

Standardized CPUE of silky shark (*Carcharhinus falciformis*) from Taiwanese large-scale tuna longline fishery in the Indian Ocean, 2005–2025

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Purpose, expectation and action intended (select one or more and include corresponding text)

Discussions (for information and open discussion):

The paper presents an updated fishery-dependent relative standardized CPUE index for Indian Ocean silky shark from Taiwanese large-scale tuna longline logbooks (2005–2025), estimated using tinyVAST, for discussion in support of the upcoming benchmark stock assessment (Sections 2–4).

Feedback (to collect input and suggestions)

The paper requests comments on the modelling framework, model selection and diagnostics, uncertainty, and the suitability of the index as a relative abundance series for the benchmark stock assessment (Sections 2–4)

Conclusion (to record a concluded position or summary)

The selected tinyVAST model provides an updated, reproducible relative standardized CPUE index, while acknowledging limitations of fishery-dependent logbook data and unpropagated model-selection uncertainty (Sections 3–4).

Recommendation (to ask the meeting to endorse a recommendation)

The paper recommends that WPEB22 consider the index, with its uncertainty, and stated limitations as candidate inputs for the upcoming silky shark benchmark stock assessment (Section 4).

Decisions (to request formal approval of actions)

No formal decision is requested; the paper is submitted for discussion, technical feedback, and consideration in the stock-assessment process.

Abstract

We revisited the previous Taiwanese silky shark catch per unit effort (CPUE) standardization using a spatio-temporal modeling framework based on tinyVAST. Taiwanese large-scale tuna longline logbook data from 2005 to 2025 (624,917 fishing sets; 2.03 billion hooks) were analyzed. We fitted and compared eight candidate models to identify the best-supported observation family and random-field structure, then evaluated four fixed-effects configurations. The best-supported model was selected to estimate a standardized CPUE index for silky sharks. Model adequacy was evaluated using numerical-convergence checks, AIC and cAIC, simulated-quantile residual diagnostics, and Moran's I. Annual relative standardized CPUE varied considerably during 2005–2025, with its highest value in 2014, its lowest level in 2015, and values generally above the long-term mean during 2018–2025. Predicted spatial distributions showed relatively high standardized CPUE (hotspots) in the northwestern Indian Ocean off Somalia and eastern Africa, around Madagascar and the Mozambique Channel, and in the central tropical Indian Ocean. Low values occurred over the southeastern Indian Ocean. The resulting fishery-dependent, relative standardized CPUE index provides an updated abundance index for the upcoming Indian Ocean silky shark benchmark stock assessment and demonstrates the applicability of modern geostatistical CPUE standardization to long-term Taiwanese tuna longline logbook data.

Keywords: CPUE standardization; Indian Ocean; shark bycatch; silky shark; spatiotemporal model; tinyVAST.

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Abstract

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longline logbook data from 2005 to 2025 (624,917 fishing sets; 2.03 billion hooks) were analyzed. We fitted and compared eight candidate models to identify the best-supported observation family and random-field structure, then evaluated four fixed-effects configurations. The best-supported model was selected to estimate a standardized CPUE index for silky sharks. Model adequacy was evaluated using numerical-convergence checks, AIC and cAIC, simulated-quantile residual diagnostics, and Moran's I. Annual relative standardized CPUE varied considerably during 2005–2025, with its highest value in 2014, its lowest level in 2015, and values generally above the long-term mean during 2018–2025. Predicted spatial distributions showed relatively high standardized CPUE (hotspots) in the northwestern Indian Ocean off Somalia and eastern Africa, around Madagascar and the Mozambique Channel, and in the central tropical Indian Ocean. Low values occurred over the southeastern Indian Ocean. The resulting fishery-dependent, relative standardized CPUE index provides an updated abundance index for the upcoming Indian Ocean silky shark benchmark stock assessment and demonstrates the applicability of modern geostatistical CPUE standardization to long-term Taiwanese tuna longline logbook data.

Keywords: CPUE standardization; Indian Ocean; shark bycatch; silky shark; spatiotemporal model; tinyVAST.

1. Introduction

The silky shark (*Carcharhinus falciformis*) is a large, highly migratory pelagic species (reaching up to 3.5 meters in length) found in tropical and subtropical oceans worldwide (Ebert et al., 2021). The species is assessed globally as Vulnerable on the IUCN Red List (Rigby et al., 2021). Like many oceanic sharks, it is vulnerable to overfishing due to its slow growth, late maturity (4–10 years for males, 7–12 years for females), lengthy gestation (9–12 months), small

litter size (1–16 pups), and longevity (22+ years) (Bonfil, 2008). Silky sharks are currently managed within broad ocean-scale jurisdictions established by tuna Regional Fisheries Management Organizations (tRFMOs) due to a limited understanding of stock boundaries (Kraft et al., 2025). In the Indian Ocean, assessments have generally assumed a single population (Coelho et al., 2019). Recent genetic studies, however, indicate structuring within and among ocean basins, including a distinct Aceh group and differentiation between Indian and Pacific samples; thus, the single-stock assumption warrants further evaluation (Li et al., 2023; Kraft et al., 2025). Silky sharks are also listed in Appendix II of CITES and the Convention on Migratory Species (CITES, 2026; CMS, 2026), reflecting the need for international cooperation in their conservation and management. Several tRFMOs have implemented management measures for silky sharks in response to increasing conservation concerns. ICCAT and WCPFC require release and prohibit retention of silky sharks, subject to specified exemptions. For 2026–2028, IATTC Resolution C-25-09 prohibits retention by purse-seine vessels and applies bycatch, size-composition, monitoring, and gear controls to longline fisheries (ICCAT, 2011; IATTC, 2025; WCPFC, 2025). Earlier assessments were highly uncertain (Urbina et al., 2018; Cramp et al., 2021), and the 2025 IOTC management advice reports that no quantitative stock assessment or basic fishery indicators are currently available; stock status in the Indian Ocean therefore remains unknown (IOTC, 2025).

Catch-per-unit-effort (CPUE) is widely used as an indicator of relative abundance, although meaningful interpretation requires careful standardization to minimize biases inherent in fisheries-dependent data (Ducharme-Barth et al., 2022; Hoyle et al., 2024). Recent advances in geostatistical spatiotemporal modeling have substantially improved CPUE standardization by explicitly accounting for spatial and temporal variation in fishing operations and catch rates (Thorson et al., 2015a; Thorson, 2019). This working paper revisits the previous Taiwanese silky shark CPUE standardization (IOTC–2019–WPEB15-24; Tsai et al., 2019) by extending the dataset to 2025 and implementing the tinyVAST framework (Thorson et al., 2025), with the objective of providing an updated standardized relative-abundance index for the upcoming Indian Ocean silky shark stock assessment within the IOTC.

2. Materials and methods

2.1. Data source and study area

This working paper used logbook data collected by Taiwan's Overseas Fisheries Development Council (OFDC) for the Taiwanese large-scale tuna longline (LTLL) fleet operating in the Indian Ocean from 2005 to 2025. Each record contained fishing date, geographic location, vessel size category (gross tonnage, CTNO), fishing effort (number of hooks), hooks per basket (HPB), and catch numbers for up to 18 tuna, billfish, and shark species. Before 2005, shark catches were recorded as an aggregated group; from 2005 onward, catches were recorded at a finer taxonomic level, i.e., blue sharks (*Prionace glauca*), mako sharks (*Isurus* spp.), silky sharks (*Carcharhinus falciformis*), and other shark species. The study area extended from 40°S to 25°N and from 20°E to 110°E, covering the tropical and subtropical Indian Ocean. Following the spatial stratification approach based on the distribution of fishing effort and the principal fishing grounds of target species (Huang and Liu, 2010), the prediction domain was divided into four broad fishing areas (Areas 1–4) for descriptive regional comparisons. These areas were used only for post hoc aggregation and visual comparison of predictions from the fitted model and were not included as a covariate or spatial stratum during model fitting. Daily operational catch and effort data were provided on a 5°×5° latitude–longitude grid. Records with missing fishing date, spatial coordinates, or CTNO were excluded. The final logbook dataset consisted of 624,917 fishing sets, representing approximately 2.03 billion hooks and 83,566 recorded silky sharks. This dataset was used for CPUE standardization (**Table 1**). Silky sharks are primarily taken as bycatch; thus, their catch distribution was characterized by a high proportion of zero-catch fishing sets.

As a descriptive check on the logbook zero-catch records, annual proportions of zero-catch sets were compared between the logbook and observer datasets. Recorded catches in both datasets included retained and discarded individuals. Across 2005–2025, zero-catch sets accounted for an average of 93.6% of logbook records and 96.2% of observer records. Annual proportions remained consistently high and showed broadly similar patterns between data sources, with no obvious major discrepancy in zero-catch frequency (**Fig. 1**). Because observer coverage was low and nonuniform, this comparison should be interpreted as a descriptive consistency check rather than a formal validation of logbook reporting. Furthermore, the annual percentage of logbook sets covered by observer data averaged 7.47% across 2005–2025 (unweighted mean of the annual percentages), although coverage varied among years and remained generally low (**Table 1**). Therefore, the logbook dataset was used as the primary data source for CPUE standardization.

