A preliminary exploration of CPUE standardisation for swordfish using IOTC catch and effort data

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The purpose of this paper is to inform the meeting of a preliminary exploration of the utility of IOTC's catch and effort dataset for CPUE standardisation.

Summary

This paper explores the utility of IOTC's geo-referenced catch and effort dataset for CPUE standardisation, using swordfish as a case study. Standardised indices were produced for several major longline fleets using both a generalised linear model (GLM) and a spatiotemporal model (sdmTMB). The resulting indices for the Japanese, Taiwanese, Portuguese and Spanish fleets are fairly comparable to those standardised by national scientists using fine-scale, operational-level logbook data, but the indices for South Africa and Réunion are markedly different. These results suggest that the IOTC geo-referenced catch and effort data can reproduce trends seen in fine-scale, operational-level data using relatively simple analyses, and could therefore serve as a useful interim monitoring tool.

1. Introduction

Under Resolution 15/02, IOTC members are required to submit catch and effort data from national fleets targeting tuna and tuna-like species in the Indian Ocean to the IOTC Secretariat. These data are managed in a central database alongside other core datasets, including retained nominal catch and size-frequency data. They are routinely reviewed and summarised by the Secretariat through standard papers at relevant Working Party meetings (e.g., IOTC-2025-WPB23-07) and disseminated to the scientific community, and are instrumental in providing key inputs to stock assessments of IOTC species.

The geo-referenced catch and effort data refer to finer-scale data, usually derived from logbooks, that are reported in aggregated form and stratified by year, month, grid (typically 5°×5° latitude and longitude), fleet, gear, school type and species (Res. 15/02). For many coastal fisheries, the data are sourced mainly from port sampling programmes, where coverage is much lower than for the logbook system and the data often lack the resolution available for industrial fisheries (e.g., they are aggregated over larger geographic areas than the standard 5°×5° grid). In recent years, many IOTC coastal states have begun implementing logbook or e-logbook programmes, improving both the coverage and quality of the catch and effort data collected and reported.

Catch and effort data are commonly used to estimate catch per unit effort (CPUE), an index of relative stock abundance. Standardised CPUE indices are used extensively in IOTC stock assessments for tuna, billfish and sharks. The 2026 swordfish stock assessment included a suite of CPUE indices from seven longline fleets: Japan, Taiwan, Spain, Portugal, Réunion, South Africa and Indonesia. These indices were standardised by national scientists using operational-level catch and effort data, which has finer resolution and richer covariate information than the aggregated data held by the Secretariat.

To date, IOTC catch and effort data have mainly been used to characterise the spatial and temporal distribution of IOTC fisheries and to reallocate retained nominal catches into spatio-temporal strata, as required by spatially structured assessment models such as that used for swordfish. There have been almost no attempts to calculate CPUE indices from these aggregated data, which have generally been considered unfit for that purpose (the 2024 WPM meeting did calculate a standardised index for yellowfin tuna from aggregated data using a VAST model, and compared it with the Joint CPUE index). Major concerns include substantial uncertainty over data quality, arising from changes in reporting as CPCs have adapted to the requirements of Res. 15/02, which may have affected the accuracy of catch estimates, species composition and coverage (e.g., a mixture of effort units used for some fisheries over time); the aggregated format of the data, which tends to underestimate variability and so could bias the standardised index; and the lack of operational-level covariates needed to characterise catchability changes in a standard standardisation analysis (e.g., vessel identifier, hooks between floats, etc.).

The impact of data aggregation on CPUE standardisation has been an active area of fisheries research (Ducharme-Barth et al. 2022, Hoyle et al. 2024). It nonetheless remains an open question whether the IOTC geo-referenced catch and effort data are sufficient for CPUE standardisation, in the sense of producing a trend broadly consistent with that derived from fine-scale, operational-level data, at least for some fishery segments (e.g., industrial longline). If so, the utility of these data could extend beyond simple fishery characterisation to serve as an interim monitoring tool for stock trends. To this end, this paper uses the aggregated, geo-referenced IOTC catch and effort dataset to produce CPUE indices for swordfish for several longline fleets and compares them with the corresponding indices produced by CPCs using operational-level catch and effort data.

