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Assessment of prediction model of the CPUE of neon flying squid with different sources of remote sensing data

Liang Chang[1, 2, 3, 4, 5, 6], Yanli Yang[1], Xinjun Chen[1, 3, 4, 5, 6*], Wei Yu[1, 2, 3, 4, 5, 6], Yangdong Li[1, 3, 4, 5, 6], Guiping Feng[1, 3, 4, 5, 6], Yang Zhang[2]

[1] College of Marine Sciences, Shanghai Ocean University, Shanghai 201306, China

[2] State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, Ministry of Natural Resources, Hangzhou 310012, China

[3] National Engineering Research Centre for Oceanic Fisheries, Shanghai Ocean University, Shanghai 201306, China

[4] Key Laboratory of Sustainable Exploitation of Oceanic Fisheries Resources of Ministry of Education, Shanghai Ocean University, Shanghai 201306, China

[5] Key Laboratory of Oceanic Fisheries Exploration, Ministry of Agriculture and Rural Affairs, Shanghai 201306, China

[6] Scientific Observing and Experimental Station of Oceanic Fishery Resources, Ministry of Agriculture and Rural Affairs, Shanghai 201306, China

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Abstract

Accurately building the relationship between the oceanographic environment and the distribution of neon flying squid (*Ommastrephes bartramii*) is very important to understand the potential habitat pattern of *O. bartramii*. However, when building the prediction model of *O. bartramii* with traditional oceanographic variables (e.g., chlorophyll *a* concentration (Chl *a*) and sea surface temperature (SST)) from space-borne observations, part of the important spectrum characteristics of the oceanic surface could be masked by using the satellite data products directly. In this study, the neglected remote sensing information (i.e., spectral remote sensing reflectance (Rrs) and brightness temperature (BT)) is firstly incorporated to build the prediction model of catch per unit effort (CPUE) of *O. bartramii* from July to December during 2014–2018 in the Northwest Pacific Ocean. Results show that both the conventional oceanographic variables and the neglected remote sensing data are suitable for building the prediction model, whereas the overall root mean square error (RMSE) of the predicted CPUE of *O. bartramii* with the former is typically less accurate than that with the latter. Hence, the Rrs and BT could be a more suitable data source than the Chl *a* and SST to predict the distribution of *O. bartramii*, highlighting that the potential value of the neglected variables in understanding the habitat suitability of *O. bartramii*.

Key words: *Ommastrephes bartramii*, CPUE prediction, remote sensing, Rrs, BT.

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1 Introduction

The neon flying squid, *Ommastrephes bartramii*, is one of the most important cephalopod with great potential for economic development, widely distributed over the Pacific Ocean (Roper et al., 1984). The life history stages of *O. bartramii* are affected by the ambient oceanographic regimes and the epipelagic environment (Alabia et al., 2016; Igarashi et al., 2017), and its spatial and temporal distributions are highly related to the variability in various oceanographic variables (Yu et al., 2015). Additionally, based on the relationships between the environmental variables and the distribution of the *O. bartramii*, the potential fishing ground and the habitat suitability of the *O. bartramii* can also be detected and assessed (e.g., Cao et al., 2009; Chen et al., 2011; Nishikawa et al., 2014). As such, understanding of the relationship between the oceanographic environmental factors and the spatio-temporal distributions of *O. bartramii* is essential for predicting its potential habitat pattern in the Pacific Ocean.

