IOTC-2025-TCAC15-07

Biomass indicators of potential use for allocation of the Total Allowable Catch in the Indian Ocean

Prepared for Indian Ocean Tuna Commission

July 1, 2025

Report prepared by:
Charles T T Edwards

For any information regarding this report please contact the author at:

CESCAPE Consultancy Services
Switzerland, South Africa & New Zealand

Email: cescapecs@gmail.com
Telephone: +41 78 300 08 91

CESCAPE Client Report

Client project code:	MTF/INT/661/MUL – TF.NFITD.TFAA970097099
Project name:	Review of biomass allocation criteria
Date of report:	July 1, 2025
Prepared for:	Technical Committee on Allocation Criteria

Introduction

Since 2011, the IOTC Technical Committee on Allocation Criteria (TCAC) has been dedicated to establishing a mechanism for the allocation of Total Allowable Catch (TAC) for IOTC species. Allocation of the TAC to contracting parties (CPs) and co-operating non-contracting parties (CNCPs; jointly referred to as CPCs) is crucial for the sustainable management of IOTC stocks. Not only does it ensure that catch is distributed in a way that prevents regional depletion, but it is also necessary for effective governance by each CP and CNCP in accordance with their allocation.

One of the primary points in recent discussions within the TCAC has been the use of historical catch data (IOTC, 2024a, 2025), which is an important criterion in allocation regimes across the tuna Regional Fisheries Management Organisations (tRFMOs; Seto et al., 2020). However, the catch data held by the IOTC Secretariat is often inadequate for this purpose, due to the significant contributions of artisanal and small-scale fisheries, which lack robust data collection and reporting protocols. This deficiency complicates the reconstruction of historical catches (Zeller et al., 2023), particularly for the coastal species (IOTC, 2024b).

The use of catch as a means of allocation is justified on the basis that it provides evidence of a legitimate historical interest in the resource. Regardless of, or in addition to, this historical interest, coastal states have an inherent sovereign right to the resource within their Exclusive Economic Zones (EEZs; Sinan & Bailey, 2020). However, sovereignty can only exercised through knowledge of the fisheries and/or biomass within each EEZ, relative to other EEZs and the high seas. In response to this challenge, the TCAC has discussed the possibility of employing allocation metrics that respect both the catch history and the biomass distribution of each of the main commercial species (yellowfin, bigeye, skipjack, and albacore tunas, and swordfish; IOTC, 2024a, 2025).

Estimating the biomass distribution for the main commercial species is difficult, because of the responsiveness of their productivity and movement to a highly dynamic marine environment, and limitations of the data. At their 14th meeting, the TCAC developed a targeted work plan, which includes provision of advice by the Secretariat on viable proxies for the biomass distribution and artisanal catch history (IOTC, 2025). The current report provides a short review aimed at identifying estimation methods and proxies that may be useful.

Biomass indicators

For species with reasonably uniform biomass distributions, the size of an EEZ would provide an indication of the biomass proportion that it contains. However, large spatial heterogeneity exists, which motivates for a more informed approach. These approaches can be process based, relying on an understanding of species biology, or empirical.

Biological principles

Knowledge of tuna biology provides a mechanistic means of understanding the biomass distribution. Spalding et al. (2012), for example, described pelagic regions of the world, including the Indian Ocean, that differ in terms of their biophysical properties. The assumption is that these differences will drive spatial differences in the biodiversity (i.e., the relative productivity of different species). As part of the Agreement on Marine Biodiversity of Areas Beyond National Jurisdiction (BBNJ), which motivates for the establishment of marine protected areas on the high seas, further scientific efforts have been made to map the biological features of the Indian Ocean (Dunstan et al., 2020, Crespo, 2025). These have delineated regions on the basis of their biodiversity. However, identification of biologically distinct regions is currently designed as a guide for ecosystem-based and spatial fisheries management (Juan-Jordá et al., 2024). In their current form these scientific efforts do not provide a quantitative, species-specific measure of relative biomass or productivity that could be useful in the current context. Nevertheless, they may guide empirical approaches that more directly assess the biomass distribution.

Empirical approaches

Recreating the spatial biomass distribution from fisheries data is increasingly being recognised as an important objective of fisheries stock assessment (Punt, 2019), and has led to the development of sophisticated spatio-temporal models of the biomass dynamics. These depend on equally representative models of the abundance, which convert raw empirical catch rate data into an index that can then be interpreted by the assessment model.