2. Methods

The data used are the geo-referenced catch and effort data provided to WPB24 (IOTC-2026-WPEB22-DATA03). The analysis was restricted to a subset of the data corresponding to the main deep-freezing longline fleets: gear code "LL" for Japan (JPN) and Taiwan (TWN), and "ELL" for Portugal (EUPRT), Spain (EUESP), Réunion (EUREU) and South Africa (ZAF). The dataset contains swordfish catches (in weight or numbers, see below) and effort (number of hooks), stratified by year, month and grid (5°×5°). These are the only variables available for the standardisation analysis.

The dataset records catches in both weight and number. Some fleets reported catch only by number (e.g., Japan), some only by weight, and others reported a mixture of the two. For fleets reporting a mixture of number and weight, three situations can occur within a given month-grid stratum: only number reported, only weight reported, or both. To determine total fleet catch, numbers reported in strata where only numbers were recorded were converted to weight using average weight-at-length derived from length-frequency data (IOTC-2026-WPB24-DATA06). However, for strata where both number and weight were reported, it was not immediately clear whether these referred to the same catch (in which case only one should be counted) or to different catches (in which case both should be summed). Treating the number and weight as referring to the same catch was found to avoid double-counting, giving totals more consistent with the retained nominal catch in IOTC-2026-WPB24-DATA02. For the standardisation analysis, therefore, only catches reported in weight were used, except for the Japanese fleet, which was analysed using catch in numbers.

For each fleet, two standardisation models were fitted. The first is a lognormal model, fitted to log-transformed catches using the "glm" function in R:

glm (log(catch) ~ year + log (effort) + quarter + grid, link = "normal") (1)

The explanatory variables include year, quarter, 5°×5° grid and log transformed effort (number of hooks). The standardised index is calculated as the predicted catch rate for each year, with other model covariates held at their median values.

The second model is sdmTMB (R package sdmTMB), which fits spatial and spatiotemporal generalised linear mixed models using Template Model Builder. Here, a GLMM was fitted to the catch data with a lognormal link:

sdmTMB(data, catch ~ year + quarter + log(effort), mesh = spde, family = lognormal(link = "log")) (2)

Rather than estimating fixed effects for each spatial grid cell, sdmTMB estimates spatiotemporal random effects at a set of "knot" locations on a triangulated "mesh", established using the "make_mesh" function:

$$\text{spde <- make\_mesh(data, c("X", "Y"), n\_knots = 100)} \quad (3)$$

where "X" and "Y" are the latitude and longitude of the centroid of each grid cell in the data, and the number of knots is chosen in proportion to the number of grid cells (i.e., 100 knots for JPN and TWN, 50 for EUPRT and EUESP, 15 for ZAF and 20 for EUREU). Spatial and spatiotemporal random effects are estimated as a multivariate normal distribution, with a covariance structure that depends on the distance and direction between knots in the mesh (Anderson et al. 2025). The standardised annual index is then obtained by predicting density over a pre-defined grid (based on the grid cells present in the data) for each year.

Both models are widely used for CPUE standardisation. The GLM lognormal model is the traditional approach, isolating the effects of covariates (other than "year") that are assumed to relate to catchability, leaving a residual "year" component assumed to represent changes in biomass over time. sdmTMB is a more contemporary model, widely used for estimating species distributions. It separates covariates into catchability effects and density effects (e.g., spatial and spatiotemporal effects), and the standardised index is effectively the sum of the estimated density over the population area.

To ensure comparability with the standardised indices provided by the respective CPCs (IOTC-2026-WPB24-18, 19, 20, 21, 22, 23), the analysis was restricted to the following periods: 1994–2024 for JPN, 2005–2024 for TWN, 2008–2024 for EUPRT (data before 2008 were excluded as catch was reported in numbers and effort in fishing days), 2021–2024 for EUESP, 2005–2024 for EUREU, and 2004–2019 for ZAF (data after 2019 have not yet been submitted to the Secretariat). For JPN and TWN, CPUE indices were derived separately for the north-west (NW), north-east (NE), south-west (SW) and south-east (SE) regions, based on the stock assessment area (see Figure 1 of Phillips 2026). This regional breakdown was implemented differently for the two models: for GLM, separate models were fitted to the data for each region; for sdmTMB, a single model was fitted to the full fleet dataset and regional indices were then extracted from the prediction grid for each region. For JPN, all catches are reported in numbers, so the resulting index represents relative biomass in numbers rather than weight.