2.2. Data exploration and CPUE standardization statistical modeling

Nominal CPUE, calculated as the number of silky sharks caught per 1,000 hooks, ranged from 0 to 62.1, with a mean of 0.043 and a standard deviation of 0.321. The nominal CPUE distribution was characterized by a high proportion of zero values (93.6%), strong right skewness (skewness = 41.7), and substantial overdispersion (variance to mean ratio = 2.38). To standardize silky shark CPUE, we fitted generalized linear mixed models (GLMMs) using the *tinyVAST* package (Thorson et al., 2025). The encounter component used a Bernoulli distribution with a logit link; conditional positive catches were modeled using either a lognormal or gamma distribution with a log link. The encounter and positive-catch components were modeled as:

$$\Pr(y_i > 0) = g_1^{-1}(p_{1,i}),$$

$$E(y_i | y_i > 0) = g_2^{-1}(p_{2,i}),$$

with

$$p_{1,i} = \underbrace{X_{1,i}\alpha_1}_{\text{formula}} + \underbrace{A_i\Omega_1}_{\text{space_term}} + \underbrace{A_iE_{1,t[i]}}_{\text{spacetime_term}}$$

$$p_{2,i} = \underbrace{X_{2,i}\alpha_2}_{\text{formula}} + \underbrace{A_i\Omega_2}_{\text{space_term}} + \underbrace{A_iE_{2,t[i]}}_{\text{spacetime_term}}$$

where

Response

- y_i : observed silky shark catch for fishing operation i

Linear predictors

- $p_{1,i}$: linear predictor for the encounter component
- $p_{2,i}$: linear predictor for the positive-catch component

Fixed effects

- X_1 and X_2 : design matrices for the encounter and positive-catch components, respectively.

- α_1 and α_2 : corresponding vectors of fixed-effect coefficients

Latent random fields

- Ω_1 and Ω_2 : spatial random fields associated with the `space_term` component
- E_1 and E_2 : spatiotemporal random fields associated with the `spacetime_term` component

Interpolation matrix

- A_i : row of the interpolation matrix projecting latent random fields defined at the mesh vertices to observation location i

Here, $t[i]$ denotes the year associated with observation i ; $g_1^{-1}(\cdot)$ is the inverse-logit transformation for encounter probability, and $g_2^{-1}(\cdot)$ is the inverse-log transformation for the conditional positive-catch mean.

The spatial and spatiotemporal random fields were represented using the stochastic partial differential equation (SPDE) approach (Lindgren et al., 2011), in which continuous spatial variation is approximated using a triangulated finite-element mesh. A spatial mesh comprising 205 nodes was generated to provide adequate spatial resolution while maintaining computational efficiency (**Fig. 2**). Fishing effort was accounted for by including the log-transformed number of hooks as an offset in the model formula for CPUE standardization.

Initial exploration of the data indicated that nominal CPUE varied among years, quarters, gear configurations (HPBC), vessel size categories (CTNO), and fishing strategy clusters (**Fig. 3**). Pairwise correlations among the candidate predictors were generally weak to moderate ($|r| < 0.5$), indicating no evidence of strong pairwise linear associations among the explanatory variables (**Fig. 4**). Accordingly, the following explanatory variables were retained for CPUE standardization:

- Year: 2005–2025 (21 years)
- Quarter: Q1 (January–March), Q2 (April–June), Q3 (July–September), and Q4 (October–December)
- Gear configuration (HPBC): categorized as shallow (<5 HPB), middle (5–10), deep (10–15), and ultra-deep (≥ 15)
- Vessel size (CTNO): classified by gross tonnage (GT) into three categories, with CT5 ($100 \leq GT < 200$), CT6 ($200 \leq GT < 500$), and CT7 ($500 \leq GT < 1,000$)
- Fishing strategy cluster: derived from hierarchical cluster analysis using Ward’s minimum variance method (Ward, 1963) with Euclidean distance, implemented via the `hclust.vector()` function in the `fastcluster` package (Müllner, 2013), based on the relative catch composition of seven species or species groups aggregated over 10-day fishing intervals (**Fig. 5**). The clustering variables included albacore tuna (ALB), bigeye tuna (BET), yellowfin tuna (YFT), southern bluefin tuna (SBT), swordfish (SWO), sharks (SKX), and other species (OTH; residual species not classified into the main groups). The dendrogram was cut to five clusters, which were subsequently treated as a categorical predictor. Shark catches have been recorded at the species level since 2005. However, sharks were grouped into a single category (SKX) for the clustering procedure to identify fishing strategies. This aggregation does not affect the species-specific analyses conducted elsewhere in this working paper.

2.3. Model selection

We fitted eight candidate models using the same full fixed-effects specification to identify the most suitable observation family and random-field structure for the data: $\text{Catch} \sim \text{Year} + \text{Quarter} + \text{HPBC} + \text{CTNO} + \text{Cluster} + \text{offset}(\log \text{ Hooks})$. Given that only 6.4% of fishing sets recorded positive silky shark catches and that catch counts were strongly overdispersed (variance-to-mean ratio = 6.45), two candidate observation families were evaluated: delta-lognormal and delta-gamma hurdle models. For each observation family, four alternative random-field structures were evaluated to account for latent spatial and spatiotemporal variation that may not be captured by fixed effects alone: (1) fixed effects only, (2) a spatial random field, (3) a spatiotemporal random field, and (4) combined spatial and spatiotemporal random fields. Spatial and spatiotemporal random fields were specified using the dynamic structural equation model (DSEM) arrow-and-lag notation implemented in `tinyVAST` (Thorson et al., 2025). The eight candidate models for stage 1 were defined as follows:

- M1: delta-lognormal with fixed effects only;
- M2: delta-lognormal with a spatial random field;
- M3: delta-lognormal with a spatiotemporal random field;
- M4: delta-lognormal with spatial and spatiotemporal random fields;

- M5: delta-gamma with fixed effects only;
- M6: delta-gamma with a spatial random field;
- M7: delta-gamma with a spatiotemporal random field; and
- M8: delta-gamma with spatial and spatiotemporal random fields.

After selecting the observation family and random-field structure (stage 1), the fixed-effects model was further refined (stage 2) by sequentially evaluating four candidate models, as follows:

- F1: Catch $\sim$ Year + Quarter + offset(log Hooks);
- F2: Catch $\sim$ Year + Quarter + HPBC + offset(log Hooks);
- F3: Catch $\sim$ Year + Quarter + HPBC + CTNO + offset(log Hooks); and
- F4: Catch $\sim$ Year + Quarter + HPBC + CTNO + Cluster + offset(log Hooks).

All candidate models were fitted using the same dataset, spatial mesh, and optimization settings. Numerical adequacy was evaluated using the optimizer convergence code, the maximum absolute gradient of the objective function, and the positive definiteness of the Hessian matrix. Models with an optimizer convergence code of zero, a positive-definite Hessian, and a maximum absolute gradient below 0.0001 were considered numerically adequate for model comparison. Model selection was based on Akaike's Information Criterion (AIC; Akaike, 1973), conditional Akaike's Information Criterion (cAIC; Zheng et al., 2024), and deviance explained. Here, AIC targets prediction for new realizations of the random effects, whereas cAIC evaluates conditional prediction given the fitted latent random effects; both criteria were reported because they address complementary prediction targets. The adequacy of the selected model was subsequently evaluated using simulated quantile residuals implemented in the DHARMA package (Hartig, 2018). Model fit was assessed using quantile–quantile (Q–Q) plots and residual diagnostic tests. Residual spatial autocorrelation was further evaluated using Moran's I applied to aggregated DHARMA residuals.

2.4. Estimation of standardized CPUE and uncertainty

The best-supported spatiotemporal generalized linear mixed model (GLMM), identified through model selection (Section 2.3), was retained to estimate annual standardized CPUE (std.CPUE). For each year, standardized CPUE was obtained by spatial integration of model predictions over the prediction grid. Model uncertainty associated with the annual standardized CPUE indices was quantified using the delta method. Approximate 95% confidence intervals

(CIs) were calculated on the log scale as: $CI_{s_t} = \text{std.CPUE}_t \exp\left(\pm 1.96 \frac{SE(\text{std.CPUE}_t)}{\text{std.CPUE}_t}\right)$, where

std.CPUE_t is the annual standardized CPUE estimate in year t , and $SE(\text{std.CPUE}_t)$ is its model-based standard error. The coefficient of variation (CV) for each annual standardized

CPUE estimate was calculated as: $CV_t = \frac{SE(\text{std.CPUE}_t)}{\text{std.CPUE}_t}$ providing a relative measure of

estimation uncertainty among years. To facilitate interannual comparisons, annual standardized CPUE estimates were scaled by their average to obtain a relative standardized CPUE index, as

$\text{Relative std.CPUE}_t = \frac{\text{std.CPUE}_t}{\frac{1}{T} \sum_{t=1}^T \text{std.CPUE}_t}$, where T is the total number of years. Nominal CPUE

was similarly scaled to obtain a relative nominal CPUE index. These intervals quantify model-based conditional uncertainty and do not propagate uncertainty from logbook reporting, covariate selection, observation-family selection, or other model-selection decisions.

All analyses and visualizations were performed in R version 4.4.3 (R Core Team, 2025) on 64-bit Windows 11. The tinyVAST package (version 1.4.0; Thorson et al., 2025; <https://github.com/vast-lib/tinyVAST>) was used.

3. Results

3.1. Selection of the best-supported model

All stage 1 models had positive-definite Hessian matrices; seven had maximum gradients below 0.0001, whereas M3 had a maximum gradient of 0.0002 (Table 2). M4 was selected among eight candidates due to the lowest AIC and cAIC, explaining 16.1% of the deviance (Table 2). Annual relative standardized CPUE estimates showed similar trends across these models, though magnitudes differed in some years (e.g., 2014, 2021–2023) (Fig. 6a). All stage 2 models also had positive-definite Hessian matrices and maximum gradients below 0.0001. Among the four fixed-effects models, F4 had the lowest AIC and cAIC and explained the most deviance (Table 3). Despite differences in model-selection criteria, annual relative standardized CPUE estimates were highly consistent among F1–F4, with only minor magnitude differences in some years (Fig. 6b). Residual diagnostics for F4 showed no significant deviations based on the Kolmogorov–Smirnov, dispersion, and outlier tests; no evident systematic pattern in residuals against model predictions; and no significant residual spatial autocorrelation (Moran's $I = -0.012$, $p = 0.429$) (Figs. 7 and 8). Overall, the diagnostics did not reveal major model misspecification; F4 was therefore selected for all subsequent analyses.