Abundance models

As part of the IOTC's stock assessment cycle, statistical models of the commercial catch rate data are used to extract a temporal or spatio-temporal index of abundance. These models are designed to remove the counfounding effects of, for example, fishing behaviour, gear use or location, with any residual change in the catch rate interpreted as a change in the underlying biomass density (Maunder & Punt, 2004). Because of their importance to stock assessment, these methods have a long history of development and application. In the current context, they could also be used to provide information on the distribution of the biomass in support of a TAC allocation procedure.

In the Indian Ocean, spatio-temporal models are used to construct an index of abundance for all the major fisheries (e.g., Fu et al., 2022, Fu, 2023, Haputhantri et al., 2023, Kaplan et al., 2023, Urtizberea et al., 2024). An index is constructed for each industrial fishing fleet. Although artisianal catches by coastal states can be significant, the quality of the data is too poor for their use in construction of an abundance index.

For each industrial fleet, the spatial resolution of the model is determined by the resolution of the data. Typically, purse seine data are aggregated per $1^\circ \times 1^\circ$ cell, whereas longline data are aggregated per $5^\circ \times 5^\circ$ cell. A $1^\circ \times 1^\circ$ aggregation is small enough to allow meaningful representation of the data within an EEZ, but a $5^\circ \times 5^\circ$ cell is not. Unfortunately, although the $1^\circ \times 1^\circ$ purse seine data does include catches from the EEZ of some of the east African coastal states, many EEZs are not included. The industrial purse seine fleets are also limited in their spatial distributions, being largely confined to the western half of the Indian Ocean. The longline data, by contrast, have a much wider spatial coverage, but at a resolution that does not permit modelling of the catch rate at the level of the EEZ. Pole-and-line catch rate data also exist, but these are restricted to the Maldivian fishery.

The gear type and resolution of the data will determine which species can be usefully modelled. In particular, it is unlikley that a useful distribution of skipjack biomass could be obtained from spatial modelling of the catch rate data, because skipjack are primarily caught using purse seine and pole-and-line fishing. The other species (yellowfin, bigeye, albacore and swordfish), are caught by longlines and are therefore more amenable to this approach.

To model the abundance at the level of the EEZ using $5^\circ \times 5^\circ$ longline data it would be necessary to: a) predict the abundance at a spatial resolution higher than that of the data; b) reliably predict the abundance in coastal regions with limited fisheries data. These requirements could be helped by the use of environmental covariates. If strong relationships can be identified between the catch rate and environmental conditions, then it may be possible to increase the spatial resolution of the prediction, and include areas where the data are sparse.

It is technically feasible to include environmental conditions when modelling abundance, and justified based on their perceived influence on the catch rate (e.g., Maunder et al., 2006). This idea was recently explored by Langley (2024), who applied the Vector Autoregressive Spatio-Temporal (VAST) model of Thorson (2019) to longline catch rate data for yellowfin tuna. The VAST model is able to include environmental covariates, and can also interpolate the predicted density surface at a resolution that is higher than the resolution of the catch rate data; two features that would make it suitable for prediction of the biomass at the level of the EEZ. In general however, the explanatory power of the measured environment appears to be small. Environmental covariates typically have limited predictive power: much less than a geo-referenced spatio-temporal interaction term. In other words, it is the time and place of fishing, rather than the environmental conditions, that determine the catch rate. Even if environmental covariates were used, this makes it hard for any model to reliably predict the biomass into areas with few data. However, this conclusion may be due, in part, to the spatial resolution of the data used to parameterise the model, meaning that environmental relationships could be more easily discerned if higher resolution data were available (e.g., Mondal & Lee, 2023).

If it is difficult to reliably predict the biomass at the level of the EEZ, for the longline species at least (yellowfin, bigeye, albacore and swordfish) it is possible to predict the biomass over much of the Indian Ocean at the level of the $5^\circ \times 5^\circ$ cell using publicly available data. Should this approach be adopted, the biomass per cell would need to be distributed between each EEZ that it overlaps. For example, the biomass could be distributed assuming that it is uniform within each cell (i.e., using the relative area size inside and outside of each EEZ).

A product of catch rate modelling approaches is an appreciation of the extent to which population dynamics can drive large seasonal and annual changes in abundance. When estimating a biomass distribution for the purpose of TAC allocation, a suitable reference period would therefore be required. This is further complicated by change at the supra-annual level due to global environmental cycles (Wu et al., 2022) and trends (Dueri, 2017, Dalpadado et al., 2024). The spatial distribution of the longline data has also become more restricted over time, particularly in the north western Indian Ocean. For these methods to be used for TAC allocation, decisions would need to be made on whether the data period should be restricted to years that are thought to be representative. Althernatively, spatio-temporal models such as VAST can estimate temporally invariant spatial effects that might provide a suitable estimate for the spatial biomass distribution.

