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# Using a Multi-Output Neural Network Model to Standardize Heterogeneous Fisheries Data

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**Abstract** Biological data in fishery ecology have complex structures and are highly heterogeneous. Catch per unit effort (CPUE) estimated from fishery-dependent data are often used to characterize abundance indices (AI) of fish species, which is critical in fish stock assessment. However, additional considerations need to be undertaken to ensure robust estimation because of the latently complicated structures in fishery-dependent data. Here, we elaborated the process of constructing multi-output artificial neural network models to standardize *CPUE* for heterogeneous fishing operations and applied it to the skipjack tuna (*Katsuwonus pelamis*) in the western and central Pacific Ocean (WCPO). Seasonal, spatial, and environmental factors were input variables, and the *CPUE* of four types of skipjack tuna fisheries were set as output variables. The optimal structure for multi-output neural network was evaluated by systematic comparison in 100 runs hold-out cross-validation. The results showed that the final multi-output neural network model with high accuracy can predict the spatial and temporal trends of skipjack tuna abundance.

**Key words** western and central Pacific Ocean; skipjack tuna; BP neural network; multi-output model; *CPUE* standardization; ENSO

## 1 Introduction

Biological data are often nonrandomly sampled and, as the consequence, highly heterogeneous. Models with complex structures thus have been used in ecology and evolution (Zuur *et al*., 2010; Schielzeth *et al*., 2020). Generally, fishery scientists use fishery-dependent data as well as fishery-independent data to do relevant research, and the heterogeneity in the fishery-independent data are more augmented. Due to the high cost and logistical challenges, fishery-independent data collected *via* scientifically designed sampling may not be available for pelagic fish species (Pennino *et al*., 2016; Karp *et al*., 2022). Alternatively, fishery-dependent data coming from scientific observers on commercial fishing vessels or industry reported logbooks are selected by fishery scientists to estimate fish population density and abundance, and subsequently the derived results are utilized for fisheries stock assessment and management (Thorson and Ward, 2013; Thorson *et al*., 2020).

Unfortunately, fishery-dependent data may be collected by vessels operated by different companies using different fishing gear types and configurations, and the data were originated from different countries with the same species (Ren *et al*., 2024). These situations can create non-probabilistic and preferential sampling schemes that must be accounted for when utilizing fishery-dependent data. Fisheries scientists still highlight the advantages of utilizing those data for various aims, such as understanding the interaction effect between fish and gear (Crear *et al*., 2021), obtaining the factors that influence the distribution of fishing locations (Pennino *et al*., 2019), making management restrictions such as bycatch avoidance, closed areas (Vidal *et al*., 2020).

One of the important and classic applications of fishery-dependent data is to estimate the relative abundance through catch per unit effort (CPUE), which is usually assumed to be proportional to the amount of fish resources. *CPUE* serves as a fundamental indicator for fish biomass or abundance in fishery stock assessment (Hilborn *et al*., 1992; Maunder *et al*., 2004). However, a problem of heterogeneity caused by different units of effort, spatial expansion or contraction fishing effort in fishery-dependent data brings statistical errors and bias in the estimation of relative abundance indices (AI) based on *CPUE* data (Harley *et al*., 2001; Ye and Dennis, 2009). Thus, many types of approaches are introduced to decrease or eliminate bias in *CPUE* standardization.

In addition, another important issue in the standardiza-

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tion of fishery-dependent data is the phenomena of hyperdepletion and hyperstability. Hyperdepletion refers to the fact that when the density of a fish stock decreases, the fishing efficiency also decreases, resulting in a *CPUE* that underestimates the true abundance of the stock. In contrast, hyperstability is the tendency for fishing efficiency to saturate when fish population densities are high, resulting in *CPUE* overestimating the true abundance of the stock (Nooteboom *et al*., 2023). Both phenomena can have a significant impact on *CPUE* and must be avoided when dealing with fishery-dependent data.

The generalized linear model (GLM) and generalized additive model (GAM) were initially used in species distribution modeling, which were then introduced into fisheries ecology for *CPUE* standardization (Augustin *et al*., 1998; Guisan *et al*., 2002; Maunder and Punt, 2004). These methods have good performance and can reveal the relationships between the explanatory variables and response variables easily with the help of automatic fitting and visual tools. Because of the strict statistical assumptions (*e.g*., linear relationship between the model parameters and some transformation the response variable; the dependent variable following the specific distribution) in GLM and GAM (Campbell, 2004; Walsh *et al*., 2015), fishery scientists actively seek more flexible models with considering complicated error structures, *e.g*., hierarchical Bayesian spatio-temporal model, to improve the precision in *CPUE* estimations (Thorson and Ward, 2013; Pennino *et al*., 2016). It was found that the *AI* of fish derived from geo-information-based models is more accurate than that without incorporating spatial covariates (Thorson and Ward, 2013). Another solution is to try flexible machine learning methods, including tree-based models, such as random forest (RF), boosting, support vector machine (SVM), and neural network to establish spatio-temporal distributions and then derive fish species *AI*. In the case of fisheries science, those methods have proven to be the practical and effective tool for the estimation of *AI*. Shono (2014) described the *CPUE* standardization using SVM, neural network, tree regression model, and two conventional statistical methods (analysis of variance and GLM). The results showed that the performance of SVM is equivalent to that of neural network, and these two models are superior to the tree regression model, analysis of variance, and GLM. In fitting the relationship between the density of brown trout spawning sites and habitat characteristics, neural network outperformed multiple regression analyses (Lek *et al*., 1996).

A common difficulty in *CPUE* standardization is when there are several *CPUE* time series estimated from different fishing operations, how to integrate or combine those inconsistent/consistent *CPUE* to reveal the 'real' dynamics in fish abundance. Basically, fishery scientists may construct one full model with fishing operation as an explanatory categorical variable to extract temporal effect for standardizing *CPUE* (Maunder and Punt, 2004). They also can establish multiple sub-models to derive separate fish abundance and then aggregate fish abundance by catch-weighted sum (Song and Wu, 2011). Each solution has its own drawbacks. For example, full model with 'fishing operation' factor simplifies the originally complex relationships, whereas fitting multiple sub-models disintegrates the original overall relationships and then the *CPUE* trends are dominated by fishing operations with the higher catch.

Neural network is a subset of machine learning and is the heart of deep learning algorithms. The name and structure of neural network are inspired by the human brain, mimicking the way that biological neurons signal to one another. For most cases, neural network achieved high predictive performance, high flexibility, non-linear fitting, self-learning, and strong generalization ability (Maunder and Hinton, 2006; Wang *et al*., 2015, 2018). In addition to those features, multi-output neural network can handle multiple related tasks simultaneously by adding an output unit to each task at the output layer. The hidden layers of multi-output neural network try to capture common features of the input data, then share and utilize them for predictions across all outputs. Each output node can specialize in optimizing for a specific task to improve the model's expressive power and makes it more adaptable to complex real-world problems (Ruder, 2017). To date, only one study has utilized the multi-output neural network to estimate the spatial abundance with four fishing operations on bigeye tuna in the Pacific Ocean (Lin *et al*., 2023).

