Journal of Marine Science and Technology

Volume 32 | Issue 2 Article 1

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Recommended Citation
Hung, Chun-Yi; Huynh, Hoang Huy; Wu, Xing-Han; and Tsai, Wen-Pei (2024) "Multimodel approach to a support stock assessment of standardized catch and effort data: A case study of blue shark (Prionace glauca) in the Indian Ocean by the Taiwanese large-scale longline fishery," *Journal of Marine Science and Technology*: Vol. 32: Iss. 2, Article 1.
DOI: 10.51400/2709-6998.2734
Available at: https://jmstt.ntou.edu.tw/journal/vol32/iss2/1

RESEARCH ARTICLE

Multimodel Approach to a Support Stock Assessment of Standardized Catch and Effort Data: A Case Study of Blue Shark (*Prionace glauca*) in the Indian Ocean by the Taiwanese Large-scale Longline Fishery

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Abstract

In the context of stock assessment and fishery conservation, determining catch per unit effort (CPUE) accurately and reliably is essential. This study estimated trends in the relative abundance of blue sharks (*Prionace glauca*) in the Indian Ocean from 2005 to 2022. Blue sharks constitute a resilient bycatch species in pelagic tuna and swordfish longline fisheries. We employed a multimodel approach that included delta-lognormal, zero-inflated negative binomial, and vector autoregressive spatiotemporal (VAST) models to standardize catch rates recorded by observers in the Taiwanese large-scale longline fishery. Our analysis concentrated on the CPUE of blue sharks, including standardizing the number of fish caught per 1000 hooks. Model residual analysis indicated that the VAST model was the most favorable of the models considered. Although the overall pattern of the standardized CPUE series indicated neither overexploitation nor a consistent downward trend, this pattern revealed fluctuations in the relative abundance of blue sharks rather than a clear and consistent upward trend from 2005 to 2022. The observed stability in blue shark catches by the Taiwanese large-scale longline fishery suggests that blue shark stocks in the Indian Ocean are currently at an optimal utilization level. Future research enhancements could involve incorporating environmental factors into the proposed model and utilizing longer-term observations to enrich the depth and scope of the present research findings.

Keywords: Blue shark, Catch per unit effort standardization, Stock assessment, Zero-catch problem

1. Introduction

Monitoring the Indian Ocean's ecosystem and fisheries is crucial for maintaining the socioeconomic and ecological well-being of the region. Monitoring nontarget species, such as sharks, is particularly crucial because of their evolutionary uniqueness [1] and their high vulnerability to overfishing [2], especially close to coral reefs [3]. Understanding pelagic shark abundance trends is essential for implementing timely and sustainable fishery practices [4,5] to preserve the diverse marine life found in the Indian Ocean.

The blue shark (*Prionace glauca*), a resilient bycatch in pelagic tuna (Thunnus spp.) and swordfish (*Xiphias gladius*) longline fisheries [6,7], has an estimated annual mortality figure of 10.74 million [8]. In the Indian Ocean, at fewest ten other bycatch shark species coexist, and the blue shark accounts for 2.0% of the catch [9]. This species is classified as "Near Threatened" on the International Union for Conservation of Nature Red List [10]. Despite the

Received 1 February 2024; revised 20 April 2024; accepted 22 April 2024.
Available online 21 June 2024

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https://doi.org/10.51400/2709-6998.2734

ecological importance of blue sharks [11], current data focus mainly on landings from major commercial fisheries, overlooking assessments of discarded, illegal, and unreported catches, all of which pose risks to the broader ocean ecosystem [9,12,13]. Concerns regarding the reliability of stock assessments, with only 72% of catches reported in 2019 [14], contribute to the underestimation of unreported landings and discards in these fisheries [15].

In the field of fisheries science, catch per unit effort (CPUE) indices play a crucial role in evaluating resource abundance. Owing to inherent biases and ongoing challenges associated with fishery-dependent data, these indices are often assumed to be directly proportional to abundance [16,17]. Standardizing catch and effort data is a vital step in mitigating potential biases and ultimately yielding a reliable and unbiased indicator of fishery resource abundance [4,18]. However, given that the shark catch data set frequently includes zero values and substantial aggregations [19,20], scientists must meticulously examine these data. Scientists closely examine cases with CPUE rates greater than or equal to zero, resulting in the creation of predictive models. These models—known as “combined,” “two-stage,” or “hurdle” models—consist of binomial components that estimate the probability and magnitude of a catch (excluding zero catches).

Typical CPUE standardization models, such as generalized linear models [21] and generalized additive models [22], are limited in their ability to handle fixed effects, interactions, and high zero-value data [23]. The delta-lognormal (DLN) modeling technique is recognized for its suitability in relation to data sets that contain high quantities of zero-value data [24,25]. In tuna longline fisheries, where sharks are common bycatches, DLN modeling is recommended to address the challenge of excessive zero catches effectively. Additionally, the zero-inflated negative binomial (ZINB) model [26] demonstrates effectiveness in modeling “extra” zero data to yield a larger proportion than expected, possibly due to reporting errors or misidentifications [27]. ZINB modeling is commonly applied in CPUE standardization for shark bycatches in tuna longline fisheries, offering a superior fit compared with alternative models such as Poisson, negative binomial (NB), and zero-inflated Poisson regression models [20].

In an alternative context, generalized linear mixed model (GLMMs) [28] have become effective in handling nonnormal response data by incorporating both fixed and random effects [29]. GLMMs are highly versatile and commonly employed for CPUE standardization. Of importance is the inclusion of a year-area interaction term, which highlights the necessity to consider temporal and spatial covariates in the model's application. The assumption is based on the belief that annual abundance trends diverge across study regions [30,31]. However, a critical limitation of GLMMs is their failure to explicitly account for spatial autocorrelation in observations. The incorporation of spatiotemporal statistical models has become indispensable in modern stock assessments, offering precise estimations by addressing spatial and spatiotemporal variations [32,33]. The effectiveness of the vector autoregressive spatiotemporal (VAST) model [34] is evident in how the model estimates relative abundance indices for highly migratory species, such as the shortfin mako shark (*Isurus oxyrinchus*) [35,36], blue shark (*P. glauca*) [35], chub mackerel (*Scomber japonicus*) [37], bluefin tuna (*Thunnus thynnus*) [38], and yellowfin tuna (*Thunnus albacares*) [39]. The VAST model exhibits promise for delivering more accurate and more biologically meaningful estimates compared with conventional models [40].