3.2. Annual trends in relative CPUE

Annual relative standardized CPUE varied considerably during 2005–2025 and generally showed a pattern similar to relative nominal CPUE (Fig. 9a; Table 4). The index reached its highest value in 2014, declined to its lowest level in 2015, and then increased, remaining generally above the long-term mean throughout 2018–2025. Annual CVs ranged from 0.125 to 0.559. Uncertainty was greatest in 2011 (CV = 0.559), followed by 2010 (0.530), 2014 (0.448), 2020 (0.393), and 2024 (0.387), corresponding to the relatively wide 95% CIs in those years (Fig. 9a; Table 4). Fishing effort also varied substantially, declining from 221 million hooks in 2005 to approximately 90–101 million hooks after 2016, with a further reduction during 2024–2025 (Table 1). Area-specific indices varied substantially among years and differed in magnitude among the four fishing areas (Fig. 9b). Area 3 showed a pronounced difference between relative nominal and standardized CPUE in 2008. Corresponding CVs also varied temporally and among fishing areas.

3.3. Spatio-temporal variability

Predicted spatial patterns of relative standardized CPUE were consistent among models F1–F4, with pairwise Spearman correlation coefficients exceeding 0.999. Relatively high predicted standardized CPUE (i.e., hotspots) were consistently observed in three regions: (1) the northwestern Indian Ocean off Somalia and eastern Africa (50–70°E, 5–20°N), (2) waters around Madagascar and the Mozambique Channel (40–50°E, 10–25°S), and (3) the central tropical Indian Ocean (80–95°E, 10°S–10°N). Relatively low standardized CPUE was predicted over the southeastern Indian Ocean, particularly east of 100°E and south of 20°S (Fig. 10).

Annual spatial predictions showed consistent distributions among models F1–F4 (Figs. 11–14), though the intensity and extent of elevated predicted standardized CPUE varied substantially among years. In 2005, high values occurred over a broad area from the western Indian Ocean into the central and southeastern parts of the basin. Between 2006 and 2014, hotspots were more spatially variable, generally appearing as discrete concentrations in the northwestern Indian Ocean, around the Mozambique Channel and Madagascar, and occasionally in the central tropical Indian Ocean. The spatial extent of elevated predicted standardized CPUE was markedly reduced in 2015, with high values restricted to a few

localized cells. High predicted standardized CPUE became increasingly apparent from 2016, and during 2018–2024, strong hotspots occurred more continuously across the western and central tropical Indian Ocean. In 2025, high values remained mainly in the central tropical Indian Ocean, whereas their intensity in the western region was lower than in several immediately preceding years.

4. Discussion

This paper revisited the previous Taiwanese silky shark CPUE standardization (IOTC–2019–WPEB15-24; Tsai et al., 2019) by extending the logbook dataset through 2025 and implementing a spatio-temporal CPUE standardization framework based on tinyVAST. Eight candidate observation-model structures and four alternative tinyVAST model configurations were evaluated to identify a standardized abundance index to support the upcoming Indian Ocean silky shark benchmark stock assessment. The previous analysis used a generalized linear modeling framework with a zero-inflated negative binomial (ZINB) distribution, a formulation designed for overdispersed counts with excess zeros (Minami et al., 2007). That analysis did not explicitly model latent spatial and temporal dependence. Ignoring this spatio-temporal heterogeneity can bias abundance indices (Thorson et al., 2015a, 2015b; Fuster-Alonso et al., 2024). Recent geostatistical approaches partition latent spatial variation, borrow strength across neighboring locations and years, and generally provide more stable and internally consistent abundance indices than conventional non-spatial methods (Grüss et al., 2023).

The standardized abundance index exhibited considerable interannual variability, reaching its highest value in 2014, declining sharply to its lowest level in 2015, and generally remaining above the long-term mean from 2018 onward. These fluctuations should be interpreted cautiously because standardized CPUE reflects changes in catchability as well as stock abundance. Internal evidence from the fishery supports this. For example, fishing effort declined markedly between 2005 and 2006 (hooks decreasing from 221.3 to 108.7 million), while the standardized index showed modest changes (**Table 1; Fig. 9a**). In contrast, between 2014 and 2015, fishing effort increased (hooks from 58.3 to 70.5 million; sets from 18,460 to 22,439), yet silky shark catches declined sharply (3,386 to 277). These contrasting patterns indicate that changes in fishing effort alone cannot explain the observed temporal variability in standardized CPUE. Instead, the fluctuations likely reflect changes in fleet distribution, encounter probability, and targeting behavior rather than genuine changes in stock abundance. Modest changes in the standardized index during early years, despite substantial reductions in fishing effort, may reflect large-scale changes in fleet operations. Taiwanese distant-water longline fisheries are known for flexible targeting strategies that shift among albacore, bigeye tuna, and southern bluefin tuna in response to fishing opportunities and market conditions (Michael et al., 2017). Such operational changes influence fishing locations and shark encounter probabilities, contributing to temporal variation in standardized CPUE. Additionally, the rapid expansion of Somali piracy after 2007 altered fishing operations throughout the western Indian Ocean (Kaplan et al., 2014), forcing many fleets to avoid traditional fishing grounds. Redistribution of fishing effort during this period may have contributed to the temporal variation observed in the standardized abundance index.

The broad spatial distribution of high standardized CPUE in this study was consistent with previous habitat-based analyses of silky sharks in the Indian Ocean (Grande et al., 2022). Previous studies identified high probabilities of occurrence off Somalia and in the Arabian Sea, with lower probabilities across much of the southeastern Indian Ocean. Although the present analysis was based on standardized fishery-dependent CPUE rather than habitat suitability, similar large-scale spatial patterns were evident.

Several limitations should be acknowledged. First, the analysis relied on fishery-dependent logbook data and therefore remains sensitive to species-identification and reporting error, changes in fishing practices and catchability, and the low, nonuniform observer coverage used

for the descriptive zero-catch comparison. Second, the $5^{\circ} \times 5^{\circ}$ reporting grid and the concentration of fishing effort in selected areas limit spatial resolution; the predicted surfaces are fishery-dependent relative-CPUE predictions, not maps of habitat suitability or absolute abundance (Ducharme-Barth et al., 2022; Hoyle et al., 2024). Third, environmental covariates were intentionally omitted because the objective was to produce a stock-assessment index rather than infer habitat drivers. Finally, sensitivity to mesh resolution, alternative prediction domains, and temporal cross-validation was not evaluated, and observation-family, covariate-selection, and model-selection uncertainty was not propagated into the reported confidence intervals. The indices should therefore be interpreted with biological and fishery information, and future updates should prioritize improved species-level reporting, greater and more representative observer coverage, and targeted sensitivity analyses.

Overall, the standardized abundance index presented here provides an updated, reproducible fishery-dependent input for future Indian Ocean silky shark stock assessments and demonstrates the applicability of modern geostatistical CPUE standardization to long-term Taiwanese longline logbook data.

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Table 1. Annual logbook catch-and-effort data for silky shark (FAL) and observer coverage of the Taiwanese large-scale tuna longline fleet in the Indian Ocean, 2005–2025.

Year	No. of sets	No. of hooks	No. of FAL catches and discards	Observer coverage rate (%)
2005	69,792	221,255,156	8,437	0.8
2006	33,836	108,736,005	2,673	1.43
2007	42,941	137,682,666	2,790	6.70
2008	29,643	95,085,057	2,773	6.59
2009	38,643	124,236,985	4,178	7.02
2010	27,841	90,408,616	2,531	9.17
2011	21,445	68,765,365	989	4.21
2012	25,152	76,474,987	2,150	4.81
2013	23,724	75,819,812	3,346	8.29
2014	18,460	58,330,538	3,386	8.95
2015	22,439	70,526,641	277	5.99
2016	31,556	101,547,237	2,464	5.34
2017	29,948	99,310,531	2,386	6.32
2018	27,996	92,934,558	3,631	7.53
2019	28,373	96,102,192	6,964	8.29
2020	26,425	89,053,763	6,276	9.14
2021	27,232	90,828,649	5,396	8.13
2022	30,278	98,012,265	5,759	8.70
2023	29,704	98,364,508	9,521	11.55
2024	20,388	69,029,090	5,126	18.92
2025	19,101	65,504,470	2,513	9.02
Total	624,917	2,028,009,091	83,566	–
Average	29,758	96,571,861	3,979	7.47

Table 2. Stage 1 model selection for eight candidate tinyVAST models fitted to silky shark catches from the Taiwanese tuna longline logbook fishery in the Indian Ocean. Δ AIC and Δ cAIC are differences from the minimum value among the candidate models. The best-supported model is shown in bold. All models used Catch ~ Year + Quarter + HPBC + CTNO + Cluster + offset(log Hooks).

Model	No of parameters	Deviance explained	AIC	Δ AIC	cAIC	Δ cAIC	Maximum gradient
M1	33	0.087	377974.7	19089.7	377974.7	20866.1	<0.0001
M2	35	0.122	367727.3	8842.4	367333.0	10224.4	<0.0001
M3	35	0.161	359247.8	362.8	357179.8	71.2	0.0002
M4	36	0.161	358884.9	0.0	357108.6	0.0	<0.0001
M5	33	0.085	395957.8	37072.8	395957.8	38849.2	<0.0001
M6	35	0.119	385710.4	26825.5	385316.1	28207.5	<0.0001
M7	35	0.158	377230.9	18346.0	375162.9	18054.3	<0.0001
M8	36	0.157	376868.0	17983.1	375091.7	17983.1	<0.0001

Table 3. Stage 2 model selection for four candidate fixed-effects specifications fitted to silky shark catches from the Taiwanese tuna longline logbook fishery in the Indian Ocean. Δ AIC and Δ cAIC are differences from the minimum value among the candidate models. The best-supported model is shown in bold.

