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# Projecting distributions of Argentine shortfin squid (*Illex argentinus*) in the Southwest Atlantic using a complex integrated model

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**Abstract**

We developed an approach that integrates generalized additive model (GAM) and neural network model (NNM) for projecting the distribution of Argentine shortfin squid (*Illex argentinus*). The data for this paper was based on commercial fishery data and relevant remote sensing environmental data including sea surface temperature (SST), sea surface height (SSH) and chlorophyll *a* (Chl *a*) from January to June during 2003 to 2011. The GAM was used to identify the significant oceanographic variables and establish their relationships with the fishery catch per unit effort (CPUE). The NNM with the GAM identified significant variables as input vectors was used for predicting spatial distribution of CPUE. The GAM was found to explain 53.8% variances for CPUE. The spatial variables (longitude and latitude) and environmental variables (SST, SSH and Chl *a*) were significant. The CPUE had nonlinear relationship with SST and SSH but a linear relationship with Chl *a*. The NNM was found to be effective and robust in the projection with low mean square errors (MSE) and average relative variances (ARV). The integrated approach can predict the spatial distribution and explain the migration pattern of *Illex argentinus* in the Southwest Atlantic Ocean.

**Key words:** *Illex argentinus*, abundance index, remote sensing environmental data, Southwest Atlantic Ocean

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## 1 Introduction

The Argentine shortfin squid, *Illex argentinus*, is a common neritic species occurring in waters off Brazil, Uruguay, Argentina, and the Falkland/Malvinas Islands in the Southwest Atlantic (Haimovici et al., 1998). It is the most economically important cephalopod species for China and many other countries (Chen et al., 2008). *Illex argentinus* is an opportunistic feeder (Ivanovic and Brunetti, 1994; Brunetti et al., 1998a) growing rapidly with a short life cycle and a high degree of intra-population differentiation (Arkhipkin, 1993, 2000). Meanwhile *I. argentinus* is migratory species, and their concentrations are usually found at 45°–46°S in January or February, while growing rapidly this squid subsequently migrate southward towards the Falkland Islands. Peak concentrations are found around the Falkland Islands between March and May. Toward the end of this period, this squid starts to migrate northward, ultimately to spawn and die in the shelf and slope waters off northern Argentina, Uruguay and Brazil around July or August (Basson et al., 1996; Brunetti et al., 1998b). The population of *I. argentinus* has been separated into four stocks based on their lengths at maturity, areas and timing of spawning, and the distribution of early juveniles and adults life stages: South Patagonic Stock (SPS), Bonaerensis-Northpatagonic Stock (BNS), Summer Spawning Stock (SSS) and Southern Brazil Stock (SBS) (Hatanaka, 1986). Of the four stocks, the SPS is the dominant commercial stock and is mainly exploited by some areas in China's mainland (Lu and Chen, 2012), Chinese Taipei (Chen and Chiu, 2009), and Falkland (Waluda et al., 1999).

The oceanographic environment for *I. argentinus* is mainly influenced by joint Brazil and Malvinas/Falkland Currents around 33°–39°S, causing an important thermohaline front that separates the subtropical waters from the subantarctic waters (Legeckis and Gordon, 1982; Olson et al., 1988; Gordon, 1989). Strong thermal and saline gradients can be observed in this convergence area, due to interactions of the two currents and the influence of the Patagonian Current and the discharge of the Río de la Plata, which provides nutrients for high levels of primary production (Haimovici et al., 1988).

Previous studies suggest that *I. argentinus* tends to be highly susceptible to environmental changes during all its life histroy. For example, Waluda et al. (2001) suggested that large-scale oceanographic variability in the location of the spawning/hatching grounds during the early life stage of *I. argentinus* was im-

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portant in determining recruitment to the fishery. Bazzino et al. (2005) identified environmental associations (depth, bottom temperature and bottom salinity) of shortfin squid in the Northern Patagonian Shelf, and found that squid distribution showed significant associations mostly with depth and bottom temperature. Sacau et al. (2005) developed generalized additive models (GAMs) of squid abundance in relation to physical and environmental conditions including sea surface temperature (SST), latitude, longitude, month, average fishing depth and year to be applied to fishery forecasting, and predictors retained in the optimal model. However, other environmental variables, such as sea surface height (SSH) and chlorophyll *a* (Chl *a*) are also important indicators of physical oceanographic processes, and their impacts on the squid distributions received little attention (Chen et al., 2012).

