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PROJECT 122A: GLOBAL JOINT TUNA RFMO LONGLINE CPUE TECHNICAL WORKSHOP

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Executive Summary

This paper provides an update on progress with the planning, organisation, and agenda for the 'Global Joint Tuna RFMO Longline CPUE Technical Workshop' to be held in Yokohama, Japan, 12-16th October 2026 (hybrid format). The workshop is being co-organised by the Pacific Community (SPC), Inter-American Tropical Tuna Commission (IATTC), and Japan's Fisheries Research and Education Agency (FRA). The broad aims of the workshop are to consolidate key recommendations and identify good practices to improve the analysis of longline CPUE data for tuna abundance indices, providing advice that will be applicable across global tuna RFMOs. The workshop and its outcomes will not only consider tuna and will have relevance to billfish and sharks. As part of the workshop planning and to provide a scene setting paper, a major review of the status of longline CPUE analysis across all tuna RFMOs has been conducted by Hoyle Consulting. This involved review of literature and consultations with relevant scientists involved in longline CPUE analysis across all tuna RFMOs. A draft version of the review paper is provided as appendix 2 in this report. The workshop is supported by *WCPFC Project 122a: Global Joint Tuna RFMO Longline CPUE Technical Workshop*, and has received generous additional funding support from the following organisations:

- International Seafood Sustainability Foundation
- Blue Marine Foundation
- The Ocean Foundation/Harvest Strategies.Org
- Sustainable Fisheries and Communities Trust
- International Pole and Line Foundation
- EU (project to IATTC)

In summary the workshop planning and organisation is mostly complete, and we expect at least 40 people to join in-person with an additional 30+ online. Five invited experts will play a key role in workshop, and all are confirmed. All donor funds have now been received or agreements signed off. The review and consultations with analysts across global tuna RFMOs is complete, with revision to the review paper after the workshop. Notification has been received for the acceptance of a special issue of the journal *Fisheries Research* featuring papers and key outcomes of the workshop.

The workshop website: https://fame.spc.int/event/global-joint-tuna-rfmo-longline-cpue-technical-workshop

We invite SC22 to note:

- The progress of workshop planning and organisation
- The generous contributions of external donors
- The draft agenda and review paper (appendices 1 and 2)
- That the outcomes will be presented to SC23

Background

WCPFC Project 122a is supporting the first 'Global Joint Tuna RFMO Longline CPUE Technical Workshop' (hereafter *the workshop*). This initiative grew out of the previous WCPFC Project 122 that focussed on effort creep in longline tuna fisheries (Day & Hamer, 2024; Hoyle, 2024). That project recognised a much broader range of issues (including effort creep) and methodological challenges and advancements, along with changes in fishing methods and technology, which were influencing the reliability and approaches for good practice analysis of longline CPUE for deriving tuna, billfish, and shark abundance indices. Few if any of the issues are unique to the WCPFC, and discussions with IATTC scientists and wider communications with scientist across all tuna RFMOs, provided strong encouragement to pursue a global tuna RFMO workshop on this topic. SPC began collaborating with the co-authors of this paper in early 2025 to make this workshop happen.

This paper provides information on the workshop objectives, organisation, funding support, agenda and format, expect outputs and other related information, such as venue and logistics. As part of the workshop planning and to provide a scene setting paper, SPC under Project 122a (ISSF funding contribution, below), contracted Simon Hoyle to conduct a major review of the status of longline CPUE analysis across all tuna RFMO. This involved review of literature and consultations with relevant scientists involved in longline CPUE analysis across all tuna RFMOs. A draft version of the review paper is provided as appendix 3 and will be finalised after the workshop.

The workshop will be held in Yokohama, Japan 12-16 October 2026, webpage link:
https://fame.spc.int/event/global-joint-tuna-rfmo-longline-cpue-technical-workshop

Objectives

This technical workshop aims to bring together analysts involved in longline CPUE modelling from across the world's tuna RFMOs. While tuna species are the focus, experience and techniques applied to billfish and sharks are also relevant. Several invited technical experts will help guide the workshop discussions and provide independent expert technical commentary and advice.

The workshop will provide a rare opportunity for global tuna analysts to share and discuss challenges and technical methods, including the latest developments in longline CPUE analysis and share insights into historic and recent developments in tuna longline fishery operational practices. The workshop will revisit the fundamentals of the use of longline CPUE data to generate abundance indices, review how they are applied in stock assessments, hear about historic and recent developments in tuna longline fishing methods and discuss how to improve the transparency and repeatability of these important analyses.

The workshop broad aims:

To consolidate key recommendations and identify good practices to improve the analysis of longline CPUE data for tuna abundance indices, providing advice that will be applicable across global tuna RFMOs.

The workshop specific objectives are:

1. *Conduct a comprehensive stocktake and synthesis of longline CPUE standardization approaches across all five tuna RFMOs.*

2. *Develop and publish technical guidelines specific to tuna longline CPUE analysis, addressing identified issues and gaps in current methods.*

3. *Provide actionable recommendations for each tuna RFMO to improve CPUE standardization for bigeye, yellowfin, albacore and bluefin tuna assessments.*

4. *Produce a set of technical peer reviewed papers exploring key issues with tuna longline CPUE analysis and recommended good practices to support best available science on longline abundance indices for tuna RFMOs.*

5. *Establish ongoing collaboration mechanisms between tuna RFMO CPUE analysts to facilitate knowledge sharing and methodological consistency.*

Planning, progress and workshop details

Funding

The workshop required a funding base before it could progress beyond a concept. Thankfully we were able to reach out to potential donors who committed funds that provided the base funding. With this base funding as leverage/co-funds, the additional required funds were committed through WCPFC project funding (i.e. Project 122a). Meeting hosting/logistical support is being provided by Japan's Fisheries Research and Education Agency (FRA), Yokohama. The table below lists the organisations and their contributions that make this workshop possible.

Organisation	Funding support (USD)
International Seafood Sustainability Foundation	20,000
Blue Marine Foundation	10,000
The Ocean Foundation and Harvest Strategies.Org	10,000
Sustainable Fisheries and Communities Trust	10,000
International Pole and Line Foundation	2,500
Western and Central Pacific Fisheries Commission (Project 122a)	20,000

The IATTC has since received funding support from the **European Union (EU)** to support their involvement and extend the technical workshop support (consultant Hoyle) for generating the workshop outputs including the coordination and publication of papers in a special edition of the journal Fisheries Research.

Planning

A workshop steering group was initiated in April 2025 to provide guidance and feedback on the workshop planning, agenda, and choice of invited experts. The steering group comprises RFMO linked technical expertise and representatives of donor organisations. The steering group has meet online at key points in the organisation process and been provided updates by emails (coordinated by SPC, Paul

Hamer). The SPC (Paul Hamer) and consultant, Simon Hoyle, with support on the ground in Japan from colleagues at FRA (Hirotaka Ijima and Hidetada Kiyofuji), and technical guidance by Mark Maunder (IATTC) have been driving the workshop planning, agenda, and organisation. After initial consultations with tuna RFMO connected scientist, and an email circular for expressions of interest to join the workshop, an email list has been developed with 73 interested attendees, 41 of these indicating in person attendance. The workshop will provide a hybrid format to the extent possible, given the mix of longer plenary presentations, shorter contributed presentations, and group discussion. It will follow the format of the successful technical workshops run by the Centre for Advancement of Population Assessment Methodology (CAPAM).

Yokohama has been chosen for the workshop, not only for its convenient location for global travel, many accommodation options, food galore and value for money, but the importance of tuna to Japan and their pioneering role in tuna longline fishing across the world's oceans. The key historic data sets used by all tuna RFMOs for longline CPUE analysis are from the Japanese fleet. The Japan Fisheries Research and Education Agency (FRA) is also close by, offering the opportunity for side meetings with FRA staff. The date of 12-16th October was the only suitable window within gaps in the other regional and global tuna RFMO related meetings; and not being too close the WCPFC annual meeting.

Various venues were considered and multiple quotes sought. Venues at hotels were out of budget, so a dedicated meeting venue was selected with a capacity for around 60 people. The VisionCentre venue is in Minatomirai close the central Yokohama in the harbour area. It has a metro station on its doorstep. There are many accommodation options in the central Yokohama area.

Vision Centre, Minatomirai, room 704 - https://www.visioncenter.jp/yokohama-minatomirai/

Google Maps

Draft agenda

The draft agenda and session summaries (appendix 1) have been developed initially through discussions of the technical leads (SPC, FRA, IATTC, Hoyle) and then reviewed by the steering group and is still amenable to changes. Proposed speakers have been contacted to brief them on topics ad confirm availability. The email list has been contacted several times regarding proposals for contributed presentations, to date four have been proposed, but the number may change. Mark Maunder (IATTC) will be the main chair of the workshop. Each meeting day will run from 9-5 pm, plan to wrap up by 4.30 pm.

The agenda key topic areas below:

- Session 1: Opening and scene setting (1h 50min)
- Session 2: Data (3h 30min)
- Session 3: Operational information and industry insights, effort creep, hyperstability/hyperdepletion (2h 50min)
- Session 4: Modelling frameworks: GLM, GAM, STM, and diagnostics (1h 30min)
- Session 5: Stock structure, defining the index fisheries, regional scaling (2h 40min)
- Session 6: Targeting, preferential sampling, & spatial contraction of fleets (2h 30min)
- Session 7: Size comps and combined CPUE-size data analysis (1h 40min)
- Session 8: Collaborative/multi-fleet CPUE (2h 30min)

- Session 9: CPUE: Code, Data, and Institutions (2h)
- Session 10: Use in assessments (1h 30 min)
- Session 11: Use in MSE and MPs (1h 30min)
- Session 12: Consolidation (3h)

Invited Experts

It was decided at the outset to invite five relevant experts and to fund their travel costs. These five people will play important roles in plenary presentations and/or driving discussion sessions and contribute to key papers from the workshop. The experts have different areas that they can contribute their technical skills, knowledge and experiences. A number of potential experts were discussed with the steering group and the five chosen were approached and all confirmed availability to attend in person. They include global experts in the statistical modelling areas and tuna longline industry practices. The invited experts and their bios are provided below.

1. Rodrigo Sant'Ana

Rodrigo Sant'Ana holds a degree in Oceanography (2008), a master's degree (2013), and a doctorate (2023) in Environmental Science and Technology. He has have worked in the field of Statistics and Data Science applied to Oceanography, Marine Ecology, and Fisheries Science for over 20 years. Throughout his career he has had the opportunity to contribute to national and international projects with institutions from different spheres, from governmental to non-governmental. Currently, he is a professor and researcher at the University of Vale do Itajaí, Brazil. He also holds the scientific leadership and statistical correspondence position for Brazil at ICCAT where he has responsibility for the western stock of Atlantic skipjack tuna. Since his graduation, he has sought to develop and apply statistical methods based mainly on Bayesian Inference to problems derived from stock and fisheries dynamics, with an emphasis on spatial structuring in CPUE standardization models, bycatch assessments, and density and biomass estimations.

2. James Thorson

James Thorson is a statistical ecologist who works to integrate population, ecosystem, habitat and climate research at the Alaska Fisheries Science Center. He has developed methods for multivariate spatio-temporal modelling (e.g., tinyVAST), which are used for basic and applied research worldwide. He has also developed new methods to predict evolutionary trade-offs among ecological traits (phylosem), mechanistic causal modelling for time series (dsem), state-space ecosystem modelling (ecostate), movement models that incorporate habitat preferences, and contributed to several stock-assessment models. Throughout these topics, his research focuses on practical methods to integrate data while understanding (and predicting) ecological dynamics to improve ocean management.

3. Francisco Blaha

Francisco Blaha offers a rare perspective that connects industry operations and economic drivers, fisheries management, and applied science, with experience spanning over 40 years. He has extensive experience both at sea (as an observer and fishermen, including on tuna longline and purse seine vessels) and within fisheries governance systems. He has a MSc in Fisheries Biology, where he studied bait effects in longline fishing, and a second MSc in Food Science (also speaks four languages!). He has worked from the deck to the board room of major fishing companies. His broad knowledge of industry operations and specific experience with longline methods, along with his academic and communication skills will provide unique perspective on longline fisheries and considerations for using longline CPUE data as abundance indices. He notes that CPUE is not just a statistical measure but is the result of intricate interactions between fishing technology and the environment, crew performance, management regulations, bait chemistry, spatial dynamics, and data systems. His long-standing public engagement with fisheries science and management communication in general and with longline fisheries, in particular, will provide valuable insights for this workshop.

4. Darcy Webber

Darcy has extensive experience working on CPUE models for various species with applications in their associated stock assessments. These species have included: New Zealand red and packhorse rock lobster, bluenose, hake, ling, and southern bluefin tuna for CCSBT. Software used for these models initially included traditional glm's (in R) but quickly changed to mixed effects models including Bayesian GLMMs (in brms and INLA) and frequentist versions (in glmmTMB), and more recently spatial temporal models using tinyVAST and sdmTMB. He is a proponent of the spatial and temporal models to be the way forward in many situations, not just for more precisely modelling CPUE, but also for better understanding the spatial patterns in CPUE and/or depletion through time.

5. Arnaud Gruss

Arnaud Grüss is a senior fisheries scientist at Earth Sciences New Zealand, based in Wellington, with over 15 years of experience in quantitative fisheries science. His core technical strengths lie in spatio-temporal modelling, stock assessment, species distribution modelling, and catch-per-unit effort (CPUE) standardisation, with high level expertise in applying modelling tools including VAST, tinyVAST, CASAL, Casal2, and the Spatial Population Model (SPM). Arnaud's work in CPUE standardisation is highly-regarded. He was a co-author of the review paper "Catch per unit effort modelling for stock assessment: a summary of good practices" (Fisheries Research) and has published extensively on spatio-temporal approaches to CPUE standardisation, spatial sampling effects, and the use of multiple data types to evaluate population trends.

Beyond the workshop

The workshop discussions, outcomes and recommendations will be summarised in a workshop summary report that will be presented to SC23. We have also received notification of acceptance for a special edition in the journal *Fisheries Research* that will feature peer reviewed key papers, the review paper and a brief workshop synopsis paper.

Summary

In summary the workshop planning and organisation is mostly complete, and we expect at least 40 people to join in-person with an additional 30+ online. The invited experts are confirmed, and all donor funds have been received. The review and consultations with analysts across global tuna RFMOs is complete, with revision to the review paper after the workshop.

Acknowledgements

This workshop and related activities have been supported by funding from WCPFC Project 122a: Global Joint Tuna RFMO Longline CPUE Technical Workshop, and the following organisations:

- International Seafood Sustainability Foundation
- Blue Marine Foundation
- The Ocean Foundation/Harvest Strategies.Org
- Sustainable Fisheries and Communities Trust
- International Pole and Line Foundation
- EU (project to IATTC)

The on-ground assistance of Hirotaka Ijima at FRA, Yokohama, has been greatly appreciated.

Appendices

Appendix 1 – Draft workshop agenda and session information

Global Joint Tuna RFMO Longline CPUE Technical Workshop

DRAFT AGENDA

12–16 October 2026 | Yokohama, Japan

Note: *Session times are indicative and include time for questions. Additional submitted presentations may be accommodated. The agenda is subject to change.*

Note that this is a draft agenda. Topics, timing, sequence, and presenters have not been confirmed so are all subject change.

Each day the meeting room is available 9-5 pm, plan to wrap up sessions by 4.30 pm

Session 1: Opening and scene setting (1h 50min)

Time	Item	Presenter	Topic detail
30 min	Introduction	Paul Hamer/Mark Maunder (chair)	Background, objectives, outputs and outcomes of workshop, housekeeping and agenda
1h	Summary	Simon Hoyle	Scene setting/background: LL CPUE principles, RFMO review highlighting recent developments, problematic areas, common issues, challenges
20 mins	Discussion		

Session 2: Data (3h 30min)

Time	Item	Presenter	Topic detail
30 min	Presentation	Simon Hoyle	Available data – focused on operational logbook data
30 min	Presentation	Jim Ianelli -TBC	Data exploration
30 min	Presentation	Hirotaka Ijima/Matt Lauretta	Covariates
Other data			
30 min	Presentation	Philip Neubauer	Observer data use in CPUE
15 min	Presentation	Shelton Harley & Hilario Murua	EM and ER – tRFMO progress and opportunities for CPUE analysis
Contributed presentations			
30 min	Discussion		

Session 3: Operational information and industry insights, effort creep, hyperstability/hyperdepletion (2h 50min)

Time	Item	Presenter	Topic detail
30 min	Presentation	Francisco Blaha	Tropical tuna (and albacore) longline fishing – operational advancements, current trends and emerging transitions/technologies
30 min	Presentation	Hidetada Kiyofuji	Japanese LL through time & future
20 min	Presentation	Yi-Jay Chang	Taiwanese LL through time & future
15 min	Presentation	Qian Yang	Chinese LL through time & future
15 min	Presentation	TBC	Korean LL through time & future
20 min	Presentation	Simon Hoyle	Effort creep and what to do about it
10 min	Commentary	Jim Thorson	Synthesis and broader perspective on the modelling implications
Contributed presentations: TBC			
30 min	Discussion		

Session 4: Modelling frameworks: GLM, GAM, STM, and diagnostics (1h 30min)

Time	Item	Presenter	Topic detail
30 min	Presentation	Arnaud Gruss	Comparing the methods: GLM, GAM, and spatiotemporal models
30 min	Presentation	Darcy Webber / Tomoyuki Itoh / Nicholas DB	Diagnostics most relevant to reliable CPUE indices: covering GLMs, GAMs, STMs
20 min	Presentation	Jim Thorson	Future directions for modeling
Contributed presentations: TBC			
30 min	Discussion		

Session 5: Stock structure, defining the index fisheries, regional scaling (2h 40min)

Time	Item	Presenter	Topic detail
30 min	Presentation	Nicholas DB	Index fisheries theory
30 min	Presentation	Carolina MV	Defining fisheries for abundance indices
30 mins	Presentation	Rodrigo Sant'Ana	Discrete spatial structure versus continuous space
20 min	Presentation	Thom Teears	Regional scaling from CPUE in spatial assessment models
Contributed presentations: TBC			
30 min	Discussion		

Session 6: Targeting, preferential sampling, & spatial contraction of fleets (2h 30min)

Time	Item	Presenter	Topic detail
30 min	Presentation	Henning Winker (TBC)	Targeting (incl. simulation testing)
30 min	Presentation	Haikun Xu	Spatial effort contraction
30 min	Presentation	Rujia Bi	Preferential sampling
Contributed presentation(s): TBC			
10 min	Commentary	Jim Thorson	
30 min	Discussion		

Session 7: Size comps and combined CPUE-size data analysis (1h 40min)

Time	Item	Presenter	Topic detail
30 min	Presentation	Simon Hoyle	Size data – general considerations for index fisheries
30 min	Presentation	Haikun Xu et al.	Combined CPUE size data analysis
10 min	Commentary	Jim Thorson	
30 min	Discussion		

Session 8: Collaborative/multi-fleet CPUE (2h 30min)

Time	Item	Presenter	Topic detail
30 min	Presentation	Darcy Webber	Technical issues with combining multiple gears / fleets in a single STM model, case example(s)
20 min	Presentation	Rujia Bi	Multi-gear methods
30 min	Presentation	Thom Teears	WCPO sdmTMB examples
30 min	Presentation	Toshi Kitakado	IOTC - GLMs
Contributed presentations: TBC			
10 min	Commentary	Arnaud Gruss	
30 min	Discussion		

Session 9: CPUE: Code, Data, and Institutions (2h)

Time	Item	Presenter	Topic detail
20 mins	Presentation	Jim Ianelli/Rob Ahrens	Scene set: Why repeatable coding practices and transparency are critical
30 min	Presentation	Philip Neubauer and others	Repeatable and transparent code and workflows, documenting changes and comparisons when CPUE indices are updated/changed between assessments etc.

30 min	Presentation	Paul Hamer	Data sharing and transparency challenges: overview of tRFMO longline operational data sharing arrangements, challenges and implications for analysts
10 min	Commentary	TBD	
30 min	Discussion		Options to work more effectively under data sharing restrictions, actionable recommendations

Session 10: Use in assessments (1h 30 min)

Time	Item	Presenter	Topic detail
1h	Presentation	Andre Punt (remote)	Splitting, weighting, conflicting indices, alternative indices, density vs catchability, sharing selectivity, regional scaling
30 min	Discussion		

Session 11: Use in MSE and MPs (1h 30min)

Time	Item	Presenter	Topic detail
20 min	Presentation	Toshi Kitakado	CPUE indices are used within the IOTC management procedures
20 min	Presentation	Nan Yao	WCPO examples: albacore, skipjack
20 mins	Presentation	Haikun Xu	Issue and influence of CPUE, ASPM, adult index v juv catches
30 min	Discussion		

Session 12: Consolidation (3h)

Time	Item	Presenter	Topic detail
3h	Discussion	Mark Maunder	

Total scheduled session time: approximately 27 hours

We expect additional submitted presentations as the meeting topic contents are refined.

Total meeting time will be around 30 hours (Daily: 9 am-4.30 pm, 6 hours in session/day, 1h 30 min for breaks, 30 mins contingency running to 5pm if needed).

Description of workshop sessions

Session 1: Opening and scene setting

Paul Hamer/Mark Maunder (chair): Welcome, housekeeping, and agenda overview. Frame the three overarching workshop objectives: advancing individual technical issues in LL CPUE standardisation; moving towards greater methodological consistency, good practices and principles across tRFMOs; and identifying opportunities for shared tools, research collaborations and infrastructure that could benefit all organisations.

The outputs will be papers describing the recommendations (good practices) from the workshop and the basis for these recommendations. The outcomes (we hope) will be improved CPUE index abundances methods that provide more robust, collaborative and transparent LL CPUE indices for tuna assessments provided to tRFMOs.

Simon Hoyle: Scene-setting on LL CPUE principles, drawing on the synthesis report and Hoyle et al. 2024.

