labels that match those in Figure 1.

Methods used in 2024

Two data types were prepared. Aggregated data (by year, month, vessel ID, cluster number and 5° cell) was created and used for CPUE standardization to prepare quarterly indices. Operational data were subsampled by 10-30% to shorten calculation time and used for annual indices. According to Table 1 (Matsumoto et al., 2024) subsampling rate for the annual indices was 20%. The indices used in the assessment were quarterly, based on aggregated data without subsampling.

Known changes between 2021 and 2024

Cluster analysis

A significant difference between the 2021 and 2024 assessment indices was the use of cluster variables in the index. The 2021 CPUE analysis developed indices with two alternative methods for addressing targeting: a cluster variable and a hooks between floats (HBF) variable. The 2021 assessment IOTC–2021–WPTT23–12 (Fu et al., 2021) chose to use indices that included a cluster variable only for temperate regions, noting (Section 2.5.1) "The CPUE for the temperate regions R2 and R3 incorporated the cluster variable to indicate the targeting effect, whereas the tropical regions R1b and R4 used hooks between floats (HBF)." However, the 2024 CPUE analysis only developed indices with the cluster variable, and so the 2024 assessment used indices that included cluster variables for the tropical areas R1b and R4.

Using cluster analysis in the standardization is problematic for indices in tropical areas, which are designed for distinguishing discrete fishing tactics that result in distinctive species composition (He et al., 1997; Hoyle et al., 2024). It has previously been recommended to use HBF rather than cluster as the main targeting indicator for tropical areas.

Hoyle et al. (2019a) noted "In tropical areas (bigeye regions 1 and 2, yellowfin regions 1b and 4) we selected figures from the analysis that omits low-target clusters from the dataset and includes HBF but not cluster in the model. Although there have been changes in targeting through time, vessels are believed to target bigeye and yellowfin at the same time and using similar methods, but to different extents by area and season, and with changes through time. In this complex situation clustering may be useful to remove data from clearly separate fisheries (such as the southern bluefin tuna fishery that occurred in eastern areas near Indonesia in the 1960s and 70s). However, including cluster in the model may be problematic due to the confounding of clusters with abundance change. We have therefore used hooks between floats in the models for tropical areas, as was done in previous years' analyses."

There are several reasons to avoid using cluster as a targeting indicator in a CPUE analysis for tropical regions.

First, the species compositions of the bigeye and yellowfin clusters are similar, apart from the proportions of bigeye and yellowfin tuna, and it is the proportions of bigeye and yellowfin that determine cluster membership. Even if the different clusters were to represent targeting to some degree, the differences in catch rates due to targeting are highly confounded with difference in catch rates due to abundance change. The cluster algorithm cannot differentiate between target change and abundance change, because that information is not available in the species composition data. Using these clusters in CPUE standardization will therefore tend to remove the abundance trend and flatten the index, rather than accurately representing abundance.

Second, when bigeye and yellowfin are both available, vessels will target both species. Vessels tend to target more productive waters, which tend to have higher catch rates of both yellowfin and bigeye tuna. Cluster analysis is useful in segregating dissimilar types of fishing effort (He et al., 1997), but problematic when targeting practices are not distinct. Hoyle et al. (2024) note that "Considering that several subjective decisions must be made (Campbell et al., 2017), the identified targeting signatures should be consistent with prior knowledge that distinct targeting practices exist. Otherwise, there is a risk of mistaking spatiotemporal abundance patterns for targeting."

This issue was examined by Hoyle and Okamoto (2013) using Japanese longline data for the Western and Central Pacific Ocean, who found that cluster analysis for bigeye and yellowfin tuna should not be used for CPUE standardization in tropical areas because it was affected by confounding with abundance change. “Clustering data from the core equatorial areas [in the west and east] produced two clearly separated groups in both regions. Examining the proportions of effort in each cluster by year suggested a decline in the proportion of effort in the yellowfin tuna cluster. This is consistent with the decline in yellowfin CPUE through time. However, the clusters appear to be reasonably well separated spatially, and yellowfin clusters have moved into areas occupied by bigeye clusters as yellowfin catch rates have declined. The clusters appear likely to represent fishing trips in areas where catch rates of one species or another are higher, rather than fishing techniques that target a particular species.”

If this change in clusters from bigeye to yellowfin genuinely represented a change in targeting behaviour, the change should appear in other indicators, such as vessel behaviour. Hoyle and Okamoto (2013) analysed vessel behaviour from 1980 to 2010 to identify factors affecting vessel movements. They found that vessels were more likely to make long movements to new fishing locations after taking small catches. Movement probabilities tended to be slightly more affected by low bigeye catches than by low yellowfin catches, indicating some preference for bigeye over yellowfin tuna. However, a similar level of preference was observed in every decade, without directional change through time. The catch of both species combined was a much stronger indicator of long movements than either species by itself, supporting the idea that vessels were targeting both species.