In this study, we evaluated the influence of SST, SSH and Chl *a* on the spatial distribution of *I. argentinus* in the Southwest Atlantic, and developed a neural network model for forecasting spatial CPUE distribution. We then linked spatio-temporal variability in these oceanographic variables with the migration pattern of *I. argentinus*. The framework developed in the study provides an approach for forecasting spatial CPUE distribution and migration pattern of *I. argentinus* in the Southwest Atlantic, which can also be used for the other oceanic squid species.

## 2 Materials and methods

### 2.1 *Fishery data*

Daily *I. argentinus* fishery data were obtained from the Chinese Squid-Jigging Technology Group of Shanghai Ocean University from January to June during 2003–2011. The Chinese squid-jigging vessels were all equipped with a main engine power of 120 kW×2, squid-attracting lamp power of 112 kW, and 16 squid-jigging machines. These vessels were similar in size and nighttime fishing operation and protocol. The data were digitized from fishing logbook of the Chinese commercial squid fishery operating on the fishing ground between 40°–50°S and 55°–70°W in the Southwest Atlantic Ocean. The catch in this area accounted for 90% in each year. The fishery data comprised fishing dates (year and month), fishing locations (latitude and longitude), daily catch (tonnes), and effort (days fished).

Most of the catches were from the South Patagonic stock of *I. argentinus* and there was no bycatch in the squid fishery (Chen et al., 2008). Fishing vessels and their operations were almost identical. Thus, the CPUE tends to be an approximate indicator of local stock abundance (Chen et al., 2008). In this study, we defined one unit of fishing area as 0.25° latitude by 0.25° longitude. The monthly nominal CPUE in one fishing unit of 0.25°×0.25° was calculated as follows:

$$CPUE_{ymi} = \frac{C_{ymi}}{F_{ymi}}, \tag{1}$$

where $CPUE_{ymi}$, $C_{ymi}$ and $F_{ymi}$ are the monthly nominal CPUE, the total catch for all the fishing vessels in a given fishing grid, and the days fished in a given fishing grid at grid $i$ in month $m$ and year $y$, respectively.

### 2.2 *Remotely sensed environmental data*

Monthly remotely sensed data, comprising SST, SSH and Chl *a* concentration for the fishing ground between 40°–50°S and 50°–70°W were downloaded from the Live Access Server of the National Oceanic and Atmospheric Administration Ocean Watch from 2003 to 2011 (http://oceanwatch.pifsc.noaa.gov/las/servlets/dataset). The method of converting spatial resolutions of remotely sensed data to those for the fishery data were discussed by Wang et al. (2015). Monthly fishery and oceanographic data were plotted allowing for overlaying and displaying of the distribution of *I. argentinus* from January to June during 2003–2011.

### 2.3 *Statistical method and forecasting model*

The generalized additive model (GAM) has been used for confirming the importance of oceanic environmental data and analysis its relationships with the *I. argentinus* distribution (Portela et al., 2005; Sacau et al., 2005). The GAMs were first proposed by Hastie and Tibshirani (1990). The model can deal with non-linear relationships between independent variable and response variable. We developed a GAM to quantify the relationship between the squid abundance (CPUE) and environmental variables. The variables built into the model include year, month, longitude, latitude, SST, SSH and Chl *a*. To deal with zero catches in log transformation, we added a constant of 10% of mean CPUE (Maunder and Punt, 2004). Thus, the GAM can be written as

$$\begin{aligned}\ln\left(CPUE + mean\left(CPUE\right) \times 10\%\right) = factor\left(year\right) + \\ factor\left(month\right) + s\left(longitude\right) + s\left(latitude\right) + \\ s\left(SST\right) + s\left(SSH\right) + s\left(Chl\ a\right) + \varepsilon,\end{aligned} \tag{2}$$

where $s$ is a spline smoother function, $\varepsilon$ is the residual error, $\varepsilon=\sigma^2$ and $E(\varepsilon)=0$.

We conducted a preliminary analysis to evaluate the significance of variables with no interaction terms being considered. Seven variables were included in the GAM by forward selection, and the most significant terms were selected based on correlation analysis, Chi-square statistical significance and AIC ($\alpha$=0.05; Jensen et al., 2005; Chang et al., 2010).