In this study, we propose a novel approach of using multi-output neural network to standardize the *CPUE* from the commercial fishery-dependent data as a relative abundance index with different fishing gear types or configurations. The process of modeling multi-output neural network is elaborated with skipjack tuna (*Katsuwonus pelamis*) from four fishing operations in the western and central Pacific Ocean (WCPO). The results show that our study can estimate skipjack tuna abundance with high robustness. The approach can also be further used for other oceanic fish species which are harvested by different fishing operations.

## 2 Methods

Multi-output neural network was established to standardize the commercial *CPUE* with several types of nominal *CPUE* based on the explanatory variables of a dataset, though it is not a new approach from the perspective of machine learning.

### 2.1 Multi-Output Neural Network

Neural network is comprised of one input layer, one or more hidden layers, and one output layer. Each layer has one or more nodes. In most cases, a single hidden layer is sufficiently effective and satisfactory. However, a more complex learning model can be constructed to deal with massive datasets, which is beyond the scope of this study (Lek *et al*., 1996; Ansari and Binninger, 2022). The relationships between the input variables and output variables, or the relationships among output variables them-

selves could be explained by the weight, which means that the positive or negative value of the weight represents the relevance of the input or output to the feature represented by that neuron in trained multi-output neural networks (Du *et al.*, 2010). A larger value indicates a greater relevance to the corresponding feature. Thus, we designed the multi-output neural network model with nodes in output layer representing the nominal *CPUE*, and nodes in input layer representing the variables, which can potentially affect the catch rates, to standardize commercial fish abundance (Fig.1). Though setting the nodes in the hidden layer is subjective and challenging, we can create several alternatives for the optimal nodes by systematic comparisons (Lek *et al.*, 1996; Wang *et al.*, 2018). The nodes in the hidden layer can be set as following:

$$h = \sqrt{n+m} + a, \tag{1}$$

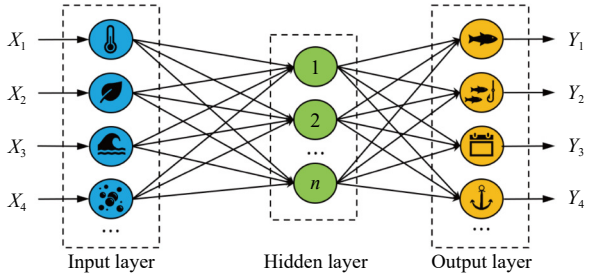



Fig.1 Structure of multi-output neural network model designed for standardizing the commercial fish abundances caught by several fisheries. The nodes in input layer represent the potential variables which affect the catch rates, and the nodes in output layers represent the nominal catches per unit effort which are calculated from different fisheries.

where $h$, $n$, $m$ are the numbers of nodes for the hidden layer, input layer, and output layer, respectively. $a$ is constant term between 1 and 10.

## 2.2 Evaluation of Neural Network Models

For numeric response variables, several performance metrics, including root mean square error (RMSE) and mean absolute error (MAE), can be selected to evaluate the precision of models with different structures, which correspond to specific fisheries (Chai and Draxler, 2014).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{3}$$

where $n$ denotes a total of $n$ items of the sample data, $y_i$ denotes the actual *CPUE*, denotes the predicted *CPUE*, and denotes the average value of the actual *CPUE*. The smaller the *RMSE* and *MAE* are, the closer the model's prediction is to the actual value, and the stronger the generalization ability of the neural network is.

Hold-out cross validation (CV) and $k$-fold cross validation are often used to evaluate the robustness for each structure. The main steps of calculating these two values are similar, while the difference is in dividing the subsets for model training and testing (Fig.2). The distributions of performance metrics are obtained by repeating CV many runs to measure the robustness of different neural networks. For example, if we run a 100-CV for a model structure, we should have 100 values of metrics for hold-out CV, and 100-$k$ values of metrics for $k$-fold CV.

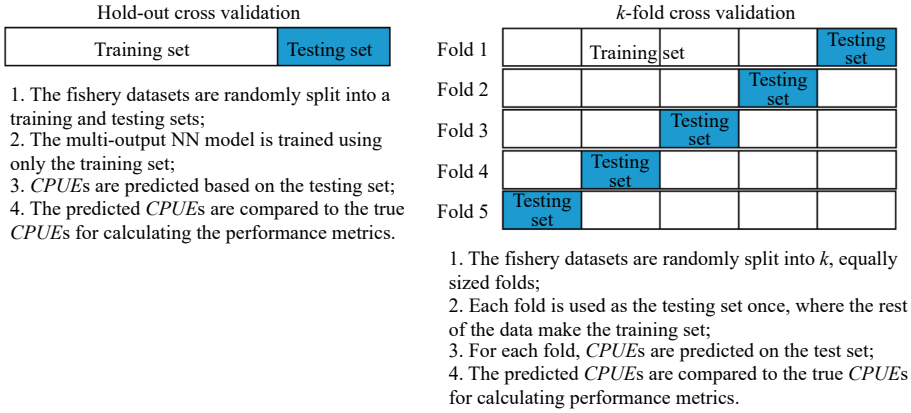



Fig.2 Main steps for hold-out cross validation (a) and $k$-fold cross validation (b) in *CPUE* standardization.

## 2.3 Calculating the Importance of Variables

Weights approach and sensitivity analysis approach are used to quantify the importance of explanatory variables across all outputs in the best neural network model (Lek *et al.*, 1996; Wang *et al.*, 2016). The contribution of each input variable is calculated as the sum square weights of the variables divided by the sum square weights of all input variables (Özesmi and Özesmi, 1999). Then those contributions were used as weights to calculate the aggregated *CPUE*. For the importance of the output layer, the square of each output weight is divided by the total sum of squares of all output weights and biases:

$$W_i = \frac{\sum_{j=1}^{n} weight_j^n}{\sum_{i=1}^{n}\sum_{j=1}^{n} weight_j^n + bias_j^n}, \tag{4}$$

where $i$ denotes the fishing type, $W_t$ represents the importance (normalized weight) for the $i$th output, and $weight_j$ is the weight connecting the $j$th neuron of the hidden layer to the $i$th output neuron. $bias_j$ is the bias associated with the $i$th output neuron.

Based on the optimal model, the sensitivity analysis method is to gradually change the variable which is to be analyzed from its minimum value to maximum value in a definite step, and the rest of the variables can be set as the mean, median, maximum or minimum of them. In this way, a simulation sample is constructed to predict the relationship between the explanatory and dependent variables (Gevrey *et al*., 2003; Olden *et al*., 2004; Wang *et al*., 2018).