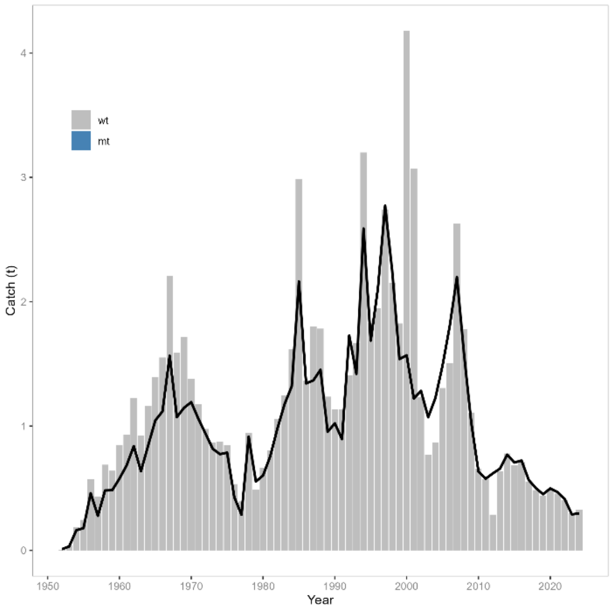
3. Results

For all fleets included in the analysis, the reported catch and effort data appear to provide full coverage of the fishery when compared with the corresponding retained nominal catches (Figure 1). For EUPRT, EUESP and EUREU, catches in the geo-referenced catch and effort data almost perfectly match the retained nominal catches, suggesting that the catch and effort data have most likely been raised to total catch. For JPN, catches in the catch and effort data are reported by number only, but are also reasonably consistent with nominal catches once converted to weight.

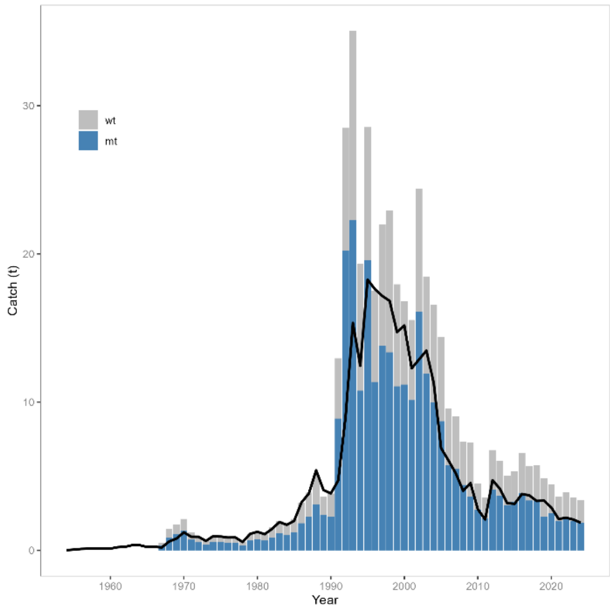
Standardised CPUE from the GLM and sdmTMB models are shown in Figures 2–4, compared with the CPCs' indices (referred to as the "logbook" index), which are based on operational-level data and different standardisation methods. Across fleets, the GLM and sdmTMB indices are fairly close to one another. For JPN, the GLM and sdmTMB indices are very consistent with the logbook index, except for the SE region (Figure 2). For TWN, both indices are also fairly close to the logbook index, although the logbook index appears smoother (Figure 3). For EUPRT (over overlapping years) and EUESP, the indices are fairly comparable to the logbook index (Figure 4). For EUREU, however, the indices show some different trends (Figure 4). For ZAF, all indices show a declining trend from 2004 to 2015/16, and then an increasing trend up to present but the logbook index is much flatter overall (Figure 4).

For the cases where the GLM or sdmTMB indices differ markedly from the logbook index, a comparison was also made using the nominal CPUE, calculated as annual total catch divided by total effort in the geo-referenced catch and effort data (Figure 5). In these cases too, the nominal indices differ substantially from the standardised logbook index. It would be useful to examine the nominal CPUE from the national logbook datasets to see whether they also deviate from the corresponding standardised index and, if so, what might explain the difference.