Reliable abundance indices for blue sharks in the Indian Ocean are crucial for stock assessment and future planning. Accordingly, the present study employed a multimodel approach (DLN, ZINB, and VAST) to standardize CPUE data in the Taiwanese large-scale longline fishery from 2005 to 2022 by using observers' records. This approach addresses uncertainties in fishery-dependent data, including zero-catch data, and also accounts for structural uncertainty. Despite the limited number of catch rate studies conducted on a hemispheric scale, our findings provide valuable insights that bridge a research gap related to assessment of the status of blue sharks in the Indian Ocean.

2. Materials and methods

2.1. Overview description

This section outlines the methods used for estimating CPUE, involving two main steps: data collection and standardized modeling of shark CPUE. Fig. 1 illustrates two key research processes, namely data acquisition and analysis.

2.2. Fishery observer data

Scientific observers from the Overseas Fisheries Development Council of Taiwan provided data regarding blue shark (BSH) catch and effort in the Taiwanese large-scale longline fishery from 2005 to 2022 for blue shark collected specifically by these vessels. The data set used for the present analysis included BSH catch quantities, the number of hooks,

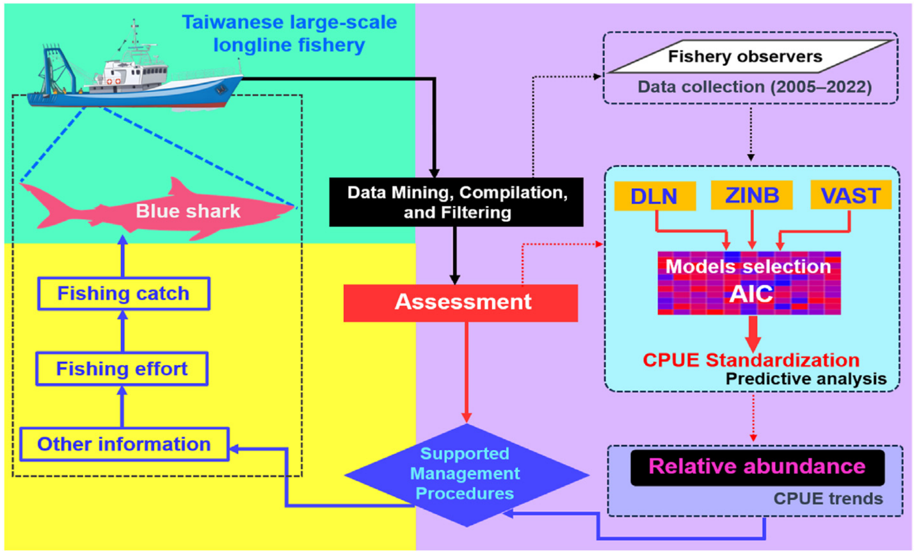

Fig. 1. Schematic illustrating the overarching steps involved in predicting CPUE in this study.

and spatiotemporal data such as year, month, day, latitude, and longitude data for each fishing operation. Other variables included in our models were branch lines between floats (i.e., hooks per basket [HPB]), vessel size (CTNO), and target species (GRP).

2.3. Data filtering and initial data exploration

Before standardization, we excluded incomplete data sets lacking essential information such as that related to latitude, longitude, hooks, and HPB. We determined CPUE through calculations of the number of BSH captured (n) per 1000 deployed hooks. Nominal CPUE was computed using the formula $CPUE = \frac{\sum n_i}{\sum e_i} = \frac{\overline{n}}{\overline{e}} \times 1000$, where n_i represents the catch number, e_i denotes the corresponding fishing effort (number of hooks in this instance), and i refers to individual observations within the data set. From 2005 to 2022, the data set recorded an effort of 71,494,053 hooks, resulting in the capture of 50,032 blue sharks. Fig. 2 illustrates the geographical distribution of observed fishing catch and effort, demonstrating area stratification and presenting nominal CPUE data for each area stratum.

Despite variations in nominal CPUE, 53.8% of the fishing sets in the Indian Ocean recorded zero BSH catches, as illustrated in Fig. 3. This finding highlights the potential influence of confounding factors on catches and emphasizes the importance of standardization to address these factors.

2.4. Statistical modeling of standardized CPUE

Zero BSH catches (CPUE = 0), as illustrated in Fig. 3, prompted the adoption of three methodologies for CPUE standardization to address mathematical challenges. These methodologies ae detailed in the following subsections.

2.4.1. DLN model

Introduced by Lo et al. [24], the DLN model integrates two distinct models: one for estimating positive catch proportions and one for predicting positive catch rates.

Within the DLN model, the following lognormal framework is incorporated for positive catch events:

$$ln(CPUE) = \mu + Year + Quarter + Area + HPBC + \varepsilon_1$$

Additionally, a binomial model is implemented to estimate the proportion of positive catches for BSH (*PA*), as expressed as follows:

$$PA = \mu + Year + Quarter + Area + HPBC + \varepsilon_2$$

In this model, the gear configuration HPB (HPBC) is divided into four classes: shallow (HPB < 5), middle (5 ≤ HPB < 10), deep (10 ≤ HPB < 15), and ultradeep (HPB ≥ 15). In addition, quarters are classified as the first quarter (January–March), second quarter (April–June), third quarter (July–September), and fourth quarter (October–December.). The parameters consist of μ for the mean, ε_1 for the normal random error term, and ε_2 for the binomial error distribution. The area stratification used for the analysis is visually depicted in Fig. 1.