Assessment models

Modern stock assessment models adopt an integrated approach whereby diverse information sources are combined to parameterise the model (e.g., Maunder & Punt, 2013, Methot & Wetzel, 2013, Doonan et al., 2016). They are typically designed to represent our best understanding of the resource status, productivity and future dynamics. Because these assessments model response of the resource to catches, and because catches are spatially allocated, the better stock assessment models attempt to partition the resource spatially, rather than aggregate the dynamics into a single spatial unit (Punt, 2019). This is a difficult problem that can be helped by information on the relative biomass in different spatial units. Given that catch rate is indicative of the biomass density, spatial stock assessment modelling therefore provides a prescedent for the use of catch rate data to partition biomass between large spatial units at an oceanic scale.

Stock assessments for yellowfin, bigeye and albacore partition the resource into regions within the Indian Ocean that are intended to allow for a more accurate estimation of the dynamics per region (Langley, 2019, Fu et al., 2022, Rice, 2022, Urtizberea et al., 2024). Estimation of the biomass distribution per region is informed by a shared relationship between the model-predicted biomass density and a standardised catch rate index (i.e., a higher catch rate index equates to a higher estimated biomass density for that region). Construction of the catch rate index makes use of a *regional scaling factor* that adjusts the index up or down depending on the relative biomass for that region (Hoyle, 2019, Hoyle & Langley, 2020).

The regional scaling factor is also derived from a model fit to the commercial catch rate data. But compared to the catch rate standardisation methods used to construct spatio-temporal trends in abundance, regional scaling factors are relatively simple. For example, they can be constructed without a year-dependent change in the biomass distribution. Instead, the biomass distribution is assumed to be constant over a multi-year period being modelled, and which has been selected as a reference period (Hoyle & Langley, 2020). The relative biomass is extracted from the spatial model coefficients, which can be summed across spatial units per region to give a measure of the relative biomass. This is the approach currently used for stock assessments of bigeye and yellowfin in the Indian Ocean (Hoyle & Langley, 2020, Fu et al., 2022, Urtizberea et al., 2024) and has a history of application for tuna assessments in the Western Central Pacific, including skipjack (e.g., Hoyle et al., 2010).

Conclusions

The best available data with which to inform estimation of the biomass distribution are likely to be commercial catch rate data. Well established modelling approaches allow the relative biomass density to be estimated across space. However, most catch rate data in the Indian Ocean comes from commercial vessels on the high seas, with less from the coastal regions (with the exception of the Maldivian skipjack fishery). These data are typically aggregated into larger spatial units prior to being reported to the IOTC. Both a lack of coastal data and aggregation of that which is recorded, prevent reliable modelling of the biomass at the level of the EEZ.

However, using publicly available longline data it is possible to estimate the relative biomass per $5^{\circ} \times 5^{\circ}$ for much of the Indian Ocean. These estimates could be used in different ways, depending on the structure of the TAC allocation process. It may be that a biomass estimate is required to allow allocation between CPCs fishing on the high seas and the combined coastal states (i.e., an estimate of the proportion of the biomass that exists outside the jurisdiction of any coastal state). Alternatively, the biomass distribution may be required to allocate the TAC between coastal and high seas CPCs simultaneously. Finally, if separate criteria are used to allocate a proportion of TAC to coastal states only, then the biomass distribution could be used to allocate this TAC amongst the coastal CPCs. Each of these uses places a different expectation on the modelling.

Potential allocation of the TAC between coastal and non-coastal states using the biomass would require a decision to be made on the presumed distribution of the biomass within each $5^\circ \times 5^\circ$ cell that is being modelled. This is necessary to allow the predicted biomass to be partitioned for instances in which a $5^\circ \times 5^\circ$ cell crosses an EEZ boundary or boundaries.

If a biomass-based allocation criteria is required only to partition the catch between the coastal CPCs, it is likely to be more successful. This is because higher quality data from the high seas can be used to inform estimates of the relative biomass in larger regions, with each region containing multiple EEZs. These regions, and their relative biomass values, would be constructed in a manner similar to that used for stock assessments of the major species in the Indian Ocean. The coastal CPCs would then recieve an allocation that is dependent on the region that contains their EEZ. It is conceivable that allocation could be dependent on both the size of the EEZ and the regional biomass scalars that are developed as part of the stock assessment cycle.