Model	No of parameters	Deviance explained	AIC	Δ AIC	cAIC	Δ cAIC	Maximum gradient
F1	29	0.158	359916.5	1031.6	358117.6	1009.0	<0.0001
F2	30	0.158	359916.8	1031.8	358117.6	1009.1	<0.0001
F3	32	0.159	359730.9	846.0	357931.5	822.9	<0.0001
F4	36	0.161	358884.9	0.0	357108.6	0.0	<0.0001

Table 4. Annual relative nominal CPUE and relative standardized CPUE for silky shark from the Taiwanese large-scale tuna longline logbook fishery in the Indian Ocean, 2005–2025. Each series was scaled by its 2005–2025 mean. Standardized estimates are from the best-supported tinyVAST model (F4); 95% confidence intervals (CIs) and coefficients of variation (CVs) are shown.

Year	Relative nominal CPUE	tinyVAST			CVs
		Relative standardized CPUE	Lower CIs	Upper CIs	
2005	0.910	1.195	0.929	1.536	0.128
2006	0.586	0.320	0.251	0.409	0.125
2007	0.483	0.577	0.305	1.093	0.326
2008	0.696	0.339	0.257	0.448	0.142
2009	0.802	0.436	0.321	0.591	0.156
2010	0.668	1.216	0.431	3.433	0.530
2011	0.343	0.365	0.122	1.090	0.559
2012	0.671	0.333	0.160	0.692	0.373
2013	1.053	0.947	0.419	2.139	0.416
2014	1.385	2.015	0.838	4.846	0.448
2015	0.094	0.076	0.040	0.143	0.325
2016	0.579	0.448	0.327	0.612	0.160
2017	0.573	0.654	0.418	1.024	0.229
2018	0.932	1.260	0.699	2.270	0.300
2019	1.729	1.228	0.740	2.035	0.258
2020	1.681	1.977	0.916	4.267	0.393
2021	1.417	1.416	0.782	2.566	0.303
2022	1.402	1.303	0.741	2.291	0.288
2023	2.309	1.925	1.077	3.441	0.296
2024	1.772	1.886	0.883	4.025	0.387
2025	0.915	1.086	0.589	2.003	0.312

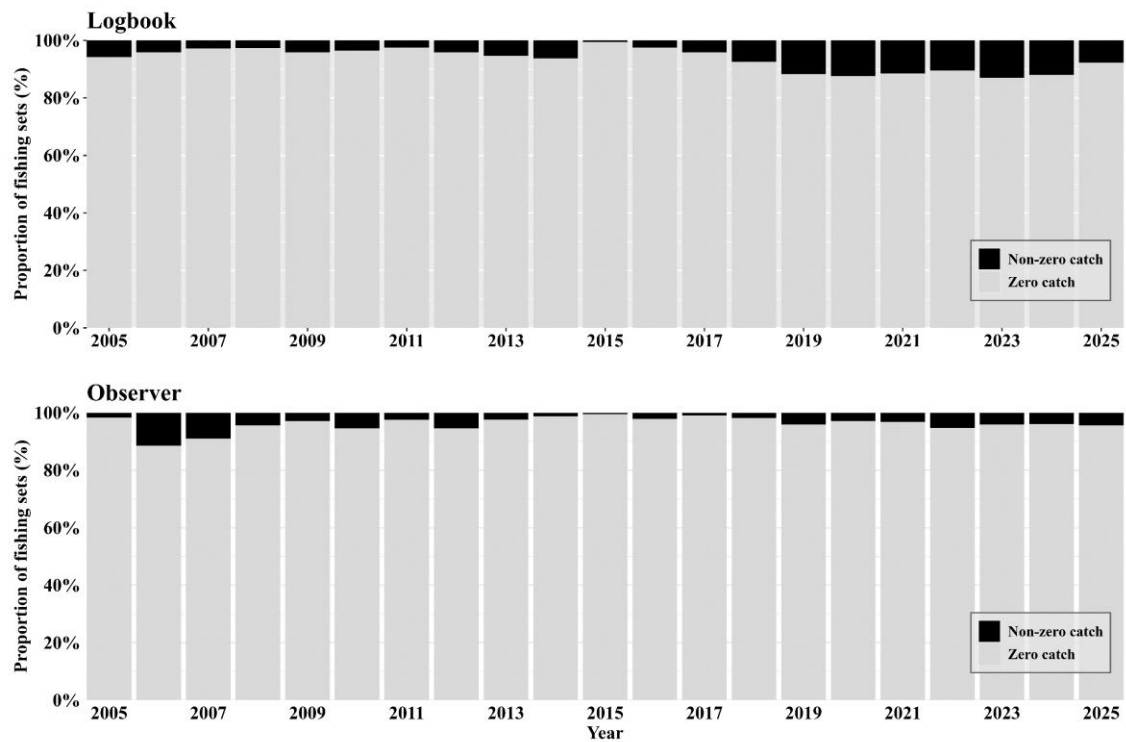


Fig. 1. Annual proportions of non-zero catch and zero catch fishing sets for silky shark in Taiwanese large-scale tuna longline logbook and observer datasets from the Indian Ocean, 2005–2025.

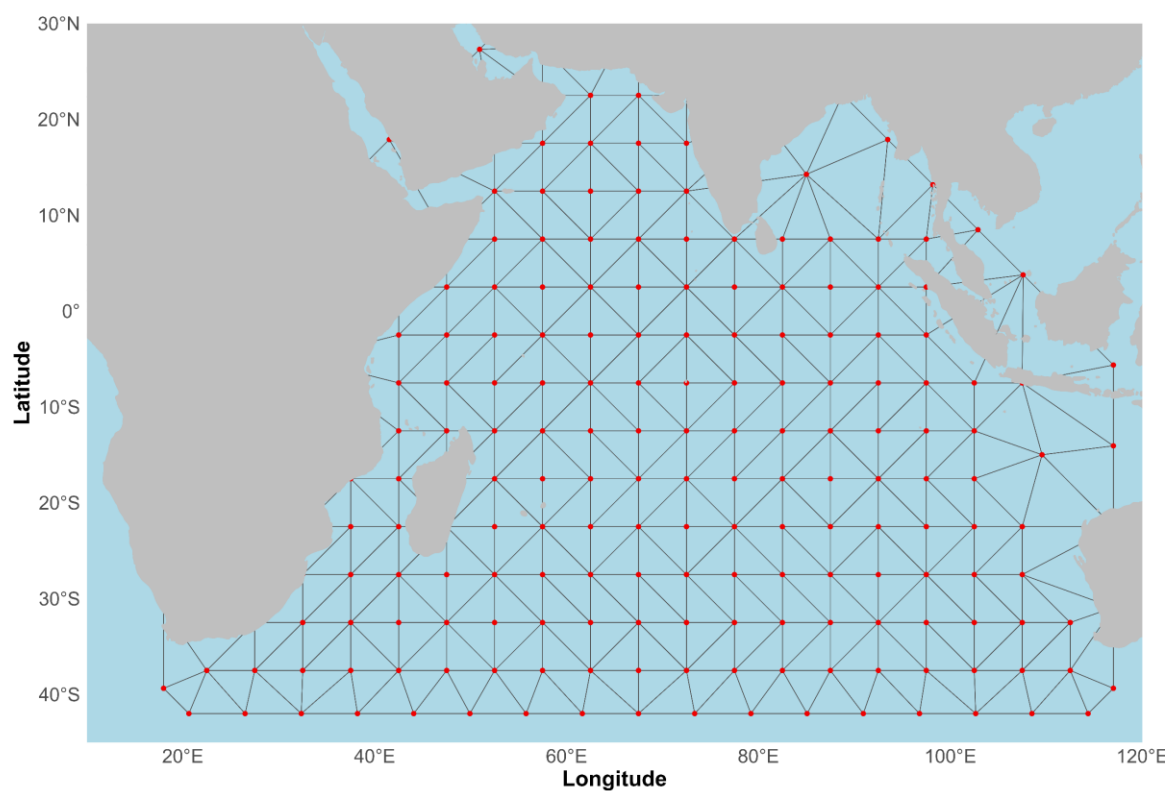


Fig. 2. Triangulated finite-element mesh used for spatial modeling in the present analysis of the Indian Ocean silky shark dataset, based on logbook data from the Taiwanese large-scale tuna longline fishery (2005–2025). Red points denote mesh nodes.

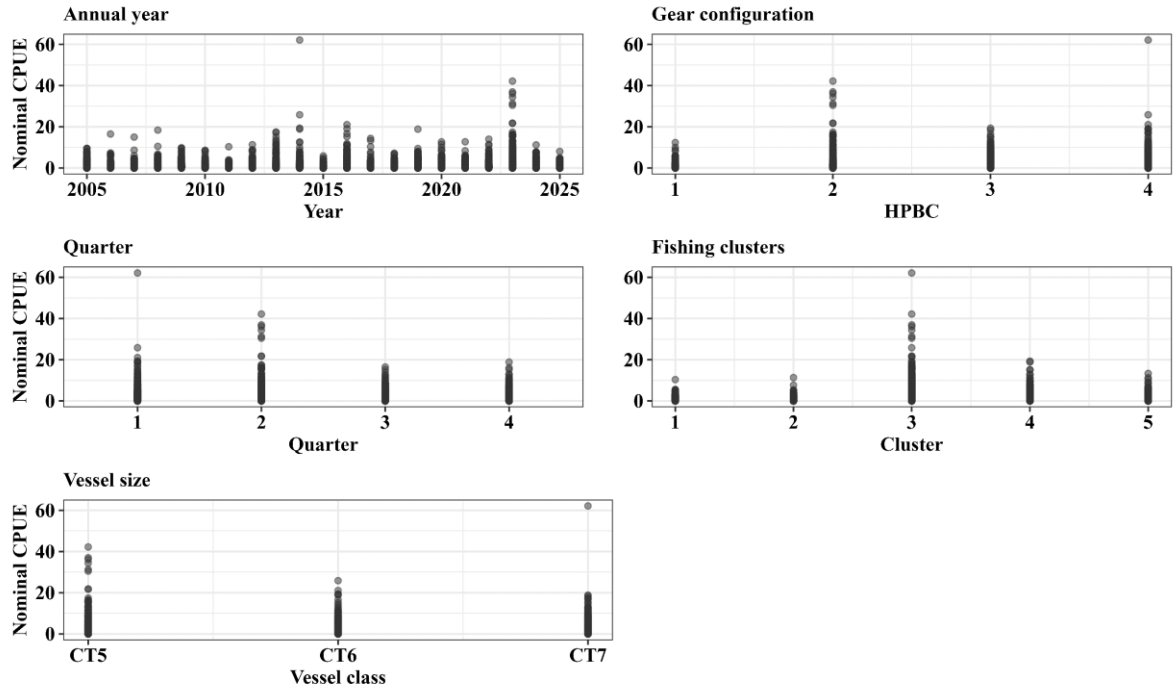


Fig. 3. Distribution of nominal CPUE (number of silky sharks per 1,000 hooks) by year, quarter, gear configuration (HPBC), fishing strategy cluster, and CTNO for the Indian Ocean silky shark dataset, based on logbook data from the Taiwanese large-scale tuna longline fishery 2005–2025.