- Review practices across all five tRFMOs, highlighting where methods diverge unnecessarily, where genuine differences in fishery context justify different approaches, and where common problems recur. This framing should help participants understand what convergence is achievable and what needs to be resolved for it to happen.
- Include in the scene-setting a specific call for better documentation and accessible archiving of information on fishing practices, gear technology, and how these change through time. This is a prerequisite for analysts being able to make informed decisions about catchability, and for assessments to be reproducible and reviewable years later. The IATTC series of reports on Japanese longline fishing in the EPO is a model worth highlighting (e.g. Matsumoto and Bayliff 2008) — that kind of systematic, publicly available documentation is rare and valuable.
- Note the importance and value of long time series of catch, effort and size data, which can be used for multiple purposes.
- Value of consolidating data from all fleets to increase spatial-temporal coverage. Example of the MOU between DWFNs and SPC for the WCPFC assessments.
- Call for the meeting to consider the value of shared data, procedures, scripts, and software for index development.

Note that the timing includes both the presentation and questions.

Session 2: Data

Objectives:

- Recommended minimum data standards for CPUE work
- Guidance for assessing historical data quality
- Standard set of exploratory plots as a cross-RFMO recommended template

Simon Hoyle (30 mins): Overview of data available for CPUE analysis across fleets and RFMOs — logbook coverage, observer coverage, electronic reporting, and operational data. Flag gaps, inconsistencies in data definitions across RFMOs, and implications for comparability of analyses. This provides a shared baseline for subsequent sessions.

Address data quality here. How to assess confidence in historical data and make defensible decisions about inclusion or exclusion by flag, vessel, or period. Where possible, include concrete examples from multiple RFMOs and fleets (if necessary, report the situation with anonymity). Propose and justify criteria for including or excluding data. Introduce the idea of prior weights on alternative hypotheses, for situations where there is uncertainty. The goal is to help analysts across all RFMOs recognise similar problems and apply consistent standards.

Jim Ianelli, Matt Lauretta or Rob Ahrens (30 mins): Importance of and methods for data exploration prior to CPUE modelling — comprehensive visualisation of catch, effort, and operational data to build understanding of how the fishery operates and changes over time. Emphasis on identifying signals of catchability change, gear modification, or reporting anomalies before modelling begins. Consider what a standard exploratory data analysis protocol might look like across RFMOs.

Hirotaka Ijima/Matt Lauretta: Review covariates used in CPUE analyses across RFMOs — what is available, how availability has changed through time, and how covariates have been treated (e.g., HBF as continuous, spline, or grouped factor). Discuss standardisation of covariate treatment as a potential area of cross-tRFMO harmonisation. Consider potential to reconstruct missing values of covariates in some datasets (HBF/vessel).

Philip Neubauer: Observer data in CPUE analyses — what observers record that logbooks do not, and how to quantify the information lost by relying on logbooks alone. Include influence plots or similar diagnostics. Catch reconstructions as well as indices, and the potential for observer data to detect misreporting in logbooks (e.g., porbeagle shark case). Consider what a minimum observer data standard for CPUE purposes should look like. Modelling challenges with observer data.

?: Electronic monitoring (EM) and electronic reporting (ER) — current uptake and tRFMO progress, what data these systems can/could provide, and the challenges and opportunities they present for CPUE analysis. How should analysts prepare now for a future in which EM/ER data are more widely available? Are there cross-tRFMO opportunities for developing common standards or shared infrastructure?

Session 3: Effort creep, operational information, and industry insights

Objectives:

- A recommendation that tRFMOs systematically document and archive fishing practice changes, particularly for the dominant fleets/flags
- A framework for representing effort creep uncertainty in assessments.

Francisco Blaha: Industry perspectives on how longline operations have changed over time — technology adoption, targeting behaviour, crew knowledge, vessel economics — and the implications for catchability trends across fleets and regions. What's happening now and what changes might be on the horizon? Provides essential context for interpreting the fleet-specific presentations that follow.

Hidetada Kiyofuji: Japanese longline fleet changes through time and anticipated future developments. Cover changes in gear configuration (reported and unreported), spatial targeting, and technology (scanners, plotters, satellite communications for information sharing). Japanese data carry the longest historical time series and are therefore influential for most tuna stock assessments — understanding how catchability by this fleet has changed is critical.

TBC: Taiwanese longline fleet — same framework as for Japan. Note that Taiwanese data are currently only used from 2005 in some assessments; understanding fleet dynamics may inform whether earlier data could be usefully incorporated.

TBC: Chinese longline fleet changes over time and catchability implications, following the same structure as the Japanese and Taiwanese presentations to facilitate cross-fleet comparison.

TBC: Korean longline fleet changes over time and catchability implications, following the same structure as the Japanese and Taiwanese presentations to facilitate cross-fleet comparison.

Simon Hoyle: Proposed analytical approaches to effort creep — how to detect and account for gradual increases in effective effort that are not captured in nominal effort metrics or covariates available for CPUE models. Present the framework from the effort creep paper and discuss how it could be applied across different tRFMOs and fleet types.

Jim Thorson: Commentary — synthesis and broader perspective on the modelling implications of the historic development of the tuna longline fisheries.

Session 4: Modelling frameworks/methods and diagnostics

Objectives:

- A recommended modelling hierarchy (when GLM, GAM, STM is appropriate).
- A recommended minimum set of diagnostics for CPUE indices specifically.
- Recommendations on how to deal with model selection and uncertainty.

Arnaud Gruss: Comparison of GLM, GAM, and spatiotemporal (STM) models (sdmTMB/tinyVAST) approaches for CPUE standardisation — which tool performs best in which situation, what data and computational requirements each has, and the practical trade-offs. Discuss why GAMs generally outperform GLMs and should be the minimum standard; STMs can provide further improvements but at greater cost – when is it worthwhile? Discuss the case for moving away from GLMs as a default across tRFMOs. Consider simulation testing results comparing spatiotemporal, spatial, and time-area interaction approaches. What do simulations tell us about when each approach produces reliable indices, and where they fail? This directly informs the guidance that the workshop should produce on model choice.

Darcy Webber + Nicholas DB, Tomoyuki Itoh?: Diagnostics for GLMs, GAMs, and STMs in the context of CPUE standardisation specifically — not generic model diagnostics, but those most relevant to producing reliable abundance indices.

Model selection and uncertainty when the goal is prediction rather than inference, and data are not iid. How to deal with structural uncertainty. When to include factors (e.g., vessel effects) a priori rather than selected statistically.

Jim Thorson: Future developments: Development areas in modeling frameworks, including issues such as artificial intelligence, methods for speeding up STMs, and approaches for modeling seasonality.

Session 5: Stock structure, index fishery, regional scaling

Objectives:

- Recommended principles for defining index fisheries consistent with stock assessment assumptions
- Guidance on when global (basin scale) vs regional (sub-basin areas) approaches are appropriate.

Nicholas DB: Index fishery theory — what is an index fishery, how indices are used within stock assessments (e.g., MFCL), and what properties they need to have. Cover the trade-off between indexing the whole stock versus a subset, and why broad spatial coverage of effort and size data is important. This session provides a conceptual framework that participants can use to evaluate data requirements and the methods presented later.

Carolina MV: Fishery definitions and stock/population structure — when setting up a stock assessment, assumptions are made about population boundaries and structure that directly constrain what the CPUE indices should represent. Indices must be consistent with those assumptions. Provide examples of cases where mismatches have caused problems, and a practical framework for ensuring consistency.

Rodrigo Sant'Ana: Global versus sub-regional modelling approaches — the trade-offs in accuracy, data requirements, and tractability. Where sub-regional approaches work better and why, and how to handle data-sparse regions.

Thom Teears: Regional scaling in spatial models — how regional scaling factors are derived and applied, and what the constraints are. Present the new two-stage approach being developed for WCPO: a global model is used to derive scaling factors, and separate sub-regional models then estimate individual abundance indices. Discuss whether this approach or variants of it could be applicable in other tRFMOs.

Session 6: Targeting, preferential sampling, and spatial fleet contraction

Objectives:

- Practical guidance on which targeting identification methods to use and when
- Recommended criteria for when target cluster analysis is appropriate and inappropriate.
- Guidance on how to detect fleet contraction and when it constitutes a problem requiring correction.
- Recommended approaches to preferential sampling adjustment.

Henning Winker (TBC): Simulation testing of methods for identifying targeting — what works in which situations, what assumptions each method requires, and where methods break down. When is it important to consider targeting effects. The goal is to give analysts across all RFMOs practical guidance on which tools to apply and when. E.g., clustering vs HBF vs other approaches – considering tropical tunas, albacore, bluefin, sharks and billfish.

Haikun Xu: Spatial fleet contraction.

Rujia Bi: Preferential sampling — formal statistical framework for dealing with non-random spatial distribution of effort, and its relationship to fleet contraction

Jim Thorson: Commentary synthesising the session, highlighting implications for cross-tRFMO practice.

Session 7: Size compositions and combined CPUE-size data analysis

Objectives:

- A cross-tRFMO stocktake of size data availability
- Recommended minimum standards for combined CPUE-size analysis

Simon Hoyle: Size data availability and quality for index fishery development across all fleets — WCPO, EPO, Atlantic, and Indian Ocean. Identify where size data are sufficient to support combined CPUE-size analysis, where gaps exist, and what minimum standards should apply. This is a cross-tRFMO stocktake that sets the scene for the second presentation.

Haikun Xu et al.: Combined CPUE-size analysis as developed for IATTC — the method, how it works, and what it adds over CPUE-only approaches. Computational challenges etc. Contrast with approaches used by other tRFMOs.

Jim Thorson: Commentary.

Session 8: Collaborative multi-fleet CPUE

Objectives:

- Conditions under which collaborative multi-fleet analysis is justified and how to assess them
- Recommended criteria for fleet inclusion.
- Identify risks and constraints on further development.

Darcy Webber: Technical issues with combining multiple gears / fleets in a single STM model. Case study with bluenose.

Rujia Bi: Multi-gear methods — combining longline CPUE with indices from other gear types (i.e., purse seine dolphin sets for yellowfin). For multi-gear approaches, a key requirement is that gears index overlapping portions of the population, which requires careful assessment of size distribution overlap.

Toshihide Kitakado: Review of the IOTC GLM-based collaborative approach and lessons for other RFMOs (institutional context, data access, combining datasets).

Thom Teears: The WCPO sdmTMB collaborative approach — how it works in practice, including data access arrangements (MOU with DWFN), analytical workflow, and the advantages of having all fleet data available to one team. Discuss whether similar arrangements could work in other tRFMOs, and what institutional and data sharing prerequisites are needed.

Arnaud Gruss: Commentary — synthesis across the two collaborative approaches, and broader observations on the feasibility of greater harmonisation.

Session 9: CPUE: Code, Data, and Institutions

Objectives:

- Specific, actionable recommendations on data sharing, code availability, and minimum documentation.

Jim Ianelli and/or Rob Ahrens – scene set for this session?: Why coding practices and transparency are critical — not just for reproducibility, but for scientific credibility and fleet/industry confidence. Initially cover the full spectrum: data sharing with appropriate confidentiality protections; open, version-controlled, and documented code; and sufficient diagnostics for reviewers to verify results. Perhaps use case studies of past instances where indices were found to be unreliable.

Address the operational problem with joint analyses during meetings that insufficient time for analysis limits analysis to simpler faster methods such as GLMs, and leads to errors that cannot be corrected even when reviewers identify them. Discuss practical approaches that could be adopted consistently across tRFMOs. Identify opportunities for shared tools or platforms.

Kyuhan / **Phil Neubauer** / Darcy / Nicholas DB: Coding practices: Recommended modern coding practices for reproducible and transparent outputs. Open software practices, GitHub, containers, scripts, etc. Minimum standards for diagnostics: comparison of current and prior indices with documented explanations for changes, availability of scripts, and summary plots.

Paul Hamer/Tiffany Vidal /Shelton – coordinate with DWFNs on practical data sharing options, given current restrictions — technical solutions (e.g., secure enclaves, federated analysis, aggregated data) and their trade-offs.

This session should aim to produce specific, actionable recommendations rather than a wish list.

Note that the IOTC SC (SC28 para 222) recommends the exploration of arrangements for giving the IOTC Secretariat operational-data access under confidentiality provisions.

TBC: Commentary

Session 10: Use in assessments

Objectives:

- Guidance on index splitting, weighting conflicting indices, and how assessment needs should feed back into index design

Andre Punt (remote, 60 mins): How CPUE indices are used within stock assessments — for example: splitting indices across regions or fleets (why to avoid it and when unavoidable), how to weight conflicting / alternative indices, sharing selectivity across fleets in multi-region models, regional scaling, confidence intervals, and key research questions. This is an important integrating session: the design of CPUE analyses should be guided by how indices will be used in the assessment, so each group needs to understand the other's constraints and requirements.

Session 11: Use in MSE and MPs

Objectives:

- Guidance on what properties a CPUE index needs to function reliably in an MP, and how this should influence standardisation choices.

Toshihide Kitakado: How CPUE indices are used within the IOTC management procedures and MSE frameworks, and the properties required for indices to function reliably in that context.

Nan Yao (TBC): Similar coverage for WCPFC context — how MSE and MP design constrains what CPUE indices need to deliver. The importance of repeatability and data availability etc. Lessons learned.

Haikun Xu: Issues affecting CPUE utility within management procedures — ASPM-type models, adult abundance indices versus juvenile catch information, and how index properties interact with assessment and MP performance. Highlight areas where improvements in CPUE methodology would have the greatest practical payoff for management.

Session 12: consolidation – led by Mark (3 hours)

Appendix 2 Longline CPUE tRFMO review paper

Longline CPUE meeting, 2026

DRAFT - Working document – not for citation!!

Introduction

Abundance indices derived from fishery-dependent catch and effort data are central to stock assessments of tuna and tuna-like species across the world's oceans. For most tuna stocks—including yellowfin, bigeye, albacore, and bluefin—pelagic longline catch-per-unit-effort (CPUE) provides the primary information on population trends, making these indices among the most influential inputs to the assessments that underpin management advice. However, extracting reliable abundance signals from longline CPUE data presents substantial challenges. Industrial longline fleets comprise thousands of vessels from different flag states, fishing over vast ocean areas with varying operational characteristics, gear configurations, and target species. Additionally, biological characteristics of the stock (e.g., growth) as well as catch-rate relationships with operational covariates and underlying environmental and oceanographic drivers may vary spatially across the target stock's distribution. The many operational and environmental processes influencing catch rates can confound the relationship between CPUE and abundance, and analysts must apply sophisticated standardisation methods to adjust for these effects. Independent stock assessment reviews across all tuna Regional Fisheries Management Organisations (RFMOs) have consistently identified CPUE standardisation as a priority area requiring attention.

Despite facing similar challenges, the five tuna RFMOs – the Commission for the Conservation of Southern Bluefin Tuna (CCSBT), the Inter-American Tropical Tuna Commission (IATTC), the International Commission for the Conservation of Atlantic Tunas (ICCAT), the Indian Ocean Tuna Commission (IOTC), and the Western and Central Pacific Fisheries Commission (WCPFC, with its scientific work conducted through International Scientific Committee (ISC) and The Pacific Community (SPC)) have developed CPUE standardisation approaches somewhat independently.

This paper provides a comprehensive synthesis comparing current practices across all tuna RFMOs, structured around key technical topics from fishery definitions through to the use of indices in assessments. For each topic, we summarise good practice guidelines drawing on recent methodological reviews (Hoyle et al., 2024) and the collective experience of analysts working across these organisations. We then document current practices within each RFMO and identify opportunities for improvement. The objective is to support harmonisation of methods where appropriate, facilitate knowledge sharing among analysts, and improve the reliability of abundance indices used in tuna stock assessments globally.

Background

Tuna assessments are increasingly using the index fishery approach (Maunder et al., 2020; Xu et al., 2024b), which employs both 'index fisheries' and 'removal fisheries' (the latter also referred to as ‘extraction fisheries’). Index fisheries generally have a wide spatial domain and assume non-time-varying selectivity. They should if possible be associated with jointly standardised CPUE and composition data, to reduce the risk that selectivity changes through time. Removal fisheries are not associated with a CPUE index and may have a smaller spatial domain and/or time-varying selectivity. This document provides advice about developing CPUE indices for these assessments.

Many stock assessments use more traditional approaches in which there is no distinction between index and removal fisheries, and CPUE indices are associated with fisheries that remove catch. We also provide advice for CPUE indices for these assessments.

The term ‘survey’ is used in Stock Synthesis (SS) for any index of abundance, but to avoid confusion in this document we will restrict that term to fishery-independent surveys.

Preliminaries

Fishery definitions

A CPUE index in any stock assessment is associated with the part of a stock sampled by a specific fishery (Maunder and Punt, 2004). In tuna RFMOs, the term fishery is generally used to describe a category of fishing effort defined in the assessment by combinations of location, gear type, flag, targeting, and time period. The terms fleet and métier are also sometimes used.

The assessment model defines the relationship between an index and the overall stock via the catchability coefficient and selectivity function, and for multi-region models, the spatial structure. Defining fisheries is therefore a fundamental aspect of CPUE standardisation. Most structured stock assessments make the separability assumption—that fishing mortality is the product of catchability, fishing effort, and selectivity—and many assume that selectivity is constant through time, even though it tends to vary (Sampson and Scott, 2012). Wrongly assuming constant selectivity can bias assessment results by affecting the proportion of the population vulnerable to the fishery, affecting removals from the population, and creating mismatches between observed and expected size composition.

To reduce these biases, fisheries should be defined in ways that minimise selectivity change through time. An important source of selectivity variation is changing spatial and seasonal distribution of fishing effort and its interaction with spatiotemporal variation in population structure and availability. Analysts should explore spatial and seasonal patterns in fish availability by size, age, and maturity to identify fishery definitions that will be robust to changing effort distribution. Tree-based analytical methods and generalised additive models can be employed to identify optimal spatial arrangements and patterns in length, maturity, and sex ratio (Hoyle et al., 2017; Minami and Lennert-Cody, 2025; Xu and Lennert-Cody, 2023). Gear selectivity may also change through time (Campbell et al., 2019; Kerstetter and Graves, 2006), and the effect can be minimised by separating gear types with different selectivity into different fisheries. The best approach to define fisheries associated with CPUE will depend on the specifics of each stock assessment, the available data, and the analyst's skills and time; but indices that represent a higher proportion of the stock being targeted are more likely to be more representative of stock abundance.

Questions/topics for review and workshop discussion:

- If fish sizes available to the fishery vary in space, how should we trade-off between a) defining separate fisheries and modelling (and adjusting for) the size variation in the context of providing different indices?
- Identify strengths and weaknesses of methods for identifying spatial size variation: regression trees / GAM / random forest / etc and when should these be used to define spatial domains for indices
- Methods to determine whether spatial / temporal size variation (for fisheries or indices of both?) is large enough to affect stock assessments.
- Best methods for defining fishery boundaries.
- Can fishery areas be small enough to allow full tag mixing?
- Incorporating different flags/fleets within an index fishery, when the coverage of each flag/fleet varies in space and time, size data also varies depending on the flag – possibly introducing variable selectivity.

CCSBT

Fishery definitions stable over a long period. Based largely on individual flags but with a spatial component.

IATTC

Regression trees are used to identify spatial regions with different homogenous catch size composition (Lennert-Cody et al., 2013; Lennert-Cody et al., 2010; Xu and Lennert-Cody, 2023) Models used in IATTC EPO assessments are implemented in Stock Synthesis and generally use an areas-as-fleets approach (Waterhouse et al., 2014), in which “fleets” or “fisheries” may be defined by gear type, target, and their geographical area of operation. Spatial differences in length composition are often considered without constructing an explicitly spatial model. The indices of abundance, however, are not associated to such fisheries. Instead, the indices are derived from the standardisation of CPUE and length composition data for a wide area (spatial domain of the index).

The purse-seine and longline fisheries are defined in space using regression tree methods (BET, S SWO) (Lennert-Cody et al., 2010) or cluster analysis (YFT, Minami and Lennert-Cody, 2025), using the length composition data as response variable. The regression tree method uses recursive partitioning to search for hierarchical binary decision rules based on the explanatory variables (latitude and longitude, quarter, cyclic quarter) that divide the data into more homogeneous subgroups. The regression tree approach was not flexible enough to allow for irregular areas that were necessary in the YFT assessment, resulting length frequency distributions that were not unimodal and could not be adequately modelled by smooth selectivity functions. The methods were implemented in the R library *FishFreqTree* (Xu and Lennert-Cody, 2023) and *FishFreqClustering* [2] Xu and Minami 2024.

Yellowfin

Due to spatial structure in the YFT stock in the EPO, the longline fisheries for the YFT assessment were defined using cluster analysis (Figure 1) combined with definitions of regions and areas within regions defined from the purse-seine data, which included areas with low longline effort, that were thought to capture the spatial structure of the stock (Figure 2). The length composition data for longline indicated

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[2] https://github.com/HaikunXu/FishFreqClustering

three areas, the areas closer to the coast and close to the Polynesian Island showed smaller fish than central, more oceanic areas (Figure 1).

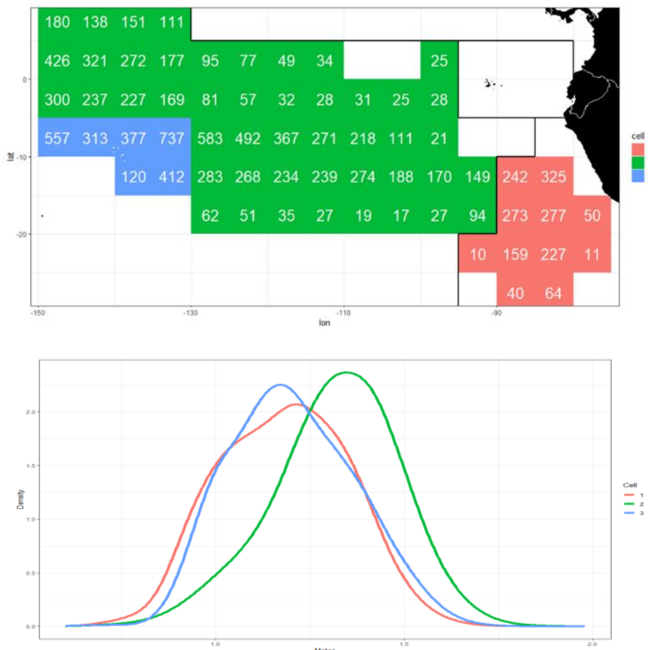


FIGURE 1. Longline. Top panel: discrimination of 5° by 5° cells in three areas using clusters. Bottom panel: average length composition weighted by the catches in each 5° by 5° cells for the three areas (Source SAC-16-INF-F)

FIGURE 2. The longline fisheries for the YFT assessment were defined based on the cluster analysis results combined with definitions of regions and areas within regions defined from the purse-seine data. The EPO models include both NE and SW regions. Independent models for NE and SW were also implemented.