To obtain the final estimate of the annual abundance index, we multiplied the estimated marginal means of the annual effects from the lognormal and binomial components while incorporating

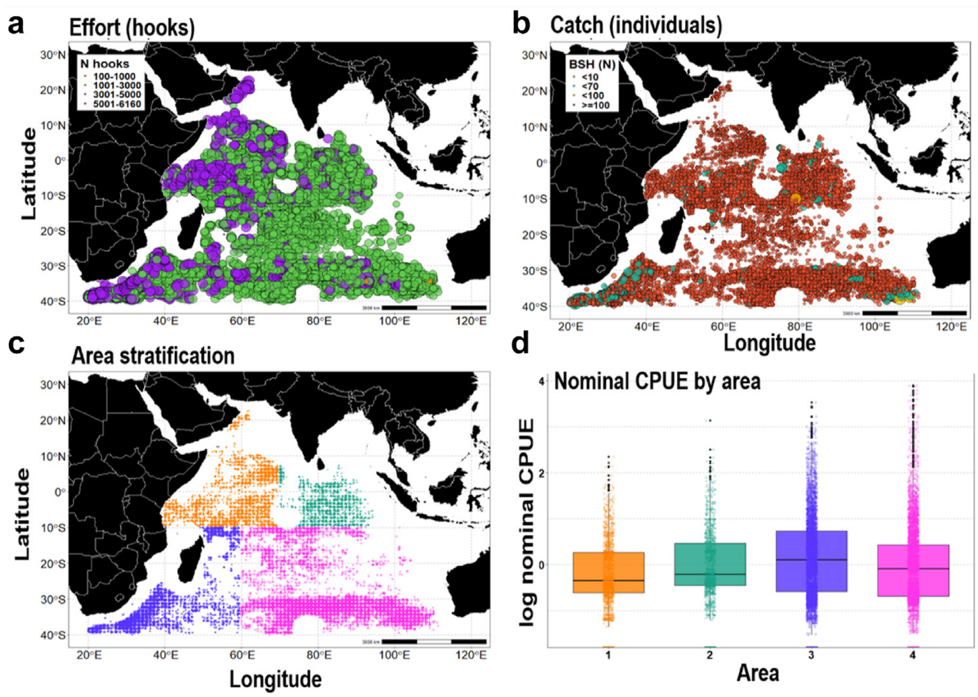

Fig. 2. Geographical distributions of the observed fishing effort (i.e., number of hooks) (a) and fishing catch (i.e., catch in number) (b) along with area stratification (c) and nominal CPUE data (d) for each area stratum by the Taiwanese large-scale longline fishery operating in the Indian Ocean from 2005 to 2022. The colors of each area in (c) are consistent with those in (d). The boxes in (d) depict the middle 50% of the data, whereas the small circles indicate outliers or extremes in CPUE.

appropriate bias correction [24]. This approach is used in the best-fitting model, which is described by the following equation: Standardized CPUE = CPUE × PA.

2.4.2. ZINB model

The ZINB method [26] is often used for data sets that have a high number of zero catches. This method distinguishes between zero and nonzero counts, employing a count model to handle overdispersion in both situations. Furthermore, the model includes a binomial component to account for the presence of "extra" zeros, which occur more frequently than expected under various count distributions [41].

The count model is expressed as follows:

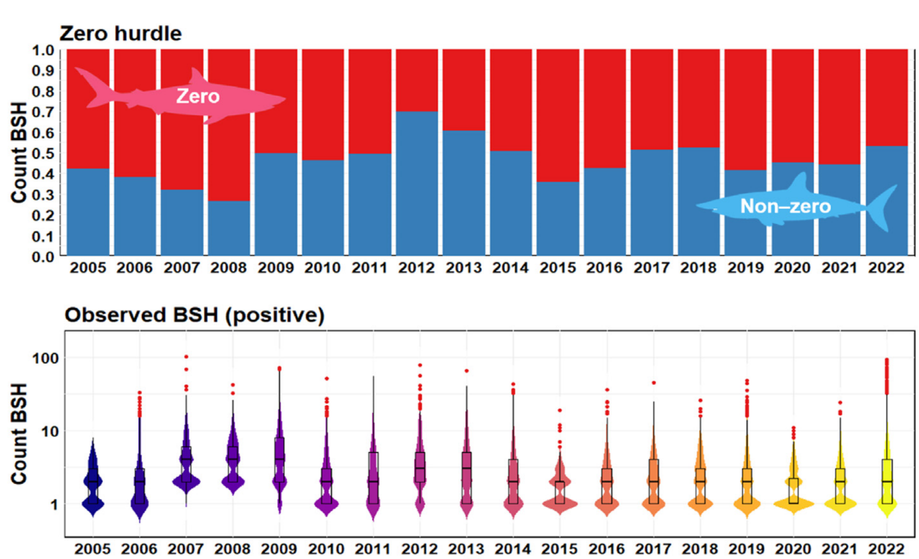

Fig. 3. Distribution of catch numbers (zero and positive values) in the Taiwanese large-scale longline fishery in the Indian Ocean.

$Catch = Year + Quarter + Area + HPBC$

The probability distribution of a ZINB random variable Y is composed of two components:

(Part 1: Count models–NB; Part 2: Binomial, link = logit)

$$\Pr(Y=y)=\begin{cases}\omega+(1-\omega)(1-k\lambda)^{\frac{1}{k}} & for\, y=0\\ (1-\omega)\dfrac{\Gamma\left(y+\frac{1}{k}\right)}{\Gamma(y+1)\Gamma\left(\frac{1}{k}\right)}\dfrac{(k\mu)^{y}}{(1+k\lambda)^{y+\frac{1}{k}}} & for\, y>0\end{cases}$$

Here, k is the NB dispersion parameter, λ is the mean, and ω is the probability of drawing an observation consistently resulting in zero.