### 2.4 Quantifying the Optimal Habitat Distribution Metrics

The neurons in the output layer made backward predictions of preferred habitats according to the optimal neural network model, respectively. The predicted *CPUE* was combined into the final *AI* value to characterize the spatio-temporal dynamics in fish abundance using the weights of the response variables in the optimal neural network model. The calculation formula is as follows:

$$AI = \sum_{t=1}^{n} (W_t \times AI_t), \tag{5}$$

where $W_t$ and $AI_t$ represent the weight and the predicted *AI* for the corresponding fishing type.

Two habitat metrics, including suitable-density areas (areas with predicted $AI$>0.6) and high-density areas (areas with predicted $AI$>0.8), are calculated to quantify changes in fish preferred habitat (Wang *et al*., 2023).

## 3 Case Study

The skipjack tuna (*Katsuwonus pelamis*) is an ecologically and commercially important top predator species which widely distribute in the tropical and subtropical waters of the WCPO. The annual catch of skipjack tuna reached 1754082 t in 2020, accounting for about 64% of the WCPO's tuna production and 60.86% of the world's total tuna production (WCPFC, 2021). The skipjack tuna is mainly caught by purse seine occurred on free school (UNA), marine mammal associated school (DFAD), natural log school (LOG) and fish aggregation devices associated school (AFAD), thus there are at least four time series lines of fishery-dependent *CPUE* to potentially characterize the skipjack tuna abundance in the WCPO.

Many anthropogenic and natural factors could affect the spatial distribution and the dynamics in abundance of skipjack tuna in the Pacific Ocean. The purse seines with different operations have unique fishing pattern, so they have varied impacts on the judgment of skipjack tuna abundance (Fonteneau *et al*., 2014). Skipjack tuna have strong swimming ability and thereby are capable of searching for suitable environmental conditions that satisfy their physiological needs (Yen *et al*., 2012). Previous studies have shown that skipjack tuna habitats in waters with sea surface temperatures (SST) 18–30 °C, and the optimum range is 23–28 °C (Barkley *et al*., 1978; Arrizabalaga *et al*., 2015). Additionally, dissolved oxygen concentration ($O_2$) at the sea surface is also an important environmental factor influencing the abundance distribution of skipjack tuna. Skipjack tuna exhibits high dissolved oxygen requirements because of the high metabolic rate, large red muscle mass and the absence of their swim bladder (Richard *et al*., 1978). Druon *et al*. (2017) found the minimum dissolved $O_2$ in the most comfortable habitat for skipjack tuna was 196 mmol/m$^3$; however, it was not a limiting condition for its survival. In contrast, Arrizabalaga *et al*. (2015) concluded that there is a minimum limit of dissolved $O_2$ for skipjack tuna to survive and therefore it limits the distribution and abundance of skipjack tuna. The favorable sea surface salinity (SSS) for skipjack tuna ranged 30.3–36.2 (Druon *et al*., 2017) when the abundance of skipjack tuna resources is high. Additionally, other environmental variables, such as sea level anomaly, sea surface height, eddy kinetic energy and mixed-layer depth, and ENSO (El Niño and La Niña) events induced rapidly variabilities in those variables can also affect the distribution and abundance of skipjack tuna (Lehodey *et al*., 1997; Mugo *et al*., 2010; Salazar *et al*., 2021).

The western equatorial Pacific warm pool is the basis for ENSO and global climate change, and it provides a good habitat for warm-loving skipjack tuna (McPhaden *et al*., 1990; Jin, 1996). Longhurst *et al*. (1995) found that skipjack tuna in the WCPO are mainly distributed throughout the equatorial mixed layer and subtropical waters, but the highest catches are achieved in the western equatorial Pacific warm pool. In normal years, the upwelling waters of the Pacific equator are rich in bait organisms. These rich bait organisms are transported westwards by the southwest equatorial current under the influence of the monsoon (Lehodey *et al*., 1997). As ENSO influences the monsoon and currents, these bait organisms (plankton and fauna) that grow along with the transport process provide more or less supplementary bait for skipjack tuna in the waters around WCPO warm pool under different climatic conditions. All these associated environmental factors should be considered in skipjack tuna *CPUE* standardization.

As mentioned above, the challenge exists with differences of fishing types and innovations of methods, thus models in standardizing skipjack tuna *CPUE* indices need to be resolved urgently for sustainable management (Vidal *et al*., 2019a, 2019b, 2020). To validate the ability of multi-output neural network model in *CPUE* standardization, we select the skipjack tuna in the WCPO as target species to demonstrate our proposed approach.

### 3.1 Fisheries and Environmental Data

The skipjack tuna fishery data were collected from the Western and Central Pacific Fisheries Commission (WCPFC, https://www.wcpfc.int/node/4648) with month-

ly temporal resolution and 1° latitude × 1° longitude spatial resolution during 1995–2018. These data contain year, month, operating points (longitude, latitude), effort of four operations (the sets for UNA, LOG, DFAD, and AFAD), and the corresponding catch.

Environmental data include SST, SSS, marine primary productivity (PP) and $O_2$, which were taken from the National Oceanic and Atmospheric Administration's Climate Prediction Center (http://www.cpc.ncep.noaa.gov) and downloaded as 'nc' files to be read and processed in R software environment (V4.2.2) using 'ncdf4' package (Pierce, 2017). The Oceanic El Niño indices (Nino3.4), which characterize ENSO events in the Pacific Ocean, were downloaded from Prediction Center (https://www.cpc.ncep.noaa.gov/data/indices/sstoi.indices). An El Niño event is considered to have occurred if the sea surface temperature anomaly (SSTA) value in *Nino3.4* exceeds 0.5 °C for 3 consecutive months, and a strong El Niño event is considered to have occurred if it exceeds 1.5 °C. A La Niña event is considered to have occurred if it is below −0.5 °C for 3 consecutive months and a strong La Niña event if it is below −1.5 °C. Other cases are considered normal years (Yuan and Yan, 2013).