Several oceanographic variables, such as chlorophyll *a* concentration (Chl *a*) (e.g., Chen et al., 2010; Yu et al., 2017; Nishikawa et al., 2014) and sea surface temperature (SST) (e.g., Chen et al., 2007; Yatsu et al., 2010; Yu et al., 2020) are demonstrated to affect the habitat variations of *O. bartramii* in the Northwest Pacific Ocean. In order to deduce the distribution of *O. bartramii*, previous studies (e.g., Gong et al., 2012; Alabia et al., 2015; Wang et al., 2015, 2016; Yu et al., 2016a, 2016b, 2021) usually build the model between the distribution of *O. bartramii* and the environmental factors. Generally, traditional models are directly built based on the satellite-based oceanographic environment vari-

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*Corresponding author, E-mail: xjchen@shou.edu.cn

ables (e.g., Chl *a* and SST). However, the Chl *a* and SST data products cannot fully describe the spectrum characteristics of the oceanic surface. On one hand, Chl *a* and SST are not the only indicators for the ocean water. On the other hand, uncertainties in Chl *a* and SST remain after making several corrections during the data processing (e.g., Cui et al., 2020; Gentemann and Hilburn, 2015). As a result, the connection between conventional satellite-based oceanographic variables and distribution of *O. bartramii* may be not able to accurately represent the habitation of *O. bartramii* under different oceanic conditions.

In fact, the Chl *a* and SST measurements are not the raw information of the satellite observations. The Chl *a* can be estimated based on the ratio (O'Reilly et al., 1998; O'Reilly and Werdell, 2019) or difference (Hu et al., 2012, 2019) of spectral remote sensing reflectance (Rrs) at blue and green bands. In addition, the SST can be retrieved with different algorithms (e.g., Shibata, 2006; Wentz and Meissner, 2007; Meissner and Wentz, 2012; Merchant et al., 2008, 2009) based on the brightness temperature (BT). As such, the Rrs and BT measurements are the more neglected remote sensing information than the Chl *a* and SST, respectively.

In this study, the neglected remote sensing Rrs and/or BT data are firstly introduced to simulate and predict the distribution of *O. bartramii* with the feed-forward back propagation (BP) artificial neural network (ANN) model in the Northwest Pacific Ocean. In order to assess the performance of Rrs and/or BT on representing the distribution of *O. bartramii*, the ANN- stimulated and -predicted CPUE of *O. bartramii* are compared with the nominal CPUE from *in situ* daily fishery logbook data. Moreover, in order to clarify the superiority of the neglected remote sensing data to the conventional oceanographic variables, the performance differences between them on predicting the distribution of *O. bartramii* are also investigated.

2 Materials and methods

2.1 *Data sources*

The *O. bartramii* daily fishery logbook data were obtained from the Chinese Squid-Jigging Technology Group of Shanghai Ocean University from July to December during 2004–2018. These data include fishing dates, daily catch (tonnes), fishing effort (days fished) and fishing locations (latitude and longitude) for the Chinese commercial squid fishery operating on the traditional fishing ground between 35°–50°N and 145°–175°E in the Northwest Pacific Ocean. The western stock of winter–spring *O. bartramii* accounted for most of the catch in the western Pacific Ocean with no bycatch. Chinese squid-jigging fishing vessels were equipped with almost identical engine, lamp and fishing power. These data were compiled into monthly data and grouped using 1°×1° grid cells. As a result, a total of 416 grids (26 columns by 16 rows) are generated. The monthly nominal catch per unit effort (CPUE) in one fishing unit of 1°×1° can then be calculated by

$$\mathrm{CPUE}_{y,m,i} = \frac{C_{y,m,i}}{F_{y,m,i}}, \tag{1}$$

where $\mathrm{CPUE}_{y,m,i}$ is the monthly nominal CPUE, $C_{y,m,i}$ is the total catch for all the fishing vessels within a fishing grid, $F_{y,m,i}$ is the number of fishing vessels within one fishing grid, i is fishing unit at 1°×1° grids, m is month and y is year. In this paper, the derived monthly nominal CPUE was used as a reliable index of squid abundance, as well as the response variable to assess the performance of the prediction model.