It is instructive that allocation criteria in the WCPFC also attempted to use a relative biomass per EEZ (Aqorau, 2009), but is now based largely on fishing effort (Clark et al., 2021) due to difficulties with the estimation of appropriate biomass scaling factors. However, these relative scaling factors (Hoyle & Langley, 2020) are subject to a process of on-going development and review, and may have potential utility in the Indian Ocean. If used when calculating the TAC allocation, the allocation would reflect regional differences in abundance that are consistent with our best understanding of the resource (i.e., the stock assessment).

Acknowledgements

Consolidation of the ideas presented in this report was achieved through helpful discussions with Adam Langley, Simon Hoyle, Graham Pilling, Emmanuel Chassot, Lucia Pierre and Sarah Martin, with guidance from Dan Fu and Quentin Hanich.

References

Aqorau, T. (2009). Recent developments in pacific tuna fisheries: the Palau Arrangement and the Vessel Day Scheme. *The International Journal of Marine and Coastal Law 24*: 557–581.

Clark, S.; Bell, J.; Adams, T.; Allain, V.; Aqorau, T.; Hanich, Q.; Jaiteh, V.; Lehodey, P.; Pilling, G.; Senina, I.; Smith, N.; Williams, P.; Yeeting, A. (2021). Adaptive management of fisheries in response to climate change. Chapter 12: The Parties to the Nauru Agreement (PNA) 'Vessel Day Scheme': A cooperative fishery management mechanism assisting member countries to adapt to climate variability and change. *FAO Fisheries and Aquaculture Technical Paper 667*

Crespo, G.O. (2025). Bioregionalization Beyond National Jurisdiction: Principles, Methods, and Applications for an Ecologically Representative MPA Network under the BBNJ Agreement. *International Union for Conservation of Nature (IUCN) World Commission on Protected Areas (WCPA) High Seas Specialist Group*

Dalpadado, P.; Roxy, M.K.; Arrigo, K.R.; van Dijken, G.L.; Chierici, M.; Ostrowski, M.; Skern-Mauritzen, R.; Bakke, G.; Richardson, A.J.; Sperfeld, E. (2024). Rapid climate change alters the environment and biological production of the indian ocean. *Science of The Total Environment 906*: 167342.

Doonan, I.; Large, K.; Dunn, A.; Rasmussen, S.; Marsh, C.; Mormede, S. (2016). Casal2: New Zealand's integrated population modelling tool. *Fisheries Research 183*: 498–505.

Dueri, S. (2017). Impacts of climate change and ocean acidification on Indian Ocean tunas. *Institute for Sustainable Development and International Relations: ANR-10-LABX-01*

Dunstan, P.K.; Hayes, D.; Woolley, S.N.C.; Bernawis, L.; Foster, S.D.; Chassot, E.; Khani, E.; Walton, R.; Blamey, L.; Bristol, U.; Porter, S.; Kanapatipillai, A.A.; Karenyi, N.; Ingole, B.; Pranowo, W.; Sreepada, R.; Shimal, M.; Bodin, N.; Mohamed, S.; White, W.; Last, P.; Bax, N.; Vanderklift, M.; Kloser, R.; Dutra, L.; Molony, B. (2020). Bioregions of the Indian Ocean. *CSIRO, Australia*

Fu, D. (2023). Indian ocean skipjack tuna stock assessment 1950-2022 (stock synthesis). *Working Party on Tropical Tuna IOTC-2023-WPTT25-09*

Fu, D.; Merino, G.; Winker, H. (2022). Preliminary indian ocean bigeye tuna stock assessment 1950-2021 (stock synthesis). *Working Party on Tropical Tuna IOTC-2022-WPTT24-10*

Haputhantri, S.; Jayasinghe, G.; Gunasekara, S. (2023). Accounting for spatial, temporal and operational effects in the Catch Per Unit Effort standardization of Skipjack tuna in tuna drift gillnet fishery in Sri Lanka. *Working Party on Tropical Tunas IOTC-2023-WPTT25-06*

Hoyle, S. (2019). Regional scaling factors for indian ocean albacore tuna. *Working Party on Temperate Tuna (Data Prep.) IOTC-2019-WPTmT07(DP)-13*

Hoyle, S.; Kleiber, P.; Davies, N.; Harley, S.; Hampton, J. (2010). Stock assessment of skipjack tuna in the Western and Central Pacific Ocean. *Regular session of the scientific committee WCPFC-SC6-2010/SA-WP-10 rev.1*

Hoyle, S.D.; Langley, A.D. (2020). Scaling factors for multi-region stock assessments, with an application to indian ocean tropical tunas. *Fisheries Research 228*: 105586.