Bigeye

The BET assessments used longline length composition data that Japan submitted through a Memorandum of Understanding with the IATTC. This dataset has fine spatial and temporal resolution (1° latitude, 1°longitude, and month) and includes additional useful information, such as the bin size associated with each length measurement.

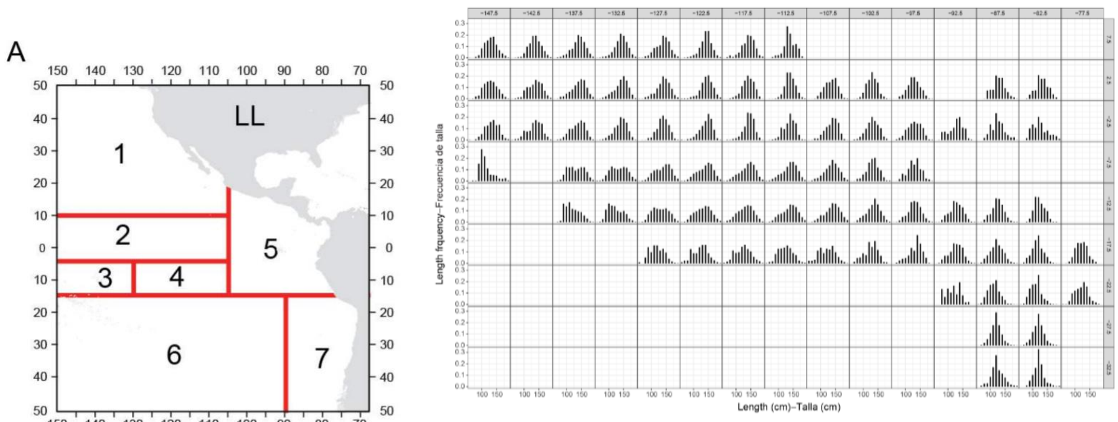


FIGURE 1. Average length frequency of bigeye by grid cell in the Japanese longline fishery.

Figure X. BET fisheries in the latest BET assessment (SAC-15-02 Figure 4A and Figure 1)

Skipjack

For the assessment of SKJ, an initial attempt (SAC-13-07) was made to use the longline data as indices of abundance but more importantly the size composition data as an indication of the distribution of the largest sizes. The LF data was very influential in the model and basically anchored the model and determined the scale. The data was not standardised and came from what was submitted by JPN. Subsequent analysis indicated the improvements in the assessment were needed (SAC-14-08) and that the use of the longline data as an index of abundance was not adequate as the reporting of SKJ catches in the logbooks was inconsistent (SAC-15-INF-U). The latest SKJ assessment (SAC-15-04) does not use longline data and relies on an index derived from tagging data to estimate the absolute scale of the model (SAC-15-INF-G).

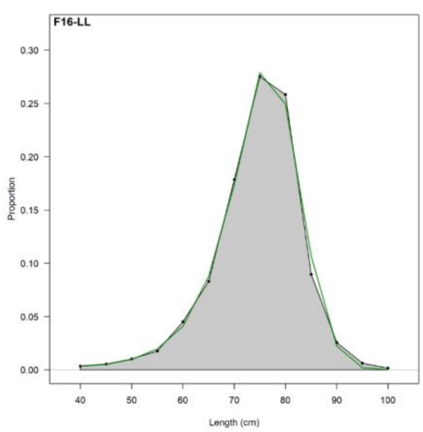


FIGURE 4b. Weighted average observed (shaded area) and predicted by the reference model (line) length-composition data for the longline fishery.
FIGURA 4b. Promedio ponderado de los datos de composición por talla observados (área sombreada) y predichos por el modelo de referencia (línea) para la pesquería palangrera.

Figure LF for the SKJ LL fishery (SAC-15-04). Only one longline fishery was defined for the whole EPO.

Dorado and south Swordfish stock

Other stocks assessed by the IATTC staff also used longline data. For the S SWO stock, the LF of several LL fleets were used to define the fisheries in space (SAC-14-15), however the indices were defined independently (see Table 3 in SAC-14-15)

It is important also to distinguish the type of longline (e.g. SAC-16-09). For tropical tunas and S SWO they used data from industrial longline. For DOR they used data from artisanal longline (SAC-07-06a).

ICCAT

Various approaches including GAM analyses of size data to visually identify spatial patterns (Hoyle et al., 2019b).

IOTC

YFT/BET/ALB:

Fisheries for YFT, BET, and ALB are defined based not on formal statistical analyses but grouped by information such as fleet (flag of vessel), gear type, purse seine set type (FAD-associated or not FAD-associated (termed 'free school')), and the type of vessel (fresh or frozen tuna) in the case of longline fleets. These are assumed to represent relatively homogeneous fishing units with similar selectivity and catchability characteristics that do not vary greatly over time. Fishery groups are then split into area-based fisheries (IOTC-2024-WPTT26-11rev2; IOTC-2025-WPTT27-15rev4; IOTC-2025-WPTmT09-10).

Some preliminary regression tree-based analyses have been completed using the YFT size data (IOTC-2024-WPTT26(DP)-17rev1) using the *FishFreqTree* R package (Xu and Lennert-Cody 2024), although these definitions have not yet been implemented in the YFT stock assessment.

Index fleets are mirrored to the model fleets and share age-based selectivity patterns with the most similar fishery based on gear, fishing practices (fresh or frozen tuna), and model area.

WCPFC-ISC

NP ALB fisheries were defined based on a conceptual model of the stock which took into account the reproductive biology and migration of the species (Minte-Vera et al., 2024). Fisheries were also defined seasonally to accommodate movement in an areas-as-fleets model.

ISC shark stock assessments, including North Pacific Ocean shortfin mako shark (SC20-SA-WP-14) and North Pacific Ocean blue shark both use longline fisheries as the basis for CPUE indices in the assessment. These are defined on the basis of a conceptual model which identifies which flag is likely to operate in an area that is likely to representatively index the population. A joint index (across multiple flags) is not developed and analysts from individual member countries are responsible for developing separate standardised indices using their fisheries data. The ISC working group for the assessment reviews these indices and decides on their use in the assessment.

Gear changes in WCPO JPN fleet:
https://www.spc.int/DigitalLibrary/Doc/FAME/Meetings/WCPFC/SC19/SC19_SA_IP_13_Satoh_LL_gears.pdf

ISC billfish stock assessments, western and central North Pacific swordfish, western and central North Pacific striped marlin, and Pacific blue marlin, all rely on longline fisheries for their CPUE indices in the assessments. At this time, each member provides an index or indices for their fleet, often subdivided based upon area, fleet operations, or targeting. A joint index across the three primary longline fleets for WCNPO striped marlin is currently under development.

WCPFC-SC

SP ALB (Teears et al., 2024a) defined fisheries using information from regression tree analysis on length data to define the fishery structure (areas-as-fleets). See SC20-SA-IP-03 (Potts et al., 2024; Xu and Lennert-Cody, 2023) and the previous assessment. A two-region spatial structure was implemented that separated the WCPFC-CA and the EPO and two index fisheries characterised the WCPFC-CA region relative abundance while the EPO was characterised with only one. In the WCPFC-CA, indices were developed using longline data from the northern subregions from 0°-25°S and using the NZ troll fishery data to capture the dynamics of juveniles. An alternate 'spawning' index was developed for the area north of 25°S in the WCPFC-CA with data filtered for only the months October through January (the peak spawning months; Farley et al. 2013) but was not used in the diagnostic case assessment model.

A similar analysis was done for BET and YFT in 2023 that included review of biological information, including SEAPODYM, and statistical analysis of size data and CPUE patterns which influenced simplification of the YFT tuna model from 9 to 5 regions. The BET spatial structure was not changed, at least partly due to consideration of other factors such as tag data. See SC19-SA-WP-02 (Hamer et al., 2023). Earlier assessments have considered spatial size patterns, CPUE trends and tag mixing constraints (Hoyle et al., 2013; Langley, 2006a; Langley, 2006b; McKechnie et al., 2014).

For most pelagic fisheries assessments, fisheries are defined according to gear type, fishing method, region, and sometimes by vessel flag or fleet with consideration of the following, including (as above) the use of technical approaches such as regression trees.

- Previous assessment structure
- Available tagging data
- Size composition data
- Genetics research
- Review of biology, fisheries, and management
- Modelling of spatial dynamics (e.g., SEAPODYM)
- Fishery coverage by fleets/gears (gears with smaller catches may be grouped if they operate similarly)

- Fishing strategy spatial dynamics; distant water fishing nations (DWFNs) and pacific island countries and territories (PICTs)
- Management jurisdictional boundaries

Data issues

Exploring and preparing data

Before standardising CPUE it is essential to thoroughly explore the catch and effort datasets to develop understanding of the data, generate hypotheses, and inform standardisation strategies. Understanding can be developed by graphically summarising the data, exploratory modelling using random forest models, and by consulting with key stakeholders including fishers and observers.

In the context of large-scale multi-flag tuna fisheries, dialogue with fishers or industry representatives is challenging for scientists (many of whom are not based in the flag countries) but must be facilitated through national fishery agency staff within the individual countries. Engagement with fishers and industry has been limited historically and remains so. Moreover, documentation has been limited, and undocumented industry knowledge held by fisheries agencies and individual staff is lost when staff leave/retire. Abundance indices are based on comparisons across long data time series, so regular, consistent engagement with industry and documentation of industry practices are required. Active measures are essential to bring industry insights and knowledge about all fleets used in CPUE indices to reviews of CPUE data and subsequent analyses.

During data exploration, a particular requirement is to identify changes in the distributions of covariates through space or time, especially those that affect catch rates, because covariates that change are most likely to influence the index. This preliminary exploration will also allow the analyst to anticipate issues with model variables such as data entry errors, missing data, and outliers. Figures 1 to 3 represent complementary ways of examining covariate distributions in time and space.

Exploratory analyses should consider the sources of data and the constraints imposed by data collection and storage methods through time. Logbooks and observer forms often change in ways that affect data quality, such as spatial and temporal resolution, the operational covariates reported, species resolution, whether catches are recorded in number or weight, and whether the effort metric is hooks, sets, or days. Graphical summaries should proceed from low to high resolution, with aggregated summaries of each variable providing overall descriptions, and spatial and temporal trends described through time-series of boxplots and maps of summary metrics. Investing time in building CPUE data exploration tools such as using R Shiny dashboards is recommended and facilitates live exploration of data and discussion with stakeholders and collaborators. Relationships between nominal CPUE (both encounter probability and positive catch rate) and candidate covariates should be explored to inform the type of modelling framework to use for continuous covariates.

Analysts should maximise the number of reliable records available for standardisation to improve model performance and estimates of uncertainty. The treatment of missing data requires careful consideration, with options including dropping records, dropping covariates, inferring values from other information, or imputation. The identification of outliers and their treatment is a key step, with common approaches including omitting values outside ranges that are either fixed (i.e. implausible values) or predetermined based on quantiles. In cases where the omission of outliers results in an appreciable change to the index, those data should be further scrutinised and if there is no reason to believe them to be invalid or implausible, an alternative index should be developed. Stakeholder engagement is an important yet often overlooked component, as fishers, observers, and fish sellers can provide valuable insights to clarify data issues, implausible catch rates and outliers, confirm or invalidate trends, advise on key covariates, and explain motivations for changes in fishing behaviour and their influence on catch rates.

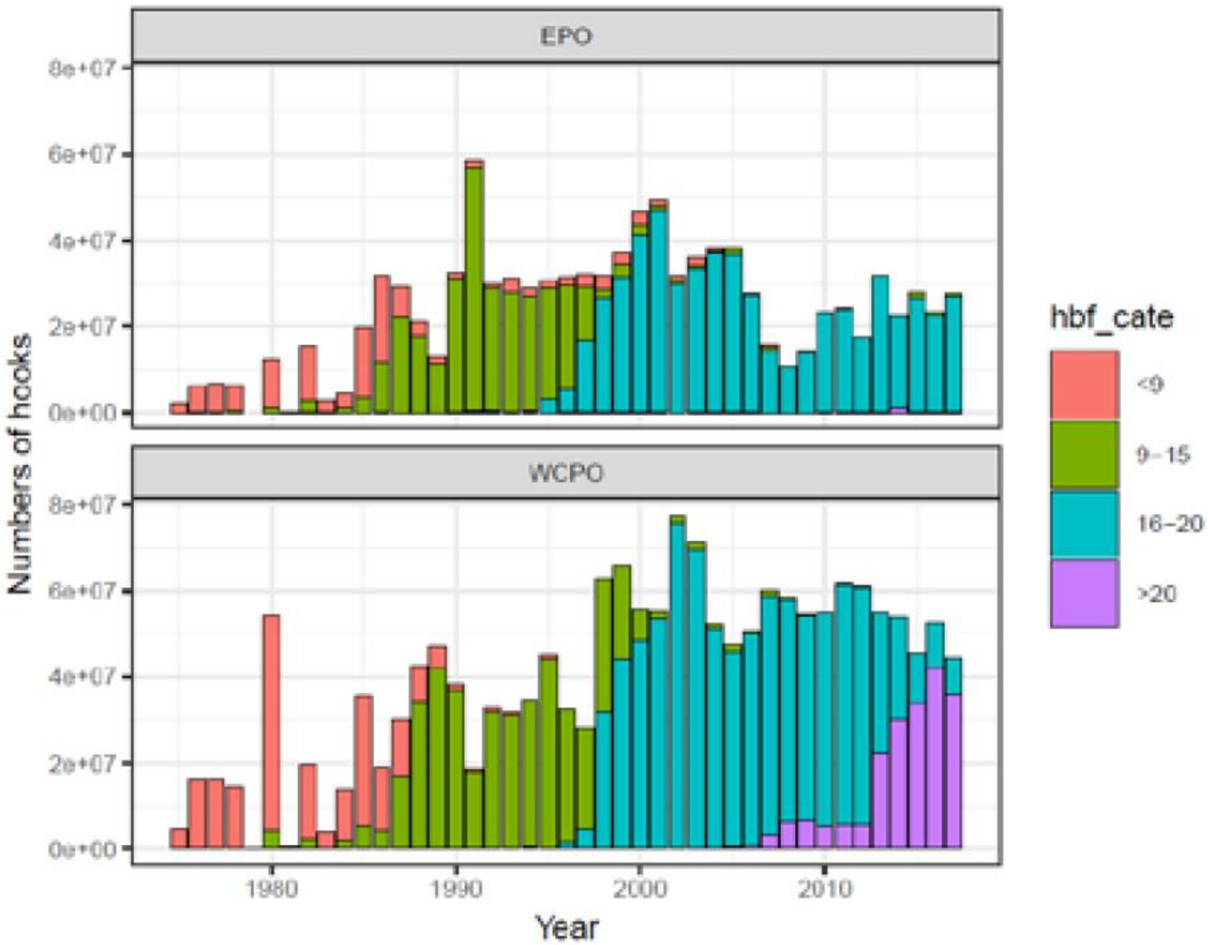


Figure 1: Number of hooks set per year by HBF category by the Korean fleet in the WCPO and EPO (from Minte-Vera et al., 2019b).

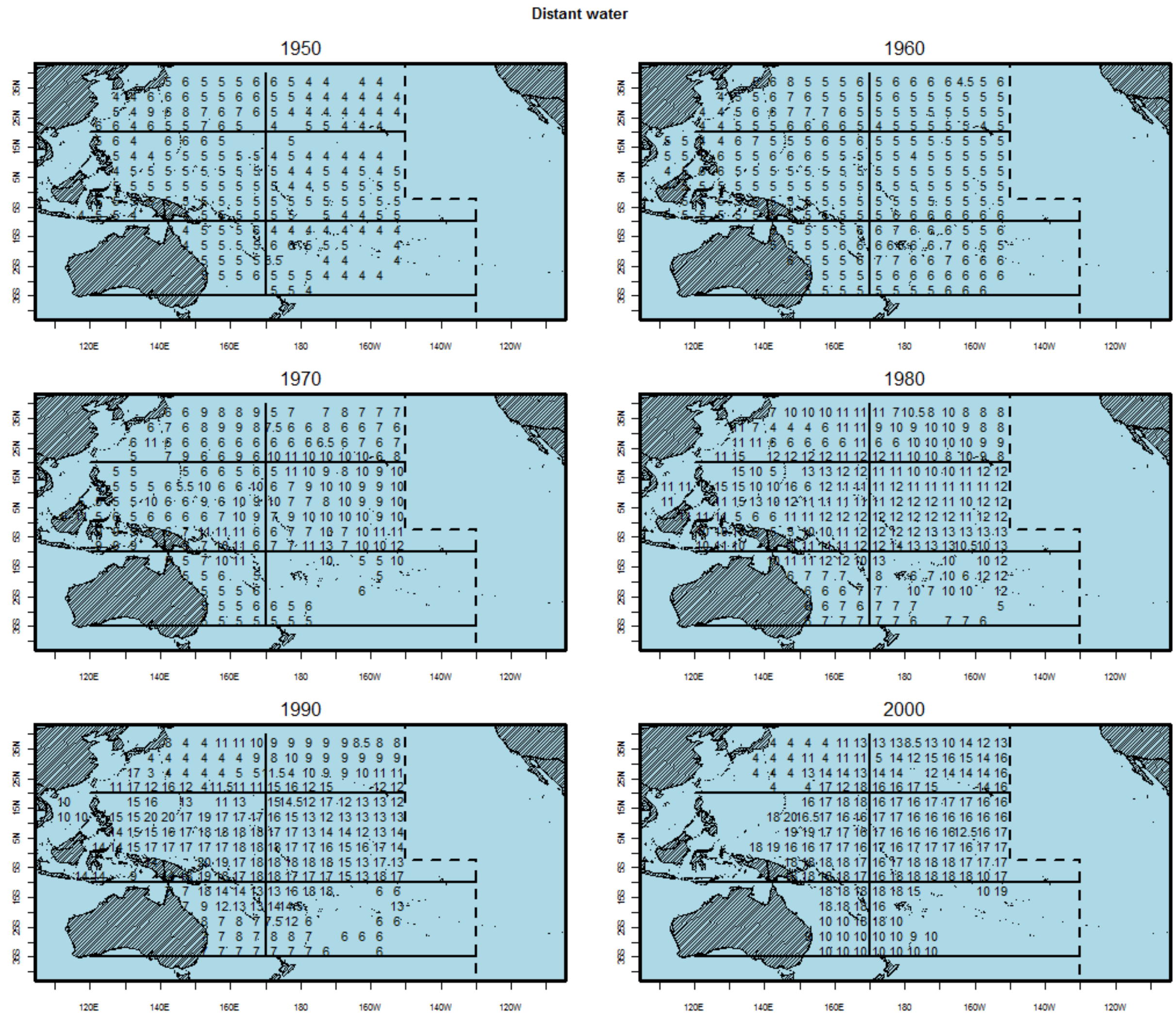


Figure 2: Median HBF for Japanese distant water vessels by 5-degree cell by decade (e.g. 1950-1959). Circle areas are proportional to the number of sets (from Hoyle and Okamoto, 2011).

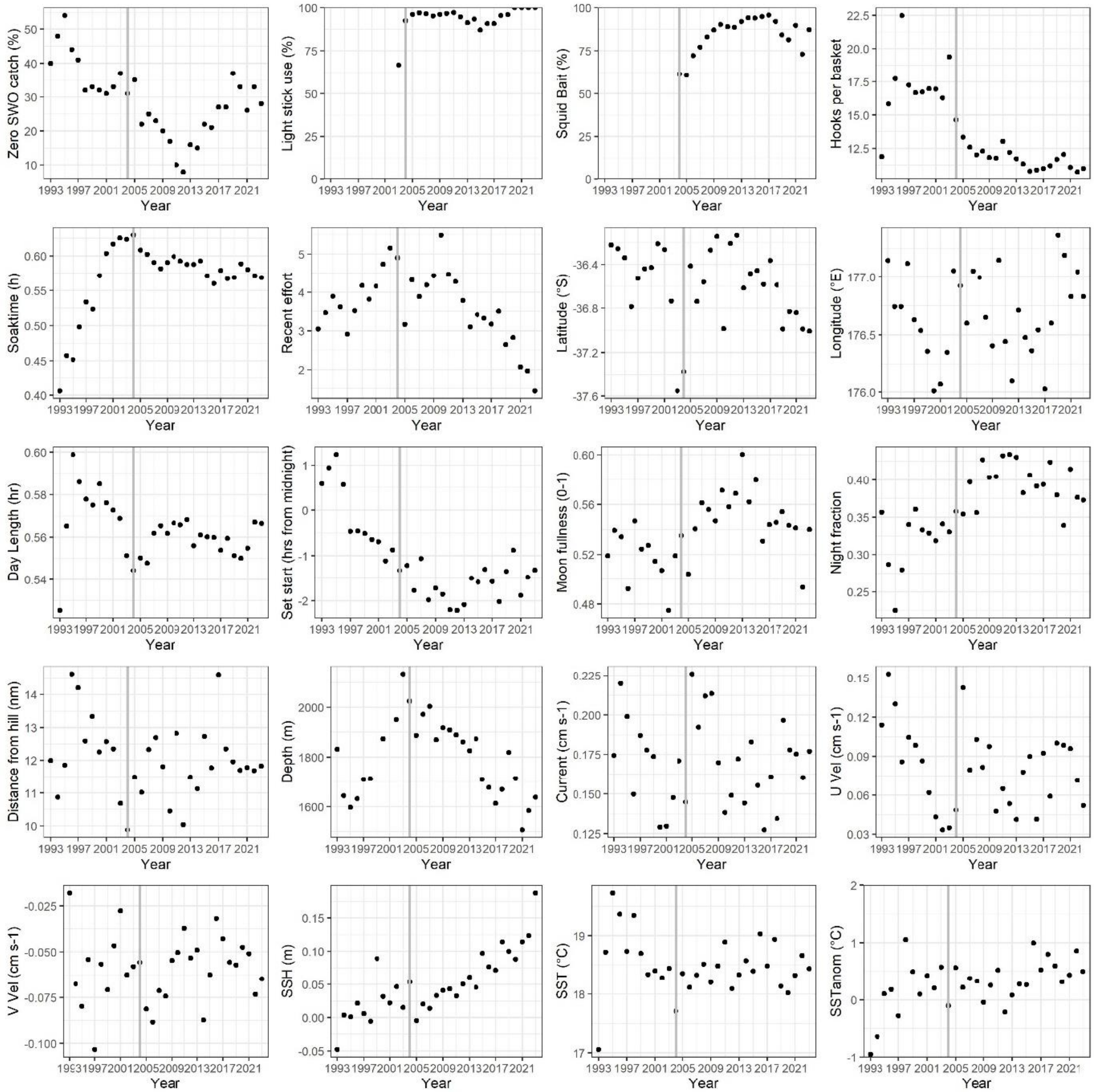


Figure 3: Changes in recorded and derived operational variables and independently estimated environmental variables associated with the longline sets used in the catch-per-unit-effort analyses. Annual means are plotted, with the exception of zero swordfish catch (first panel). Swordfish introduction into the New Zealand Quota Management System (QMS) in 2004 is indicated by the grey vertical line (from Finucci and Moore, 2025).