The generation of standardized CPUE series for BSH was derived through the application of adjusted means, specifically least squares means, for the effect parameters within the optimal ZINB model.

2.4.3. VAST model

Our study utilized the VAST model [34], which is notable for its ability to effectively manage spatio-temporal correlations by addressing catch variations across temporal and spatial dimensions and by capturing spatial heterogeneity and autoregressive effects. The VAST model is adaptable and can accommodate individual differences and non-normal data distributions.

The default structure of the VAST model uses a delta-GLMM, which divides the catch probability distribution into (1) encounter probability and (2) expected catch rate conditional on catch occurrence [34]. To improve computational efficiency, the VAST model utilizes predefined spatial knots to assess correlations in spatial and spatiotemporal effects. The estimation process involves k-means analysis, which divides all grid cells into 200 spatial knots (Fig. 4). Researchers assume that spatial and spatiotemporal random effects originate from their nearest spatial knot, following the methodology of Grüss et al. [40].

The prediction of BSH CPUE is detailed as follows:

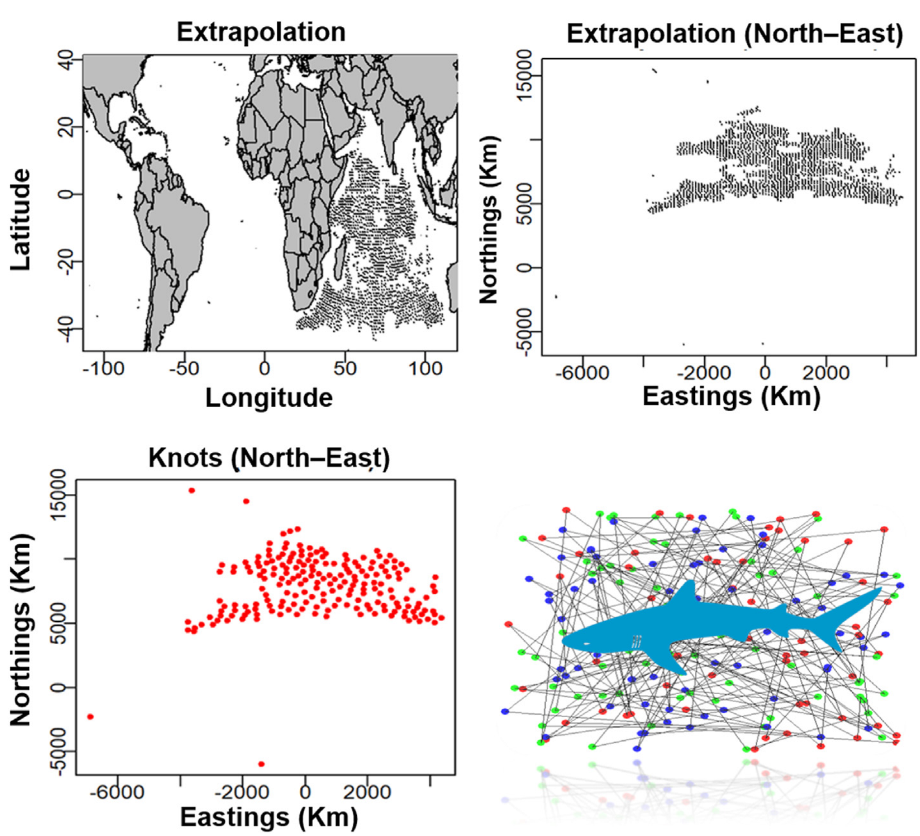

Fig. 4. Distribution of the 200 core knots within the VAST model, with "Northing" indicating northward distance and with "Easting" representing eastward distance.

We modeled the encounter probability (p) for observed CPUE (i) by using a logit-linked linear predictor:

$$logit(p_i) = \beta_1(t_i) + L_{\omega 1}\omega_1(s_i) + L_{\varepsilon 1}\varepsilon_1(s_i, t_i) + L_{\delta 1}\delta_1(v_i) + \sum_{k=1}^{n_k}\lambda_1(k)Q(i,k) + \sum_{p=1}^{n_p}\gamma_1(p)X(s_i, t_i, p)$$

Additionally, we modeled the positive catch rate (λ) for observed CPUE (i) using a log-linked linear predictor:

$$\log(\lambda_i) = \beta_2(t_i) + L_{\omega 2}\omega_2(s_i) + L_{\varepsilon 2}\varepsilon_2(s_i, t_i) + L_{\delta 2}\delta_2(v_i) + \sum_{k=1}^{n_k}\lambda_2(k)Q(i,k) + \sum_{p=1}^{n_p}\gamma_2(p)X(s_i, t_i, p)$$

The terms in these equations are defined as follows:

$\beta(t_i)$: intercept in year t_i; $\omega(s_i)$: spatial variation at location s_i; L_ω: scaling factor (sd); $\varepsilon(s_i,t_i)$: spatiotemporal variation at location s_i in year t_i; L_ε: scaling factor (sd); $\delta(v_i)$: vessel/targeting effects on catchability, and $\delta(v_i)$~Normal (0,1); L_δ: scaling factor (sd); $Q(i,k)$: catchability covariate (s); $\lambda(k)$: associated catchability parameter (s); $X(s_i,t_i,p)$: habitat covariate (s); $\gamma(p)$: associated habitat parameter (s).