The IOTC discussed the utility of target identification issue in 2021 and 2022. It was recognized that there is confounding between cluster membership and the abundance trend, and that targeting of yellowfin and bigeye are often not discrete fishing tactics, and/or do not result in distinctive species composition.

For example, in 2022 joint CPUE indices were developed for bigeye tuna (Kitakado et al., 2022) using either a cluster variable or HBF in all regions. They found that trends differed between the two approaches, and for continuity and based on earlier discussions, recommended that HBF be used in tropical regions. The IOTC WPM agreed, because ‘the clustering method may not perform well as changes in relative proportion of bigeye tuna (BET) and yellowfin tuna (YFT) in the catch may not always reflect changes of targeting’. The issue was not discussed again in 2023.

Given its importance and complexity, this issue represents a key topic to be addressed by a cross-RFMO CPUE review process, as recommended by the independent review of the yellowfin tuna assessment (Maunder et al., 2023).

Data for area 1

CPUE analyses in 2024 (Matsumoto et al., 2024) combined data from R1a and R1b and analysed them together as a single region (Figure 2), whereas the 2021 indices were based on R1b alone, without data from R1a (the Arabian sea). Each model included time and spatial effects as additive terms, without interactions between time and space. This approach (combining areas R1a and R1b) would be reasonable if both areas have followed similar abundance trends. However, it would be inappropriate if the areas have had different abundance trends through time. In that case, the areas should be analysed separately, or spatiotemporal models should be used (Campbell, 2015; Hoyle et al., 2024; Maunder and Punt, 2004).

There appears to be considerable evidence for differences between the areas R1a and R1b. The oceanographic environment and yellowfin population structure of R1a appears to differ from R1b (Lan et al., 2020). Fish sizes have been found to be smaller on average in R1a, in data from multiple fleets (Hoyle et al., 2021). Significant genetic differentiation has also been observed for yellowfin tuna collected in the Arabian Sea versus other areas of the north-central Indian Ocean (Kunal et al., 2013). Taiwanese catch rates for yellowfin tuna in R1a appear to have been considerably higher at times than in R1b (Hoyle et al., 2015c), but fishing has also been episodic, so vessels may only fish there when catch rates are high. In contrast, bigeye catch rates in R1a have been much lower than in R1b, indicating different ecological dynamics and fishing behaviour.

In addition, fishing in R1a since 1990 has been largely by Taiwanese fleets, although Taiwanese data is only included in the indices after 2005. There has been almost no effort by Korean vessels (Hoyle et al., 2015a). Japanese effort in R1a has been episodic, limited to the far south, averaging a few sets per day since the 1960s, and with minimal effort since the mid-2000's (Hoyle and Okamoto, 2015).

Perhaps most importantly, unstandardized CPUE trends in area R1a are dissimilar from area R1b. It is therefore not appropriate to combine data from R1a and R1b into one CPUE analysis using the current approach without time-area interactions.

Moreover, in 2018 the north and south of R1b were analysed separately to improve tag mixing, and the abundance trends were found to be somewhat different (Hoyle et al., 2018). It was also noted that temporal trends appeared to vary within regions, with more CPUE decline in tropical areas close to the equator. Similar spatial patterns were found for Atlantic yellowfin tuna (Hoyle et al., 2019b). There appears to be good justification for including time-area variation by using spatiotemporal models at least at the regional level.

The 2023 independent review (Maunder et al., 2023) noted considerable spatial complexity and uncertainty about stock structure. They recommended a comprehensive review of information related to stock structure, to better understand how to set up the assessment. They also recommended exploring the connectivity of the Arabian sea (i.e., R1a) with the rest of the assessment.