The Level-3 Moderate Resolution Imaging Spectroradiometer (MODIS) Chl *a* and the neglected Rrs monthly data, collected by both Terra and Aqua from 2004 to 2018, were acquired from National Aeronautics and Space Administration (NASA) Goddard Space Flight Center (http://oceancolor.gsfc.nasa.gov). Both Chl *a* and Rrs data are at a 9 km×9 km (at nadir) spatial resolution. The MODIS Chl *a* is calculated using an empirical relationship derived from *in situ* measurements and Rrs in the blue-to-green region of the visible spectrum. Specifically, Rrs at 465 nm, 555 nm and 645 nm spectral regimes are used to estimate the near-surface MODIS Chl *a* product via merging the standard OC3/OC4 (OCx) band ratio algorithm (O'Reilly et al., 1998) and the color index of Hu et al. (2012). Therefore, only MODIS Rrs data at 465 nm, 555 nm and 645 nm spectral regimes are incorporated for further analysis in this paper. In addition, after averaging the monthly Chl *a* (and Rrs) data from Terra and Aqua platforms, the averaged Chl *a* (and Rrs) data were resampled according to the location of the monthly nominal CPUE grids (i.e., at a horizontal resolution of 1°).

SST and the neglected BT measurements were retrieved from Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) onboard Aqua launched in May 2002 and decommissioned in October 2011, as well as the follow-on instrument AMSR2 flown on the Global Change Observing Mission (GCOM-1) launched in May 2012. In this paper, BT measurements at 6 GHz horizontal (H) and vertical (V) polarization, 10H, 10V, 23 V, 37H and 37V are used for comparisons with SST. Both AMSR-E and AMSR2 Level-3 monthly data products, with a spatial resolution of 25 km and 10 km, respectively, were obtained from Japanese Aerospace Exploration Agency (JAXA; https://sharaku.eorc.jaxa.jp/AMSR/index.html). In order to obtain the spatiotemporally synchronized matchups between CPUE and SST (and BT) data, SST and BT data are also resampled at 1°×1° grid cells.

2.2 *CPUE modelling*

In this paper, we use the ANN to build the prediction model between the CPUE of *O. bartramii* and oceanographic information. The ANN is a model that is motivated by the biological neural network of the human brain and is used to simulate the processes that depends on a huge number of unknown inputs (Priddy and Keller, 2005). ANN is the collections of interconnected neurons that interchanges information among each other, and the connections are weighted and adjusted to get appropriate results. ANN contains mainly input layer, hidden layer and output layer. Neurons in the input layer accept the inputs for further processing. Neurons in the hidden layer accept the input from input layer with allotted weights, as well as forward the output to the output layer. In the output layer, neurons are represented with expected attribute values to the external world as output.

Back propagation (BP) algorithm is utilized in the layered feed-forward ANN in this study to build the prediction model of *O. bartramii* in the Northwest Pacific Ocean. The feed-forward BP neural network is a supervised learning ANN and based on the learning rule for decreasing error till the ANN becomes skilled at the data training (Wang et al., 2015). In addition, the Levenberg–Marquardt algorithm (trainlm) training algorithms is selected during the implementation of the feed-forward BP ANN (Zhang et al., 2015). Trainlm training function is based on Levenberg–Marquardt optimization and updates the bias to weight values. Trainlm falls in the supervised training algorithm category and serves as the fastest BP algorithm (Sangwan et al., 2020). The disadvantage of trainlm is that it takes more memory than other algorithms.