### 3.2 Data Preprocessing

Firstly, the monthly nominal *CPUE* was calculated using following formula.

$$CPUE_{ymijt} = \frac{\sum Catch_{ymijt}}{\sum Effort_{ymijt}}, \tag{6}$$

where $CPUE_{ymijt}$, $\sum Catch_{ymijt}$ and $\sum Effort_{ymijt}$ denote nominal *CPUE*, total catch and effort per unit, respectively. And $y$, $m$, $i$, $j$, $t$ denote year (1995–2018), month (1–12), longitude, latitude and type of fishing, respectively. The unit of *CPUE* is metric tons/set. All the environmental data were converted into 1°×1° for each month to correspond to the spatial resolution of the fishery data using the 'mean' method *sensu* developed by Wang *et al.* (2015). Finally, we made 123, 651 fishing records with eleven variables '*Year*', '*Month*', '*Lon*', '*Lat*', '*SST*', '*SSS*', '*PP*', '$O_2$', '*Nino3.4*', '*Effort*', '*Catch*', and '*CPUE*'. The *CPUE* were normalized by maximum-minimum feature scaling approach (Wang *et al.*, 2018). The standardized function is as follows:

$$\breve{m} = \frac{m - m_{\min}}{m_{\max} - m_{\min}}, \tag{7}$$

where $m$, $\breve{m}$, $m_{\min}$ and $m_{\max}$ denote nominal '*CPUE*', normalized '*CPUE*', minimum '*CPUE*' and maximum '*CPUE*', respectively. The normalized '*CPUE*' value was used as an indicator for the abundance of skipjack tuna resources (0–1).

The multicollinearity of environmental explanatory variables was checked by variance inflation factor (VIF). *VIF*s are less than 10, indicating that there is no serious multicollinearity among explanatory variables (Table 1; Tien *et al.*, 2011).

Table 1 Variance inflation factor among explanatory variables

| Explanatory variables | Variance inflation factor (VIF) |
|---|---|
| *SST* | 8.650437 |
| *SSS* | 1.138457 |
| $O_2$ | 8.834304 |
| *PP* | 1.152670 |
| *Nino3.4* | 1.243880 |

### 3.3 Establishment of Multi-Output Neural Network Model and *CPUE* Standardization

The back propagation algorithm in neural network was used for *CPUE* standardization of skipjack tuna in the WCPO (Parlos *et al.*, 1994). For skipjack tuna, there are 9 nodes ('*Year*', '*Month*', '*Lon*', '*Lat*', '*SST*', '*SSS*', '*PP*', '$O_2$', '*Nino3.4*') in the input layer, 4 nodes ('UNA', 'LOG', 'DFAD', 'AFAD') in the output layer, while the alternative nodes in the hidden layer are 1–17 according to the empirical formula.

The performance of the multi-output neural network model was evaluated using the distribution of *RMSE* and *MAE* in 100 runs hold-out. In each experiment, the dataset is randomly divided into training and test sets in the ratio of 70% and 30%. During the training process, we set the number of iterations to search for optimal parameters in the range of 1000–2000 to maintain convergence at the same convergence threshold. The threshold of maximum error was determined to be 0.28 after several iterations. After the model training, the test sets were used to calculate *RMSE*s and *MAE*s to confirm the optimal structure for multi-output neural network model. We fitted the multi-output neural network models using the 'neuralnet' package version 1.8 in the R software environment (V4.2.2) (Peng *et al.*, 2021). Moreover, we used the optimal model to forecast the spatial distribution and standardize the nominal *CPUE* in each year and month.

## 4 Results

### 4.1 Optimal Model Selection

Based on the results of multi-output neural network model, the *RMSE* and *MAE* values both fluctuated depending on the number of nodes in the hidden layer. The model with a 9:12:4 architecture (9 input neurons, 12 hidden neurons, and 4 output neurons) demonstrated the smallest *RMSE* and *MAE* values among all tested configurations. And this optimal structure was subsequently selected as the final model for predicting skipjack tuna relative abundance in the WCPO from 1995 to 2018 (Figs.3 and 4). The width and color of lines connecting the nodes represent the absolute value and the positive/negative of weights between neural network layers. The varied color and width of lines demonstrated the complex relationship between the selected input variables and the four types of *CPUE*. The spatio-temporal relative abundances for skipjack were more influenced by UNA fishery and LOG fishery as the lines connected to the nodes of 'UNA' and

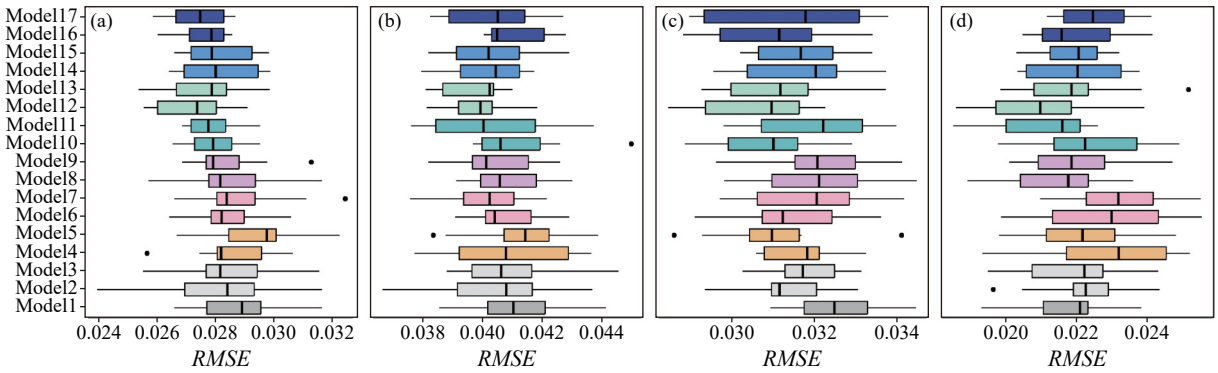



Fig.3 Variation of *RMSE* between observed and estimated values in the testing set for (a) UNA fishery, (b) LOG fishery, (c) DFAD fishery and (d) AFAD fishery, where the number of neurons in hidden layer change from 1 to 17.

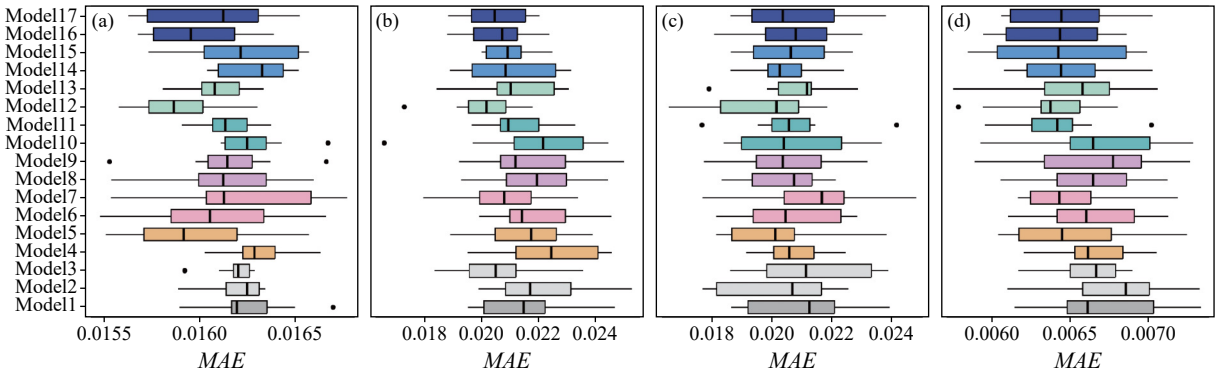



Fig.4 Variation of *MAE* between observed and estimated values in the testing set for (a) UNA fishery, (b) LOG fishery, (c) DFAD fishery and (d) AFAD fishery, where the number of neurons in hidden layer change from 1 to 17.