The probability of catching data c for sample i was calculated as follows:

$$\Pr\begin{pmatrix} c_i = 0 \\ c_i > 0 \end{pmatrix} = \begin{pmatrix} 1 - p_i \\ p_i \times Lognormal\left(c_i \middle| \log(\lambda_i), \sigma_m^2\right) \end{pmatrix}$$

Annual abundance index I was estimated as follows:

$$I(t) = \sum_{k=1}^{n_k}[Area(k) \times Density(k,t)] = \sum_{k=1}^{n_k}\{Area(k) \times [logit(p_i) \times \log(\lambda_i)]\}$$

2.5. Model selection

The final optimal DLN, ZINB, and VAST models were chosen on the basis of the lowest Akaike information criterion (AIC) weight [42]. In addition, after model selection, we conducted a thorough goodness-of-fit test by using the analysis of deviance method. This process involved evaluating the significance of each model term (Year, Quarter, Area, HPBC) in explaining the variation in the response variable. The F-test and associated p values from the analysis of deviance tables provided information regarding the statistical significance of each term in the DLN model, whereas the chi-squared test (χ^2) provided similar information for the ZINB model. After a rigorous goodness-of-fit assessment, we selected the models that best captured the observed data patterns for further analyses.

2.6. Computational procedures

All statistical analyses and visualizations in this study were conducted using the R language for statistical computing. We used R version 3.6.3 for the DLN and ZINB models, and R version 4.2.2 [43] for the VAST models. The "glm" function was employed for DLN analysis, and the ZINB models were computed using the "zeroinfl" function in the "pscl" package. The VAST models were implemented using the VAST R package (version 3.10.1). Additionally, graphical outputs were produced using the "ggplot2" package [44].

3. Results

3.1. Exploring diagnostics and model selection

Blue shark bycatch data exhibit numerous zero values and a right-skewed distribution (Fig. 5). The DLN models with the lowest AIC values were "*ln(CPUE)* = μ + *Year* + *Quarter* + *Area* + *HPBC* (AIC = 25,645)" for the lognormal component and "*PA* = μ + *Year* + *Quarter* + *Area* + *HPBC* (AIC = 33,581)" for the binomial component. In the ZINB model, the best fit for the Indian Ocean region was "*BSH* = *Year* + *Quarter* + *Area* + *HPBC* (AIC = 94,218)," which addressed zero inflation and overdispersion in catch data. Regarding the VAST models, the optimal model was "*BSH* = *Year* + *Latitude* + *Longitude* (AIC = 65,632)," which comprised 10,949 coefficients, including 43 fixed and 10,906 random coefficients. These selections were made after an evaluation of AIC values. Consequently, these most favorable models were utilized for further analyses.

All examined variables (Year, Quarter, Area, and HPBC) significantly contributed to explaining observed deviations. The analysis of variance columns in Tables 1 and 2 display high significance levels ($p < 0.001$) for the main effects included in the final models. Year effects accounted for the majority of the variability, followed by Quarter effects, whereas the influences of Area and HPBC in the ZINB model were relatively minor.

Diagnostic assessments confirm that CPUE assumptions are based on lognormal distributions, which approximate normality. DLN residual distributions and Q–Q plots revealed no significant deviation from model assumptions (Fig. 6a, b). In ZINB modeling, rootogram results aligned with ZINB assumptions (Fig. 6c) because the observed values (bars) closely matched the predicted line (red line), indicating satisfactory model fit. However, the Q–Q plot indicated deviation from the ideal normal distribution (Fig. 6d). VAST DHARMa residual

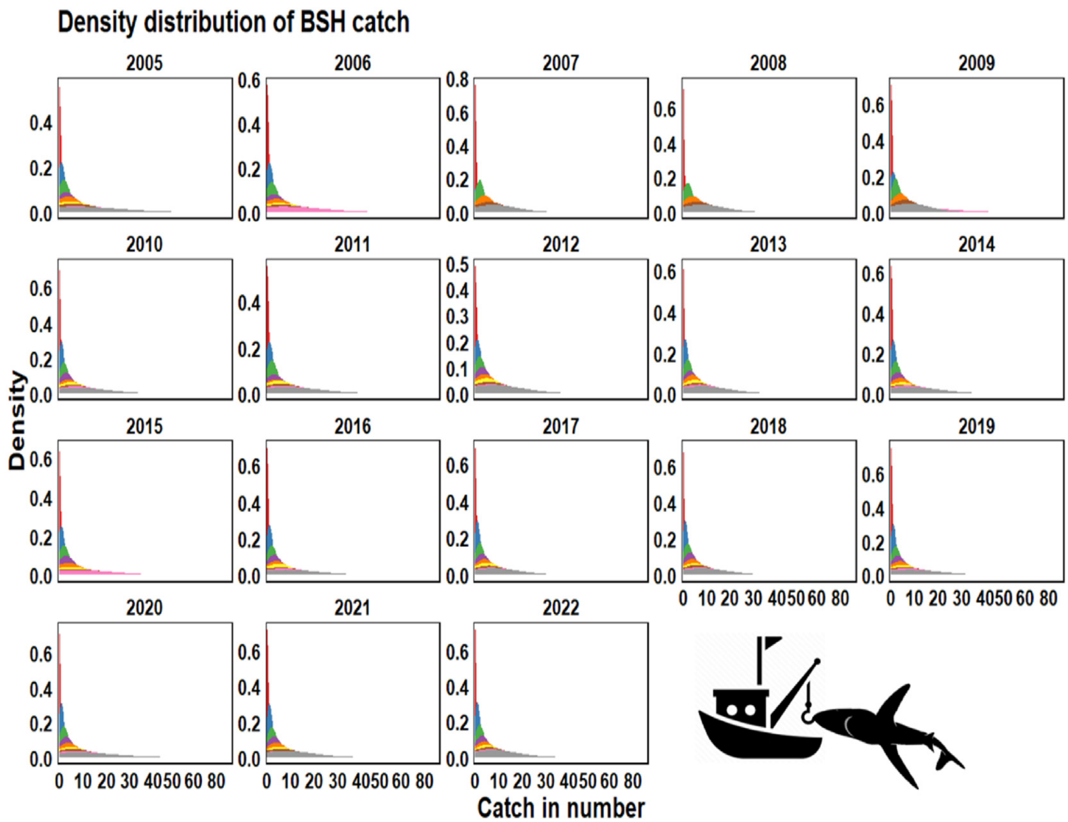

Fig. 5. Density distribution of BSH catch in number in the Taiwanese large-scale tuna longline fishery in the Indian Ocean, 2005–2022.

histograms depicted an even distribution with no trend, indicating model adequacy (Fig. 6e). The Q–Q plot was nearly linear, suggesting an acceptable overall distribution (Fig. 6f).