After selecting significant variables in the GAM, we developed neural network models to predict the spatial distribution of squid abundance on the fishing ground of *I. argentinus*. The neural network models with functions of self-learning, good generalizations, and fault tolerance provides an approach to evaluate and predict complex non-linear relationships (Weigend et al., 1990). The neural network models are basically composed of input layer, hidden layer and output layer. Input and output layers consist of explanatory and response variables, respectively. In most cases, only one hidden layer is enough effective and satisfactory (Funahashi, 1989; Lek et al., 1996). However, how to confirm the number of nodes in the hidden layer is quite important and difficult. We utilized back-propagation algorithm in neural network models and added the number of nodes one by one in the hidden layer to search the optimal structure of model. For each different number of nodes in the hidden layer, 70% of data samples during 2003 to 2010 were randomly assigned to train, whereas the remaining 30% were used to validate the model, and the data samples in 2011 were used to test the model. We calculated mean square error (MSE) and average relative variance (ARV) (Nowlan and Hinton, 1992) to quantify the comparison results and confirm the best structure of neural network model. If ARV=1.0 implies that the model has come to a result of prediction average value, ARV=0.0 implies that the model achieves the desired result.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2, \tag{3}$$

$$ARV = \frac{\sum_{i=1}^{n}\left(\widehat{Y}_i - Y_i\right)^2}{\sum_{i=1}^{n}\left(\overline{Y}_i - Y_i\right)^2}, \quad (4)$$

where $Y_i$ is observed CPUE in fishery data, $\overline{Y}_i$ is average CPUE in fishery data, and $\widehat{Y}_i$ is estimated CPUE in neural network models. The MSE value measures the accuracy of models. The ARV value reflects the stability of models; the smaller is the ARV values, the more robust is the model. We used R package including "mgcv", "neuralnet" to select significant variables and establish neural network models respectively.

## 3 Results

### 3.1 *Spatio-temporal distribution of squid abundance index*

The monthly distributions of squid abundance index (CPUE) from January to June in 2003–2011 were plotted in Fig. 1. It is found that the high catch locations for *I. argentinus* occurred on the Patagonian Shelf of the north of 50°S during January to June with the peak values higher than 10 t/d mainly located within 42°–46°S and 50°S.

From the January to June, there was a clear "route" of high CPUE for Argentine shortfin squid (Fig. 1). High CPUEs are found at 46°S in January or February and then the vessels moved southward towards the Falkland Islands gradually. The peak concentrations were found around the Falkland Islands between March and May. At the end of this period, the vessels started migrating northward, and then the Chinese jigging fishing was stopped. In some years (such as 2003, 2009 and 2010) there was no fishing in June because of low CPUE in end of fishing season.

### 3.2 *Environmental factors affecting CPUE*

The final model included effects of year, month, latitude, longitude, SST, SSH and Chl *a* after significance tests. The GAM with the seven variables explained 54.8% variances for CPUE (Table 1). The GAM confirmed the non-linearity of the relationships between squid CPUE and variables (Fig. 2). *Illex agrentinus* CPUE appeared to decrease from shelf to the high sea (Fig. 2a), and the relationship between CPUE and latitude was a curve of "V" shape, with peak values at about 50°S and 42°S (Fig. 2b). The highest squid CPUEs were associated with a range of SST (10–16°C) (Fig. 2c), concentrating at the range of –60 to –20 cm of SSH (Fig. 2d). In the range of 0–2 mg/m$^3$ of Chl *a*, the squid CPUE showed an increasing trend (Fig. 2e).

### 3.3 *Predicting model of squid CPUE*

The neural network models were constructed using month, longitude, latitude, SST, SSH and Chl *a*, which were significant in the GAM, as the input vector and CPUE as the output vector. The MSE and ARV values showed that the model had higher accuracy and more robustness (Fig. 3) when the count of nodes in the hidden layer was equal to 9 (the structure of neural network model is 6:9:1, Fig. 4). In the best neural network model, the MSEs of training, validation and testing are 6.98, 7.77 and 7.79, respectively, the ARVs of training, validation and testing are 0.2, 0.4 and 0.45, respectively.

Based on the best neural network model, the predicted neural interpretation diagram also showed for complex relationships between the input variables and the squid CPUEs (Fig. 4). The weights of each node in the input and hidden layers showed the positive and negative impact synchronously on the squid abundances. The importance of the input variables including month, longitude, latitude, SST, SSH and Chl *a* in the prediction model was 5%, 9%, 27%, 26%, 15% and 18%, respectively. The latitude, SST and Chl *a* were the more important variables than month, longitude and SSH (Fig. 5).