Questions:

-
- Should a standard set of plots and tables be generated for data associated with each index per assessment, and if so, what would these be?
- Alternative effort metrics.
- What information is required, and how do requirements and availability vary by fleet and over time?

- What level of documentation is desired versus what is available on the history of each fishery? What does lack of documentation imply for the use of a dataset?
- How can industry and analysts engage more on CPUE analysis/data review for large scale, multi-flag tuna fisheries? How will better engagement improve CPUE standardisation?

CCSBT

Each year a document describing patterns and changes in the Japanese fleet (e.g., Itoh, 2022) is provided as part of the index development process.

A document with fleet characterisation information is also provided annually for the Korean fleet that is the basis of a complementary CPUE index (e.g., Lim et al., 2025).

IATTC

IATTC has valuable historical information on the Japanese longline fleet through a series of collaborations with Japanese scientists based at the IATTC office (Matsumoto and Bayliff, 2008; Miyabe and Bayliff, 1987; Nakano and Bayliff, 1992; Okamoto and Bayliff, 2003; Shingu et al., 1974; Suda and Schaefer, 1965; Uosaki and Bayliff, 1999).

More recent work has been based on shorter collaborations during joint workshops.

Lennert-Cody et al. (2014) (SAC-04-05b) analysed Japanese longline operational-level catch and effort data for bigeye tuna in the eastern Pacific Ocean. The report includes good examples of exploratory figures for covariates and response variables.

A series of data collaborations have helped to improve the assessments, particularly the indices and length composition data.

- Korea:
    - Review of catch, effort, and size data SAC-11-INF-K (Lee et al., 2020),
    - Comparing size data from observers and fishers SAC-11-INF-L (Lennert-Cody et al., 2020)
- Japan:
    - Identifying size data error due to reporting SAC-07-3d (Satoh et al., 2016),
    - Size-specific spatiotemporal dynamics of bigeye in the EPO Satoh et al 2021 (Satoh et al., 2021b),
    - Mis-specifying biological processes affects fits to size data (Minte-Vera et al., 2017).

Minte-Vera et al. (2019b) (OTM-30-Rep) surveyed longline information across multiple fleets and compared analysis methods.

Other papers of interest:

- SAC-08-05d need for spatiotemporal models (Maunder et al., 2017)
- SAC-08-07d metadata for longline fisheries (Griffiths and Duffy, 2017)
- SAC-09-INF-F TWN CPUE (not used in the assessments) (Wang et al., 2018)

- SAC-10-INF-F and SAC-10-Pres: Evaluating inconsistencies in the YFT indices in the EPO (Minte-Vera et al., 2019a).

Benchmark assessments in 2020:

- BET SAC-11-06 – bimodal distribution (Xu et al., 2020)
- YFT SAC-11-07 – spatial structure persists (Minte-Vera et al., 2020)

Stock status indicators including longline CPUE indices started to be produced:

- e.g. SAC-12-05, SAC-13-06 (Xu et al., 2022), SAC-14-INF-

IATTC does not have a standard set of regularly updated CPUE-related plots. Various plots appear in meeting papers but are rarely repeated. Similarly, there are no standard plots in the bigeye assessment and CPUE indices papers.

One reason for the lack of standard repeated plots is irregular access to the data – access is only available during collaborative meetings. Furthermore, the type and resolution of the data available to the staff can change from year to year according to the MOUs requirements.

Extensive data exploration occurs in collaboration with Japanese colleagues when using the data from that fleet (e.g. Satoh, Takaaki's paper). The MOU with Korea also produced some exploratory data analysis (Lee et al., 2020; Lennert-Cody et al., 2020). For southern EPO swordfish, collaborative work with JPN has also resulted in data exploration (SAC-13-INF-N) (Ijima et al., 2022) and comparison with indices from other CPCs (SAC-13-INF-M) (Minte-Vera et al., 2022).

Some explanation and figures in the stock assessments:

Latest benchmark assessments:

  - BET in 2024: SAC-15-02 (Xu et al., 2024b)
  - YFT in 2025: SAC-16-03 (Minte-Vera et al., 2025)

ICCAT

In ICCAT, data characterisation in support of CPUE indices is not formalised or routine. For example, in 2025 there was a bigeye stock assessment, for which indices were developed based on joint standardization of data from the Japanese, Chinese, Chinese Taipei, Brazilian, Uruguayan, USA, and Portuguese fleets (Matsumoto et al., 2025). SCRS documents for 2025 do not appear to include any characterization of the data used in this index.

(I was unable to find documents. Some data characterisation summaries are available.)

IOTC

A set of standard plots and data summaries for each fleet included in the tropical tuna indices (Japanese, Korean, Taiwanese) was developed in 2015 and used to prepare 3 fleet characterisation documents (Hoyle et al., 2015a; Hoyle and Okamoto, 2015; Hoyle et al., 2015c). Regular updates are needed.

Data preparation 2015-2019 followed standard scripts available at cpue.rfmo. Approaches since 2021 have varied, most recently documented in the latest update of the joint longline CPUE indices for bigeye tunas: IOTC-2025-WPTT(DP)-09. Data preparation, exploration, and formal analyses of the LL CPUE indices are carried out independently of the IOTC. The IOTC does not have access to data, or scripts relating to these indices.

WCPFC-ISC

In the ISC-SHARKWG data preparation is not standardised across member countries. Each member country is responsible for preparing and standardising their own fisheries data.

WCPFC-SC

HBF when unavailable for early data is imputed by flag. This process is computationally burdensome and requires substantial storage.

Data provision by member countries can be delayed resulting in difficulties in data preparation.

CPUE standardisation needs to be considered in conjunction with corresponding size compositions. CPUE spatial estimates (i.e. VAST or sdmTMB) are applied to re-weight size data for index fisheries across the regions of the indices so the size data for index fisheries provides a better representation of the selectivity of the index fisheries (ref). Member countries have varying levels of data quality and sometimes, time-varying differences in data quality as well as fishing strategies (and targeting), further complicating the appropriateness of various data sources. Criteria for the inclusion of various data sources is difficult to define and often can be complicated by political influences or uncertainty in historical practices by current staff.

Mapping effort spatially and temporally can indicate important changes in fishery dynamics. Some fisheries are not consistent over time and can leave areas with little or no data to inform the model.

The time periods for each fishery are highly dependent on the quality of the data based on the best information we have from the member countries, investigation of the data, or auxiliary information. Some fishery definitions can be truncated based on catch magnitude (e.g., negligible catches).

Variables available for analysis

The variables available for longline CPUE standardisation vary between fleets, as do data quality and reporting resolution. Core variables typically include catch by species, effort, location, date, and vessel identifier, usually reported at the set level. The reliability, resolution, and temporal and spatial coverage of each may vary. For example, effort is typically reported in hooks fished per set, but in a few cases at the set or day level. It is preferable to model effort at the hook level as modelling at the set or day level could mask catchability changes if the number of hooks fished per set or day changes over time.

Longline catch is usually recorded in numbers but sometimes in weight. Additional covariates that can improve standardisation—such as hooks between floats (HBF), bait type, branch line and main line material (e.g., changes from kuralon to mono, single strand, multistrand mono), wire/shark lines used or not, hook type, and targeting information—are recorded by some fleets and some periods but not others, with logbook forms and reporting requirements changing over time. A novel fishing method that is currently unreported in most logbooks is the use of traplines (Garibaldi et al., 2025; Garibaldi et al., 2024), also known as meka-rings (Ochi et al., 2025a; Ochi et al., 2025b). Other factors such as line tension (i.e. setting speed), the use of weights, and other longline shooting methods that can change how the longline is set and behaves in the water are rarely recorded.

Joint analyses of data from multiple fleets are constrained to use variables that are consistently recorded across all contributing datasets. At minimum, joint analyses require catch of the target species, effort in comparable units, spatial coordinates at sufficient resolution to capture distribution patterns, temporal information, and ideally vessel identifiers to account for vessel effects. When key covariates are missing from some fleets, analysts face trade-offs between broader spatial coverage with reduced ability to correct for catchability variation, versus restricting analysis to better-documented fleets with narrower coverage. Efforts to harmonise data collection and reporting standards across fleets would improve the potential for joint analyses and the quality of resulting indices.

Questions:

- Can information on trapline use be reliably added retrospectively to logbooks?
- What is the minimum spatial resolution required for CPUE standardisation – e.g. how fine-scale does the information really need to be?
- How are we converting from numbers to weight – e.g. is there a standardised process for this / how are size distributions included / do we also include sex information (if sex-based length/weight differences?

Specifically for joint analyses, how similar do catchabilities and selectivities need to be before they can be considered together in a joint analysis? Is it sufficient to only include a flag effect in the standardisation model?

CCSBT

IATTC

ICCAT

IOTC

Raw data are not provided to the Secretariat (hence the Secretariat cannot standardise CPUE indices). Individual CPCs would need to comment on the data available.

WCPFC-ISC

In the ISC-SHARKWG and ISC BILLWG, model covariates and resolution of analysis are not standardised across member countries, and each member is responsible for preparing an index from their own data. Members analysing observer data as opposed to logbook data are typically able to include more gear configuration covariates (e.g., bait type, leader material, etc) in the analysis. Logbook analysis is typically limited to hooks between floats.

WCPFC-SC

HBF is imputed by flag for periods when unavailable. This process is computationally burdensome and requires substantial storage.

HBF was typically below 20 when mainline material changed to monofilament. This saw an increase to above 20 to compensate for the difference in weight as monofilament is lighter. But HBF has changed in regimes across time, and the changes differ among flags.

There are also issues with some fleets reporting catch in numbers and not weight.

Flag may be used as a covariate in modeling CPUE, with multiple flags with similar fishing strategies grouped into DWFNs or PICTs. However, vessels initially associated with a DWFN country may be chartered by a PICT for several years, in this case the catch might be allocated to the PICT despite being taken by the DWFN vessel. In most case the vessel flag however does not change. Thus, flag of vessel origin or vessel ID is the best indicator of fishing strategy. Other variables like freezer type and the skipper nationality could be proxies for fishing strategies but are not currently used. Vessel reflagging from DWFNs to PICs may also occur, in this case the origin of the vessel is better than the flag, as the vessel would not typically change its fishing strategy.

Misreporting & biases

Misreporting the catch of the species of interest or the associated effort is a consistent and sometimes major problem in many fisheries, which can affect data used in CPUE standardisation. Indices are more prone to bias when rates of misreporting are higher or change through time. To understand the potential for bias, the analyst needs to become familiar with fishing industry dynamics and data collection processes and to explore the data. It is useful to construct a timeline of changes—regulations, gear specifications, logbook forms, observer training, market conditions—that may affect reporting for the species and fishery being evaluated. If both observer and logbook data are available from the same trips, cross checks can be performed, however, in practice these comparisons are not routinely done by tuna RFMO data teams.

Rates of misreporting can change through time, which is particularly problematic for the development of CPUE indices. For example, shark reporting rates in logbooks from the Japanese longline fishery in the southern Indian Ocean were stable between 1992 and 2007, more than doubled in 2008, and then were relatively stable at a higher level until 2014 (Hoyle et al., 2017).

One cause of misreporting is errors in species identification, which can be common for bycatch species (Clarke et al., 2014; Macbeth et al., 2018), but can also affect target species, especially smaller fish. In some cases, species such as sharks are reported at an aggregated level comprising multiple species.

Other types of misreporting occur when sets with zero catch are omitted, when only the target species is reported, or when catches of some species are deliberately not reported due to regulations that limit their catch ('choke' species).

Species are more likely to be misreported or under-reported when they are bycatch or of little interest to the crew due to low commercial value (Morrell et al., 2024).

Under-reporting of target species can occur due to discarding or high grading based on size or relative commercial value. Under-reporting can also be associated with quotas that limit the reported catch at the vessel or fleet level (ICCAT, 2005; Pitcher et al., 2002; Polacheck, 2012).

Reporting rates may vary between fleets and vessels, and they may change through time. After initial analyses of existing data, routine cross checks between observer and logbook data could help monitor this issue.

Biases can also arise if the available data are not representative of the fleet, depending on the cause. Analysts should examine data coverage and identify reasons for reduced coverage. Concerns arise when only a small proportion of the fleet is covered, or when the vessels with missing logbooks are distinct from the rest of the fleet. For example, Taiwanese coverage was very low during the early 1990s, when "many vessels targeting tropical tuna traded their catch in Japan and were therefore unlikely to provide logbooks, while vessels targeting albacore were more likely to retain their traditional Taiwanese fishing agents, so that logbooks were more likely to be submitted" (Hoyle et al., 2015b).

Changes in misreporting rates may be linked to administrative factors such as changes in logbooks and regulations, the introduction of electronic reporting, or the introduction of electronic monitoring which can influence the accuracy of reporting (Emery et al., 2019).

Observer data generally reports more species and is more accurate than vessel logbooks, but misidentification can occur, due to inadequate training, poor species identification guides, observer error (e.g., writing the wrong species code), and specimens that are genuinely difficult to identify morphologically, particularly if identification is attempted after removal of key morphological features (Sharples et al., 2000; Williams et al., 2018). Low coverage levels and the resulting unrepresentativeness is a particular problem that makes it difficult to use observer data to develop indices. Most tuna RFMOs mandate only 5% coverage for longline vessels, and the levels achieved vary by RFMO and through time. See CapMarine (2022) for details of the 5 years to 2020. Low observer coverage in 2020 due to covid, and prior to 2015.

Misreporting and sampling bias can be difficult to address but there are options in some circumstances. Analysts can compare catch rates between data types to identify unreliable records, such as comparisons between observer data and logbook data, or between logbooks before and after introduction of electronic monitoring (e.g., Brown et al., 2021). When rates of misreporting vary between vessels, analysts can focus on vessels that report more reliably, which may be determined by calibrating against observer data (e.g., Hoyle et al., 2017; Kai, 2019). The data used in CPUE indices may need to be restricted to periods when it is sufficiently reliable. For example, indices for Indian Ocean tropical tunas omit Taiwanese data before 2005, due to concerns about coverage and misreporting during several periods, but retain data from other fleets (Hoyle et al., 2015b).

Summary of mandated observer coverage requirements, coverage metrics, achieved coverage levels by major longline fleets (2016–2020), and key issues for each of the five tuna RFMOs.

RFMO	Required coverage	Required metric	Achieved coverage by major longline fleets (2016–2020)	Key issues
CCSBT	10% (non-binding target)	Observed hooks / total hooks	**Australia:** 7–12% (EM from 2017) **Japan:** 5–22% **Korea:** 10–22% (0% in 2020, COVID) **New Zealand:** 9–20% **Taiwan:** 10–17% **Indonesia:** 0–1% **South Africa (JV):** 51–100% **South Africa (dom.):** 1–15%	Coverage highly variable between members and years. Indonesia consistently well below 10% target. Australia uses EM exclusively since 2017; not yet counted as ROP coverage by other RFMOs. Representativeness across statistical areas ranges 0–100% for different fleet/year combinations.
IATTC	5% (vessels >20m LOA)	Effective days fishing *or* hooks deployed	**USA:** 16% (hooks, 2020) **Japan:** 6% (eff. days, 2020) **Mexico:** 6% (eff. days, 2020) **Ecuador:** 6% (eff. days, 2020) **Korea:** 3% (eff. days, 2020) **Taiwan:** 0.6–11% (preliminary) **China:** 5% (hooks, 2020) **EU:** 4% (eff. days, 2020)	CPCs use different effort metrics (hooks vs days), making cross-fleet comparison problematic. Discrepancy between 'effective' coverage (hooks in observed sets / total hooks) and 'actual' coverage (hooks actually observed / total hooks). Multiple CPCs had no longline observer programme in some years. IATTC staff concluded 5% coverage inadequate to estimate total catch even for target species.

				Observer data for 3 of 4 fleets studied not geographically representative.
ICCAT	5% (Rec. 16-14); 10% for tropical tuna LL (Rec. 21-01, from 2022); 20% for BFT LL	Fishing days, sets, or trips (varies by CPC)	**USA:** ~8–9% (sets; since 1992) **Japan:** ~6% (operations) **Korea:** ~22% (other) **Taiwan:** ~11% (days at sea) **China:** ~6% (hooks) **EU-Portugal:** ~10% (sets) **Mexico:** 100% (trips) **EU-Malta:** 0.2% (vessels) Range across all CPCs: 0.2–100%	Coverage metric varies dramatically between CPCs (vessels, hooks, trips, sets, days, operations), making aggregation across fleets impossible without standardisation. No publicly available data on observer-recorded bycatch of seabirds, turtles, or marine mammals. Observer data reporting began as early as 1992 (USA, Japan) but as recently as 2019 for some CPCs.
IOTC	5% of operations/sets (vessels ≥24m, or <24m outside EEZ)	Number of hooks observed / total hooks	**EU-France:** 11–17% (average 14%) **EU-Portugal:** 8–15% (average 10%) **Australia:** 12–13% (EM only) **Japan:** 6–12% (average 9%) **Kenya:** ~5% **Korea:** 0.5–5% (average 4%) **Taiwan:** 2–5% (average 3%) **China:** 0–5% (average ~1%) **Indonesia:** 0–2%	SC23 reported overall coverage at only 2.15%—well below the 5% requirement. Zero coverage of artisanal fleet, which comprises a large portion of Indian Ocean catches. Recurrent non-compliance by multiple fleets since adoption of Res. 11/04. Publicly available ROS data limited to EU-France and Japan longline fleets only. Large DWFN fleets (China, Taiwan) with substantial effort have very low or zero coverage.

			India: 0% Many coastal states (Madagascar, Malaysia, Maldives, Seychelles, Oman, Mozambique, Sri Lanka, Tanzania): 0% *Overall estimated: ~2–3%*	
WCPFC	5% of effort (CMM 2018-05; in effect since 2012)	Trips (as proxy for effort)	**USA (Hawaii):** 21–28% **Fiji:** 7–31% **EU:** 0–33% (0% in 2020, COVID) **Taiwan DWLL:** 4–14% **Taiwan STLL:** 0–8% **Korea:** 4–10% **China:** 3–6% **Japan (fresh):** 0.2–6% (0.2% in 2020) **Japan (frozen):** 0–11% **Indonesia:** 0–0.2% Many Pacific Island fleets: variable, 0–38% *Overall LL coverage declined from ~6% to ~3% during COVID (2021–2022)*	Most comprehensive data management system (SPC/TUFMAN2) among tuna RFMOs. LL fleet divided into 29 sub-fleets for stratified coverage reporting. Many Pacific Island domestic fleets fishing within EEZ are not subject to ROP LL coverage requirement. COVID-19 moratorium on PS/carrier observers (Apr 2020) also caused LL coverage decline as Pacific Island observer programmes shut down. No agreed EM standards yet, despite EM working group since 2014.

Notes:

Sources: CapMarine (2022), Norman et al.; IOTC-2021-SC24-07; WCPFC SC13–17 Status of ROP Observer Data Management papers; Griffiths et al. (2021) IATTC BYC-10 INF-D; CCSBT CC14–16 Annual Reports on ERS Performance; Ewell et al. (2020); ISSF benchmarks (2025).

Coverage figures in the ‘achieved coverage’ column represent the range observed across the 2016–2020 period unless otherwise noted. Figures should be interpreted with caution as coverage metrics are not standardised across or within RFMOs.

EM = Electronic Monitoring; DWLL = distant-water longline; STLL = small-scale/coastal longline; JV = joint venture; dom. = domestic fleet.

Observer coverage is expressed as the proportion of fishing effort (typically hooks) that was observed by onboard scientific observers, not the proportion of logbook data available relative to total reported catch.

Questions:

- Need guidance from the workshop about what constitutes 'good' data.
    - When should analysts discard data as not useful?
    - Are there circumstances in which data may be useful but less reliable - perhaps assign inflated CVs?
- Have there been analyses using 'sentinel fleets' or similar e.g. fleets (flags) where data are 'known' to be reliable – to identify misreporting in other fleets which fish in similar ways? Or observer vs. Logbook...etc.