'LOG' are wider (Fig.5).

### 4.2 Using Neural Network to Interpret Spatio-Temporal Distributions

The sensitivity analysis of marine environmental variable (*SST*, *SSS*, $O_2$, and *PP*) was conducted based on the optimal model by setting each of them in steps (from its minimum value to maximum value) at a time, and the remaining variables were taken as fixed values (median value) (Fig.6). The suitable range of *SST* (*AI*>0.6) was 15–31 °C, and the predicted *AI* value increased significantly from 15 °C, with the highest predicted *AI* value obtained at 25–26 °C. The suitable range of *SSS* was 31–35 and two peaks were observed (32.1 and 34.1). For *dissolved*

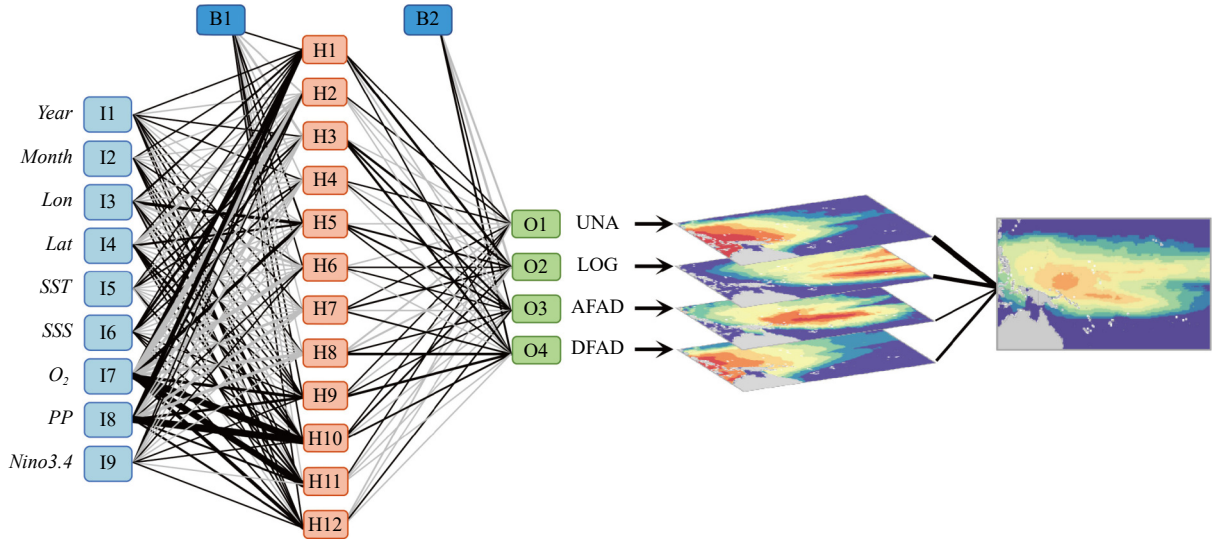



Fig.5 The optimal multi-output neural network demonstrates the complex relationships between the nine input variables and four output variables (UNA fishery, LOG fishery, DFAD fishery, AFAD fishery) for skipjack tuna in the WCPO. B1 and B2 are the biases in the hidden layer and output layer. Black lines represent positive weights, whereas grey lines represent negative weights. The linewidth indicates the signal strength (the absolute value of weight).

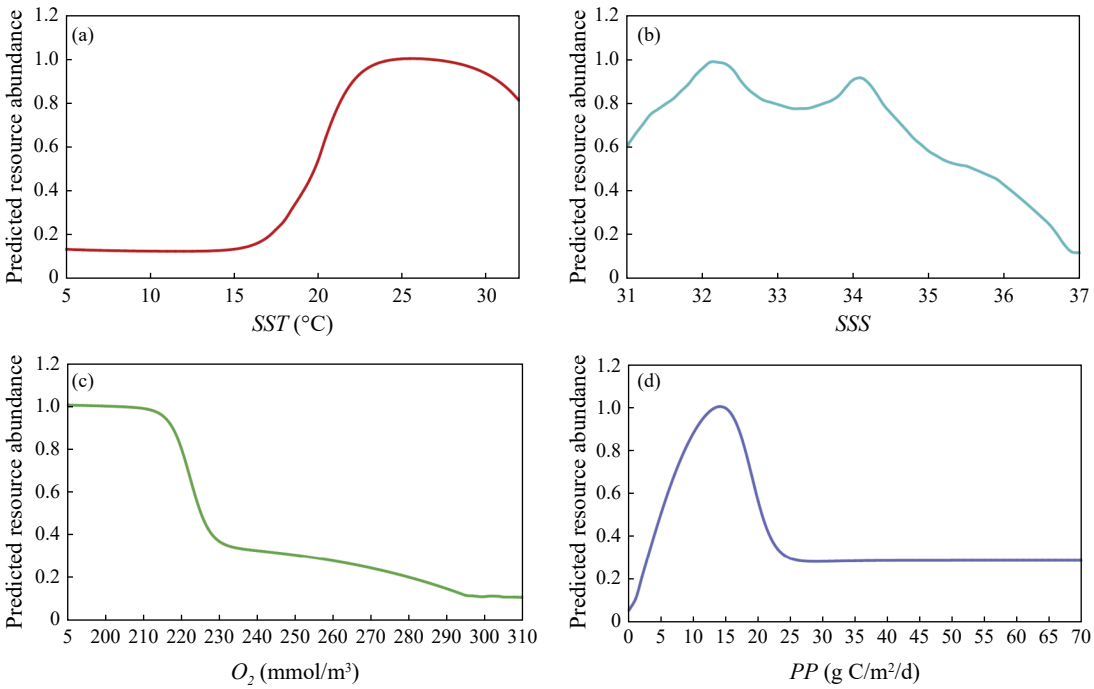



Fig.6 Sensitivity analysis of environmental variables for predicted abundance index.

$O_2$ concentration, the suitable range is 190–225 mmol/m³. For *PP* value, the suitable range is 5–20 g C/m²/d.

By comparing the importance of input variables, *dissolved* $O_2$ concentration was the most significant variable in determining fishery-dependent relative abundance of skipjack tuna. The order of environmental explanatory variables importance from high to low was $O_2$, *SST*, *PP*, *SSS*, and *Nino3.4* (Fig.7).