IOTC (2024a). Report of the 13th technical committee on allocation criteria. *IOTC-2024-TCAC13-R[E]*

IOTC (2024b). Uncertainty in IOTC data for neritics: exploring the interest of catch reconstruction from the Sea Around Us project. *IOTC-2024-WPNT14-INF08*

IOTC (2025). Report of the 14th technical committee on allocation criteria. *IOTC-2025-TCAC14-R[E]*

Juan-Jordá, M.J.; Murua, H.; Idárraga-Garcés, V.; Andonegi, E. (2024). Ecosystem Fisheries Overviews - Assessing the applicability of IOTC candidate ecoregions as a spatial framework for developing ecosystem-based advisory products. *IOTC-2024-WPEB20(AS)-24*

Kaplan, D.M.; Grande, M.; Correa, G.M.; Lourdes, M.; Alonso, R.; Báez, J.C.; Uranga, J.; Duparc, A.; Imzilen, T.; Floch, L.; Santiago, J. (2023). CPUE standardization for skipjack tuna (*Katsuwonus pelamis*) of the EU purse-seine fishery on floating objects (FOB) in the Indian Ocean. *Working Party on Tropical Tunas IOTC-2023-WPTT25-08*

Langley, A. (2019). Stock assessment of albacore tuna in the indian ocean using stock synthesis for 2019. *Working Party on Temperate Tuna IOTC-2019-WPTmT07-11*

Langley, A. (2024). Exploratory analysis of yellowfin tuna longline catch and effort data using VAST. *Working Party on Methods IOTC-2024-WPM15-INF01*

Maunder, M.; Hinton, M.; Bigelow, K.; Langley, A. (2006). Developing indices of abundance using habitat data in a statistical framework. *Bulletin of Marine Science 79*: 545–559.

Maunder, M.N.; Punt, A.E. (2004). Standardizing catch and effort data: a review of recent approaches. *Fisheries Research 70* (*2*): 141–159.

Maunder, M.N.; Punt, A.E. (2013). A review of integrated analysis in fisheries stock assessment. *Fisheries Research 142*: 61–74.

Methot, R.D.; Wetzel, C.R. (2013). Stock synthesis: A biological and statistical framework for fish stock assessment and fishery management. *Fisheries Research 142*: 86–99.

Mondal, S.; Lee, M.A. (2023). Habitat modeling of mature albacore (*Thunnus alalunga*) tuna in the Indian Ocean. *Frontiers in Marine Science 10*

Punt, A.E. (2019). Spatial stock assessment methods: A viewpoint on current issues and assumptions. *Fisheries Research 213*: 132–143.

Rice, J. (2022). Stock assessment of albacore tuna (thunnus alalunga) in the indian ocean using stock synthesis. *Working Party on Temperate Tuna IOTC–2022–WPTmT08-09*

Seto, K.; Galland, G.R.; McDonald, A.; Abolhassani, A.; Azmi, K.; Sinan, H.; Timmiss, T.; Bailey, M.; Hanich, Q. (2020). Resource allocation in transboundary tuna fisheries: A global analysis. *Ambio 50*: 242–259.

Sinan, H.; Bailey, M. (2020). Understanding barriers in indian ocean tuna commission allocation negotiations on fishing opportunities. *Sustainability 12* (*16*): 6665.

Spalding, M.D.; Agostini, V.N.; Rice, J.; Grant, S.M. (2012). Pelagic provinces of the world: A biogeographic classification of the world's surface pelagic waters. *Ocean & Coastal Management 60*: 19–30.

Thorson, J.T. (2019). Guidance for decisions using the Vector Autoregressive Spatio-Temporal (VAST) package in stock, ecosystem, habitat and climate assessments. *Fisheries Research 210*: 143–161.

Urtizberea, A.; Correa, G.M.; Langley, A.; Merino, G.; Fu, D.; Chassot, E.; Adam, S. (2024). Stock assessment of yellowfin tuna in the indian ocean for 2024. *Working Party on Tropical Tuna IOTC-2024-WPTT26-11*

Wu, Y.L.; Lan, K.W.; Evans, K.; Chang, Y.J.; Chan, J.W. (2022). Effects of decadal climate variability on spatiotemporal distribution of Indo-Pacific yellowfin tuna population. *Scientific Reports 12*: 13715.

Zeller, D.; Ansell, M.; Andreoli, V.; Heidrich, K. (2023). Trends in indian ocean marine fisheries since 1950: synthesis of reconstructed catch and effort data. *Marine and Freshwater Research 74*: 301–319.