CCSBT

IATTC

For most of the recent IATTC stock assessments, the indices of abundance standardise both the CPUE and the associated size composition. For JPN most of the size composition data prior to 2011 was measured (in weight) by fishermen, after which observers starting recording sizes in lengths. From 2017, only data from observers is available. Similar changes occurred for Korea (SAC docs). Other countries, which did not report size data previously, started to do so after data reporting from observer programs became mandatory (resolution C-19-08)

Vessel IDs (call signs) are available in Japanese data from 1975, but not before that period. License numbers (renewed annually) are available in data held by Japan from 1959 and can be used to identify sets by the same vessel within a year, but not across years.

China has an MOU with the IATTC and reports operational level (set by set) data (2017?-2023). However, the data is "selected", and it is not clear what the data selection criteria are.

Some CPCs report only the target species (e.g. Spain only reports SWO) and only reports those sets with non-zero catches (Spain up to 2022). This precludes the analysis of changes in target species (e.g. between SWO and BSK).

SKJ tuna catch reporting (and other species): only reported in the observer data, not in the vessel logbook data (SAC-15-INF-U). It was used in the SKJ exploratory models but dropped due to this bias.

Some suspected changes in gear or gear configuration are either not reported or not reported reliably (e.g., when they started using light sticks, line material changes to monofilament). The only gear configuration available to analysts is HBF, and this is only consistent since 1976. Some gear configurations are not available for the whole fleet, so if we want to use gear covariates, we will need to drop a lot of data (e.g. branch line length, main line material for JPN fleet – paper Haikun). There is confounding between HBF and location, we do not know if changes in HBF in space is a tactic to be able to target the same species in different oceanographic conditions.

In the last 15 years (?) a new gear has been used in the longline fisheries (lazo – rings), it is not clear which fleets, when, how much and how many vessels used it, and how much the CPUE can change for target secondary and bycatch species.

Korea changed logbook in 2015 to electronic log books (Report OTM-30-Rep) which allowed for the sudden appearance of multiple shark species that were not reported previously (or were reported in an aggregated form as "SHK – sharks) (IATTC Special Report N.25)

ICCAT

Japanese vessel identification was not consistently available before 1979, which affects the ability to include vessel effects in CPUE standardisation models for the early time series. Sets without vessel identifiers from 1979 onward likely represent a non-random subset of the fleet. This has been addressed by standardising two separate time series — one from 1959 to 1979 without vessel effects and one from 1979 onward with vessel effects — which can be merged with adjustments at the overlapping year (Hoyle et al., 2019a; Hoyle et al., 2019b; Matsumoto et al., 2025; Matsumoto et al., 2024a).

Species reporting varies among fleets and has changed over time. In the Chinese-Taipei logbook, columns for bluefin were only added in 1994; prior to this, bluefin were recorded only when fishers manually changed the logbook heading, and reported numbers increased substantially after the change (Hoyle et al., 2019a; Hoyle et al., 2019b; Matsumoto et al., 2025; Matsumoto et al., 2024a). Korean data reported sharks only at an aggregated level in earlier years (Hoyle et al., 2019a; Hoyle et al., 2019b). The Chinese-Taipei "other" species categories are imprecise: "other tunas" are thought to be mostly neritic tunas, "other billfish" mostly sailfish and longbill spearfish, and "other fish" included pomfrets, dolphinfish, ocean sunfish, and increasingly oilfish (Hoyle et al., 2019a; Hoyle et al., 2019b; Matsumoto et al., 2024a).

Chinese operational data were first made available at an ICCAT meeting in 2018 but could not be included in joint analyses due to insufficient time to explore the data (Hoyle et al., 2019a). Chinese data subsequently provided for the 2025 BET joint analysis (2015–2023) reported no catches of bluefin, southern bluefin, or sharks, suggesting incomplete species reporting or selective data provision (Matsumoto et al., 2025).

For the US pelagic longline fleet, minimum size regulations for swordfish (from 1991) and mandatory circle hooks (from 2004) created regulatory discards of undersized swordfish that may not be recorded in vessel logbooks. Observer data are therefore preferred, and the response variable for US swordfish CPUE standardisation includes both kept and discarded fish (Lauretta, 2022). For bluefin tuna, the US fleet was additionally required to use weak wire circle hooks in the Gulf of America from 2011, designed to allow large BFT to free themselves (Lauretta et al., 2021). These regulatory changes affect both catchability and what gets reported.

The introduction of individual quota (IQ) management for the Japanese bluefin longline fishery — voluntary from 2007, mandatory from 2009 — substantially changed fishing patterns, area coverage, and size selectivity, as small fish were rarely landed under IQ management (Tsukahara et al., 2022). This indicates that the reported Japanese data do not include discards.

Portuguese longline data come from three sources — fishery observers, port landings, and voluntary skipper logbooks — with varying levels of completeness for individual specimen information across species (Coelho et al., 2022).

The ICCAT size composition database includes multiple size resolutions (1, 2, 4, or 5 cm) and rounding standards, with unknown rounding method for approximately 6% of records, which may introduce bias (Hoyle et al. 2019a).

Spatial resolution differs among fleets: Japanese, Korean, and most Chinese-Taipei data (from 1994) are reported at 1° resolution, while US data are at 5° resolution and earlier Chinese-Taipei data use a 5° logbook code. These differences constrain joint analyses.

Occasional very large catches of individual species appear in logbooks across fleets. These have generally been retained in joint analyses as they may be genuine and are unlikely to affect results substantially, but the treatment of such potential catch outliers warrants further consideration (Matsumoto et al., 2025).

IOTC

Standard issues with catch misreporting in IOTC. Unsure with regards to the LL CPUE indices, as the CPCs deal with the data inputs (catch data are not from the IOTC databases).

WCPFC-ISC

WCPFC-SC

Some issues with some CCMs' operational data including gaps in coverage (e.g., we assign missing catch to high seas, as has been done in the past, but certainly an uncertainty). In addition, there seem to be position errors in data coming from iFIMS.

Data aggregation

Analysis of aggregated CPUE data may be required or convenient given data availability and quality. Due to privacy concerns, public domain fisheries data are often available only at aggregated spatial and temporal scales (Hinz et al., 2013). Aggregation may begin with fishing logbooks with effort reported at the day or trip level, and may be further aggregated across vessels, time, and space. Pelagic longline data for most tuna RFMOs are publicly available aggregated by year, month, flag, and 5° cell. Data for bycatch and byproduct species may be aggregated across species due to identification problems or convenience.

Although analyses of aggregated data may be the only option when finer-scale data are unavailable, their results should be treated with caution due to the biases and analytical difficulties that aggregation introduces. Indices derived from data aggregated spatially, temporally, or across species may not vary in proportion to the target stock.

Covariates that affect catch rates at the set or vessel level, such as gear settings, or that summarise effects on catchability like vessel IDs, are often unavailable in aggregated data. This loss of information may limit the ability of standardisation to correct for variation in catchability spatially and over time, including effort creep (Hoyle et al., 2014).

Aggregating data temporally and using a coarser temporal definition of effort than the higher-resolution effective unit of effort can change the relationship between CPUE and abundance. Spatial and temporal aggregation may create a mismatch between actual oceanographic conditions and the covariate associated with aggregated CPUE data, potentially leading to spurious relationships and inappropriate spatial imputations.

It can be difficult to identify an appropriate statistical distribution to model aggregated data. Observations that aggregate more effort will be less variable, so if strata with higher catch rates attract more effort, there will be an inverse relationship among strata between CPUE and variance (Hoyle, 2021).

CPUE of an assemblage of species may be hyper-responsive or hyper-stable depending on the circumstances and the distributions of productivity and vulnerability of the species in the aggregation (Kleiber and Maunder, 2008).

Perhaps most importantly, aggregating data can remove fine-scale information that allows analysts to understand fishing behaviour (Hoyle et al., 2024). The key process of data exploration is limited by loss of information about individual vessel behaviour, fine-scale fish and vessel distributions, and movement patterns. In addition, analyses to identify targeting strategy based on species composition (e.g., He et al., 1997) may remain possible (e.g., Fu et al., 2016), but with lower resolution and sensitivity than with operational data.

There can be advantages associated with aggregating data before standardisation, particularly for fisheries where pseudo-replication and serial autocorrelation are issues (Hoyle et al., 2024). However, trade-offs should be explored through simulation or by working with more computationally tractable subsets of operational data.

Questions:

- Trade-offs between data aggregation vs subsampling vs subsetting, when datasets are too large to analyse.
- Are there forms of aggregation that adequately preserve the important information in the data (e.g., by vessel + 5 cell + yr-qtr + cluster)? Has simulation testing been applied to this question?
- What opportunities are lost when operational data are unavailable?

CCSBT

Historically, analyses were based on based on aggregated data, but Japanese analysts have used operational data in recent years (Itoh and Takahashi, 2022; Itoh and Takahashi, 2025).

Analyses of Korean data are carried out using operational data (Hoyle et al., 2022; Lim et al., 2025).

IATTC

Comparisons between 1 by 1 by month by HBF, 1 by 1 by month by vessel HBF, and operational (only HBF as covariates) (Haikun's paper) – Bias is larger when vessel information is not available.

YFT and BET: 1 by 1 up until 2024. Operational level in 2025.

S SWO: Operational level – analyses done by JPN colleagues

JPN: Gear effects with operational level data could be explored for part of the data set only due to availability of covariates (e.g. length of branch line).

Availability of detailed gear information may vary by fleet. And even if collected, may not be available for the staff to analyse.

Access to operation level data vary by fleet and is time restrictive (the data is not available long term).

ICCAT

Bigeye and yellowfin indices based on operational data (Matsumoto et al., 2025; Matsumoto et al., 2024b).

IOTC

Operational data: bigeye, yellowfin and albacore, before and after the covid period (Hoyle et al., 2015b; Kitakado et al., 2025a; Kitakado et al., 2025b; Wang et al., 2025).

Analyses during covid period based on aggregated data due to online access restrictions.

WCPFC-ISC

NP ALB: Environmental data associated with set location (Laura's analysis)

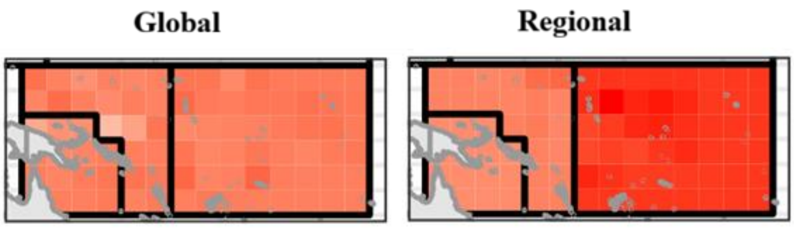
WCPFC-SC

Data is not typically aggregated for CPUE analyses however, associated length comps have issues with spatial resolution. Due to the large size of longline datasets, subsetting has been done as random sampling 5 observations for each 5x5° cell-year-quarter-flag. This approach can be problematic as it may not provide adequate coverage, also has possible repeatability issues. As such, work has been underway to explore sensitivity to different subsampling rates and try alternative model structures to reduce computational burden while using more of the available data. One approach is to run the full data from each flag separately. Performing separate analyses for each flag provides multiple advantages.

- Higher proportion of the data included in the analysis (improved uncertainty estimation)
- Vessel random effects included in analysis
- Explore flag-specific environmental covariates
- Gear main effects (such as HBF) may differ by flag and are more representative of flag-specific strategies when modelled separately

A disadvantage to this approach is there may be differences in expected vessel catchability between flags, causing the bootstrapped density estimates to be biased.

Another approach involves including all flags but performing the analyses by region which, may alleviate the bias from the flag-specific analyses. However, this approach can result in a stark contrast at the region boundary (as below).



A possible solution may be to have some overlap of regions and bootstrap where regions overlap to smooth the transition between regions thus providing more realistic results.

Density & catchability covariates

Stock assessment scientists have long standardised fishery CPUE to remove confounding effects of vessel size and power, including only variables that may influence catchability (the proportion of the stock removed by a unit of effort). In contrast, spatial ecologists focus on covariates that affect population density (the abundance in each stratum) and condition upon their effect when predicting densities across space. These approaches are complementary, and analysts may incorporate both by distinguishing between catchability and density covariates (Thorson, 2019). Both are included to explain catch rates, but only density covariates are conditioned upon when predicting densities across space. The index is constructed using the predict-then-aggregate approach – by aggregating predictions across a specified spatial and temporal domain such that the effect of catchability is removed (Campbell, 2015).

Note that in this context we include availability (the proportion of the population accessible to fishing (Marr, 1951)) as a component of catchability.

The analyst must model each covariate as affecting either density or catchability, but the true process may be unclear or a combination of both density and catchability. For example, a species may migrate to maintain its desired temperature such that local temperature predicts population densities, while simultaneously temperature might affect digestion, metabolic rates, or the abundance of prey species, leading to greater attraction towards baited hooks. Resolving these hypothesised mechanisms requires an understanding of the biological processes and may require research. For example, electronic tags or acoustic telemetry can be used to infer information about availability at depth given the temperature and other environmental factors (Brill and Lutcavage, 2001). Similar inferences can be made through local depletion studies, paired sampling with different gear types, or process studies using small-scale experiments.

Analysts should justify why each covariate affects density or catchability. When the mechanism is uncertain, analysts should explore sensitivity to alternative assumptions. Such alternative hypotheses are an important component of stock assessment uncertainty (Hoyle et al., 2024).

Observations of catchability covariates are only needed for effort events, whereas during the predict-then aggregate process used to construct indices, values of density covariates are needed for all temporal and spatial strata included in the index irrespective of whether there is effort.

We note that the use of density covariates may help to avoid prediction of unrealistic densities into areas without fishing. For example, SST may be effective for predicting the seasonal distributions of tropical tunas.

Questions:

- What are some guidelines for determining whether covariates should be treated as catchability or density covariates?

CCSBT

IATTC

Standard models: catchability (HBF, vessel effect and flag effect for joint indices) and spatiotemporal effect for density.

ICCAT

Indices for bigeye (Matsumoto et al., 2025) and yellowfin (Matsumoto et al., 2024a):

Catchability covariates:

- HBF, cluster, hooks, vessel id.

Density covariates not used

IOTC

Bigeye, yellowfin and albacore (Hoyle et al., 2015b; Kitakado et al., 2025a; Kitakado et al., 2025b; Wang et al., 2025).

Catchability covariates only:

- HBF, hooks per set, cluster (from species composition), vessel ID.

WCPFC-ISC

WCPFC-SC

In indices for the 2023 YFT and BET assessments (Teears et al., 2023) and ALB assessments (Teears et al., 2024b):

Catchability covariates:

- HBF and flag.
- Vessel id and cluster not used.

Density covariates

- BET: season, depth of the 15° isotherm (iso.15), difference in depth between the 12° and 18° isotherms (delta.temp.12.18), and season
- YFT: depth of the 15° isotherm, difference in depth between the 12° and 18° isotherms, and season
- SPALB: none

Upcoming BET and YFT assessments, exploration of covariates including PDO, ENSO, SST, iso.15, delta.temp.12.18, sss, chlorophyll, and diffuse attenuation coefficient (kd-490).

SST species tolerance thresholds are used for masking spatiotemporal predictions, to prevent extrapolation into unviable areas.

Environmental variables

Aspects of the aquatic environment, such as water temperature, surface chlorophyll-a concentration, oxygenation, and light at depth, affect both fish density and catchability. The task of CPUE standardisation is to eliminate the effect of catchability variables so the analyst can employ CPUE data to infer differences in fish density across time and space. Catchability covariates are fixed at a base value when predicting density, thereby filtering out variation associated with different values in the fitted data. By contrast, density covariates have assigned values at every location across the modelled spatial and temporal domain, and the analyst conditions upon these values when predicting densities.

Several environmental variables are commonly used in CPUE models. Sea surface temperature, sea surface salinity, sea level height, chlorophyll-a concentration, and dissolved oxygen concentration have been found to be significant predictors of spatial distribution for some species, particularly for pelagics. Some environmental variables, such as moon phase, eddies, water turbidity, and cloud cover, may affect availability or catchability of certain species and gear types. Environmental variables are often not recorded by fishers at the time of fishing but obtained from other sources such as meteorological organisations, which is particularly true for density covariates that must be available for all locations and time periods.

Despite being important factors affecting fish distribution, many environmental variables are confounded with spatial and seasonal coordinates that are often employed as predictors in CPUE models. Spatial-temporal effects can act as proxies for comprehensive dynamic environmental variables, especially if interactions between these effects are included to help account for temporal changes in environmental conditions. If environmental conditions generally exhibit consistent spatial and temporal patterns, explicitly including environmental variables may explain little additional variation. In cases where using environmental variables does increase accuracy, their inclusion may also increase annual coefficients of variation compared to models without environmental variables, likely due to the added requirement of estimating relatively imprecise relationships.

Questions:

- What methods are recommended for addressing the changes associated with climate change?

CCSBT

IATTC

Spatiotemporal models

Habitat -based standardisation: catchability is a function of which oceanographic condition the hooks is in. The calculation uses the depth of the hook and oceanographic condition at depth plus habitat preference for the fish (fixed from archival tags – Hinton) or estimated statistically (Mark). Estimated a retrieval effect (as the hook when through the habitat, even if they were not set at that depth they could pass through the habitat as they are retrieved). Catch rates were modified based on the total habitat available, the less habitat that was available the more you could catch the target fish (higher density)

Exploratory analysis for use of environmental variables:

- Unpublished preliminary exploration on using environmental variables for main species (BET, YFT)
- Changes in catchability with El Nino were explored

ICCAT

IOTC

WCPFC-ISC

WCPFC-SC

In recent years, the following variables have been used as density covariates: ENSO, sst, temperature profiles used to develop depth 15° isotherm and Δ depth of 12° to 18° isotherms (SC19-SA-WP-03 YFT_BET_assesment_CPUE_Inputs_Finl_Rev1.pdf).

Season has also been implemented in BET CPUE standardisation as BET indicated highly seasonal density dynamics.

For the upcoming BET/YFT assessments, chlorophyll and diffusion attenuation coefficient are also being considered as potential covariates.

Analysis

Modeling framework

The objective of CPUE standardisation is to remove effects of changes in fishing practice through time from observed catch rates such that the trend in standardised CPUE reflects relative abundance of the stock component selected by the fishery. This is accomplished by building a statistical model that predicts CPUE as a function of variables thought to impact local abundance or catchability. Recent standardisations mostly use generalised linear models or expansions thereof (such as GAMs and STMs), implemented in R. There are five key factors to consider when selecting a modelling framework: the form of relationships between CPUE and explanatory variables, the probability distribution of CPUE, the type of correlation present in the dataset, whether CPUE will be jointly standardised with composition data, and how results are processed to yield an overall index.

CPUE standardisations consider both categorical and continuous covariates. In the GLM framework, categorical covariates are typically modelled as deviates from a baseline intercept level and estimated as fixed effects. An alternative is to fit categorical covariates as random effects in a mixed-effect framework, where level coefficients are constrained to belong to a distribution, resulting in shrinkage of covariate levels towards an overall mean. Random effects can be useful for covariates with multiple levels that may be expected to belong to a common distribution, such as vessel effects, where poorly sampled levels would otherwise have unreliable coefficient estimates. A common strategy is to define a core fleet comprised of vessels that meet activity thresholds, though treating vessel ID as a random effect can be an alternative that avoids arbitrary threshold decisions.

Non-linear relationships between CPUE and continuous covariates are best implemented via splines, which are a useful improvement over polynomials as they are not constrained in the shapes they can take. The R package mgcv (Wood and Wood, 2020) implements GAMs using penalised splines, with the algorithm attempting to maximise fit while minimising wiggliness. Care must be taken to prevent overfitting or extrapolating far beyond the range of available data. Model fitting can be implemented in frequentist or Bayesian frameworks, with Template Model Builder (TMB; Kristensen et al., 2016) enabling considerably faster fitting for large datasets through automatic differentiation and Laplace approximation, while Bayesian approaches using MCMC with packages like brms offer options to specify priors and more intuitive uncertainty estimates.

Questions:

- Something about joint analysis of CPUE and composition data.

CCSBT

The Japanese indices that drive the assessment (Itoh and Takahashi, 2022; Itoh and Takahashi, 2025) use GAMs implemented with mgcv.

The whole spatial domain is fitted with a single model.

IATTC

The main indices are produced using sdmTMB Xu 2024.

Approaches explored and applied:

- Neural networks (see refs below) (Maunder and Hinton, 2006)
- Regression trees (see refs below)
- Habitat based models (deterministic and statistical) (Bigelow et al., 2003; Bigelow and Maunder, 2007; Langley et al., 2005; Maunder et al., 2002; Maunder et al., 2006a)
- Delta – lognormal model (Hoyle and Maunder, 2006) (SAR-07-07 and Presentation)
- GLM and GAMMS (Lennert-Cody et al., 2014)
- VAST (Maunder et al., 2020)
- VAST with size comps
- VAST with autocorrelation (Xu et al., 2024a)
- sdmTMB (selected after comparison with VAST, based on speed, after checking that results were the same) – 2024 BET assessment and 2025 YFT assessment
- Preferential sampling – simulation work by Haikun (Xu et al., 2024a)
- Effect of spatial contraction - simulation work by Haikun (Xu et al., 2024a)
- Rujia's customed TMB models to combine size and CPUE, multigear, where selectivity is important (work in progress).
- Spatial stock assessment work: do spatiotemporal models of CPUE data deal with spatial structure in the assessment? YFT IO simulation study (Goethel et al 2024). (Goethel et al., 2024)
- Reviews (Hinton and Maunder, 2004; Hoyle et al., 2007)
- Refuting Myers and Worm 2001 (Hampton et al., 2005; Maunder et al., 2006b; Sibert et al., 2006)

ICCAT

GLMs are used for the main indices (Matsumoto et al., 2025; Matsumoto et al., 2024a), which use the R package *cpue.rfmo* (Hoyle, 2025b).

Regional indices are estimated independently. There are no time-area interactions within regions.

There has been some exploration of STMs such as VAST and sdmTMB, but they have not been used in assessments. Development has been affected by the limited time available during collaborative analysis meetings (Satoh et al., 2024).

IOTC

GLMs are used for the main indices: bigeye, yellowfin and albacore (Hoyle et al., 2015b; Kitakado et al., 2025a; Kitakado et al., 2025b; Kitakado et al., 2025d). From 2015-2019, indices were developed using the R package *cpue.rfmo* (Hoyle, 2025b). Since 2020, indices have been developed using scripts developed by the analysis team.