### 3.4 *Forecasting migration pattern of squid*

The monthly CPUE gravities were calculated for the predicted CPUE and observed CPUE to show the gravity shifts from

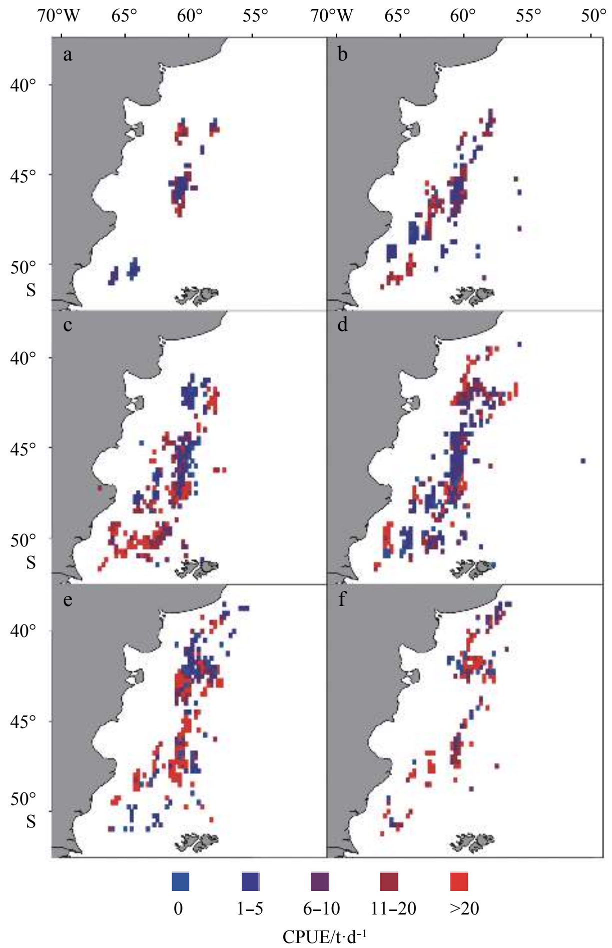


**Fig. 1.** Monthly catch distribution for *Illex argentinus* during 2003–2011: January (a), February (b), March (c), April (d), May (e), and June (f).

**Table 1.** Model selection and performance for the GAMs

| Model formula | $P$ | $R^2$ adj | GVC | Dev.Exp | AIC |
|---|---|---|---|---|---|
| $Y$+$M$+$s$($Lo$)+$s$($La$)+$s$($SST$) | <0.001, <0.001, <0.001 | 0.508 | 0.605 | 51.6% | 4 609.765 |
| $Y$+$M$+$s$($Lo$)+$s$($La$)+$s$($SST$)+$s$($SSH$) | <0.001, <0.001, <0.001, <0.001 | 0.517 | 0.596 | 52.6% | 4 577.056 |
| $Y$+$M$+$Lo$+$La$+$s$($SST$)+$s$($SSH$)+$s$($Chl\ a$) | <0.001, <0.001, <0.05, <0.001, <0.01 | 0.538 | 0.554 | 54.8% | 4 102.478 |

Note: $M$ represents month, $Y$ year, $Lo$ longitude, $La$ latitude, $R^2$ adj adjusted $R^2$, GVC global cross validation, and Dev.Exp deviance explained (%).