In this study, the input layer of the feed-forward BP ANN may include one or more kinds of remote sensing data, and the output layer is the CPUE of *O. bartramii*. Additionally, we implement the ANN training at each grid cell in each month. In order to assess the performance of conventional oceanographic variables and neglected remote sensing information on building the prediction model of *O. bartramii* in the Northwest Pacific Ocean, six schemes are designed to build the feed-forward BP ANN model in this paper (see Table 1). The schemes differ from each other by using different data sources as the model input. Schemes Ⅰ, Ⅱ and Ⅲ use the conventional Chl *a*, SST and their combination as the input, and Schemes Ⅳ, Ⅴ and Ⅵ use the corresponding neglected Rrs, BT and their combination as the input. Additionally, performances of the schemes also provide us an opportunity to examine the potential of neglected remote sensing information on improving our understanding of the distribution of *O. bartramii*. Moreover, both the *O. bartramii* fishery data and remote sensing measurements are split into two temporal groups for model training and validating, respectively. The first group in July–December of 2004–2013 is used to build the prediction model between the remote sensing data and the CPUE of *O. bartramii*, and estimate the internal coincidence precision of the model by comparing the model output with the monthly nominal CPUE *of O. bartramii*. The other group in July–December of 2014–2018 is used to validate the performance of the built model in terms of external coincidence precision via comparing the model predictions with the nominal CPUE

3 Results

In order to assess the performance of the ANN-derived distribution of CPUE of *O. bartramii* in the Northwest Pacific Ocean, we analyzed the precision of the prediction model of *O. bartramii*. Figure 1 displayed the root mean square error (RMSE) of the ANN-simulated CPUE of *O. bartramii* from July to December during 2004–2013 with the conventional oceanographic variables (Figs 1a–c) and the neglected remote sensing data (Figs 1d–f) as input. Uncertainties in the ANN-simulated CPUE of *O. bartramii* with Chl *a* as input (Fig. 1a) generally exhibited similar spatial distribution to those with Rrs as input (Fig. 1d). Additionally, the overall RMSE of the ANN-simulated CPUE in Schemes Ⅰ and Ⅳ was approximately 0.49 t/d and 0.47 t/d, respectively, indicating both Chl *a* and Rrs were suitable to simulate the CPUE of *O. bartramii* with the feed-forward BP ANN. Moreover, the overall RMSE of the ANN-simulated CPUE of *O. bartramii* with both SST (Fig. 1b) and BT (Fig. 1e) as input was about 0.45 t/d. When the conventional Chl *a* and SST from July to December during 2004–2013 were combined as the input to the feed-forward BP ANN (i.e., Scheme Ⅲ), the ANN-simulated CPUE of *O. bartramii* agreed well with the nominal CPUE (Fig. 1c). Moreover, the combined Rrs and BT also successfully simulated the CPUE of *O. bartramii* (i.e., Scheme Ⅵ). The overall RMSE of ANN-simulated CPUE was approximately 0.46 t/d and 0.42 t/d in Schemes Ⅲ and Ⅵ, respectively. In general, when the conventional oceanographic variables were input to build the prediction model (i.e., Schemes Ⅰ, Ⅱ and Ⅲ), the RMS of the ANN-simulated CPUE of *O. bartramii* was greater than the simulation results with the corresponding neglected remote sensing data as input (i.e., Schemes Ⅳ, Ⅴ and Ⅵ) (Fig. 2).

Table 1. The input and response data for the feed-forward back propagation artificial neural network (BP ANN) model between *Ommastrephes bartramii* and oceanographic information from July to December during 2004–2018 in the Northwest Pacific Ocean

Scheme	Input data	Response data
Ⅰ	chlorophyll *a* concentration (Chl *a*)	monthly nominal CPUE of *O. bartramii*
Ⅱ	sea surface temperature (SST)	monthly nominal CPUE of *O. bartramii*
Ⅲ	Chl *a* and SST	monthly nominal CPUE of *O. bartramii*
Ⅳ	spectral remote sensing reflectance (Rrs)	monthly nominal CPUE of *O. bartramii*
Ⅴ	brightness temperature (BT)	monthly nominal CPUE of *O. bartramii*
Ⅵ	Rrs and BT	monthly nominal CPUE of *O. bartramii*