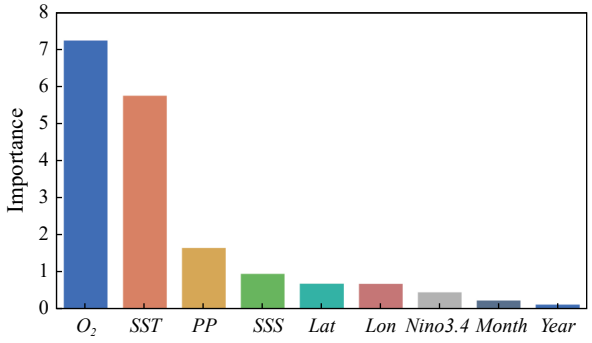



Fig.7 Importance of nine independent variables based on the optimal multi-output neural network models.

The mean monthly and yearly spatial distribution of skipjack tuna abundance predicted by the optimal neural network model during 1995 to 2018 were used to show the predicted seasonal variability and interannual trends in WCPO. Generally, the areas with high predicted abundance were mainly in the range of 10°S–10°N and 140°E–180°. The pronounced changes occurred on the annual spatial distribution and abundance for skipjack tuna. In some years such as 1997, 2002 and 2015, suitable habitat conditions favored skipjack tuna abundance and expanded the range of high *CPUE* values. In contrast, the range of suitable habitat was significantly reduced in years of 1999, 2000, 2008, and 2010 (Fig.8).

For the seasonal changes in spatial distribution of relative abundance, the suitable-density and high-density habitat areas (*AI*>0.6) are still in the tropical waters yearround, though the range has seasonal variations. During the northern hemisphere summer and autumn, the high-density habitat areas are evenly spread near 30°N. The ranges of suitable-density and high-density areas during June to October are wider than in other months. The suitable preferred area also exhibits east-west movement, and they have an eastward expansion during August to November, and then retract the west after December in the tropical WCPO (Fig.9).

### 4.3 Standardized *CPUE* of Skipjack Tuna

Comparing the nominal and standardized *CPUE*, there are some deviations and the relationship between nominal and standardized *CPUE* was not statistically significant. Meanwhile, the variation in nominal *CPUE* was not similar to the variation in standardized *CPUE* in some years. The standardized *CPUE* was quite higher than nominal *CPUE* during 2011 to 2018, while it was lower than nominal *CPUE* during 2005 to 2008. The highest and lowest standardized *CPUE* occurred in 2015 and 1999, respectively. The standardized *CPUE* time series was generally consistent with *SSTA* in Niño 3.4 region ($r$= 0.9782, $p$<0.05, Fig.10).

## 5 Discussion

The multi-output neural network model was applied to standardize the heterogenous fisheries data with the case of four types of skipjack tuna fisheries in the WCPO. Our final model provides a powerful tool (the results with high

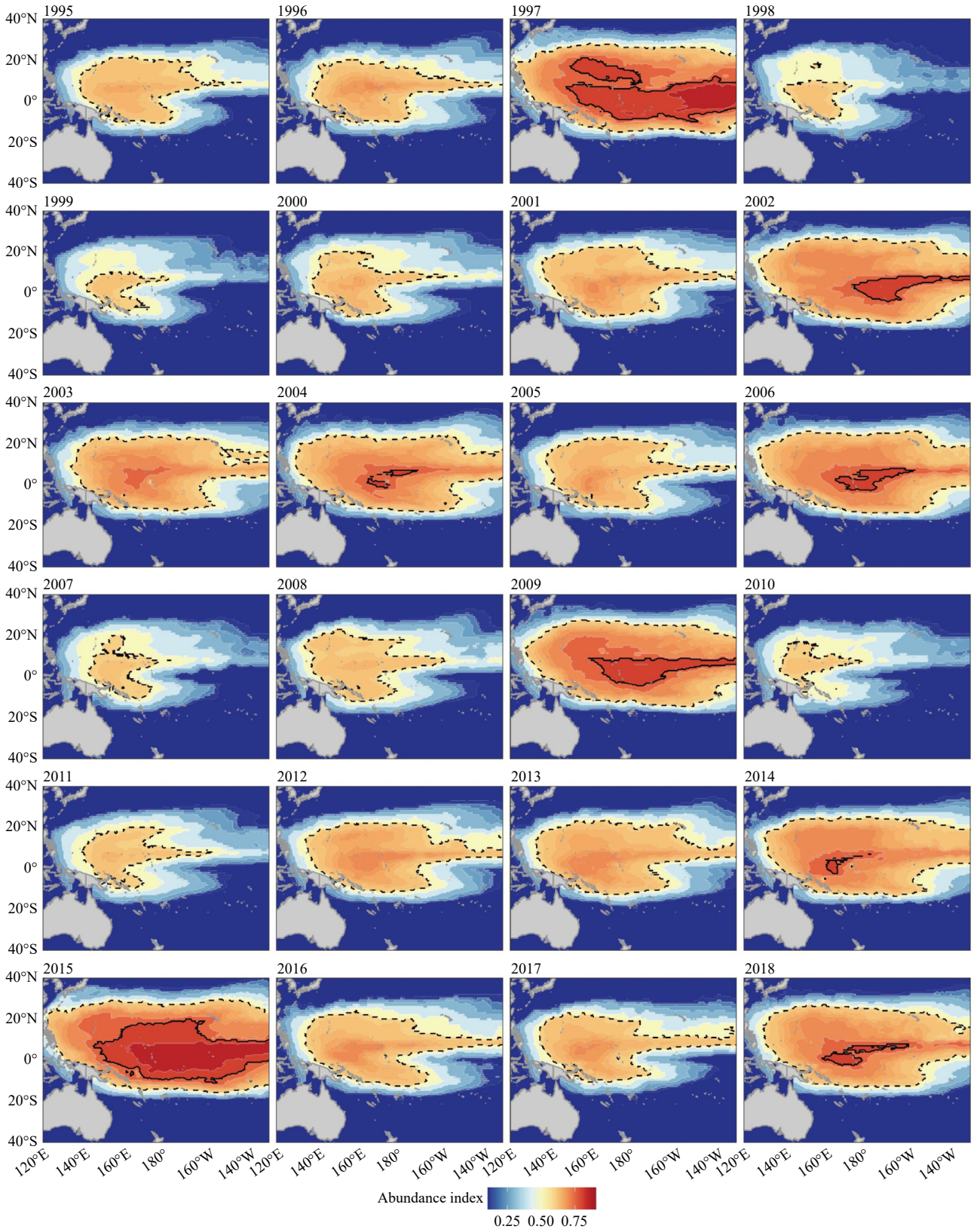



Fig.8 Aggregated yearly spatial distribution of standardized *CPUE* for skipjack tuna during 1995–2018. The dashed black lines and solid black lines indicate the suitable-density and high-density habitat areas with *AI* values of 0.6 and 0.8, respectively.

accuracy and reasonable interpretation) to standardize the complex relationships between the four types of skipjack tuna fishery abundance and the related environment variables. The results demonstrated that the aggregated *CPUE* predicted by using the multi-output neural network model was more relevant to the reality and had a better performance. The projected seasonal and annual variabilities in abundance could be reasonably explained by the knowl-

edges of the fishery oceanography and biology. The results of standardized *CPUE* could serve as cornerstone indicator for skipjack tuna stock assessment in the west-central Pacific Ocean.