3.2. Annual trend of standardized catch rate index for BSH in the Indian Ocean

The standardized CPUE series for BSH in the Indian Ocean—obtained from the DLN, ZINB, and

Table 2. Deviance table for the ZINB model of blue sharks in the Indian Ocean.

Source	Df	χ^2	Pr ($>\chi^2$)	
Year	17	2181.63	<2.2e-16	***
Quarter	3	239.96	<2.2e-16	***
Area	1	789.12	<2.2e-16	***
HPBC	1	195.63	<2.2e-16	***

Significance codes: 0: "***"; 0.001: "**"; 0.01" "*"; 0.05" "."; 0.1: " "; 1.

Table 1. Deviance tables for the DLN model of blue sharks in the Indian Ocean.

Lognormal framework positive catch rate							
Source	Df	Deviance	Resid. Df	Resid. deviance	*F*	Pr (>*F*)	
NULL			13,706	43.608			
Year	17	5.119	13,689	38.489	108.968	<2.2e-16	***
Quarter	3	0.252	13,686	38.237	30.360	<2.2e-16	***
Area	1	0.040	13,685	38.197	14.399	0.0001485	***
HPBC	1	0.380	13,684	37.817	137.629	<2.2e-16	***
Binomial model							
Source	Df	Deviance	Resid. Df	Resid. deviance	*F*	Pr (>*F*)	
NULL			30,147	41,546			
Year	17	960.37	30,130	40,585	56.492	<2.2e-16	***
Quarter	3	63.33	30,127	40,522	21.111	1.139e-13	***
Area	1	124.16	30,126	40,398	124.160	<2.2e-16	***
HPBC	1	325.10	30,125	40,073	325.103	<2.2e-16	***

Significance codes: 0: "***"; 0.001: "**"; 0.01" "*"; 0.05: "."; 0.1" " "; 1.

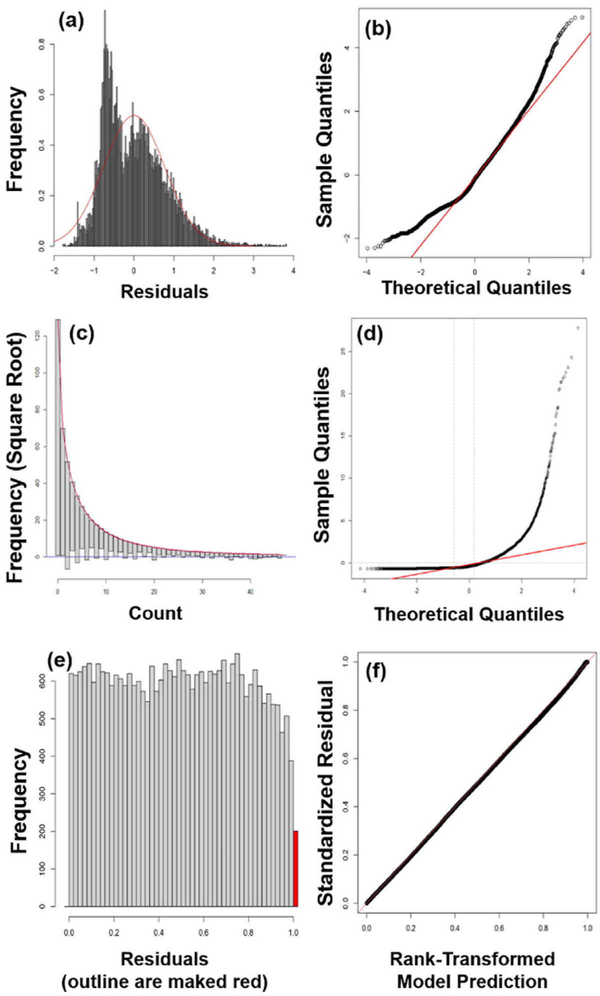

Fig. 6. Diagnostic results for the DLN, ZINB, and VAST models applied to longline BSH bycatch data. The histogram of the residuals (left) and the Q–Q plot (right) illustrate the results for the DLN model (a, b), ZINB model (c, d), and VAST model (e, f). In the Q–Q plot, the thick black lines represent the consistency between theoretical CPUE and predicted CPUE, and the circles indicate abnormal data points.

VAST models—is illustrated in Fig. 8. A noticeable pattern of interannual fluctuations was observed in both the nominal and standardized CPUE for BSH from 2005 to 2022. Specifically, the annual values for standardized CPUE closely mirrored those of nominal CPUE during this period (see Fig. 7). Nominal CPUE consistently recorded lower values compared with standardized CPUE; this result highlights the effectiveness of the standardization process in reducing variability associated with explanatory variables.

Over time, standardized CPUE reveals fluctuations in the relative abundance of BSH. A slight drop occurred from 2009 to 2010, followed by annual increases from 2010 to 2013. Subsequently, a decline occurred from 2013 to 2015, and then a significant rise occurred from 2015 to 2022 (see Fig. 7). The years 2019–2020, possibly affected by COVID-19, experienced disruptions in fishing activities, which could have influenced the observed trends. Although the overall pattern does not indicate overexploitation or a consistent downward trend, the relative abundance of BSH demonstrates fluctuations rather than a clear and consistent upward trend from 2005 to 2022.