Regional indices are estimated independently. There are no time-area interactions within regions.

There has been some exploration of STMs such as VAST and sdmTMB (Satoh et al., 2021a), but they have not been used in assessments. Development may have been affected by the limited time available during collaborative analysis meetings.

WCPFC-ISC

WCPFC-SC

Historically, SPC analyses of longline data have been modelled in GLM or GAM frameworks (e.g., Hoyle and Okamoto, 2011; McKechnie et al., 2015). Analyses fitted data for each region independently. Analyses lacked time-area interactions.

Spatial temporal models (STMs) have increasingly been used in standardisation of CPUE data for the WCPFC-SC. The first developments (Tremblay-Boyer et al., 2018; Tremblay-Boyer et al., 2017) used the R package SpatialDeltaGLMM, which later became integrated in R package VAST (Thorson et al., 2015). Subsequent analyses (Ducharme-Barth and Pilling, 2019; Ducharme-Barth and Vincent, 2020) began using VAST (Thorson, 2019) as the R package. Subsequently, analyses switched (Teears et al., 2023) to sdmTMB (Anderson et al., 2022) based on recommendations from the yellowfin independent peer-review (Punt et al., 2023). The sdmTMB geostatistical software takes a similar approach to VAST but is optimised for single species modeling and has a more user-friendly interface. The sdmTMB package produces comparable results to other STM software packages (including VAST). A recent standardisation of CPUE for billfish assessments included a comparison of sdmTMB, VAST and tinyVAST, which gave identical results (Kim et al., 2025).

Until 2026, all SPC analyses using STMs fitted data from all regions together, with parameters shared. Indices for individual regions were generated by predicting (and aggregating) for those regions. This contrasts with the approach used with GLMs, where each region was analysed independently. Tremblay-Boyer et al. (2018) compared indices using the two approaches and found that they were substantially different. However, it is unclear how each of the many differences between the approaches (different covariates, independent vs shared covariate effects across regions, spatial smoothing, error distributions, etc.) contributed to these outcomes.

Spatial considerations

All fish populations and fisheries exhibit spatial structure to some extent. The introduction of spatial considerations into CPUE standardisation raises questions of how space should be considered in a model and whether complex models will necessarily perform better than simpler ones. Classically, CPUE standardisation is performed using a GLM, often a two-step delta GLM to account for zeros. The simplest way to consider space consists of dividing the study region into area strata and including the fixed effect of area stratum as a categorical covariate, aiming to account for spatial heterogeneity in stock density assumed to be homogeneous within each stratum.

As noted by Punsly (1987) and Campbell (2004), changes through time in the spatial distribution of effort can bias indices derived from linear models that do not include time-area interactions. This can be resolved by adjusting the statistical weights so that the total weight in each time-area stratum is the same.

A more flexible approach than the GLM is the spatial GAM approach, which fits an interaction term between longitude and latitude depicting spatial variation at a broad scale. This can be extended to a spatiotemporal GAM via inclusion of an interaction between longitude, latitude, and time representing spatiotemporal variation. Spatiotemporal models (STMs) constitute an even more flexible approach by depicting spatial and spatiotemporal variation at very fine scales, yielding very precise estimates. Over recent years, STMs implemented with VAST have been increasingly employed to standardise CPUE data.

Because STMs represent latent spatial and spatiotemporal variation at fine scales, inclusion of habitat variables that are themselves inherently spatial or spatiotemporal may not improve predictive capabilities and may even degrade performance in some cases (Ducharme-Barth et al., 2022; Thorson, 2015).

Analysts should not assume a priori that STMs will outperform spatial or spatiotemporal GAM approaches. Simulation experiments permit evaluation of accuracy, error, and confidence interval coverage of STMs compared to simpler approaches. When choosing the sampling frame, analysts must consider whether to include regions at the edge of the fishery that are fished infrequently. Including such regions increases uncertainty as abundance will be inferred from limited information. One option is to limit the spatial domain to a core fishery defined as regions where most catch is taken or that are fished for a majority of the modelling period. Sensitivity of the resulting abundance index to different spatial domain definitions should be considered, as limiting analysis to a core region could mask hyperstability or changes in species range.

Questions:

- When do STMs outperform spatial GAMs, and STMs and spatial GAMs outperform GLMs? Identify factors affecting trade-offs between alternative methods.
- Should STMs and GAMs be run for the whole spatial domain or separate models by regions or core areas?
- What approaches are recommended for dealing with a) changing (reduced) areas of spatial fishing coverage, b) increasing effort concentration?
- What methods are recommended for addressing the changes associated with climate change?

CCSBT

Spatial GAMs based on mgcv with time area interaction terms (Hoyle, 2022; Hoyle, 2020; Itoh and Takahashi, 2022; Itoh and Takahashi, 2025). GAM interaction terms use te() which permits anisotropy in each interaction.

IATTC

STMs implemented with sdmTMB with anisotropy. Issues include:

- Different directions of correlation according to locations in space, although the software does not allow this. Directions may need to be guided by currents.
- Number of knots, how to distribute the knots.
- How to select the spatial domain (PS- index spatial domain by El Nino and quarter – 12 spatial domains)
- Contraction and expansion of the fleet (data)

ICCAT

GLMs for tropical tuna species (BET, YFT) (Matsumoto et al., 2025; Matsumoto et al., 2024a). Independent analyses by region. Regions include no time area interactions. Spatial reweighting applied.

Independent northern ALB indices developed for multiple fleets using various methods.

Preliminary STMs for tropical tunas (Satoh et al., 2024).

IOTC

GLMs for tuna species (Kitakado et al., 2025a; Kitakado et al., 2025b). Independent analyses by region. Regions include no time area interactions. No spatial reweighting.

WCPFC-ISC

WCPFC-SC

For longline CPUE standardisation of BET, YFT, SPALB, MLS and SWO, STMs (VAST and sdmTMB) have been used for several SA cycles to include the spatial temporal correlation structure in the GLMs. The yellowfin independent peer-review (Punt et al., 2023) indicated this to be an improvement over the conventional GLMs.

Joint analysis of data from multiple fleets

In many tuna fisheries, no single longline fleet covers the full spatial and temporal range of a stock. Different flags or fleets may fish in different areas depending on access arrangements to exclusive economic zones versus high seas, and the spatial distribution of effort from individual fleets often changes over time. For example, the Japanese fleet historically fished widely in the Pacific, but its effort contracted overtime, and areas it historically fished became more heavily fished by other distant water nations as their fleets developed. Therefore, to maintain good spatial coverage of CPUE over a long time series in the Pacific, analysts rely on Japanese data in early time periods but add data from more fleets to improve spatial coverage in recent decades. Analysts must therefore consider how to incorporate data from multiple fleets to achieve adequate coverage for stock-wide abundance indices. Traditionally, analysts produced separate CPUE indices for each fleet, resulting in multiple abundance indices that the assessment model would implicitly average with equal weighting regardless of their spatial coverage or reliability. Dynamic factor analysis (Peterson et al., 2021) has been used to combine multiple indices into a consensus index, but this approach has drawbacks including implicit weighting where indices representing small or large areas receive equal weight, and residual variation in constituent indices being ignored.

Given the difficulty of reconciling differences in multiple indices within an assessment, analysts increasingly seek to include data from multiple fleets during index standardisation itself. Joint analysis expands data coverage spatially and temporally and ensures consistency of analytical methods, removing a key source of differences between indices. This approach has been applied to combine fleets from multiple nations to increase spatial and temporal coverage of indices for tropical tunas. Joint indices for Atlantic tropical tunas were judged to have improved resulting stock assessments by reducing data conflicts, improving model diagnostics, and ensuring broad and consistent coverage. The approach has also been used to estimate relative population scale across regions for use in multi-region stock assessments, most notable in the WCPFC assessments conducted by SPC.

Prior to joint analyses of data from multiple fleets, individual national datasets should be thoroughly explored to identify and eliminate sources of data conflict. Analysts should standardise each dataset individually using broadly consistent methods and compare resulting density maps and abundance indices both visually and using goodness-of-fit criteria. Any apparent conflict in indices should be investigated to determine whether it can be explained by differences in spatial extent, temporal coverage, or catchability among fleets. Differences between datasets should be explained mechanistically where possible, such as by including covariates that can account for differences in catchability. These recommendations arise from the expectation that data conflicts imply model misspecification—the law of conflicting data. Analysts should also consider that selectivity differences between fleets may require simultaneously modelling catch rate and length composition data to estimate differences in selectivity, in which case calibrating catchability and selectivity may require spatial overlap among fleets.

Questions:

- What criteria are needed when deciding whether to include a fleet in an index?
    - Qualities of the data in each dataset
    - Consistency between datasets
    - How to deal with the size data for the different fleets to best represent the index selectivity? Also, the observations may vary a lot depending on the fleets that provide size data across time and space (maybe dealt with later ??). The CPUE data will typically cover much more space and time than the size data.

CCSBT

Under development (Hoyle, 2023; Hoyle, 2025a).

IATTC

LL indices for YFT and BET included KOR and JPN: comparisons of LF and catch rate in smaller regions showed similar trends, indicating that the fleets may be combined (Xu et al., 2025).

New method by Rujia to combine PS and LL: underlying abundance is the same, but the selectivities of gears differ. Both are included in one spatiotemporal model.

ICCAT

Bigeye and yellowfin: (Matsumoto et al., 2025; Matsumoto et al., 2024a; Satoh et al., 2024).

Swordfish – north Atlantic: (Gillespie et al., 2022).

IOTC

Bigeye, yellowfin and albacore (Hoyle et al., 2015b; Kitakado et al., 2025a; Kitakado et al., 2025b; Wang et al., 2025).

Shark and billfish indices not based on joint analyses.

WCPFC-ISC

WCPFC-SC

For BET and YFT, different flags have been combined in a global model with flag as a covariate (Teears et al., 2023). For SPALB, an areas-as-fleets approach was used with NZ troll data standardised using a conventional GLM and input as a juvenile index and longline data from 0°-25°S with all flags standardised with an STM (Teears et al., 2024b).

Analyses for the index fishery approach

The index fishery approach treats the CPUE-based abundance index and the catch as if they originated from two separate fleets in the stock assessment, even when both can come from the same underlying fishery. The "index fleet" carries the abundance signal with composition data weighted by predicted CPUE and is configured so that its selectivity can be held stable through time. The "extraction fleet" takes the actual removals with composition data weighted by catch and is allowed time-varying selectivity to absorb shifts in targeting, gear, and effort distribution. Hoyle et al. (2024) recommend it as good practice, and Maunder et al. (2020) provide the supporting analytical framework.

The CPUE analysis to support this approach is more demanding than a conventional standardisation because it must produce both an index and an internally consistent index-fleet composition from a single fitted model. The recommended structure is a spatiotemporal model fitted at fine spatial resolution (e.g. 1°×1°) to operational catch and effort data, including all density and catchability covariates needed to remove apparent selectivity drift from the index fleet — spatial, seasonal, vessel, gear, hooks-between-floats, technique, and targeting. The model is extended to size or age by adding length/age as a model dimension, with interactions between length and time, length and space, and length × time × space. Predictions are then made cell-by-cell (and bin-by-bin), and aggregated using the predict-then-aggregate principle: area-weighted summation across cells gives the index, the same predictions weighted by predicted CPUE give the index-fleet composition, and weighting by predicted (or observed) catch gives the extraction-fleet composition. Computation is the main practical constraint — the four-dimensional model is expensive — so length is typically binned coarsely (e.g. 10 cm), knot counts are reduced, and temporal correlation among bins is often suppressed to keep the problem tractable.

In most tuna longline fisheries, however, the size data cannot be combined with the catch and effort data at fine resolution because they are collected and reported independently and at much coarser strata. The IOTC longline size review illustrates this (Hoyle et al., 2021): tropical tuna longline size data are held at three main spatial resolutions (1°×1°, 5°×5°, and 10°×20°), with all 10°×20° data being Japanese and covering the period from the start of the time series until 2008; from 2009 the IOTC-held Japanese data switch to 5°×5°, while the Taiwanese fleet is reported entirely at 5°×5°. Temporally, IOTC-held Japanese data are quarterly from 1952–2008 and monthly from 2009, and Korean, Seychelles and Taiwanese data are provided at monthly resolution. CPUE data, by contrast, are normally available and standardised at much finer resolution (set or 1°×1°×month). The two streams therefore cannot be joined record-by-record, and the cell used in any joint model has to fall back to the coarsest common stratum, with attendant losses of resolution and information about within-stratum heterogeneity in size.

Several practical procedures are available when only coarse, independently reported size data exist. The simplest is the approach used in the Maunder et al. (2020) yellowfin example: aggregate the catch and effort data up to match the size-data resolution (e.g. 5°×5° × quarter × 10 cm), and fit the joint model on that coarser grid; the index is still constructed at the finer grid from the CPUE component, but the size predictions live at the coarser grid. A second option is the two-model variant suggested in the same paper — fit the abundance index on the full operational dataset at native resolution, and fit a separate spatiotemporal size model on the (smaller, coarser) subset of strata for which size data exist, then weight the predicted size compositions by the predicted abundance from the index model to produce the index-fleet composition. This decouples the computational and resolution constraints of the two components at the cost of some inconsistency between them. A third option, where size data resolution changes through time (the typical Japanese case: 10°×20° pre-2009, 5°×5° after), is to fit at the coarser historical resolution throughout, or to fit two epoch-specific size models and stitch them — the latter risks step changes that should be checked carefully against the index. In all cases the analyst should document the resolution mismatch explicitly, run sensitivity analyses on the aggregation choice, and be aware that coarser size strata blend areas with different mean sizes and so weaken the signal (selectivity stability of the index fleet) that the index fishery approach is designed to preserve.

CCSBT

In the OM and assessment models the Japanese CPUE is now included as a separate fleet with CPUE-weighted length-comps instead of catch-weighted. This is likely the base model now. In June 2025 the effects on results seemed to be relatively minor.

Others??

Multispecies targeting

CPUE standardisation aims to account for non-random catchability change caused by targeted fishing operations, which typically seek to optimise profits. This is complicated in multispecies fisheries where fishers can make discrete operational choices to increase catchability of specific species or complexes. Allocating targeted effort to one species over another can relate to choice of fishing ground, habitat type, fishing technique, or gear deployment. In the best case, unaccounted variation in targeting only inflates uncertainty, but large short-term shifts or long-term trends can systematically change catchability and severely bias abundance indices.

Subsetting approaches aim to select only records where effort was likely to have been targeted towards the species of interest (Stephens and MacCall, 2004). Methods include using catch proportions or CPUE (Satoh and Matsumoto, 2017) by species to determine thresholds. However, such subsetting can be sensitive to subjective threshold choices and associated with risks of introducing hyperstability, and use of CPUE at the set level risks confounding target change with abundance change. Subsetting to non-zero catches will introduce bias, because the proportion of zeroes is affected by the abundance of the species of interest (Langley, 2019). A cleaner approach involves selecting records based on indicative factors such as core vessels, gear configurations, areas, and seasons (e.g., indices for SBT; Hoyle et al., 2022; Itoh and Takahashi, 2022).

Another approach is to include information from catch rates of other species. However, if used as a covariate, changes in the abundance of the other species can bias the index (Su et al., 2008). Ratios of the other species and the species of interest have been used as covariates in CPUE standardisations, after ranking either annually or across the whole time series, and discretising into categorical variables (Hiraoka et al., 2012; Mejuto et al., 2009). However, these approaches are not recommended due to either confounding with abundance trends of the other species, or ineffective treatment of target change (Hoyle et al., 2014).

If discrete fishing tactics result in distinctive species composition in the catch, clustering techniques can categorise multispecies CPUE records into groups with similar compositions. The identified clusters are assumed to represent fishing tactics which may be treated as categorical variables in the standardisation model. A related approach is the Direct Principal Component procedure (DPC, Winker et al., 2013; Winker et al., 2014) using continuous principal component scores as linear or nonlinear predictor variables. Approaches have been proposed to overcome confounding effects by inferring latent fishing tactics from residual structure, including the directed residual mixture approach (Okamura et al., 2017) and the spatial dynamic factor analysis embedded in VAST (Thorson et al., 2016). The latter presents a statistically coherent method for simultaneously estimating spatial-temporal variation, random vessel effects, fishing tactics, and relative abundance. Different approaches can be effective in some circumstances and fail in others, but simulation testing has been limited.

In analyses for bigeye and yellowfin tuna, IOTC and ICCAT developed an approach in which temperate regions may include cluster as a factor in the CPUE analysis model, while tropical regions should omit cluster and include HBF. This distinction was recommended (Hoyle et al., 2015b) because there is considerable overlap between BET and YFT targeting strategies in tropical regions, so that clusters are not based on distinct strategies and species compositions. This issue has also been noted in analyses of WCPO data (Hoyle and Okamoto, 2013). Using cluster in these models for tropical regions results in confounding between target change and the relative biomass trends of the two species, such that the model attributes a decline in the proportion of a species (e.g., YFT) in the catch to a change in targeting away from that species towards the other (e.g., BET). This tends to average the index trends of both species. In contrast, temperate regions often include substantial effort with distinct fishing strategies that target other species (ALB, SBT, SWO, oilfish). Clustering is more appropriate in these circumstances.

Covariates usually available to analysts in logbook data can help to indicate targeting strategies. These covariates include the vessel ID, since vessels tend to specialise in particular fishing strategies; the number of hooks used in a set – e.g., vessels targeting swordfish often use more hooks; and HBF

– vessels targeting bigeye may set deeper and use more HBF than those targeting albacore. However, these covariates are also flawed as targeting indicators. Vessels may change targeting strategies on short-term, seasonal, and annual time scales. Setting strategies such as the number of hooks used in swordfish and tuna sets also change through time and vary spatially. The HBF associated with each target varies spatially given factors such as current shear and thermocline depth, changes with setting strategy such as set time (e.g., shallow night sets targeting bigeye) and the use of line weights, and has changed through time given factors such as the transition from kuralon to monofilament in mainline and branchline materials.

One concern when addressing targeting is the difficulty of estimating catchability effects in the presence of density changes. Although vessels may choose a fishing strategy to optimally target their preferred species or group of species, vessels also tend to target different species in different areas, given that species densities vary spatially. This affects clustering based on species composition, which often results in clusters with significant, if incomplete, spatial separation. Although these clusters are intended to represent catchability effects, they may also represent density effects to some degree for the species of interest. Operational factors must be implemented in CPUE standardisation as catchability variables, but the confounding may lead to overestimation of biomass in non-target areas. To some degree, similar concerns apply to other operational variables linked to targeting, such as HBF. Mitigation may require sufficient spatial overlap for catchability parameters to be estimated while density parameters can be assumed constant. Methods are needed to identify and minimise this confounding, and potentially to estimate and adjust for it.

Questions:

- What other methods are available that allow for the effects of targeting strategies on catchability?
- How should the 1990s gradual transition from kuralon to mono be accounted for in standardisation i.e., with HBF? See the approach trialled by IATTC.
- Cluster analysis is designed to identify different fishing strategies, so it can be effective for distinguishing, e.g., tropical tuna vs swordfish vs bluefin tuna. Should it be avoided for bigeye vs yellowfin targeting in tropical areas given the lack of differentiation between fishing strategies, and the risk of confounding abundance trends with targeting?
- Are there methods that would allow the use of clustering in these fisheries? What about DPC?
- How many species are needed to identify targeting strategies from species composition data? How should analysts test this with their dataset?
- Various clustering methods are available (e.g., kmeans, Ward’s hclust). Is there a preferred method?
- Should analyses be run independently by region, period, season? If so, how can the results be integrated into the CPUE index for stock assessment?
- How can operational characteristics be included when identifying targeting strategies?

CCSBT

Cluster analysis for southern bluefin tuna (Itoh and Takahashi, 2022; Itoh and Takahashi, 2025), using species composition of 5 species (SBT, BET, YFT, ALB, SWO), and the *clust_PCA_run* function of *cpue.rfmo*, which applies Ward's hclust method. The JP SBT fishery operates largely in temperate regions. Data were separated into either 2 or 4 groups, which provided similar results.

IATTC

Exploratory analyses addressing target change were carried out in the 2019 workshop (Minte-Vera et al., 2019b) (OTM-30). The motivation for this work was an apparent decrease in the Japanese catch of some species including albacore, and the increase of others including swordfish, at the same time as gear changes (HBF increase) were detected. Four methods were applied, including cluster analysis of species composition using the *clust_PCA_run* function of *cpue.rfmo* (Hoyle et al., 2019a), Gaussian mixture analysis of relative BET CPUE residuals (Okamura et al., 2017), a hybrid method (cluster analysis of relative CPUE residuals for multiple species), and Potential Target Species (PTS) method (Satoh and Matsumoto, 2017).

Prior to the 2023 IATTC external review of data, Haikun Xu ran an analysis adding 3 to HBF for sets since 1995, to adjust for the difference in HBF before and after the introduction of monofilament (IATTC, 2023). This assumes that full transition occurred in 1995, whereas the actual transition to monofilament was more gradual. The change had little impact on results for EPO bigeye in this particular analysis. However, it appears reasonable *a priori* to adjust for the effect of mainline type on the HBF associated with alternative targeting strategies (Jardim et al., 2023). This transition is important for many fleets and fishing locations / ocean basins. Further exploration may be of interest, particularly with data on the mainline type used in each set, and information from industry on fishing practices.

ICCAT

Cluster analysis is applied to generate cluster categories for the bigeye and yellowfin indices (Matsumoto et al., 2025; Matsumoto et al., 2024a; Satoh et al., 2024). Clustering in general uses the approach of Hoyle et al. (2015b).

IOTC

Cluster analysis: for bigeye, yellowfin and albacore (Hoyle et al., 2015b; Kitakado et al., 2025a; Kitakado et al., 2025b; Wang et al., 2025).indices.