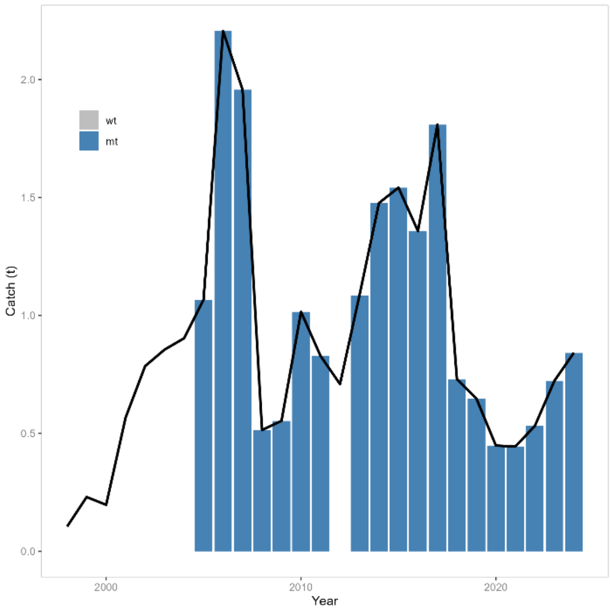
JPN



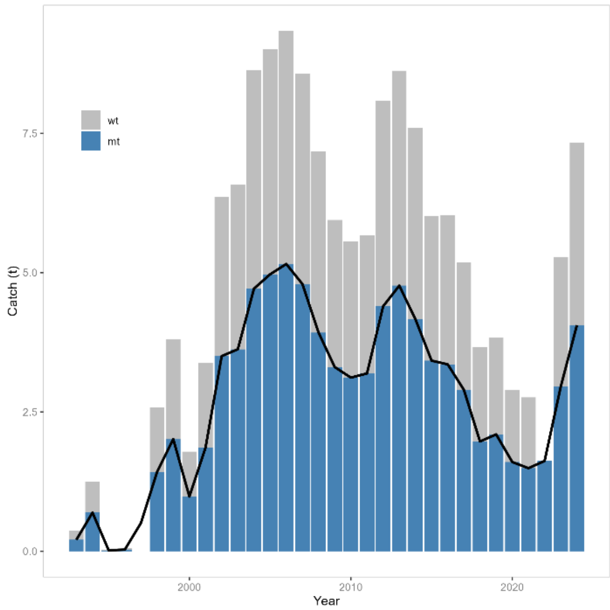
TWN



EUPRT



EUESP



EUREU

ZAF

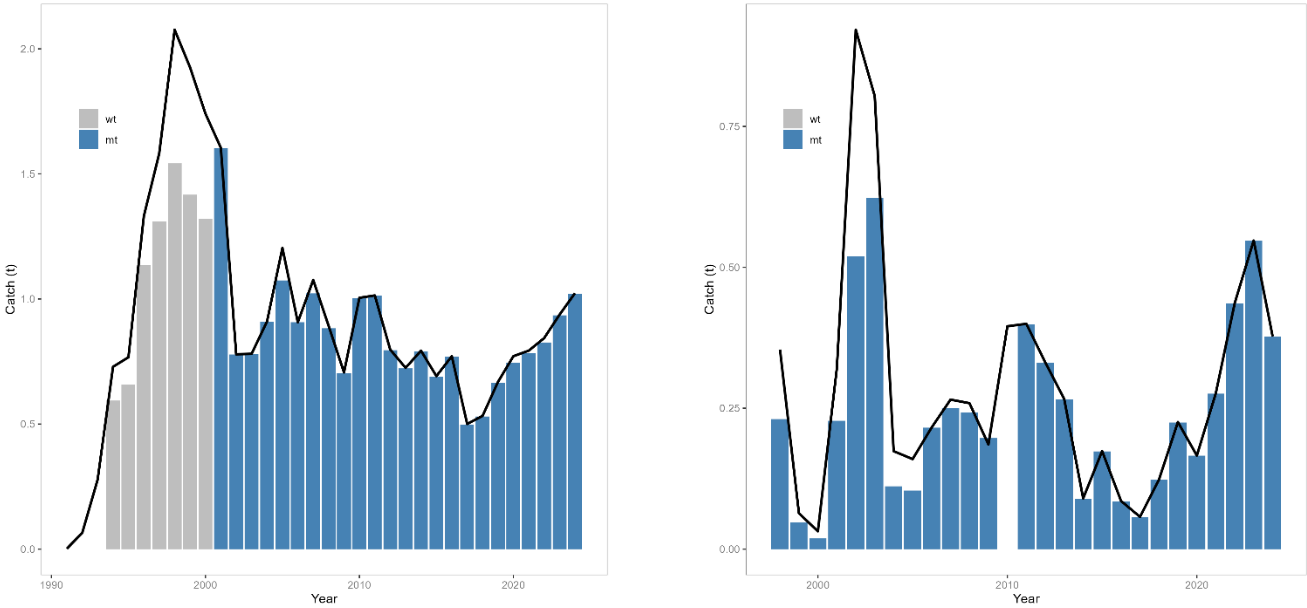


Figure 1: Comparison of catches from the geo-referenced catch and effort data and from the retained nominal catch data for JPN, TWN, EUPRT, EUESP, EUREU and ZAF. For the geo-referenced catch and effort data, both catches reported in weight (mt) and catches reported in numbers (converted to weight, wt) are shown.