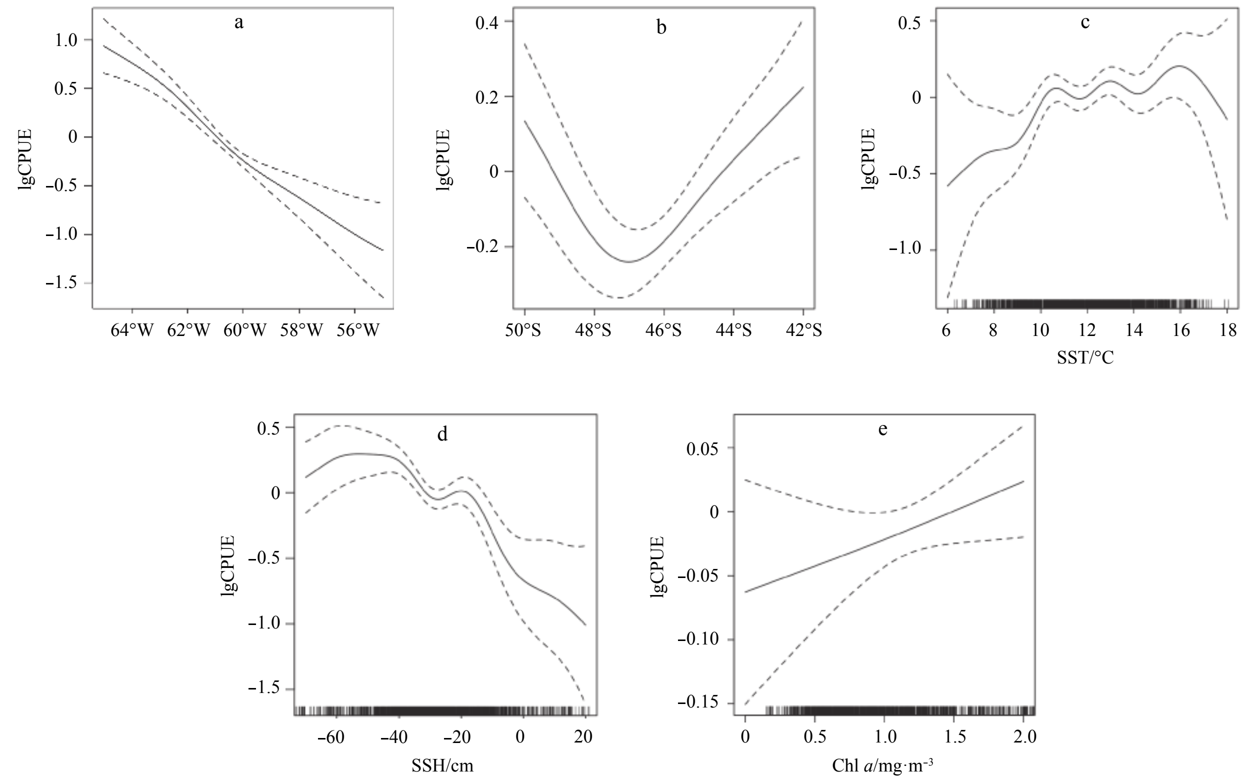


**Fig. 2.** Impact of longitude (a), latitude (b), SST (c), SSH (d), and Chl *a* (e) on squid abundance in GAM. Dashed lines represent two standard error boundaries around covariate main effect (95% confidence intervals).

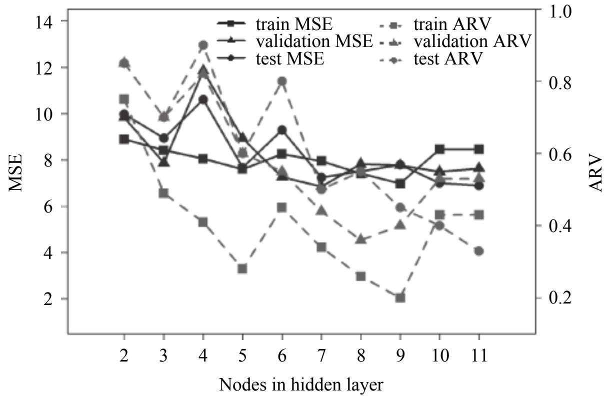


**Fig. 3.** MSE and ARV values of neural network model with different nodes in hidden layer.

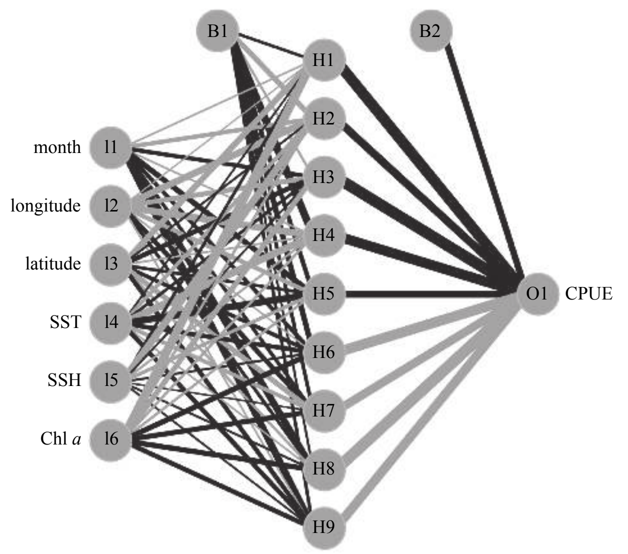


**Fig. 4.** The structure of neural network model for spatial CPUE distribution of *Illex argentinus*. I, H and O represent nodes in input layer, hidden layer and output layer. B represents the bias of neural network. Black lines represent positive signals, whereas gray lines represent negative signals.