The biological characteristics of skipjack tuna result in their need for high levels of $O_2$ to meet energy expenditure requirements (Richard *et al*., 1978). The detected suitable ranges of environmental variables in the high density-areas of skipjack are generally consistent with the physiological needs of skipjack. From the results, it can be concluded that high dissolved oxygen concentration provides suitable living conditions for skipjack tuna, which is consistent with the conclusions from other studies (Arrizabalaga *et al*., 2015; Druon *et al*., 2017). *SST* was also confirmed as one of the most important variables and the basic pattern of distribution for skipjack in the WCPO, and it seemed to determine by the waters with 20.5–26.0 °C (Wang *et al*., 2016; Salazar *et al*., 2021). The preferred habitats of skipjack tuna could reach the latitude near 30°N during the northern hemisphere summer, which is close to the low side of suitable interval (Fig.6). Additionally, the primary productivity is higher in equatorial waters, decreasing from low to high latitude and from east to west longitude (Boyce *et al*., 2010). It seems to provide food for foraging which shapes the similar distribution in skipjack tuna abundance in the WCPO (Yen and Liu, 2016; Fig.7). Thus, the multi-output optimal neural network model exhibited good predicting and interpreting performance, which were validated by the above knowledge of the fishery oceanography.

The weight of *Nino3.4* index is not big; however, this does not mean that the ENSO has a trivial impact on the distribution of skipjack tuna fisheries (Kim *et al*., 2020). During El Niño events, the water temperatures in the western Pacific Ocean are abnormally low and *vice versa* in the eastern part. Warm waters in the western Pacific accumulate eastwards, deepen the mixed layer, and reduced the vertical upward transport of nutrients and the primary productivity in the western equatorial Pacific (Huang *et al*., 2012). Skipjack tuna prefer higher temperatures and higher primary productivity, so they migrate to warmer waters in the east and forage there (Yen *et al*., 2016). This could be demonstrated by our results: El Niño events cause a clear eastward shift extending to near 180° in the high-density skipjack tuna, and the relative decrease abundance occurred in the west coast of WCPO. During strong El Niño years of 1997 and 2015, the high-density area could reach near 160°W or even further east in the equator of the Pacific Ocean (Fig.8). When La Niña events occurred, the significant warm sea temperature in WCPO created an ideal habitat for skipjack tuna to grow and reproduce. The cold tongues increase in both longitudinal and latitudinal directions, which significantly increases the primary productivity in the tropical western Pacific Ocean compared to the normal years (Behrenfeld *et al*., 2001). As a result, the high-density habitat area has a tendency of moving westwards and the skipjack tuna concentrate in the west coast of WCPO, such as in years of 1999, 2000, 2008 and 2010. Generally, the declining trends in the skipjack abundance would be observed in La Niña years (Fig.8).

Our results also showed that there was a significant difference between the nominal and standardized *CPUE* for skipjack tuna in the WCPO. Considering the oceanographic knowledge mentioned above, these differences seem more reasonable. Specifically, the El Niño event expands the warm pool eastward to increase the suitable habitat, resulting in the relatively high abundance of skipjack tuna in 1997 and 2015. The La Niña event forms the strong cold temperature to aggregate the tunas, resulting in the relatively high nominal *CPUE* but low actual abundance of skipjack tuna in the whole WCPO (Yen *et al*., 2016; Salazar *et al*., 2021). The consistency of *SSTA* with standardized *CPUE* is attributable to the strong influence of *SST* on skipjack tuna, with *SST* also being an important driver of other marine environmental factors. However, when human fishing factors are taken into consideration, the nominal *CPUE* in relation to *SSTA* is certainly not as high as the standardized *CPUE*.

For comprehensive comparison, we established other three widely accepted standardization models, including GLM, GAM, and single-output neural network based on the similar process and the same datasets (Figs.S1–S23, Tables S1–S3). While all models demonstrated basic predictive capabilities, their performances varied significantly across different data conditions and ecological scenarios (Figs.3, 4 and Table S3). The GLM and GAM models produced relatively stable *CPUE* estimates due to their linear or additive structure of parameters, but showed limited ability in capturing nonlinear environmental interactions, especially under extreme climate events when predictive relationships become unstable (Grüss *et al*., 2019). Although single-output neural networks have the advantage of nonlinear modeling, their single-task learning architecture fails to account for ecological relationships among different fishing methods or species. This leads to a decline in trend fidelity, which is a key limitation in multi-species fisheries management scenarios. Additionally, model selection should consider the specific research context. GLM/GAM is still preferable for small datasets (<1000 samples), however, in our case ($n$=123651 samples), the multi-output neural network demonstrated greater robustness in addressing the complexities of marine ecological networks (Fig.S1). The excellence of our multi-output neural networks stems from their ability to simultaneously simulate species-environment interactions and interspecies relationships through shared hidden layers. Thus, we should inspect the usability of the results for subsequent stock assessment not only from the accuracy of the models, but also from the fisheries oceanography based on our common sense.

However, tuning multi-output neural network models is difficult. Our experience is that the threshold of error and the iteration of optimization are critical tuning options. While large iterations increase computational demands and training time, they paradoxically become essential for