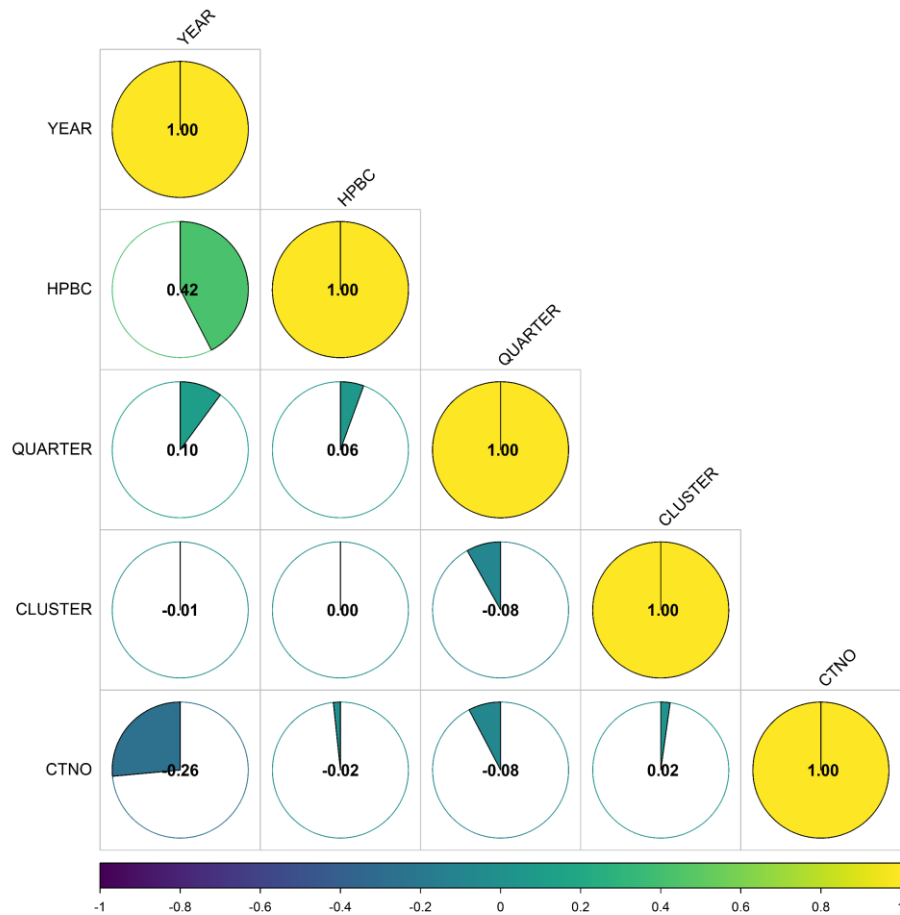


Fig. 4. Correlation matrix among predictors (year, HPBC, quarter, fishing clusters, and CTNO) for the Indian Ocean silky shark dataset, based on logbook data from the Taiwanese large-scale tuna longline fishery 2005–2025.

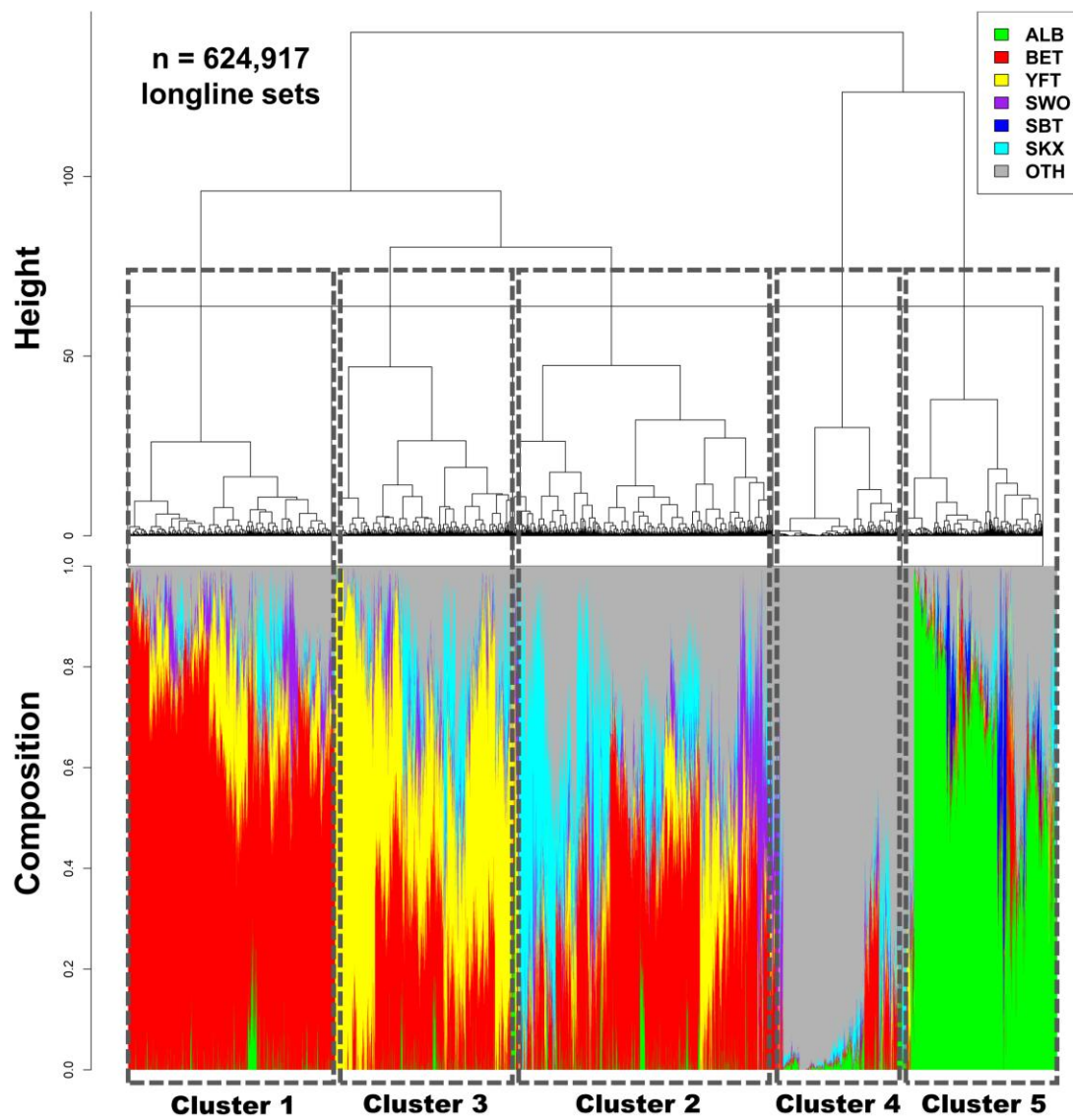


Fig. 5. Hierarchical clustering dendrogram and corresponding relative species composition used to identify fishing strategies based on logbook data from the Taiwanese longline fishery operating in the Indian Ocean (2005–2025).