Analyses prior to 2020 used methods described in detail by Hoyle et al. (2015b), with HBF in tropical regions and cluster categories by fleet (using Ward's hclust method) in temperate regions. Additional differentiation between targeting strategies was provided by the use of vessel IDs and by fitting a cubic spline on log(hooks) as a covariate, while using CPUE as the response variable.

Analyses in 2025 used the clustering approach described by Wang et al. (2021). The approach for defining clusters is similar to Hoyle et al. (2015b), with a few changes. Data were aggregated by vessel-10days rather than vessel-month, based on agreement by the trilateral working group (Kitakado et al., 2021). In addition to the hclust dendrogram and the elbow method, the number of groups was determined using the function *nonpartest* from the R package *npmv* (Burchett et al., 2017).

Since 2020 there have been some changes in the variables used to identify targeting. Analyses in 2021 and 2022 were constrained by the need to use aggregated data due to covid-related data sharing restrictions. Analyses from 2024 returned to using operational data but made further changes to targeting variables.

Some CPUE analyses maintained the use of HBF as catchability variables for tropical regions and clusters for temperate regions (Kitakado et al., 2025a; Kitakado et al., 2025b; Kitakado et al., 2021), while others used clusters for all regions (Kitakado et al., 2022; Lim et al., 2024; Matsumoto et al., 2024b). All analyses that fitted HBF used 3 depth categories (shallow, medium, deep) rather than a smoother. Analyses in 2025 generated and fitted independent HBF categories by fleet (Kitakado et al., 2025b). No post-2020 analyses included a smoother on hooks as a covariate. The 2024 yellowfin analyses omitted vessel effects from all index components, and only the 2025 yellowfin analyses included vessel effects in the binomial components of delta-lognormal indices.

WCPFC-ISC

WCPFC-SC

Targeting has been difficult to address when standardising longline fishery catch and effort data, due to the multiple species typically caught together (YFT, BET, SPALB, SWO, and MLS). In 2020 analyses (Ducharme-Barth and Vincent, 2020), the CPUE standardisation models used both species cluster and HBF as catchability covariates. Cluster was derived from longline catch species composition (i.e., YFT, BET, SPALB, and other species). This approach assumes that changes in individual species' composition represent changes in targeting behaviour. However, species composition may be confounded with changes in individual species' abundance. Therefore, in the 2023 assessments of SPALB, YFT, and BET (Teears et al., 2023; Teears et al., 2024b), the final models used to generate the CPUE indices included HBF in place of species cluster as a catchability covariate, along with vessel flag. Teears et al. (2024b) state that testing of models with HBF gave similar results to those with species cluster.

Effort in longline CPUE standardisation is typically defined as the set, and the HBF variable is an important indicator of target strategy via depth changes associated with number of hooks that influence how the main line affected by currents and other oceanographic conditions. The way in which targeting interacts with effort is difficult to define due to lack of adequate information. For example, the speed at which the mainline is shot can influence depth of the mainline. Mainline material can also affect targeting, catchability, and selectivity and there was a significant change in mainline material (from kuralon to monofilament) for important fleets such as Japan in the mid-1990s that is difficult to account for because little or no research has been done to quantify these effects.

Error distributions

It remains important to select an error distribution and modelling approach that match the structure of the data. An appropriate error structure is needed to accurately represent variance around the standardised index and to determine both trend and scale. For discrete observations such as catches recorded as counts, the Poisson distribution may be suitable if variance approximately equals mean, though in practice this is rarely the case. If variance is larger than mean, the negative binomial distribution may be appropriate, while the flexible Conway-Maxwell-Poisson distribution can account for either over- or under-dispersed data.

Continuous observations such as catch per unit effort are typically right-skewed, and appropriate distribution choice can be informed using Taylor's power law. If variance is proportional to the square of the mean, lognormal or Gamma distributions may be appropriate; if proportional to the cube of the mean, the inverse Gaussian distribution might be fitted. Recent testing found that Gamma and Tweedie distributions provided best performance for estimating index scale, followed by lognormal, with inverse Gaussian performing worst (ref). When selecting error distributions, proportions of zero observations should be scrutinised. Discrete variables with excess zeros are typically fitted with zero-inflated models, while continuous response variables use two-stage hurdle or delta modelling approaches where catch rate is modelled conditional on positive encounter. The Tweedie distribution when the power parameter is between 1 and 2 is equivalent to a compound Poisson-Gamma distribution that can simultaneously account for zeros and positive catch. Poisson-link delta models represent a computationally efficient alternative that can explicitly account for potential positive correlation between encounter rate and positive catch.

Newly developed flexible modelling approaches like VAST more readily model multivariate data within CPUE standardisation frameworks. Multivariate approaches can account for correlation between modelled categories such as species or age/length/sex categories. Accounting for correlation between species can improve predictions of spatial density for rare species, and accounting for correlation across size classes can allow for size-class specific indices or standardisation of composition data.

Questions:

- How important is it to get the right statistical distribution?
- Can we prescribe an 'expert system' series of steps to choose the optimal distribution for a particular dataset?

CCSBT

Delta lognormal (Itoh and Takahashi, 2022).

IATTC

Gamma and lognormal were compared, lognormal used for YFT and gamma for BET by looking at qqplots (Haikun's)

SWO – look

Lognormal by default

ICCAT

Yellowfin: STM (still under development) delta lognormal (Satoh et al., 2024), and GLM delta lognormal (Matsumoto et al., 2024b).

IOTC

Yellowfin: GLM delta lognormal, and STM Tweedie (Kitakado et al., 2025a).

Bigeye: GLM delta lognormal (Kitakado et al., 2025b).

WCPFC-ISC

WCPFC-SC

For the most recent BET, YFT (Teears et al., 2023), and SPALB (Teears et al., 2024b), a delta-Gamma distribution has been used in standardising longline CPUE data. This decision was primarily based on (Thorson et al., 2021), which indicates that when the underlying distribution is mis specified, the delta-Gamma distribution has demonstrated optimal performance. However, in preliminary modelling of BET and YFT CPUE data for the 2026 assessments, a delta-lognormal has shown superior fit and diagnostics.

Uncertainty estimation

Uncertainty associated with CPUE indices used in stock assessment includes observation error associated with estimated time effects and process error associated with variation in catchability. Observation error in temporal effects can be estimated as part of model fitting and index construction. Many GLM analyses estimate categorical time effects relative to the base time, which can be recalculated as canonical confidence intervals to associate uncertainty with all temporal effects. Observation error for two-step delta or hurdle models can be estimated using parametric or bootstrap methods and subsequently applied within the predict-then-aggregate process. Alternatively, uncertainty can be characterised by draws from the posterior predictive distribution if fitted in a Bayesian framework.

However, standardisation usually underestimates observation error in temporal effects because it does not fully account for dependencies in input data. Dependencies occur among consecutive sets by a vessel and among sets by vessels from the same company which may communicate. There is also overdispersion due to aggregation of fish and unavailability to the analyst of important factors affecting catch rates. Some overdispersion can be accounted for by including random effects, but many sources of catchability variation are not amenable to standardisation. As a result, uncertainty estimates from CPUE standardisation models are often seen as useful for suggesting relative uncertainty among year effects, as estimates of minimum uncertainty, and to determine relative uncertainty between indices.

Process errors occur when average catchability across the fleet varies between time intervals, effectively changing the relationship between abundance index and true abundance. This variability cannot be measured directly but can be estimated indirectly with stock assessment models. This variation is often estimated or assumed to be larger than observation error in the time effects, particularly for large industrial fisheries with low observation error due to high effort data sample sizes.

Questions:

- How important is parametric uncertainty given the significance of process uncertainty?
- Recommended default approach for tRFMO longline CPUE indices?

CCSBT

Analyses are carried out using generalised additive models (GAMs).

IATTC

Process error in catchability is accounted for using random effects for vessels, hooks between float fixed effects, and fixed flag effects for joint indices.

In addition, spatiotemporal random effects are used to account for process error due to unknown causes, which allows for correlation among observations due to proximity in space and time, thus decreasing the "pseudoreplication" effect of CPUE data. No intra-trip random effects and correlation have been explored to account for potential lack of independence of sets within a trip (thus reducing the effective sample size).

In the spatiotemporal models used (VAST and sdmTMB), the uncertainty of the indices is estimated using the delta-method by combining the uncertainty in abundance estimated at fine spatial scale (i.e., in each cell).

To address the potential underestimation of uncertainty from the standardisation method, the CV are upscaled so that the average is a set number. For example, for BET the spatiotemporal model average coefficient of variation of the index of abundance was 0.13, the CVs were upscaled to average 0.20 when used in the assessment model. [Check for other species -YFT, SWO]

The data distribution in space impacts the uncertainty estimates. The indices for BET and YFT have relied on data from the Japanese fleet, which has contracted during the last 20 years towards the western Pacific, decreasing the effort in eastern areas. The contraction increased uncertainty in the most recent estimates (figure for YFT). Adding a fleet (Korea) to the dataset slightly increased effort and the amount of data in some areas, which translated into smaller CV (figure).

Figure YFT JPN and JPN + Korea

In addition to including a new fleet, another assumption used to remediate the contraction of the effort in some areas was to assume autocorrelation of the spatiotemporal random effects, via a random walk. This decreased the uncertainty by sharing information (spatiotemporal components of estimates) from earlier years with more data to the recent years with less data (Figure)

Figure: CV estimates when using random walk and when not using.

ICCAT

IOTC

The CV estimates are not included in indices when provided for assessments. The CV is generally set to 0.2 within assessment models, but this value can change according to the advice provided during data prep meetings.

WCPFC-ISC

WCPFC-SC

The CV estimates typically have been included in the indices time-series in the assessment model and rescaled if needed.

Diagnostics

Traditional model validation diagnostics such as residual analysis are important for determining if the analyst has specified the model correctly, treated zero observations appropriately, and selected the proper error distribution. However, non-Gaussian error structures, mixture distributions, and mixed-effects frameworks commonly applied in contemporary CPUE standardisation analyses complicate using traditional diagnostic approaches. One solution is to define residuals as probability-integral-transform (PIT) residuals, generated in a model-free bootstrap by comparing observations to a distribution of predicted values. The R package DHARMa is useful for calculating PIT-residuals and has tests for assessing distributional assumptions, outlier detection, identification of over- or under-dispersion, and zero-inflation.

In addition to model validation, diagnostics can develop intuition on how the standardisation model is transforming nominal CPUE. Step plots sequentially showing how the index changes with each additional covariate or model component show incremental changes. Influence and coefficient-distribution-influence plots quantify relative influence of each covariate on the final fitted model by incorporating both estimated coefficients and sampling across covariate levels each year. Applied in a spatial or spatiotemporal modelling framework, large annual influence values for year-area interaction terms could indicate misspecification of spatial structure that failed to account for large shifts in spatial sampling. Counterfactual analyses can also evaluate impact of key structural assumptions.

Additional diagnostics can be applied to interrogate spatiotemporal models specifically. Calculated residuals should be evaluated for temporal, spatial, and spatiotemporal patterns, and cross-validation can identify spatial outliers. Spatial and spatiotemporal random effects are often assumed normally distributed with mean-zero, and estimated random effects should be checked to ensure they match assumed distributions. STMs can predict abundance into un-sampled areas, influenced by adjacent observations given modelled covariance structure and modelled relationships with density covariates—these predictions should be scrutinised for consistency with expectations given understanding of species biology and fishery dynamics.

Questions:

- Can we prescribe a standard (minimum) set of diagnostics, along the lines of Carvalho et al. (2021)?
- Which diagnostics are most useful for model comparison?

CCSBT

IATTC

We do Step analysis: we compare models with increased complexity (e.g. spatiotemporal random effects, add vessel effects, add HBF, add fleet effect) and with different assumptions (e.g. independent vs spatiotemporal random effects, or gamma versus lognormal distributions for positive catch rates).

Plots of PIT residuals in space and time, qqplots of PIT residuals. We don't check the distribution assumptions of the random effects.

[Cleridy's work before Haikun]

ICCAT

GLM: Standardised residuals, QQ plots, influence plots, residuals by stratum (Matsumoto et al., 2024a)

IOTC

GLM: Standardised residuals, QQ plots, influence plots (Matsumoto et al., 2024b).

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STMs: Histograms and spatial plots of PIT residuals, time-series plots of encounter probability and positive component, effects and/or influence plots.

Model selection

Model selection is an important part of the analysis process. Analysts often employ automated procedures such as stepwise selection algorithms, although these can be problematic. Throwing all covariates into an automated procedure is unlikely to identify the most appropriate model and neglects opportunity to generate useful understanding. The analyst should first consider the objective—when generating an index rather than making inferences about covariates themselves, the goal is to correct for covariate influence and avoid potential bias. The focus on prediction rather than estimation has implications for model selection, making AIC an appropriate tool if statistical assumptions are met.

The analyst should determine a priori whether a parameter is likely to affect CPUE and whether it affects density or catchability. Starting with plausible models saves analysis time and reduces risk of overfitting. Predictive cross-validation methods can be useful for selecting between models with different structures—they can be time-consuming but are very flexible and broadly applicable. Model selection based on likelihood is compromised by lack of independence, with operational data representing time series of fishing events by same vessels with potential information sharing. The intra-vessel or intra-trip correlation can be represented by treating that factor as a random effect to account for reduction in effective sample size.

When the objective is accurate prediction for the year effect, a primary consideration for variable selection is influence. Influence is affected by combination of the extent to which covariate affects response and the extent to which its value changes through time. A variable that affects catch rates but is completely balanced may have no influence on the resulting abundance index yet can be useful if it improves precision and helps estimate other effects. Sometimes it is important to retain covariates that do not meet selection thresholds because it is clear a priori, they will affect CPUE—for example, catch rates almost always vary consistently between vessels, and analysts should confirm vessel ID is not influential before dropping it from a model.

Questions:

- If influence is the key criterion for including variables in CPUE, what metrics and approach should be used for model selection?

CCSBT

IATTC

For YFT and BET:

Comparison of Gamma and lognormal distributions: selected model based on the residual diagnostics.

200 vs 50 knots: We develop models sometimes with small number of knots and for the final model we use the largest number of knots

RW vs independent random effects: We did simulation studies that showed the RW was adequate for our case. We also compare the CVs to see which one is more realistic (when we don't use RW the CV of the area with low samples was low, and using RW the CV increased over time, which is more realistic)

Random effects for vessels proved necessary when we compared the models with aggregated data (month, 1 by 1 by HBF) with and without vessel information. When the data was aggregated to the month, 1 by 1 by HBF by vessel scale the models produced results closer to the models using operational level data (no aggregation).

How did we select the model? By default, we use HBF and vessel effects (and fleet for joint models) as catchability covariates, we do not use any environmental covariates.

ICCAT

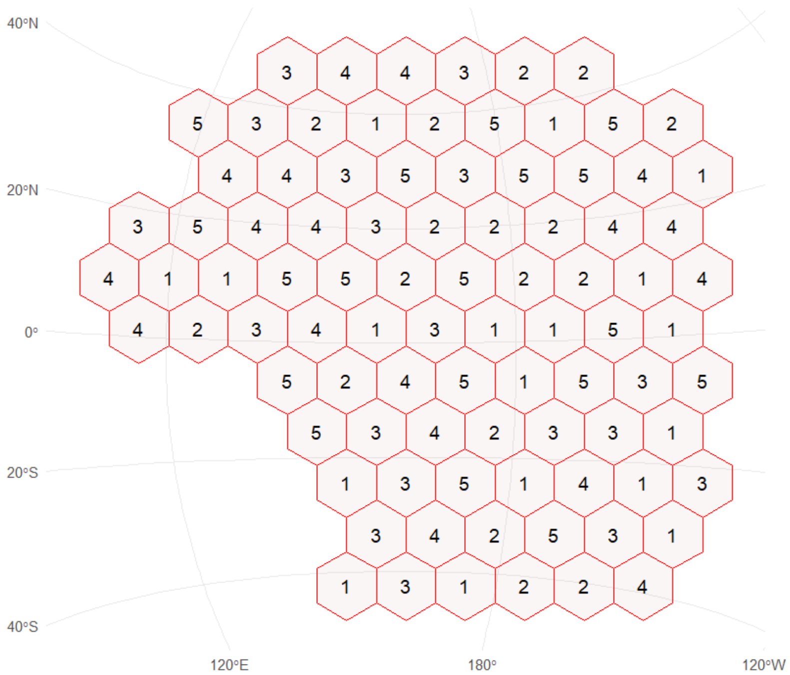
IOTC

WCPFC-ISC

WCPFC-SC

To compare predictive performance of potential models, K-fold cross-validation was applied for longline data where data is split into K, approximately equal sized datasets or "folds", by randomly sampling the data without replacement. For spatially explicit data, spatial blocking is performed to ensure that training and testing data sets are separated spatially to test the model performance in both nearby and distant locations. The sum of the expected log predictive density (ELPD) values for all the fold predictions are used for comparing performance among models.

Spatial blocking example:



Index preparation

Previous reviews of CPUE standardisation typically assumed that the index is constructed by fitting a statistical model and extracting a coefficient representing the partial effect of year—the year-effect as index method. However, this method has many limitations, most generally that treating the partial effect of year as the index does not include effects of other covariates that vary among years. One interpretation is that all other covariates are implicitly treated as catchability covariates with their effect filtered out. Research has converged upon a generic approach called predict-then-aggregate for index construction.

The predict-then-aggregate approach involves several steps: explicitly define a sampling frame ideally corresponding to the stock being assessed with spatial or other partitions; predict CPUE for each sampling unit conditioning upon density covariate values and dropping partial effects of catchability covariates by setting them at reference levels; aggregate across sampling units often by taking the area-weighted sum of CPUE; and calculate variance of the aggregate using delta method, MCMC quantiles, or bootstrapping. Predictions into un-sampled areas should be carefully scrutinised, potentially using different approaches for areas un-sampled because low catch rates make fishing uneconomic versus areas where management measures exclude fishing.

The once-common approach of extracting the year effect or equivalently predicting the year effect with each covariate fixed at a single value, cannot allow for either density covariates, interactions with the year effect, or the variable spatial stratum sizes associated with high latitudes and coastlines. Similarly, although the LS-means approach is adequate under restrictive conditions (balanced design, equal-area spatial strata, no time interactions, no density covariates needing integration), it can be biased outside these conditions. It is a special case of the more flexible predict-then-aggregate approach.

Habitat area weighting should where possible use the area of available habitat in each spatial stratum, assuming density is uniform within each. For pelagic fishery CPUE, approximate ocean areas are often determined from grid cell area at latitude after subtracting land area, but habitat available to individual species can vary seasonally, with environmental variables, and long-term with climate change. Inclusion of oceanographic density covariates or applying a post-hoc environmental filter can restrict index calculation to viable spatial strata.

For hurdle models with the binomial component fitted using logit transformation, the reference levels of catchability covariates affect predicted annual probabilities of non-zero catch, and analysts should adjust the mean of the index to avoid bias in trends and variability. Binomial rescaling adjusts the mean of the binomial year effects on the logit scale to equal the mean of the annual probabilities of nonzero catch in the observed data (Hoyle et al., 2024).

Questions:

- What are the pros and cons of LS-means versus prediction-based methods?

CCSBT

The Japanese SBT indices include time-area interactions and are constructed using a predict-then-aggregate approach, with weighting by available ocean area and binomial rescaling. (Itoh and Takahashi, 2022; Itoh and Takahashi, 2025).

IATTC

In the spatiotemporal modelling approach used in IATTC the spatial domain of the index is defined before fitting the model. We apply selection criteria to remove the 1° x 1° spatial strata and vessels that are fished only sporadically and have sparse data (e.g., 1° by 1° strata and vessels need to have at least 20 quarters of data since 1979 to be included in the model). Then based on the spatial distribution of the resulting data set, aggregated over years, the spatial domain of the model is defined.

Summing of the estimated density by stratum X stratum area over the spatial domain of the index. Because we assume either lognormal or gamma distributions for positive catches [check], bias correction is applied to the index in the spatiotemporal models.

Habitat variables are not used. We assume that the whole area in each stratum has the same density.

The spatial domain does not change based on habitat or El Nino – La Nina. (for the PS- index for YFT we used variable spatial domain giving El Nino – La Nina conditions and quarter SAC-16-INF-F).

ICCAT

Indices for BET and YFT tuna (Matsumoto et al., 2025; Matsumoto et al., 2024a) are constructed using the R package *cpue.rfmo*, which uses a predict-then-aggregate approach, with weighting by available ocean area and binomial rescaling.

IOTC

From 2015 to 2019, *cpue.rfmo* was used, with a predict-then-aggregate approach, weighting by ocean area, and binomial rescaling. Spatial reweighting (Punsly's approach) is also used to adjust for the effects of effort moving through time.

From 2020 to 2024, indices were constructed using LS-means, without weighting by ocean area or binomial rescaling. From 2025 binomial rescaling was reintroduced (Kitakado et al., 2025c).

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Prediction is performed by creating a grid of 5x5° cells for each year-quarter with catchability covariates held at a reference level and environmental variables allowed to vary over space and time to provide improved density estimates where sampling may be poor. These density covariates are specified at the averages for each specific cell-year-quarter stratum. Then the resulting density estimates are area-weighted by region with cell area varying over space dependent on latitude.

Regional scaling estimates

Regional scaling estimates are derived from CPUE data.

Questions

- Are there ways of independently validating regional scaling estimates from CPUE indices using other data sources or modelling platforms (e.g., SEAPODYM)?

CCSBT

IATTC

ICCAT

IOTC

WCPFC-ISC

WCPFC-SC

Regional scaling is estimated from differences in scale from CPUE indices derived in a 'global' model (all assessment regions modelled collectively).

Process

Coding practices

CPUE standardisation analyses for pelagic longline fisheries are typically conducted in R, involve large datasets often spanning millions of observations across ocean basins, and must be updated regularly as new data become available for stock assessments. The coding and workflow practices underlying these analyses affect reliability, reproducibility, and efficiency. Poor coding practices can introduce errors that are difficult to detect, make analyses difficult to update or transfer between analysts, and undermine confidence in results. As analytical methods become more sophisticated with spatiotemporal models like VAST and sdmTMB, the complexity of the underlying code has grown correspondingly, making good practices essential.