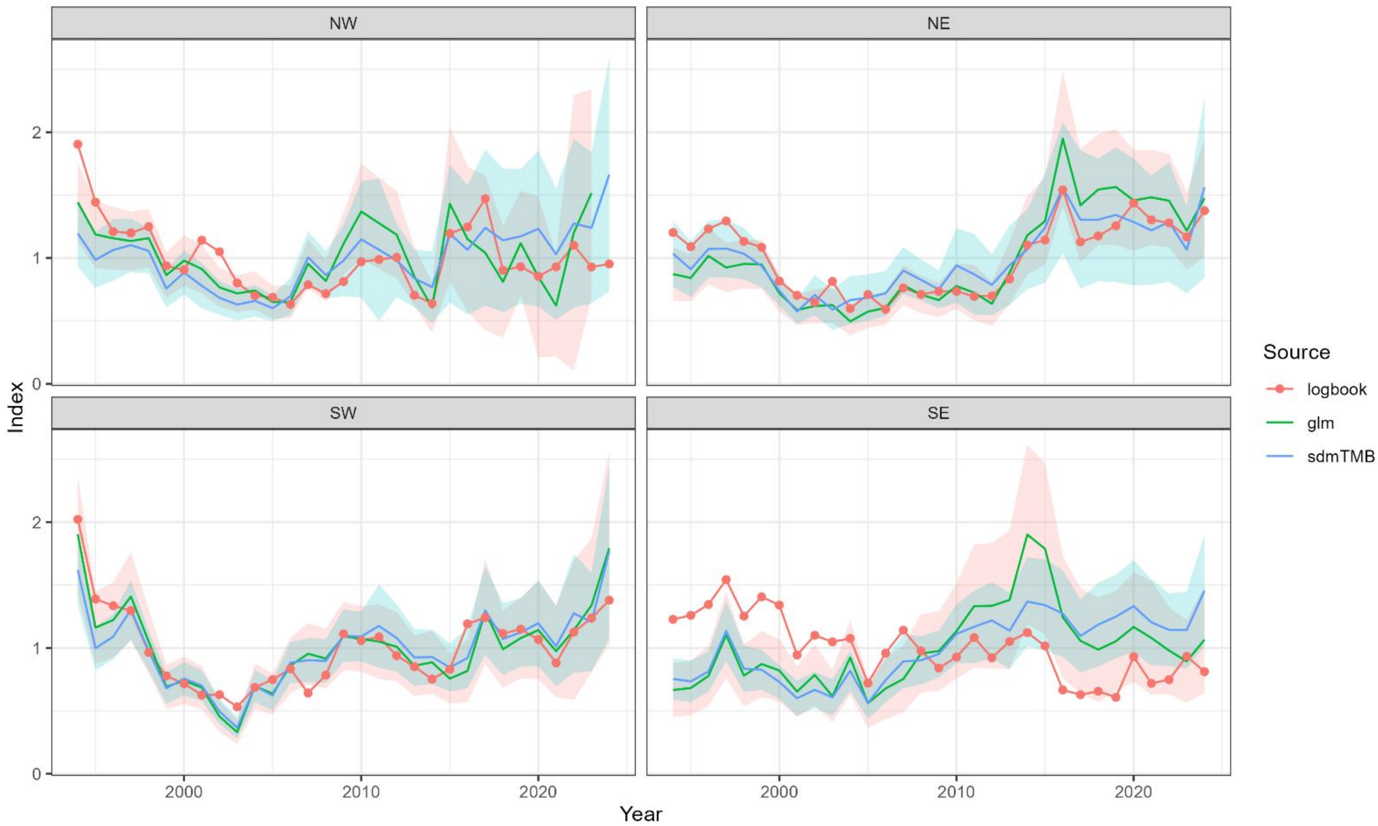


Figure 2: Comparison of indices from the geo-referenced catch and effort data (GLM and sdmTMB models) with the index from operational logbook data (IOTC-2026-WPB24-22) for the JPN longline fleet, for the NW, NE, SW and SE regions.