3.3. Modeling of spatiotemporal distribution dynamics of BSH

Fig. 8 illustrates the projected spatial density patterns of BSH from the optimized VAST model from 2005 to 2022. The Indian Ocean is identified as a significant habitat for BSH, with a wide distribution range and some degree of stability over the years. The temporal density distributions for BSH closely match those of the nominal CPUE (Fig. 7). Regarding the spatial distribution, BSH is most densely located along the southern boundary of the Indian Ocean, covering a large part of the equatorial and southern areas, particularly in 2009, 2013, 2018, and 2022. Differences in sampling locations between 2013 and 2015 (displayed in Fig. 8) may have contributed to the observed variations in both nominal CPUE and standardized CPUE. Additionally, the hotspots in the Indian Ocean exhibit a more irregular distribution in the broader temporal-spatial context.

4. Discussion

In the large-scale tuna longline fishery of the Indian Ocean, we used multimodel methodologies to analyze shark captures and to clarify instances of zero BSH catch observations. No signs of overexploitation or a consistent downward trend in the abundance of BSH emerged across the analyses conducted from 2005 to 2022; rather, the data revealed substantial interannual fluctuations without a clear upward trend. These findings align with the findings of Wu and Tsai [45] from the 2004–2019 Indian Ocean Tuna Commission report, suggesting optimal utilization of BSH stock. The diagnostic results informed the fitting of three models to the observers' data from the fishery, namely the DLN, ZINB, and VAST models. Model residual analysis for nontarget shark species (see Fig. 6) indicated that the VAST model was the most suitable, suggesting that the VAST model's ability to account for spatial variations in CPUE data could improve the accuracy of the assessment. Additionally, including spatial and temporal random effects enabled the model to effectively address inherent

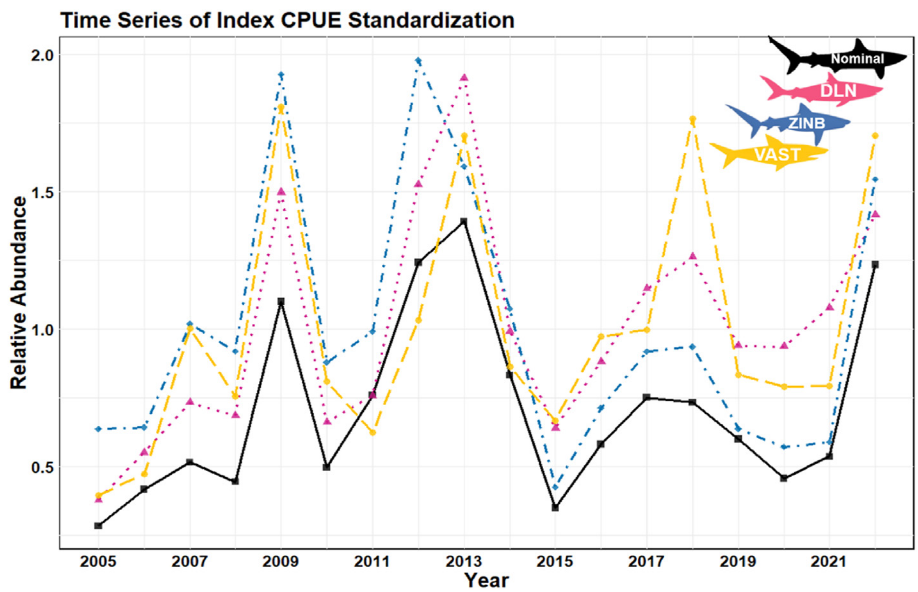

Fig. 7. Relative annual nominal CPUE and annual standardized CPUE for the three models.

correlations and disparities in the CPUE data set [46]. Overall, the present study's approach constitutes an objective methodology for addressing the treatment of zero catches when analyzing bycatch CPUE in a variety of contexts, as supported by the present models used.

The DLN model, frequently applied in studies regarding nontarget species [47,48], effectively manages data sets with zero values. The model's effectiveness in this regard has been particularly evident in studies involving blue and mako sharks [49–52]. In the present study, we employed the delta method to create two models. The first of these models predicted the probability of capturing at fewest one specimen per set by using a binomial distribution with a logit link function. The second model estimated the mean catch rate under the condition of capturing at fewest one specimen,

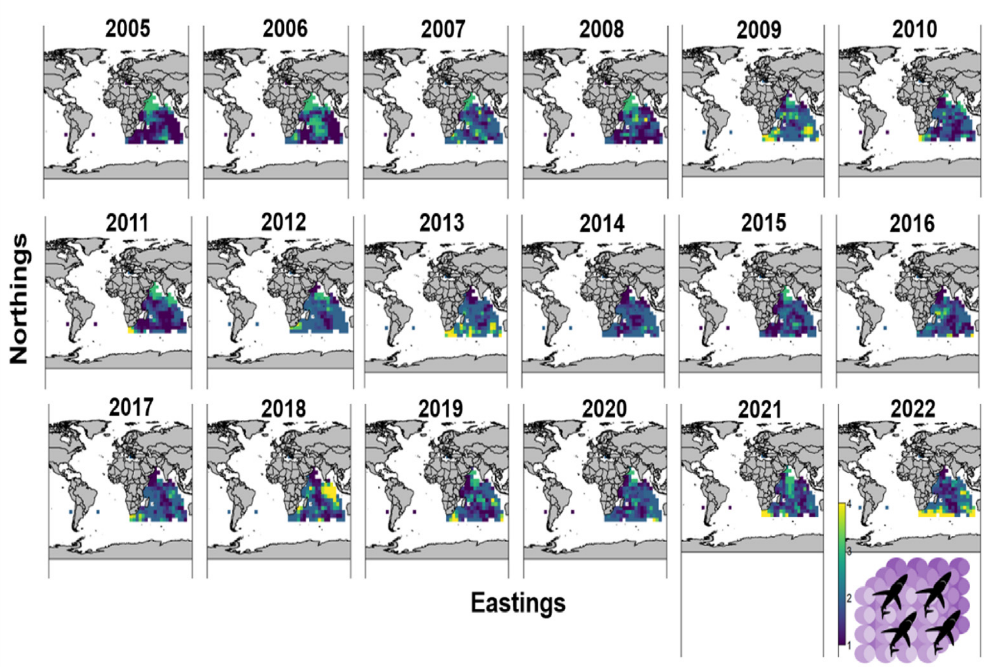

Fig. 8. Estimated log density of BSH by year in the alternative index from the VAST model for former time series (2005–2022).

assuming that log-transformed catch rates (from positive sets) followed a normal distribution. This approach is particularly beneficial for continuous response variables with numerous zeros, as demonstrated in our study, where CPUE was derived as catches per effort (1000 hooks).