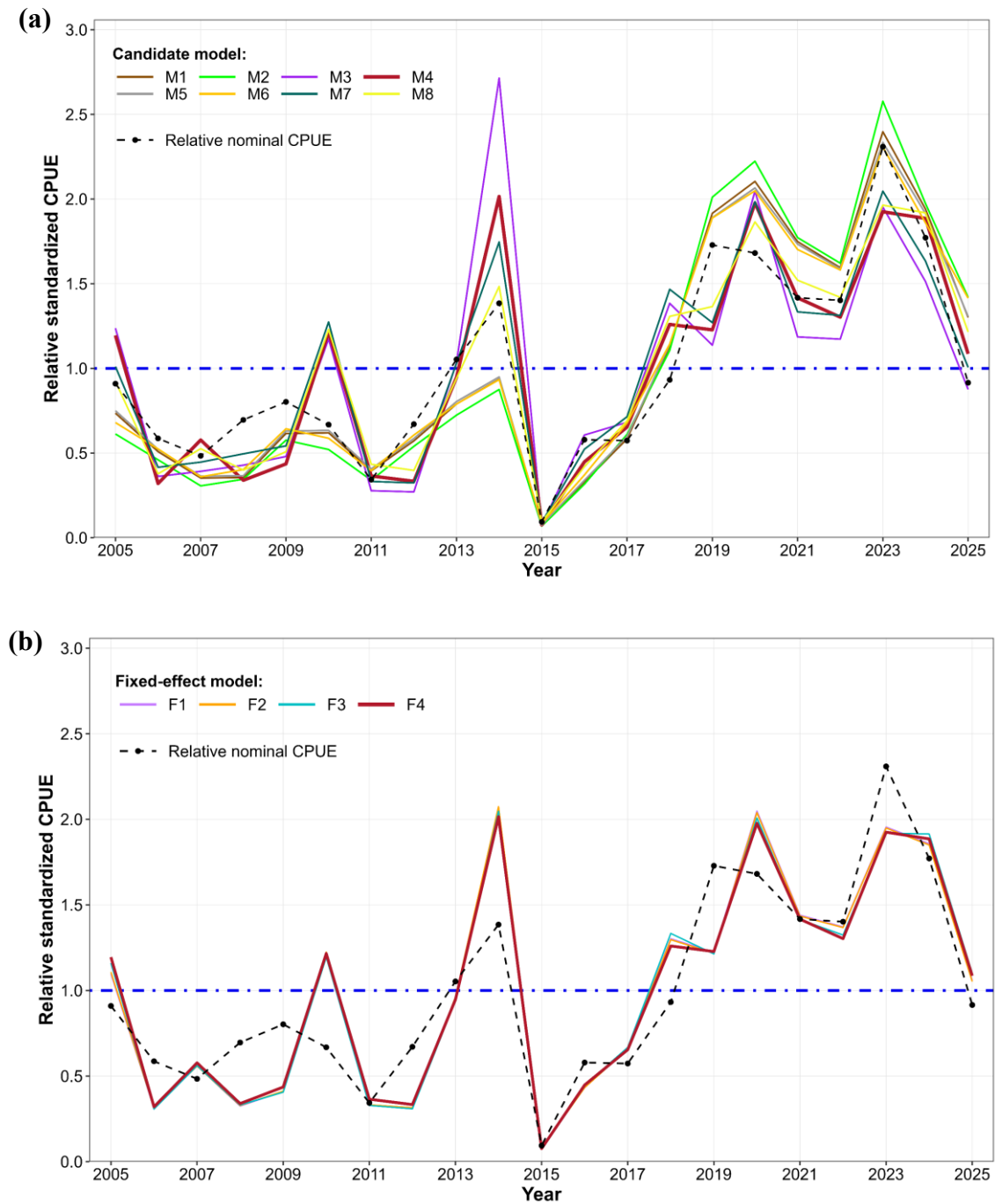


Fig. 6. Comparison of annual relative standardized CPUE (annual standardized CPUE scaled to its average) estimated from candidate tinyVAST models fitted to silky shark catch data from the Taiwanese tuna longline fishery in the Indian Ocean during 2005–2025. (a) Stage 1 model selection showing results from the eight candidate models (M1–M8) used to evaluate alternative observation families and random-field structures. (b) Stage 2 model selection showing results from the four candidate fixed-effects models (F1–F4). The black dashed line indicates relative nominal CPUE (nominal CPUE scaled to its average), and the blue dot-dashed line represents the mean relative value (1.0).

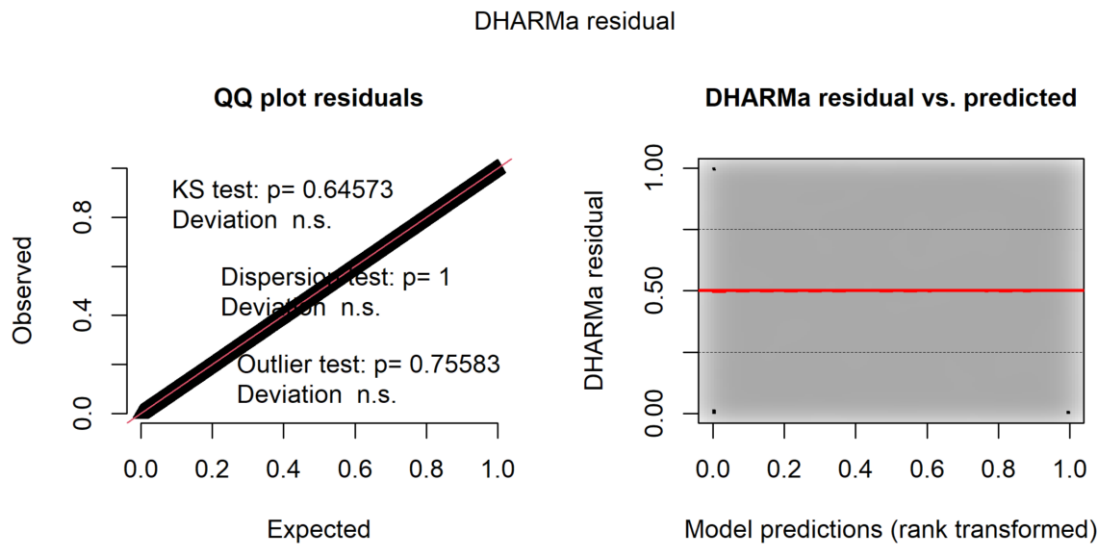


Fig. 7. DHARMA residual diagnostic plots for the selected tinyVAST model F4 fitted to silky shark catch data from the Taiwanese tuna longline logbook fishery in the Indian Ocean.

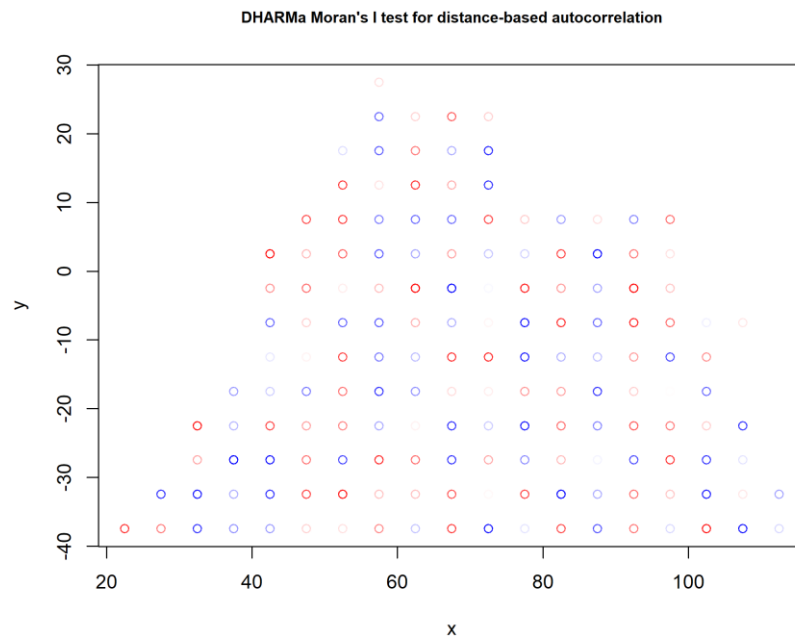


Fig. 8. Moran's I diagnostic plot for the selected tinyVAST model F4.

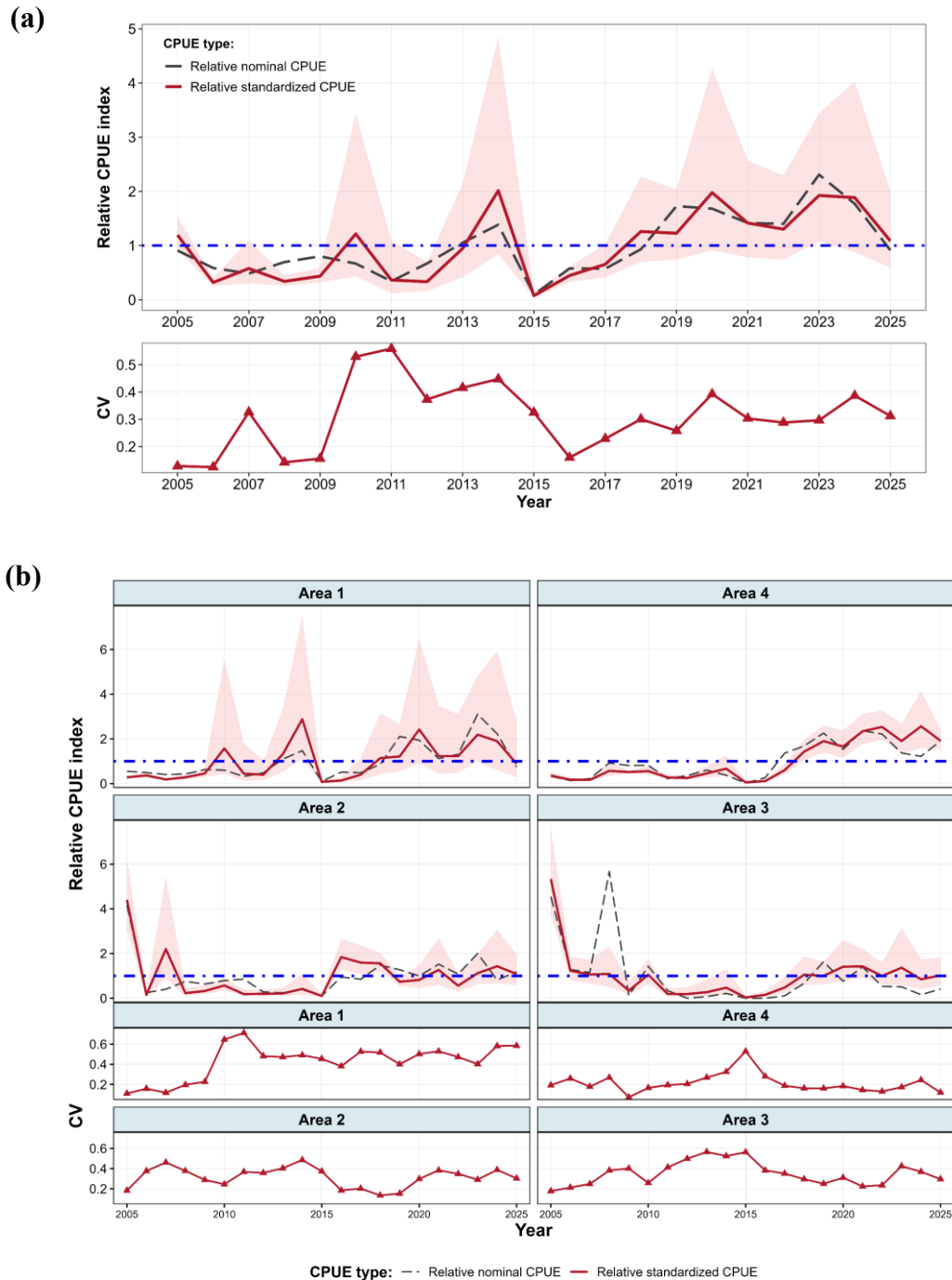


Fig. 9. (a) Annual relative standardized CPUE (standardized CPUE scaled to its average; upper panel) and corresponding coefficients of variation (CVs; lower panel) for silky shark estimated from Taiwanese large-scale tuna longline logbook data in the Indian Ocean (2005–2025) using the best-supported tinyVAST model (F4). Shaded areas represent 95% confidence intervals (CIs). The blue dot-dashed line indicates the mean relative value (1.0), and the black dashed line represents relative nominal CPUE (nominal CPUE scaled to its average). (b) Area-specific annual relative standardized CPUE estimates with corresponding 95% CIs (upper panels) and CVs (lower panels) for Areas 1–4.