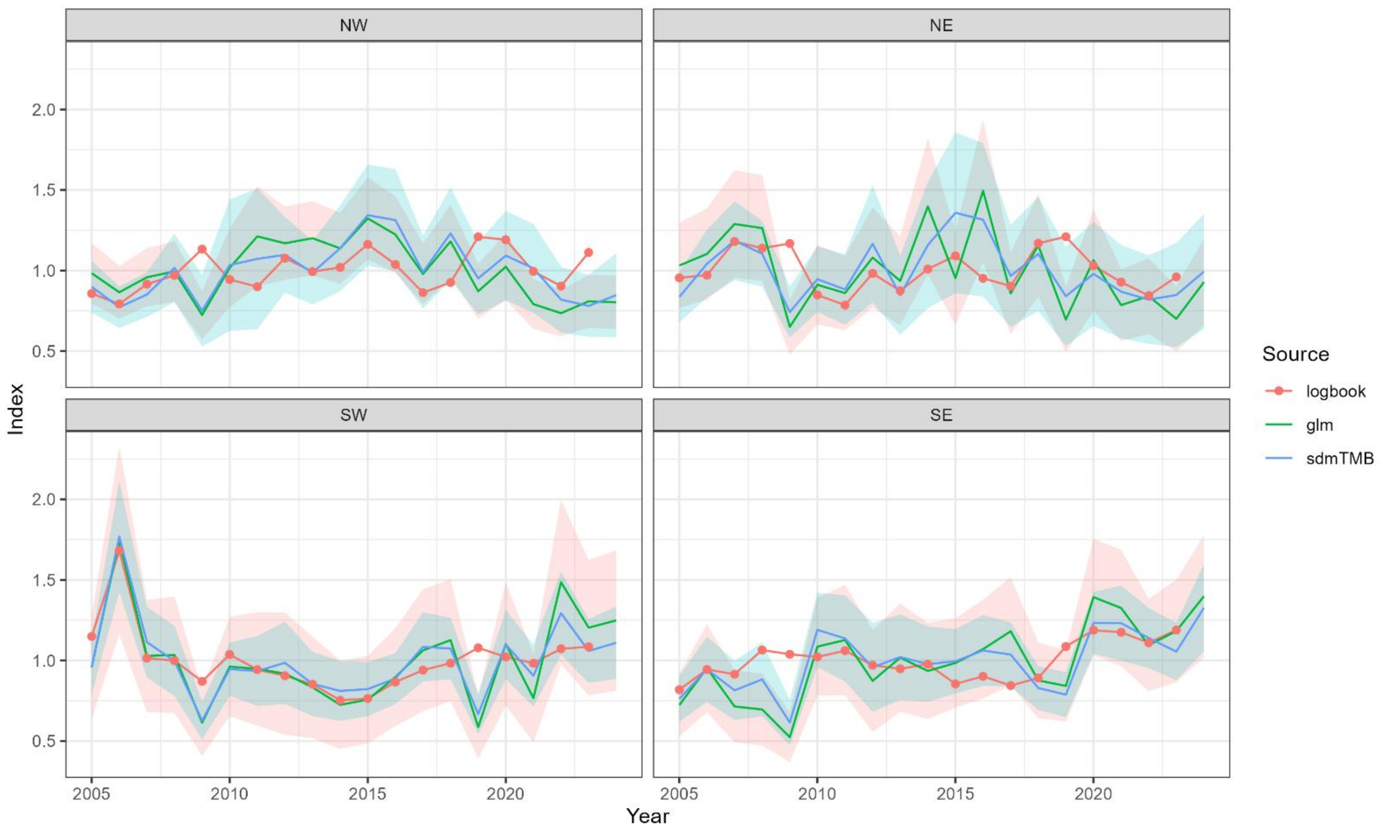


Figure 3: Comparison of indices from the geo-referenced catch and effort data (GLM and sdmTMB models) with the index from operational logbook data (IOTC-2026-WPB24-23) for the TWN longline fleet, for the NW, NE, SW and SE regions.