January to June for *I. argentinus* in 2005 (Fig. 6a) (The method of calculating CPUE gravities was stated by Wang et al. (2016)). The longitudinal change of CPUE gravity was more stable than latitudinal change of CPUE gravity, either forecasting gravity shift or observed gravity shift could better represent the "south-north" migration pattern of *I. argentinus* in the Southwest Atlantic Ocean.

## 4 Discussion

Understanding and projecting how fish species react to climate change and variability in the regional/local oceanographic environmental is essential for the effective management of marine resources (Waluda et al., 2001). *Illex argentinus* abundance and distribution are found to be significantly influenced by surrounding environmental conditions (Waluda et al., 2001; Bazzino et al., 2005; Chen et al., 2012; Sacau et al., 2005). In this study, the integrated approach which using GAM to select significant variables and using NNM to establish relationships may overcome disadvantages associated with the use of sub-models alone. The GAM can interpret the relationships between results and factors,

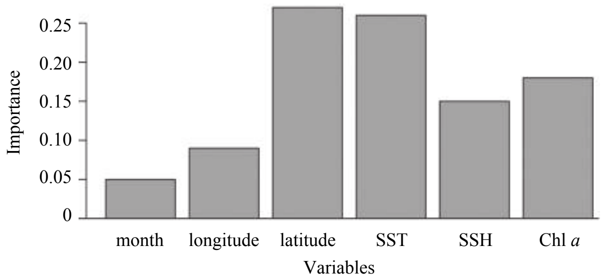


**Fig. 5.** The importance of input vector of neural network model.

but its inference ability may be somewhat problematical, such as hypothesis test or obtaining confidence intervals for the fitted values caused by fitting process (Venables and Dichmont, 2004); neural network model is a "black box" model of obtaining a good understanding of the underlying mechanisms difficultly, but has strong ability of fitting non-linear relationships (Paruelo and Tomasel, 1997). The aim of combining the GAM and the ANN is to obtain more accurate prediction with better explanatory between independent and dependent variables, though the ANN is more capable in dealing with nonlinear relationships than GAM.

In the GAM analysis, all the environmental variables (SST, SSH and Chl *a*) had significant impacts on squid abundance (Table 1). The highest CPUE was found in temperature between 10–16°C, this was similar to the conclusion obtained by different methods based on different fishery data in other studies (e.g., Sacau et al., 2005). The other two environmental variables (SSH and Chl *a*) are rarely utilized for analyzing the distribution of *I. argentinus*, but have been used to other species, such as neon flying squid *Ommastrephes bartramii* in the Northwest Pacific Ocean (Wang et al., 2015). The Chl *a* concentration maybe a good indicator of the food availability for squid with high Chl *a* concentration yielding good feeding environments (Nishikawa et al., 2014). The relationship between Chl *a* concentration and squid abundance is possibly linear in the GAM. The SSH filed may be effective for predicting a water mass front, which is a potential aggregation mechanism for planktons as well as their predators, such as squid (Polito et al., 2000). The relationship between SSH and squid abundance demonstrated non-linearity being the highest CPUE found at SSH between –60 and –20 cm.

For the NNM, one of the greatest advantages is predictive ability. Though there are some methods to try to interpret model mechanism (Özesmi and Özesmi, 1999), it is insufficiently specific in our research. For example, we just knew the relationship between squid abundance and environmental variables is non-linear in neural interpretation diagram, but did not know the exact form of non-linear. Thus, we just took full advantage of NNM to predict spatial CPUE of *I. argentinus*. In fact, we also did try to predict spatial CPUE distribution using GAM model fitted on the same data samples, it was found that the outcomes were not better than NNM's. Additionally, the relationships between squid and environmental variables may be varied among different life-history stages. However, the current neural networks developed in this paper were general models those mixed the effect of environmental gradients (spatial effects) with life-history changes (temporal effects), it tends to be risky.