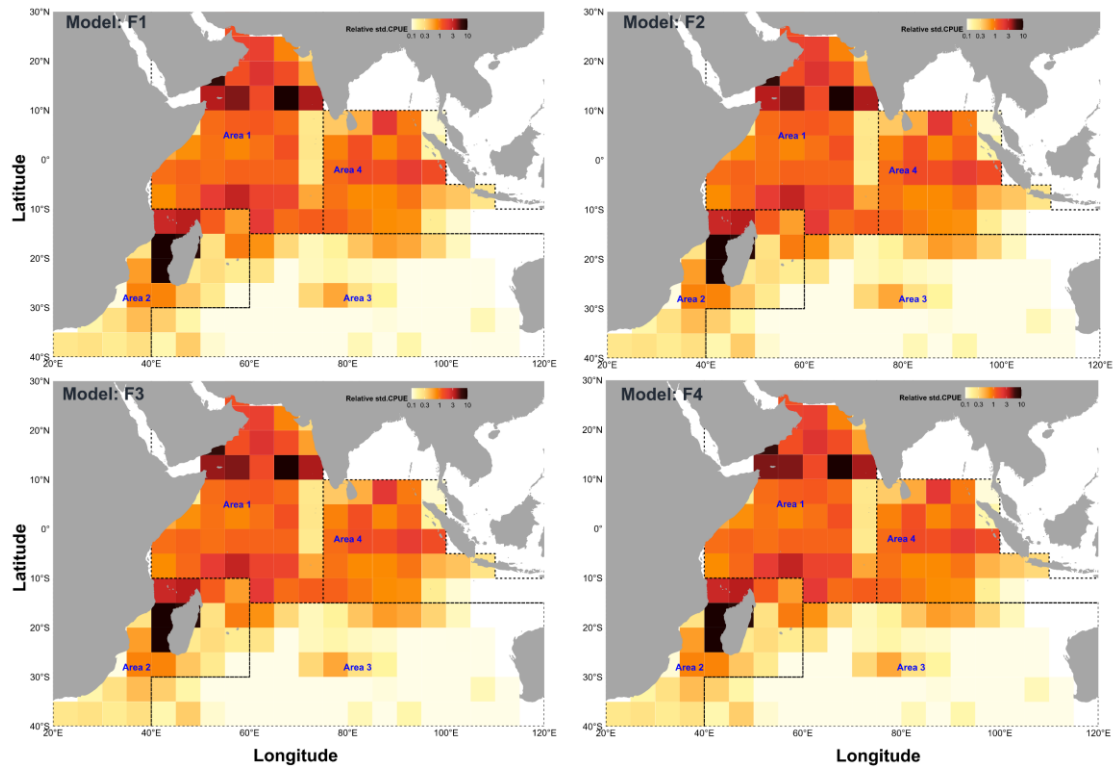


Fig. 10. Spatial distribution of relative standardized CPUE (standardized CPUE scaled to its average) for silky shark, aggregated into 5°×5° grid cells using logbook data from the Taiwanese large-scale tuna longline fishery in the Indian Ocean (2005–2025). Results are shown for models F1, F2, F3, and F4, respectively.

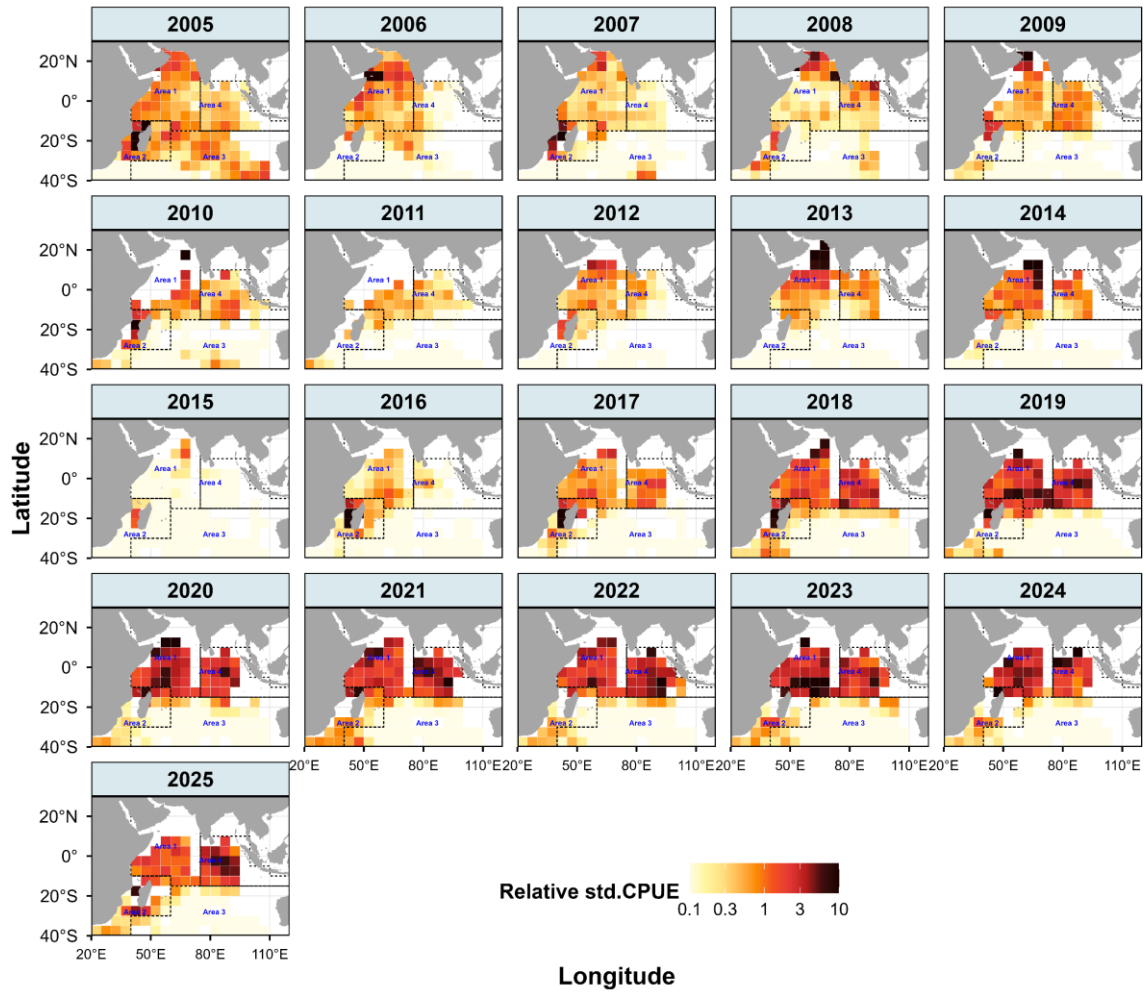


Fig. 11. Annual spatial predictions of relative standardized CPUE (standardized CPUE scaled to its average) for silky shark, aggregated into $5^{\circ} \times 5^{\circ}$ grid cells using logbook data from the Taiwanese large-scale tuna longline fishery in the Indian Ocean (2005–2025), based on model F1.