In their investigation of oceanic whitetip sharks, Brodziak and Walsh [27] emphasized the efficacy of ZINB modeling. They assessed five models, namely Poisson, NB, zero-inflated Poisson, ZINB, and delta-gamma models. The ZINB model demonstrated notable effectiveness in scenarios characterized by high shark catch rates, consistent with similar findings in studies regarding mako sharks [53,54] and silky sharks [55]. However, the ZINB model may overestimate coefficients in data sets with high quantities of zero values [20]. In the present study, BSH catches with zero values comprised only 53.8% of the total (see Fig. 3); this proportion contrasts with the high zero-catch rates observed in some studies regarding Taiwanese large-scale longline fishing [54,55]. On the basis of this comparison, we assert that the DLN model was marginally more suitable for CPUE standardization in our study.

Conversely, the modeling process encountered difficulties due to imbalances in factor levels, particularly variable interactions. These imbalances hindered effective capture and led to conflicts, such as those observed between the GRP and CTNO factors in this study. Although we utilized extensive data sets from scientific observers, not all available data were included in this study. However, the key variables that influenced nominal BSH CPUE—namely Year, Quarter, Area, and HPBC—were found to be essential. These fundamental variables consistently aligned with the CPUE standardization findings of related studies regarding sharks [51,54,55].

Furthermore, studying highly migratory species such as blue sharks presents a number of challenges. These challenges arise from variations in fishing practices, geographic regions, GRP, and gear types used by nations such as Japan, Indonesia, Portugal, and France, each of which has its own longline fisheries targeting various species. Therefore, recognizing the potential for significant variations in fishery mortality rates owing to variations in contributing factors is crucial.

Our study employed a spatiotemporal modeling approach to estimate relative abundance indices in fished and unfished regions. We employed area-weighted methods that extend beyond traditional approaches such as DLN and ZINB modeling. The VAST model is particularly comprehensive in dealing with spatiotemporal variation, considering the need to consider such variation associated with environmental changes or depletion, unlike methods that rely solely on large spatial areas for prediction weighting. As a result, the adoption of spatiotemporal models for standardizing fishery-dependent CPUE data is likely to increase [40]. Although the reliance on observer data and specific data set attributes may limit the degree of improvement in model fit, our findings confirm the effectiveness of the VAST model in addressing spatiotemporal variation [40]. The observed changes in abundance from year to year for most sharks deviate from their expected biological behavior (Fig. 3) [56]. Management measures, such as quota reductions, are unlikely to influence the catch rates of blue sharks given that pelagic longline fisheries do not typically target such measures. Furthermore, the catch rates considered in the present analysis included animals that were kept, discarded because of death, or released alive. Most relative abundance indices used in stock assessments for highly migratory populations, such as tunas and billfishes, rely on fishery-dependent CPUE data because of a lack of fishery-independent surveys [57]. The spatiotemporal standardization approach, as described by Xu et al. [39], offers notable advantages by providing a relatively representative index for the entire population. This approach considers catch rates in fished and unfished areas by using an area-weighted approach, unlike the sample-weighted nominal index, which places disproportionate emphasis on heavily fished areas. Additionally, the spatiotemporal approach accounts for variations in fishing efficiency among vessels by considering differences in vessel characteristics. These observations highlight the potential benefits of using the spatiotemporal standardization approach [40] and suggest avenues for further improvement in future studies.

The observed declines in BSH catches in 2005 and 2015, which may have been due to reduced fishing efforts in the southern Indian Ocean, was clearly visible in the log-density data for those years (Fig. 8). However, these findings provide only a partial understanding of the stock status because of potential limitations in spatial coverage. To address this limitation, a more comprehensive approach that includes fishery-independent data, such as surveys, as well as sole reliance on commercial fishing records for abundance indices, is crucial. Robust studies are essential for thoroughly evaluating the status, ecology, and distribution of BSH in the Indian Ocean. Our modeling efforts revealed zeros in catch data, and both the DLN and ZINB models demonstrated effectiveness in fitting shark bycatch data. The introduction of regional patterns that detail size- or sex-specific habitats holds promise for enhancing the management of blue shark populations. Despite certain limitations, such as the absence of environmental effects in the standardization model and a relatively short time series, the conclusions of our study remain valid and provide valuable information regarding the population dynamics of Indian Ocean blue sharks. To extend the contributions of the present study, future research efforts should prioritize longer observer data time series and the inclusion of environmental factors to yield more comprehensive understanding.

Ethics Information

The study used data on blue sharks that was collected from the Overseas Fisheries Development Council of Taiwan. Since the study relied on pre-existing data and did not involve any direct interaction with live animals, ethical clearance is not applicable.

Conflicts of interest

The authors named in this study have confirmed that they do not have any conflicts of interest, whether financial or otherwise.

Acknowledgments

The authors thank the Overseas Fisheries Development Council, Taiwan for providing shark catch and effort data of longline fisheries. We also thank two anonymous reviewers for their helpful comments, which greatly improved this manuscript. This study was financially supported by the Fisheries Agency, Ministry of Agriculture (Taiwan) under Contract No. 112AS-6.4.1-FA-F2(5) and 113AS-6.4.1-FA-F2(5). This manuscript was edited by Wallace Academic Editing.

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