In this study, the annual maps of monthly CPUE distribution (Fig. 1), especially in monthly CPUE gravities shift (Fig. 6a), exhibit the migration pattern of *I. argentinus* during January to June. The results were consistent with the conclusion reported by Sacau et al. (2005) and Waluda et al. (2001). Previous work suggests that the life-cycle of *I. argentinus* is associated with the subtropical confluence of the Brazil and Falkland Currents during reproduction and the early life stages (Brunetti and Ivanovic, 1992; Hatanaka, 1988) and with the Falkland Current over the Southern Patagonian shelf during maturation, feeding and growth (Rodhouse et al., 1995). In order to evaluate this mechanism with environmental variables, we plotted maps of monthly catch distribution in 2005 overlapped it with SST, SSH and Chl *a* concentration, because the catch in 2005 was relatively steady (Figs 6, 7 and 8). From the maps, the catch locations were basically distributed in warm-cold (Brazil-Falkland) confluence in the SST map

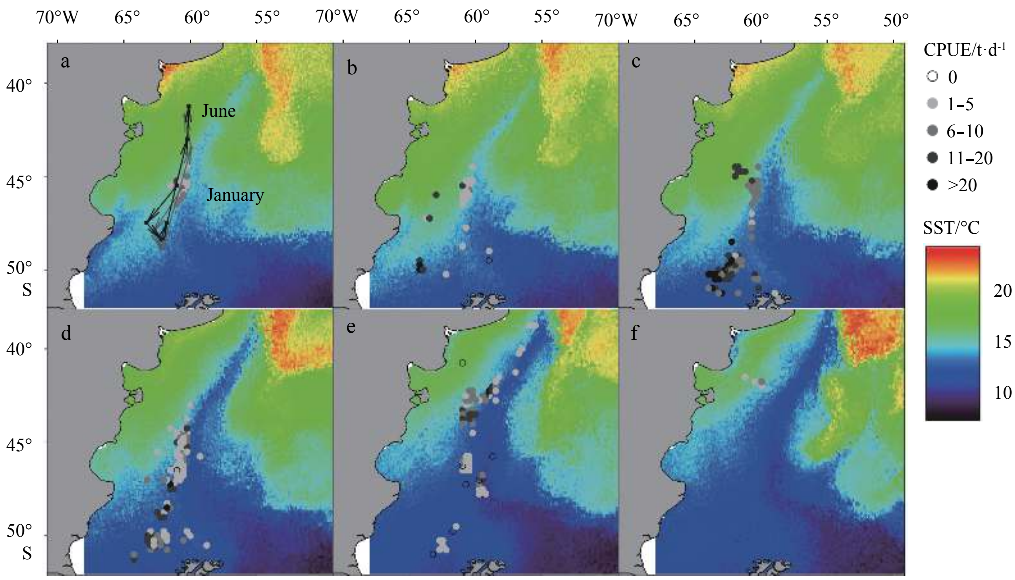


**Fig. 6.** Monthly CPUE distribution overlapping SST map for *Illex argentinus* in 2005: January (a), February (b), March (c), April (d), May (e), and June (f); and monthly CPUE gravity shift of *I. argentinus* from January to June (a). The gray line with arrows represents the gravity shift of operation and the black line with arrows the gravity shift of forecasting.