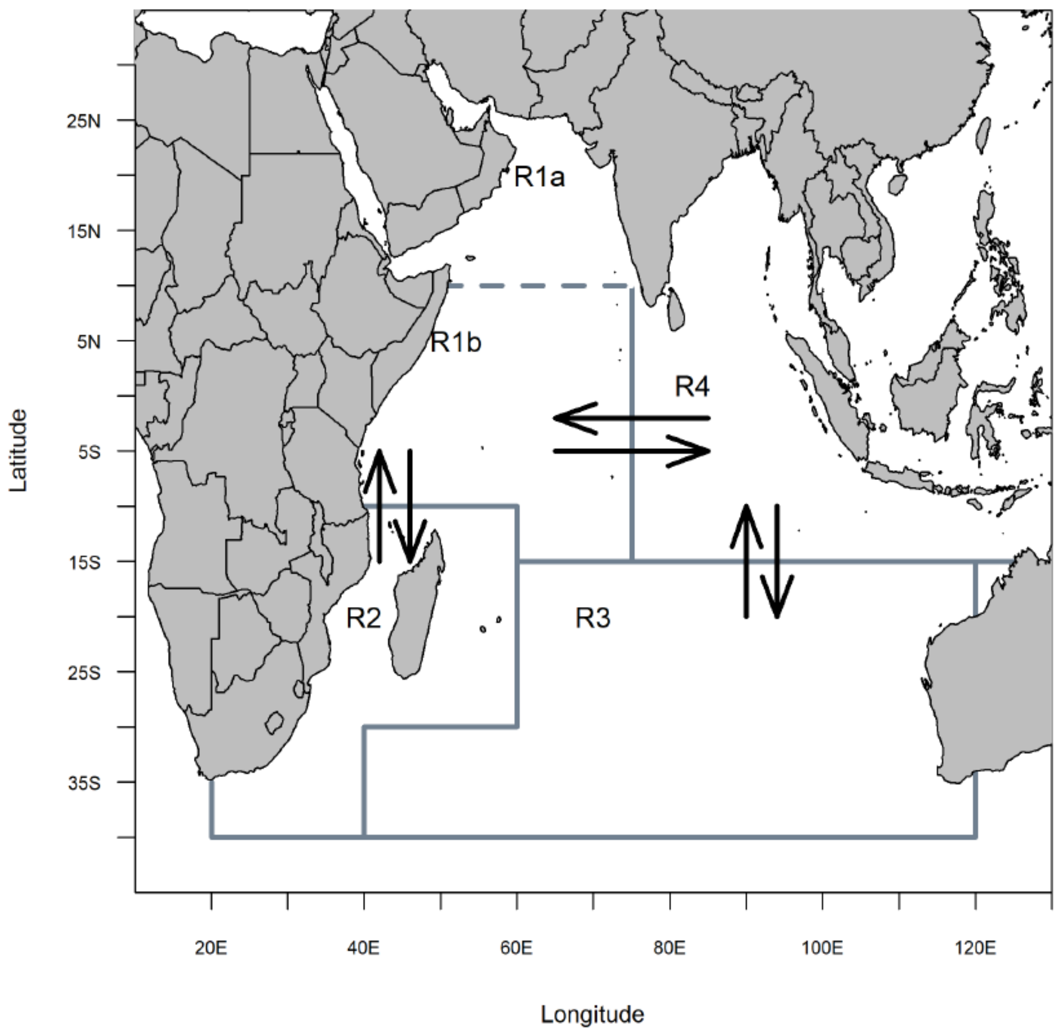

Figure 2: Definition of areas used in the 2024 CPUE analysis study. From Fig. 1 in Matsumoto et al. (2024).

CPUE model

Indices in 2021 were based on aggregated data, due to pandemic-related problems with data access. Zeros were a significant component even in the aggregated dataset. To deal with zeros and permit use of a lognormal distribution, the analysis used the traditional approach of adding a constant to the independent variable: log(CPUE + c) ~ main effects + interactions + error.

In 2021 a delta lognormal model (as used in 2015-2019) was also applied but only for R3. This method used the same covariates as above, but adding the number of hooks in the binomial part of the analysis.

In 2024, the delta lognormal approach was used for all model runs. The standardization model for the binomial component was reported as
g(w)=($CPUE$=0)~ yrqtr + vessid +latlong5+$cluster$+ϵ,+ϵ, where g is the logistic function and ϵ is the error term.

The 2024 model omits effort (number of hooks) as an explanatory variable. Effort is an important covariate in the binomial model, because fishing with more hooks increases the chance of catching at least one fish. Aggregated data was used for the quarterly indices used in the assessment, which means that different observations (rows of data) are based on different numbers of sets. Therefore, there would have been considerable effort variation between observations in the dataset, making it important to include effort as a covariate. Omitting effort from the right-hand side of the equation appears to be an error, either in the model setup or the model description.

In summary: the delta lognormal approach used in 2024 should be an improvement over the lognormal constant model 2021. However, omitting effort from the right-hand side of the binomial equation in 2024 appears to be an error and would have affected the indices to some degree.

Subsampling

The annual indices based on subsampled operational data were not used in the assessment, but they were used for comparison with the quarterly indices.