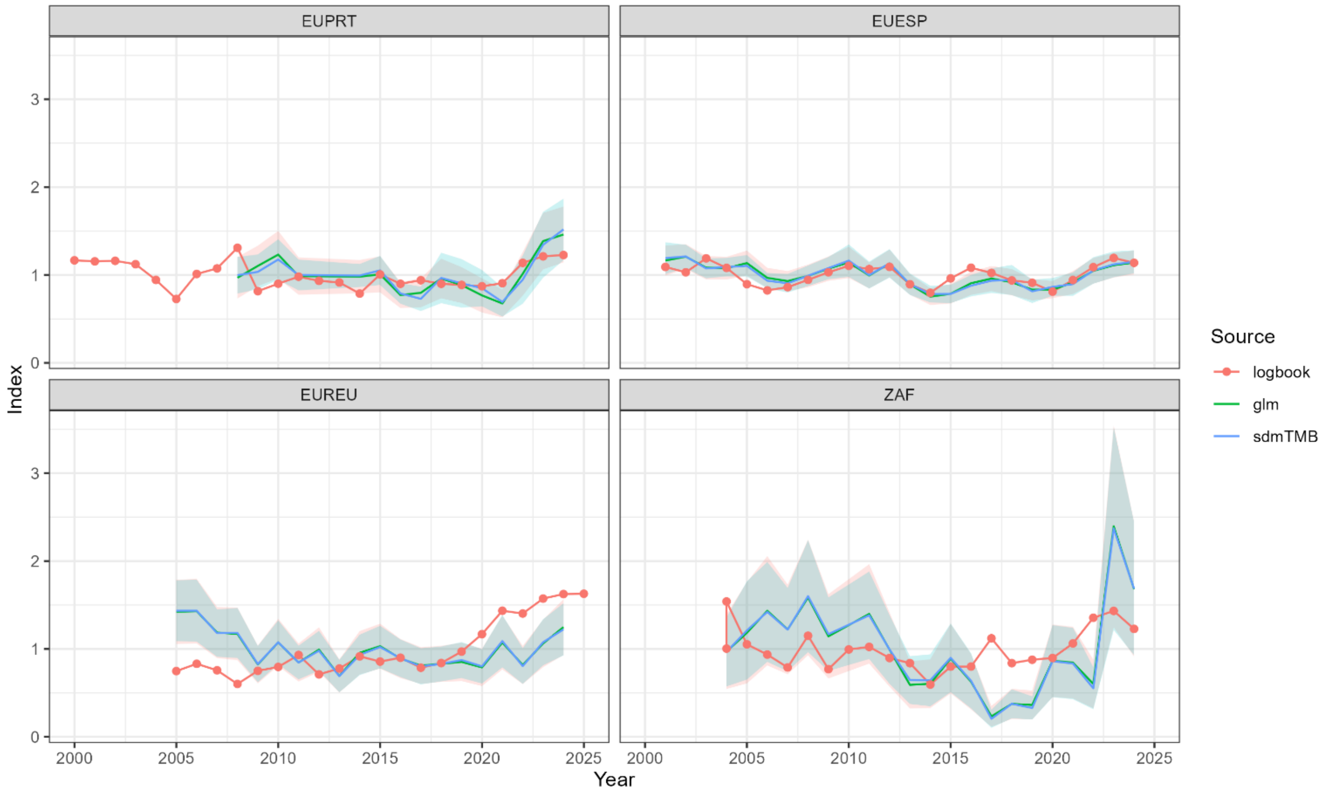


Figure 4: Comparison of indices from the geo-referenced catch and effort data (GLM and sdmTMB models) with the index from operational logbook data for EUPRT (IOTC-2026-WPB24-18), EUESP (IOTC-2026-WPB24-19), ZAF (IOTC-2026-WPB24-20) and EUREU (IOTC-2026-WPB24-30).