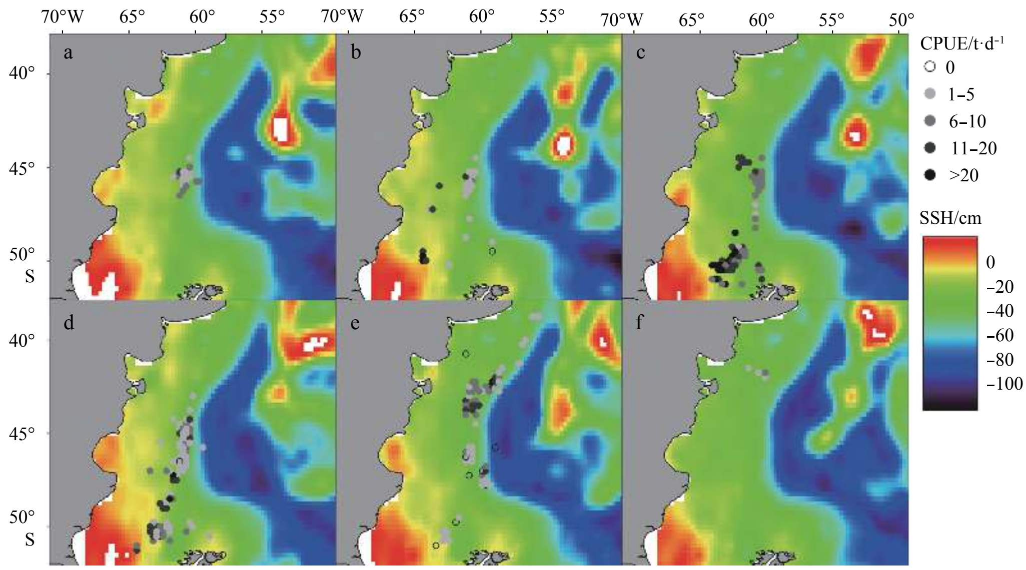


**Fig. 7.** Monthly CPUE distribution overlapping SSH map for *Illex argentinus* in 2005: January (a), February (b), March (c), April (d), May (e), and June (f).

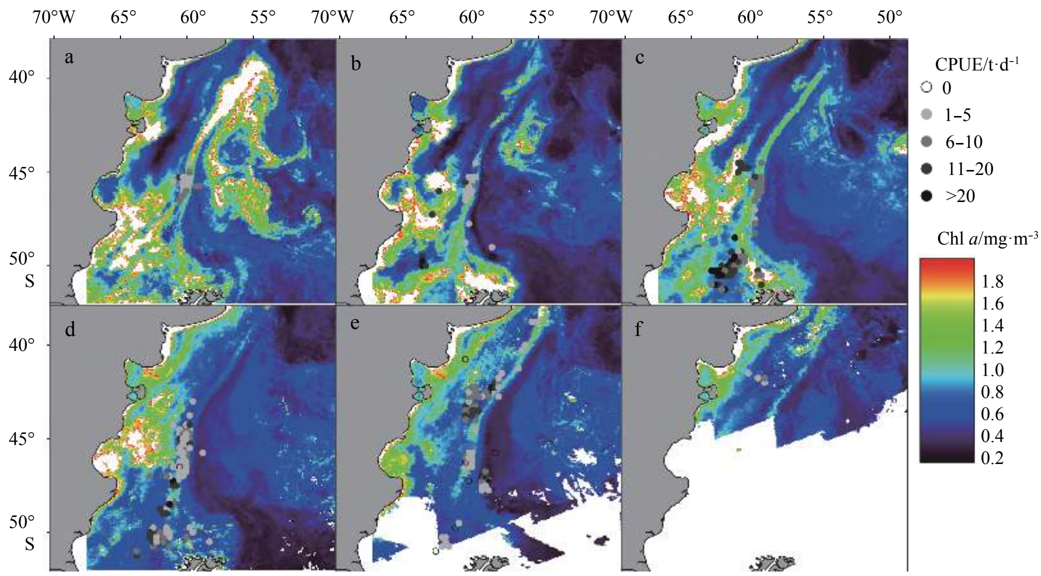


**Fig. 8.** Monthly CPUE distribution overlapping Chl *a* map for *Illex argentinus* in 2005: January (a), February (b), March (c), April (d), May (e), and June (f).

(Fig. 6), between high and low surface layer especially along low surface layer (about –80 cm) in the SSH map (Fig. 7), on the road of high Chl *a* concentration that interweaved with dark environment where almost no Chl *a* concentration in the Chl *a* concentration map (Fig. 8). The south-north migration pattern for *I. argentinus* was consistent with the change of warm-cold (Brazil-Falkland) confluence from January to June. However, the migration pattern was not obvious in SSH and Chl *a* maps, because the catch locations were looked like constant in a fixed environmental surrounding. This suggested that *I. argentinus* lives in special habitat from SSH and Chl *a* concentration perspective.

In summary, the integrated model was well developed for representing and predicting the spatial distribution of *I. argentinus* squid with approximately 82% average accuracy, the model could be further used for spatial habitat reconstructing. But more work should be done in further. For example, if the neural network models of *I. aregentinus* were developed by monthly or other environmental variables, such as sea surface salinity and sea depth temperature (Yu et al., 2015), can be obtained, the better model would be developed.

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