The paper indicates that, for operational data analyses, the operational data in each subregion were randomly subsampled "by 10-30% (in each latitude-longitude and year-quarter)". This subsampling was needed to reduce analysis time, due to time limitations at the analysis meeting. Previous analysis meetings were also time limited, but there may have been additional constraints at the 2024 meeting. Among these may have been the laptop used for the analyses – i.e., RAM may have been too limited. Analyses 2015-2019 used a purpose-designed laptop with 64GB of RAM, which allowed multiple analyses to run in parallel. The laptop also used the Intel MKL multithread BLAS libraries which allow GLM analyses in R to run much more quickly.

Subsampling may not introduce bias or change the trend, but testing is required to establish whether this is the case. It will introduce random noise into indices if the subsample fraction is too small, which may occur when some strata start with low sample sizes. It may even introduce bias if some strata are omitted. Analyses during 2015-2019 used a different type of subsampling, which had been simulation tested and shown not to cause bias or significant noise (Hoyle and Okamoto, 2011). This approach randomly selected the same number of observations (rather than the same proportion) from each stratum (5° cell by year-quarter).

The approach used in this analysis does not appear to have been simulation tested to check whether it introduces bias or adds noise.

Possible changes

Data filtering process

In 2021 some data screening was applied, but no screening is described in the 2024 paper. It is possible that just the description was omitted, but perhaps more likely that the screening itself was omitted.

Screening in 2021 involved retaining only the top 50% of vessels by the amount of effort, as long as they had fished in at least 20 strata.

Changes since 2019

Use of aggregated data

Although indices based on aggregated data can be informative and close to operational indices, particularly when vessel IDs are retained, there is still a range of potential concerns (Hoyle et al., 2024). For example, effort tends to be higher in areas with higher catch rates, and rows of data that are based on more effort have lower observation error. Together, these process result in an inverse relationship between the mean and variance, which breaks the assumptions of the GLM (e.g., Hoyle, 2021). Results are usually quite robust to this issue, but it can still have a small impact, and operational data should be used if possible when the results are important.

Spatial reweighting

Samples were not reweighted to have consistent spatial weighting. This method (a different process from regional weighting) has been demonstrated to reduce bias in indices based on models of the type 'CPUE ~ time + location + covariates' when effort distribution changes through time (Campbell, 2004; Punsly, 1987). It was therefore used in CPUE analyses 2015-2019. Testing with Japanese longline data in the WCPO indicated that spatially reweighted indices tended to have different trends from those that were not reweighted (Hoyle and Okamoto, 2011). The size and direction of the adjustments were determined by changes in effort distribution through time.

If these models did not use spatial reweighting, both 2021 and 2024 indices are likely to retain some bias due to the redistribution of effort through time.

Binomial rescaling

Indices for binomial models were not rescaled to adjust for the selected 'base' levels of categorical variables in the GLM. This process ensures that the mean of the index is the same as the mean of the annual means of the unstandardized data. It was applied in analyses 2015-2019, and is recommended so that trends in the binomial component of the model are appropriate (Hoyle et al., 2024; Hoyle et al., 2022).

If these models did not use binomial rescaling, both 2021 and 2024 indices may have a small amount of bias due to the selected base levels of categorical variables in the GLM prediction.

4. Discussion

The differences in the CPUE indices between the 2024 and 2021 assessments appear to be largely due to changes in the analysis methods. Methods used to develop the 2024 indices were based on earlier approaches but have omitted some processes. The most significant changes appear to have been driven by the inclusion of data from the Arabian Sea, and the use of indices for tropical areas that include cluster variables. Additional and perhaps less consequential changes occurred in data filtering, and an error appears to have been made in one of the model formulae. Indices without these changes were not provided, so the assessment analysts were unable to develop alternative assessment models using indices based on 2021 methods.

These methodological changes may have caused the changes observed in stock status, but this is uncertain because indices without these changes are not available for comparison.

Additional changes are noted between the approaches used before the pandemic (2015-2019) and approaches used since. During the period affected by the pandemic, analysts were required to use aggregated data given the prevailing rules for data access. In 2024, however, aggregated data were used because of limited time and computer resources during the analysis meeting. A solution to this problem is needed. Analysts in 2021 made several changes that were agreed to be improvements, such as aggregating data for clustering over 10 days rather than 1 month. However, they also appear to have omitted several components without discussion: spatial reweighting and binomial rescaling.

Noting the recommendation by the 2023 Independent Review for a cross-RFMO workshop to improve longline CPUE index methods, SPC has proposed such a workshop towards the end of 2025. Supporting this meeting would help IOTC to identify and agree on better methods for the wide range of issues associated with CPUE analysis. Analysts in other RFMOs are dealing with similar problems, and there is much to learn by collaborating and sharing expertise.

5. Acknowledgements

This project was funded by the Sustainable Fisheries and Communities Trust – SFACT.

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