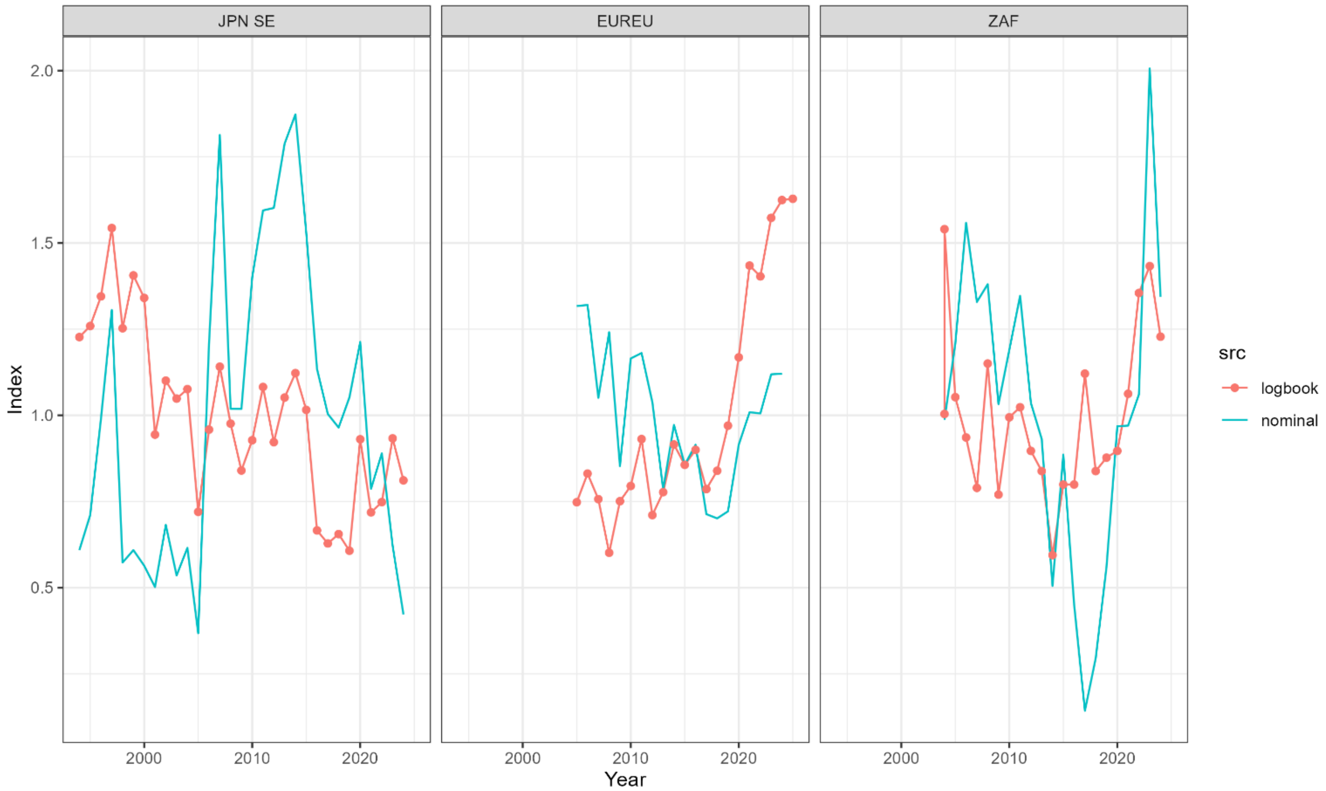


Figure 5: Comparison of nominal CPUE indices from the geo-referenced catch and effort data with the index from operational logbook data, for the JPN South-East region (SE), ZAF and EUREU.

4. Discussion

The analysis presented here, though rudimentary, shows that for several key longline fleets targeting swordfish (JPN, TWN, EUPRT and EUESP), the index derived from the aggregated, geo-referenced catch and effort data is fairly consistent with the index derived from fine-scale, operational-level national data, despite the latter using different model structures and additional covariates. This suggests that, at least in these cases, data resolution and model choice do not have a large impact on the standardised index. It is important to stress, however, that this consistency does not itself validate the "correctness" of either index as a measure of abundance; nor does the inconsistency between the IOTC-based and national indices for ZAF and EUREU imply that the national index is invalid. It would nonetheless be useful to investigate the causes of these differences.

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5. References

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