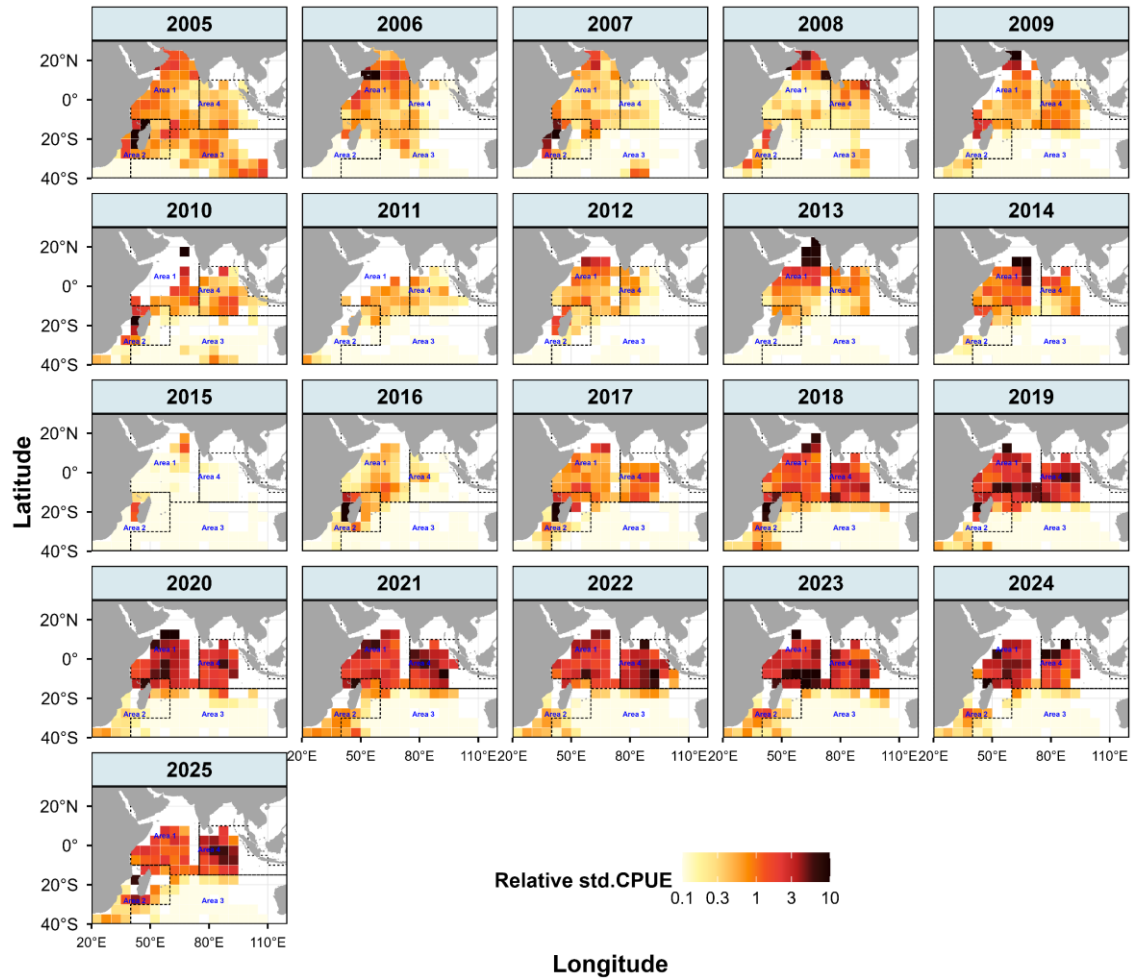


Fig. 12. Annual spatial predictions of relative standardized CPUE (standardized CPUE scaled to its average) for silky shark, aggregated into 5°×5° grid cells using logbook data from the Taiwanese large-scale tuna longline fishery in the Indian Ocean (2005–2025), based on model F2.

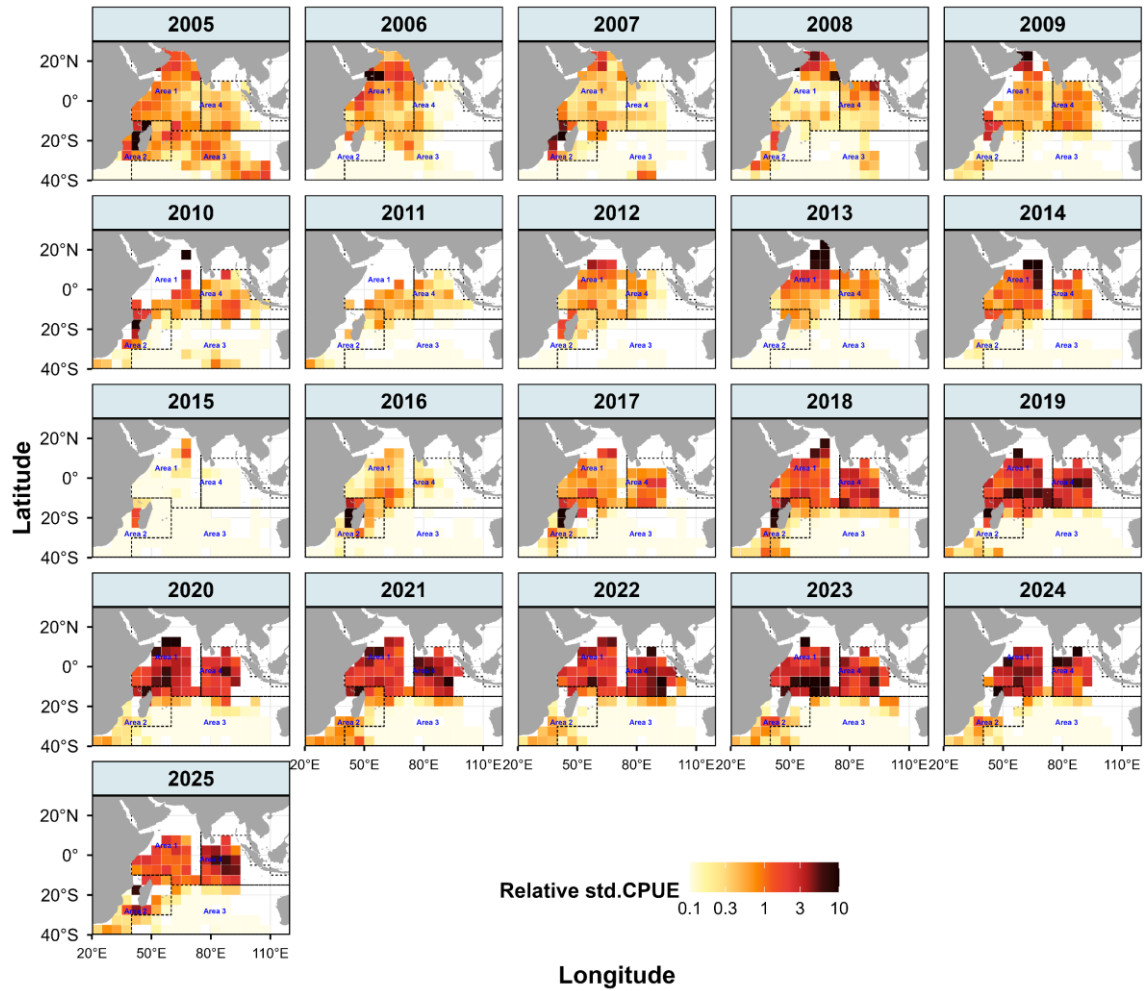


Fig. 13. Annual spatial predictions of relative standardized CPUE (standardized CPUE scaled to its average) for silky shark, aggregated into 5°×5° grid cells using logbook data from the Taiwanese large-scale tuna longline fishery in the Indian Ocean (2005–2025), based on model F3.

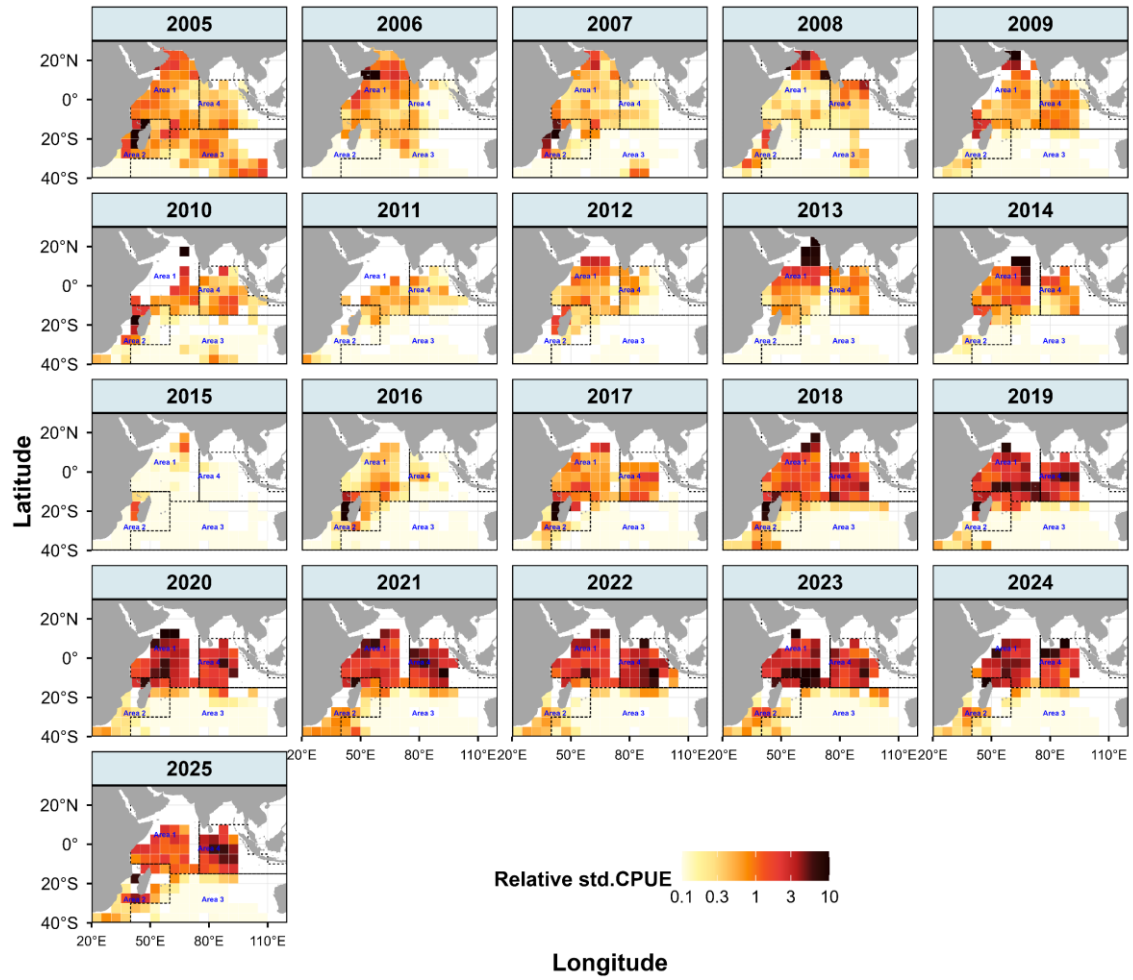


Fig. 14. Annual spatial predictions of relative standardized CPUE (standardized CPUE scaled to its average) for silky shark, aggregated into $5^{\circ} \times 5^{\circ}$ grid cells using logbook data from the Taiwanese large-scale tuna longline fishery in the Indian Ocean (2005–2025), based on model F4.