Key principles for pelagic longline CPUE analysis code include reproducibility, readability, and avoiding repetition. Analyses should be fully reproducible, with clear documentation of computing environments, package versions, and complete workflows from raw data to final outputs. Code should be written for human readers first, with consistent formatting, descriptive variable names, modular organisation, and comments explaining the rationale for analytical decisions rather than just describing what the code does. The DRY principle (Don't Repeat Yourself) is particularly relevant to longline CPUE analyses, which often involve running similar standardisations across multiple species, regions, or model configurations—repeated code blocks should be consolidated into functions, reducing the risk of inconsistent modifications.

Version control systems, particularly Git, have become essential tools for scientific computing and provide complete change histories, the ability to revert to previous versions, branching workflows for exploring alternatives, and collaboration support through platforms like GitHub. For stock assessment CPUE analyses that must be repeated regularly, version control enables clear tracking of what changed between assessment cycles, with tagged releases corresponding to specific assessment versions providing an audit trail for scientific review. Well-organised projects should include clear directory structures, main workflow scripts, separate files for custom functions and configuration, and comprehensive documentation at multiple levels—from inline comments explaining specific decisions to project-level overviews and analytical documentation recording methodological rationale.

As pelagic longline CPUE analyses increasingly involve multiple analysts, institutions, or RFMOs, collaborative practices become important. These include shared coding standards and style guides, code review processes where changes are examined by colleagues before integration, clear protocols for contributions and version management, and shared repositories with appropriate access controls. Adopting these practices would support consistency across RFMOs, facilitate collaboration on joint indices, and improve the overall reliability and transparency of CPUE-based abundance indices for tuna stock assessments.

Questions:

- Is there a need for a shared set of CPUE analysis tools across tuna RFMOs?

CCSBT

IATTC

The code is available upon request, not published. We used the R libraries VAST until 2024 and sdm.tmb in 2025 after testing whether the two libraries produce the same results for models with the same assumptions and data.

We have Rmarkdown code for data visualisation, filtering and processing and a separate R code for standardisation with spatiotemporal models, production of the final results and diagnostics. The codes are stored internally at IATTC for each assessment, so there is a possibility to verify the changes done from year to year.

In previous years, code and description of the methods were put into internal reports to be shared with the Japanese scientists who brought the operational level data to work with us, while a description was included in the assessment document for BET.

In 2025, the collaborative work was expanded to include Korea, China and Chinese Taipei. The code was shared with collaborators from those distant water longline fleets that contributed to the join CPUE analyses, and a stand-alone SAC-INF document was prepared to describe all the analyses done jointly as well as the final indices. The work focused on YFT to be able to use the indices in the 2025 YFT assessment and further work is planned to extend these analyses to BET.

One challenge to share the code is the confidential nature of the operational-level data used in the most recent longline CPUE analyses done at the IATTC. Code could be publicly shared but without accompanying data to run it and reproduce the results. Generating data to test the code will increase analyst workloads.

In addition, data may be shared in different formats each year, thus requiring fine tuning the code to tailor it to the new data format. This may preclude the usefulness of a version control system.

One aspect that contributes to transparency is hosting scientists from collaborating CPCs in our offices in La Jolla for extended periods. We provide one-on-one capacity building on spatiotemporal methods and associated analysis. Therefore, the collaborators can reproduce analyses with their own data and understand the results. Full analyses can only be reproduced by IATTC staff authorised to access the operational level data from several fleets simultaneously.

The IATTC Stock assessment program has a repository where we store most of the code used in the stock assessments https://github.com/HaikunXu/IATTCassessment, so adding the code for CPUE standardisation could be a relatively simple step once we decided what to do about the confidential data needed to run the analyses.

ICCAT

In 2018 and 2019 bigeye and yellowfin assessments, analysts used the R package cpue.rfmo (Hoyle, 2025b).

IOTC

From 2015 to 2019 analysts used the R package *cpue.rfmo* (Hoyle, 2025b) for bigeye, yellowfin, and albacore indices.

Analyses since 2020 have used various

WCPFC-ISC

WCPFC-SC

Code for CPUE analyses is typically made available through github repositories created specifically for each analysis. However, due to the confidential nature of the data, the data are not available to the public. Reproducibility is important for future analysts and all analyses are performed on virtual machines (VMs) that have very limited accessibility (2 or 3 analysts). Code, raw data, processed data, results, and plots are all maintained on the VMs for reproducibility.

Reports on CPUE analyses are written with the intention of making the analyses relatively reproducible even without the code.

Use of indices in assessments

Each CPUE index in a stock assessment is associated with a fleet, and an approach using joint standardisation of CPUE and composition data can define two separate fleets with different purposes. One fleet is associated with the CPUE index and assigned composition data weighted by spatial distribution of CPUE representing abundance, with time-invariant selectivity so that changes represent changes in underlying population composition. The other fleet is assigned composition data weighted by time-varying spatial distribution of catch so that time-varying selectivity can extract fish of appropriate composition.

Often two or more indices or other datasets provide information in conflict. The law of conflicting data states that since data are facts, conflict implies model misspecification. If information from different sources conflicts, analysts should try to identify the cause and resolve it. If resolution is not possible, analysts should create alternative models that omit conflicting datasets, with remaining datasets well fitted in each model. In general, information about population trends in CPUE should have priority over information in composition data because it is usually more reliable (Francis, 2011).

It is relatively common practice to split CPUE series by time into separate non-overlapping sections in separate fisheries, but this is often counterproductive. Splitting can occur in response to changes to logbooks, availability of species-specific catch data, or operational patterns, but it should be avoided where possible unless there is another reliable abundance index. Even when there is reliable information to suggest that catchability has changed, splitting the time series into two indices with independently estimated catchabilities may be inadvisable. Without the stabilising constraint through time provided by a continuous index, the model will adjust catchability and the abundance scale independently before and after the split. The estimated catchability change can be unreasonably large and counterintuitive, because the abundance scale information, usually obtained from size composition data, is unreliable.
There are usually better alternatives to splitting: if data availability changes, analysts should strive to retain similar catchability and selectivity; if catchability changes are expected due to technology change, analysts should consider whether the catchability changes estimated in the stock assessment are plausible (e.g., see IATTC BET example below).

Trends in catchability over time can bias indices. Technological creep increases catchability in almost all analyses involving time series exceeding one decade in temporal coverage.

Questions:

- Do we have reliable data to inform the actual rate of 'effort creep' in LL fisheries, and what further work is needed?
- What is the appropriate response to uncertainty associated with rates of effort creep?
- Consensus about rates of effort creep has been difficult to achieve. What steps might help to address this?
- Do we need to consider different variables in the CPUE standardisation if the index is going to be used in a Management Procedure as opposed to an assessment?

CCSBT

IATTC

Main piece of data in BET, SW YFT, S SWO and DOR assessments

1) We treat the longline-CPUE derived indices of abundance as an independent fleet ('survey') with no associated catches. The indices have their own length-composition data that are obtained by standardising the length composition from longline catches using spatiotemporal models in VAST (RVDTT-01-03). These models include categories for each 10-cm length class for BET and YFT. The bin size was chosen for computational considerations, as smaller bin sizes would require longer computation times and more RAM. The composition data cover only ~10% of the CPUE data and do not have vessel identification, which precludes the modelling of both data types in the same spatio-temporal models. The final length composition for the index in each time step (quarter) is obtained by multiplying the predicted abundance in each 1° by 1° by quarter stratum by the standardised length frequencies in the 1° by 1° by quarter stratum and summing them across space. Selectivity for the index is assumed to be time-invariant.
2) An important consideration is data weighting, in the case of conflict between the index and the length composition. To reduce the impact of longline composition data on the scaling parameter (R0) in comparison with the index, due to double use of that data in both the index and the catches, the selectivity of the longline catch fisheries (i.e. not surveys) is assumed to be time-variant and/or the length composition data for the catches are downweighted according to a fraction of what the Francis method suggested (e.g. 20% for BET ref).
3) We encountered conflict between indices derived from longline data with indices derived from purse-seine data for yellowfin tuna, indicating model misspecification. The spatial domains of the two indices overlapped only slightly, if at all. The conflict was resolved after spatial structure was accounted for via independent models for the two areas.
4) In the previous BET model, the longline index was split in 1993 due to changes in HBF and mainline material. However, the estimated catchability coefficient for the late period index was lower than that for the early period, contrary to what would be expected due to technological creep. Following this discovery, a single index was produced for the whole period in the 2024 assessment for BET and in the 2025 YFT SW model.
5) Both BET and YFT assessment include scenarios of technological creep represented as increase in catchability of % a year in the longline index. For BET is 0, 1 and 2% annual increase, while for YFT is 0, 1%.

ICCAT

Joint CPUE indices for BET and YFT are provided as regional indices (North, Tropical, South Atlantic) for use in Stock Synthesis assessments. The transition from multiple individual CPC indices to single joint indices per region represented a significant improvement in consistency.

BET assessments also use a single joint index per region. The 2025 analysis compared results from the new joint index with the 2021 assessment index (which used aggregated data), providing insights into the effects of data resolution on assessment inputs (Matsumoto et al., 2025). BET

For YFT, the 2024 workshop produced both continuity GLM indices and preliminary VAST indices, allowing the assessment to evaluate sensitivity to modelling framework (Matsumoto et al., 2024a; Satoh et al., 2024).

For SWO, combined indices from multiple CPCs (Gillespie et al., 2022) are available for the north Atlantic, as are multiple national indices. The assessment scenarios (Anonymous, 2022) include Stock Synthesis models with alternative combinations of national indices, and another fitted to the combined index, although it is unclear whether this index was additional or replaced the other indices. JABBA scenarios included either nine CPC indices, one of two subgroups of indices, or the combined index alone.

For BFT, Japanese longline CPUE indices are a key input, with indices provided separately for West Atlantic and NE Atlantic areas (Tsukahara et al., 2022), alongside joint indices from observer programs (Lauretta et al. 2021).

Information on how ICCAT handles index splitting, conflicting indices, and catchability creep in assessments would strengthen this section (noting that practices vary by species group).

IOTC

Due to changes in targeting and fishing practices, JPN data are typically split around the 1990s for standardisation, for billfish and sharks. TWN, China have data starting from the 1970s, but there are concerns over data quality so TWN, China CPUE indices generally begin from the 2000s. Other CPCs generally have CPUE data from the 2000s onwards or later.

Conflict between CPUE indices is checked prior to inclusion within assessment models (e.g. IOTC-2025-WPTT27(AS)-15rev4.

WCPFC-ISC

WCPFC-SC

In recent assessments, for YFT, BET, and SPALB, analyses using LL data have been modelled using a ‘global’ model (all spatial regions modelled together) with all flags included to ensure cohesive indices with differences in catchability modelled collectively. However, due to large data sets and the need to include vessel ID, regional analyses are being explored for the current YFT and BET CPUE analyses.

Differences in selectivity are more difficult to manage due to differences in coverage, resolution, and quality over space, time, and by flag as evidenced by data conflicts in recent YFT and BET assessments. This is an area needing further investigation and development to ensure assumptions are being met for stock assessments purposes. Models for standardising length data have not been investigated thoroughly for adoption. As such, corresponding length data are typically weighted using CPUE indices surfaces.

Issues specific to management procedures

Transparency, review, and independence

CPUE indices are often the most influential data inputs to tuna stock assessments, directly shaping estimates of stock status and the management advice that follows. The standardisation process involves numerous decisions—regarding data selection and filtering, covariate inclusion, model structure, and index construction—each of which can substantially affect resulting abundance trends. Given this influence, analysts should clearly document not only the methods employed but also the rationales for key decisions, alternatives considered, and the sensitivity of results to different choices.

Information requirements to support acceptance of abundance indices should include fishery descriptions covering catch, effort, size composition, nominal CPUE by area and season, and history of fishery development. Analyses should detail data selection criteria, model specification, and any filtering applied. Results should include model diagnostics, comparison of nominal and standardised indices, residual analyses, and characterisation of uncertainty. Reviewers must be able to assess whether analyses are appropriate for the data and whether conclusions are robust.

The complexity of modern methods, particularly spatiotemporal models, has increased beyond the review capacity of most RFMO scientific committees. Specialised statistical expertise is needed to ensure insufficient scrutiny and resolve technical issues. Independent peer review, either through external reviewers or dedicated methods working groups, can address this gap. Independent stock assessment reviews across RFMOs have consistently highlighted CPUE standardisation as a priority area (refs).

Safeguards against analytical bias are important given the influence of indices on assessment outcomes. These may include pre-specification of approaches before examining effects on trends, sensitivity testing across plausible configurations, and external review. Reproducible code allows others to verify results and test alternatives. Where analysts develop both indices and assessments, separating these tasks in the workflow can help ensure index development is not influenced by assessment expectations. Methods should be applied consistently across assessment updates; changes to methodology should be justified and their effects documented using a stepwise approach.

When multiple analysts or institutions produce indices for the same stock, standardised approaches and shared code can increase consistency. The complexity and resource requirements of CPUE analyses argue for shared infrastructure, common analytical frameworks, and collaborative development of methods across RFMOs, which can improve both efficiency and the consistency and transparency of the science underpinning tuna management.

Questions:

- What level / forms of independent review are needed for CPUE standardisations in key assessments?
- How can independent review of CPUE standardisation be implemented, and sustained, through time in RFMOs?

CCSBT

Proposed changes to index methods are reviewed by the CCSBT CPUE working group.

All aspects of stock assessment methods are reviewed by the CCSBT expert panel of stock assessment scientists, which includes experts on CPUE standardisation methods.

Analysis code is not publicly available.

IATTC

Primary analyses for BET & YFT are carried out by IATTC staff in collaboration with JPN scientists.

S SWO with JPN data was done by Japanese Scientists (ref) using INLA

Review? The IATTC had an external review of the data aspects of stock assessment (RVDTT-01 report), during which the indices of abundance derived from longline CPUE, and length composition data were discussed. A document was produced which described the methods in detail and provided the rationale for decisions during CPUE standardisation, including data filtering, model structure, sensitivity analyses and model diagnostics (RVDTT-01-02)

We collaborate with scientists from member countries, so they also understand the methods and get the full code and results.

The level of documentation is limited in documents that repeat analyses done in previous years, but key reports are publicly available, as well as publications done by the team in the peer-reviewed literature that analyse aspects of the methodology (e.g. simulation experiments to assess the effect of contraction of the longline effort and sampling, evaluation of impact of including vessel effects in purse-seine indices).

Analysis code is not publicly available.

Methods have evolved over the years from GLMs to spatiotemporal models of CPUE and length composition data as listed in the "Modeling Framework" topic. We are in the process of transitioning from the R library VAST to sdmTMB library because the sdmTMB library is more efficient, i.e. requires less computation time.

Work dynamic: The same scientists work on both the indices of abundance and the stock assessments; however, we work as a team that constantly reviews each other's work through weekly team meetings, using "scrum" group dynamics https://www.scrum.org/learning-series/what-is-scrum//. During the CPUE standardisation season, we have visiting scientists and may meet more than once a week to speed up the iterative model development process. Several team members are proficient in spatiotemporal modelling and statistical modelling which turns the weekly meetings into peer-review sessions.

The IATTC staff also participates in ISC working groups where the data preparation and CPUE standardisation processes follow a different approach. Each CPC brings its own index of abundance and the chosen methods vary widely among CPCs (e.g. habitat standardisation models, spatiotemporal models, GAMMS for BUM in the Billfish Working Group).In those WGs the staff does not have access to the data, so it is not involved in analysis, but does the "peer-review" of the analysis produced by the national scientists. Clear guidelines would be useful both for the analyst and the reviewers.

ICCAT

The primary joint analyses used in stock assessments for BET and YFT are carried out by national scientists from participating CPCs, sometimes with overview from an independent expert (Matsumoto et al., 2025; Matsumoto et al., 2024a). Following preparatory analyses by each CPC, in-person workshops bring together all data providers for collaborative analysis.

Review occurs during the CPUE workshops themselves (among participating scientists), at data preparatory meetings (Tropical Tuna Species Group), and during stock assessment sessions. However, specialised independent external review of CPUE methods has not been a regular practice at ICCAT.

Analyses are based on code that is publicly available in a GitHub repository, cpue.rfmo (Hoyle, 2025b), but changes to the code since 2019 have not been posted to the repository.

Documentation of CPUE methods is relatively good through joint workshop SCRS documents Satoh 2024 (Matsumoto et al., 2025; Matsumoto et al., 2024a; Satoh et al., 2024). Ongoing documentation of rationales for analytical decisions and sensitivity to alternatives could be strengthened.

Unlike CCSBT, ICCAT does not have a dedicated CPUE working group or external expert panel specifically reviewing CPUE methods.

IOTC

Primary analyses for ALB, BET, YFT carried out by university scientist with input from national scientists. In 2025 there was some overview by independent experts and secretariat scientists, but this does not seem to be ongoing.

Review of final documents by attendees at WPTT, WPTmT, and WPM working parties, with SC reviewing science processes. However, documentation of recent tropical tuna indices has often been limited and provided late, which has not permitted much review by IOTC working parties.

All documents provided publicly on IOTC website.

The current analysis code is not publicly available. The analysis code used from 2015-2019 is publicly available via cpue.rfmo.

Recent methods have varied considerably from year to year, and errors associated with changes have affected stock assessment results.

ICCAT does not have a dedicated CPUE working group or an external expert panel specifically reviewing CPUE methods.

WCPFC-ISC

Analyses carried out by national scientists.

Review of final documents during ISC working group meetings.

Some documents provided publicly on ISC working group website.

Level of documentation varies between indices.

Analysis code not publicly available.

Methods for each index are generally consistent from year to year.

WCPFC-SC

Analyses of ALB, BET, and YFT indices mostly carried out by SPC scientists, though with some analyses of national datasets by national scientists.

Limited review of methods during pre-assessment workshops.

Limited documentation that varies each year.

Analysis code is not publicly available.

Methods for each index are generally consistent each year.

Discussion

Needs, wants, issues:

Data

Document major changes in data collection, national regulations, technology that may contribute to effort creep.

Information on the differences in fishing strategies/configurations/practices between CPCs and changes across time within a CPC (including secondary targets such as swordfish in the bigeye fishery).

Continuous provision of operational level data

Inclusion of fields in the logbooks to account for changes in gear (e.g. trapline/lazo/ring)

Data quality metrics (e.g. have data undergone QC or are they raw) to help with inclusion/exclusion decisions.

Provision of CV to assessment scientist prior to stock assessment...?

Analyses

Explore environmental covariates

Explore habitat models (e.g., Bigelow et al., 2003; Hinton and Nakano, 1996; Maunder et al., 2006a)) integrating tagging information regarding habitat utilisation.

Explore changes in spatial random effects correlation direction because of currents.

WCPFC

Data issues

- Characterisation and preparation

    - HBF is imputed by flag. This process is computationally burdensome and requires substantial storage
    - Data provision by member countries can be delayed resulting in difficulties in data preparation
- Exploration of the data
    - CPUE standardisation needs to be considered in conjunction with corresponding size compositions. Member countries have varying levels of data quality and sometimes, time-varying differences in data quality as well as fishing strategies (and targeting), further complicating the appropriateness of various data sources. Criteria for the inclusion of various data sources is difficult to define and often can be complicated by political influences.
- Mapping the effort
    - Mapping effort spatially and temporally can indicate important changes in fishery dynamics. Some fisheries are not consistent over time and can leave areas with little or no data to inform the model
    - Effort is typically defined as the set with HBF being an important variable indicating targeting via depth changes associated with number of hooks that influence how the main line affected by currents and other oceanographic conditions. The way in which targeting interacts with effort is difficult to define due to lack of adequate information. For example, the speed at which the mainline is shot can influence depth of the mainline. Mainline material also can have impacts on targeting, catchability, and selectivity and there was a significant change in mainline material (from for kuralon to monofilament) important fleets such as Japan in the mid-1990s that is difficult to account for because little or no research has been done to quantify these effects.
- Understanding how HBF has changed
    - HBF was typically below 20 before the change in mainline material to monofilament which saw an increase to above 20 to compensate for the difference in weight as monofilament is lighter and to achieve the correct depth of the mainline, more hooks were included between each float
- Which fleets report data well or not
    - From Tiffany Vidal (Principal Fisheries Scientist-Data Management):
        - "China's operational data is a mess, and there remain some gaps in coverage (e.g., we assign missing catch to high seas, as has been done in the past, but certainly an uncertainty). We do the same for TW, but it seems there is much less missing catch (missing as in not reported in operational data) as compared to their ACE. In addition, it seems there are position issues form data coming from iFIMS. I am not sure if this affects purse seine more than longline, but I expect it could impact both. We're planning for an analysis this year to try to compare logbook positions to VMS to see how prolific these position errors might be, but with datetime issues and polling frequency, I suspect it will be tricky, especially for longline."

"There are also issues with some fleets reporting catch in numbers and not weight (US and KR specifically). It seems an average weight has been applied in the past, but we are still struggling to sort out how to do this. My preference is to go back to the countries and encourage them to provide catch in kgs. We are working with KR and US right now. We'll chat with Corey and Jed as well to think this through if the countries can't provide these data."

        - "VN, PH, ID – very little longline data, so some uncertainties there, but their catches have declined significantly in recent years. Seems longline is a dying gear in that region. Bait and gear are more expensive that using other gears. Hard work, etc."
- Covariate availability
    - Flag is often a covariate used in modeling CPUE and multiple flags with similar fishing strategies can be grouped into DWFNs or PICTs. However, vessels can initially be associated with a PICT country (e.g., Kiribati), get chartered by a DWFN country (e.g., China) for several years, and then be flagged back to their original PICT country. Thus, flag might not be the best indicator of fishing strategy whereas, freezer type might be the best indicator.
- Environmental variables available
    - Variables used as density covariates: ENSO, SST, temperature profiles used to develop depth 15° isotherm and Δ depth of 12° to 18° isotherms (SC19-SA-WP-03 YFT_BET_assesment_CPUE_Inputs_Finl_Rev1.pdf).
    - Season has also been implemented in BET CPUE standardisation as BET indicated highly seasonal density dynamics.

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