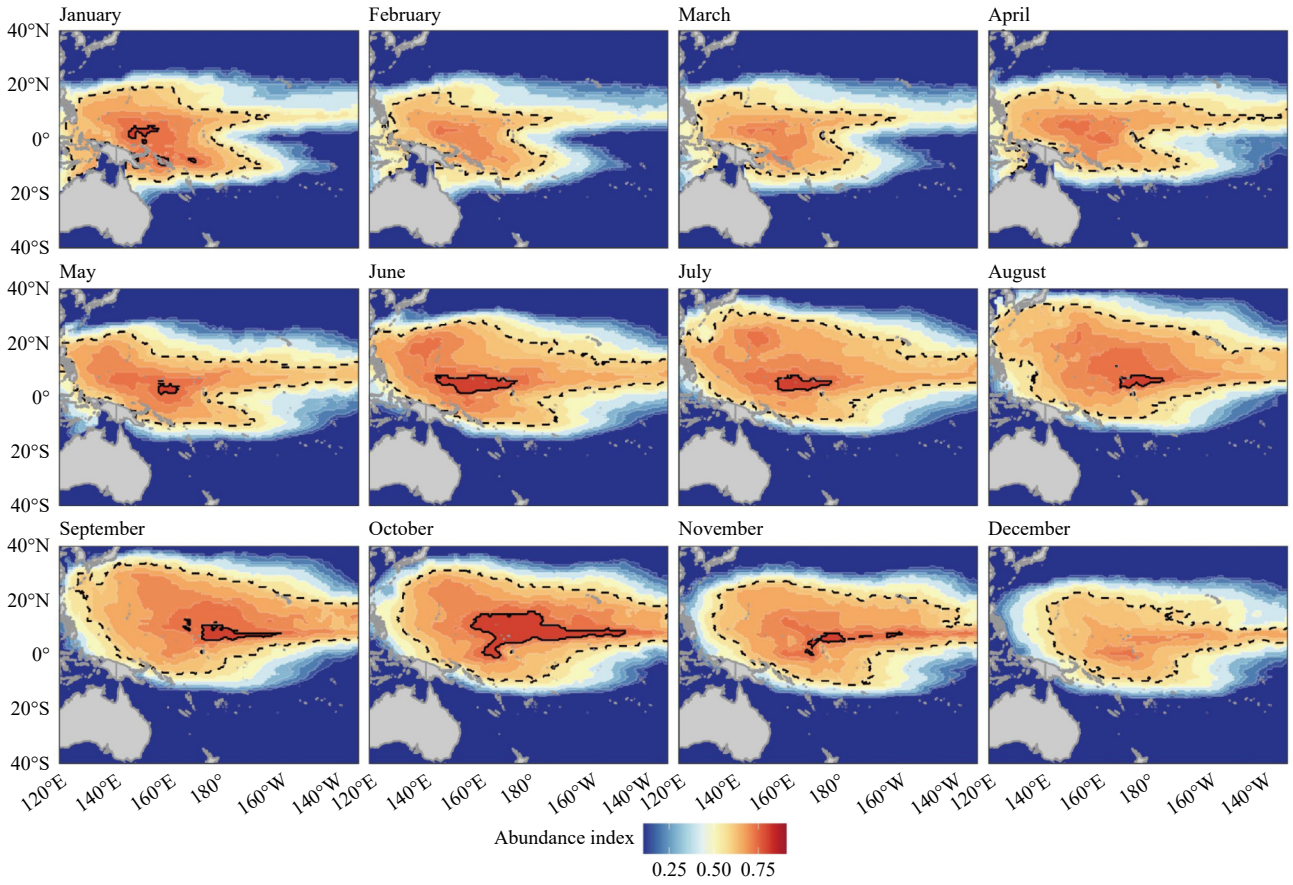



Fig.9 Aggregated monthly spatial distribution of standardized *CPUE* for skipjack tuna during1995–2018. The dashed black lines and solid black lines indicate the suitable-density and high-density habitat areas with *AI* values of 0.6 and 0.8, respectively.

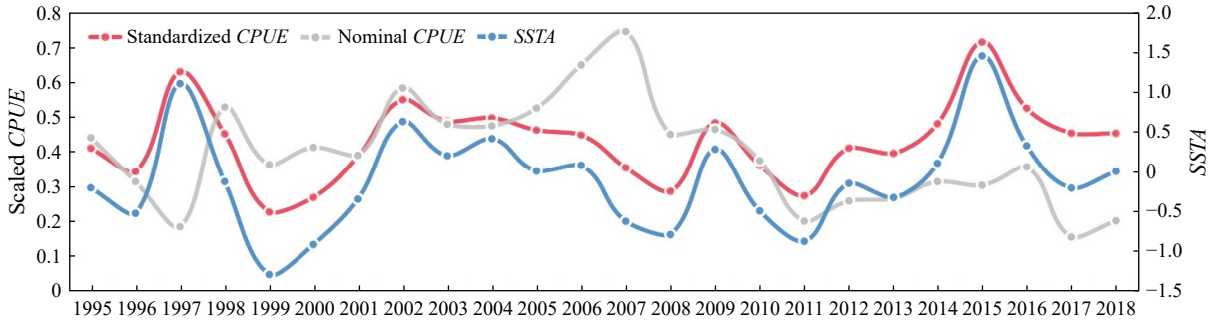



Fig.10 Comparison of nominal and standardized annual *CPUE* for skipjack tuna during 1995–2018, and the annual sea surface temperature anomaly in Niño 3.4 region (5°N–5°S, 170°E–120°W).

capturing delayed ecological feedback loops. The threshold selection embodies a critical trade-off: Too small a threshold could potentially lead to overfitting the model, while a larger threshold could have the risk of underfitting. Initially, we can set the relative comfortable conditions, such as large iteration and acceptable error, to grasp the basic information of your dataset fitting by neural network. The structured settings, including the number of nodes in hidden layer, maximum iteration, threshold of error based on the obtained information, are passed to the procedure of cross validation to evaluate the performance of alternative models (Jiang *et al.*, 2023). Additionally, neural networks are decoupled from the mechanistic understanding, there is no quantification of uncertainty (Kühn *et al.*, 2024). The approach we used is focused on prediction over inference, and the interpretability of multi-output neural network must be strengthened in future. Furthermore, these methods can be applied to heterogeneous fisheries data for other pelagic migratory species.

In summary, commercial fish species with multiple fishery-dependent *CPUE* indices can be standardized by the multi-output neural network model, which can decrease or eliminate the associated effects on fishing types. This study demonstrated that the four fishery-dependent *CPUE* indices were able to reflect the population dynamics of skipjack when considering spatio-temporal, environmental, and climate factors in the WCPO. The approach will be useful for other marine fish species that

were captured by different fishing operations, and the derived indices can be the elementary information for stock assessment and management.

## Supplementary Materials

Supplementary materials are available in the online version of this article at https://doi.org/10.1007/s11802-025-6136-0.

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Tip: The part of code and data are available at JintaoSHOU/neural network_SKJ_CPUEStd (github.com).

## Author Contributions

Zhenqi Xu was responsible for data statistical analysis, manuscript writing, and revision. Yang Liu participated in the manuscript revision and method innovation. Jintao Wang participated in the research design and polished and revised the manuscript. All authors have read and approved the final manuscript.

## Data Availability

The data and references presented in this study are available from the corresponding author upon reasonable request.

## Declarations

### Ethics Approval and Consent to Participate

All methods used in this study were conducted according to the guiding principles of the Chinese Legislation on the Use and Care of Laboratory Animals. The Academic Council approved the animal protocol of the Ocean University of China.

### Consent for Publication

Informed consent for publication was obtained from all participants.

### Conflict of Interests

The authors declare that they have no conflict of interests. Yang Liu is one of the Editorial Board Members, but he was not involved in the journal's review of, or decision related to, this manuscript.

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