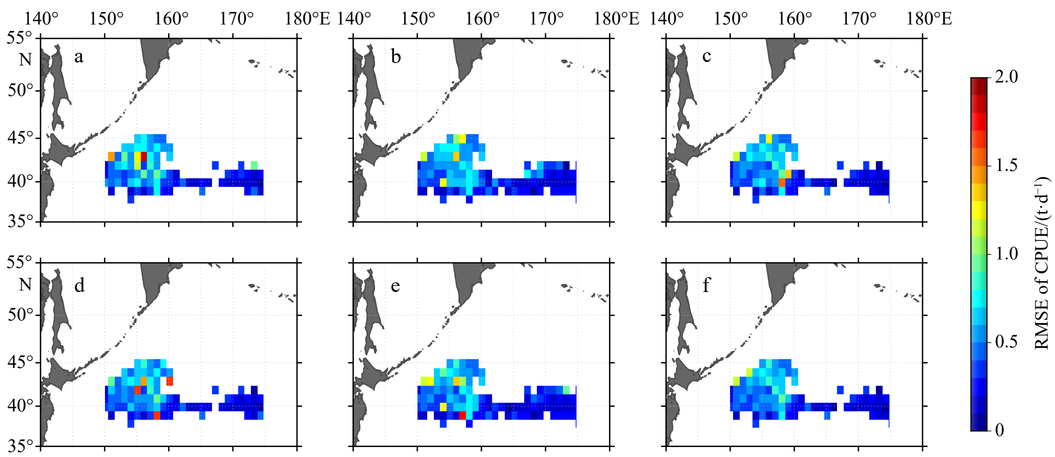

Fig. 1. Spatial distribution of root mean square error (RMSE) of the artificial neural network (ANN)-simulated catch per unit effort (CPUE) of *Ommastrephes bartramii* from July to December during 2004–2013. a. Scheme I with chlorophyll *a* concentration (Chl *a*) as input; b. Scheme Ⅱ with SST as input; c. Scheme Ⅲ with Chl *a* and SST as input; d. Scheme Ⅳ with remote sensing reflectance (Rrs) as input; e. Scheme Ⅴ with brightness temperature (BT) as input; f. Scheme Ⅵ with Rrs and BT as input.

When the conventional oceanographic variables are inputted to the ANN, remarkable uncertainties (e.g., RMSE > 7.0 t/d) were observed in the predicted CPUE of *O. bartramii* (Figs 3a–c). After replacing with the neglected remote sensing data as input, the uncertainties of the ANN-predicted CPUE of *O. bartramii* were obviously mitigated (Figs 3d–f). The overall RMSE of the ANN-predicted CPUE with conventional oceanographic variables as input was approximately 1.55 t/d, 1.29 t/d and 1.51 t/d in Schemes Ⅰ, Ⅱ and Ⅲ, as well as 1.48 t/d, 1.18 t/d and 1.30 t/d with the neglected remote sensing data as input in Schemes Ⅳ, Ⅴ and Ⅵ, respectively. Although the incorporation of the neglected remote sensing data also worsened the RMS of the ANN-predicted CPUE of *O. bartramii* at some grids, the RMS improvements were more widely observed in the Northwest Pacific Ocean (Fig. 4).

4 Discussion

The distribution of fish species is highly related with the environmental variations (Chen, 2004). Hence, accurately building the relationship between fish species and ambient environment is essential to understand the habitat preferences of fish species and predict the dynamics of the fish population (Dickey, 2003; Ishikawa et al., 2009; Nakada et al., 2014). The ANN model has been used to predict the distributions of capelin (*Mallotus villosus*) (Huse, 2001), European eel (*Anguilla anguilla*) (Laffaille et al., 2003, 2004), Eurasian perch (*Perca fluviatilis*) (Brosse and Lek, 2002), neon flying squid (*O. bartramii*) (Wang et al., 2015) and skipjack tuna (*Katsuwonus pelamis*) (Wang et al., 2018). The input parameters of the ANN model in previous studies were mostly the conventional oceanographic variables, such as Chl *a*, SST, and/or sea surface height (SSH). However, these conven-

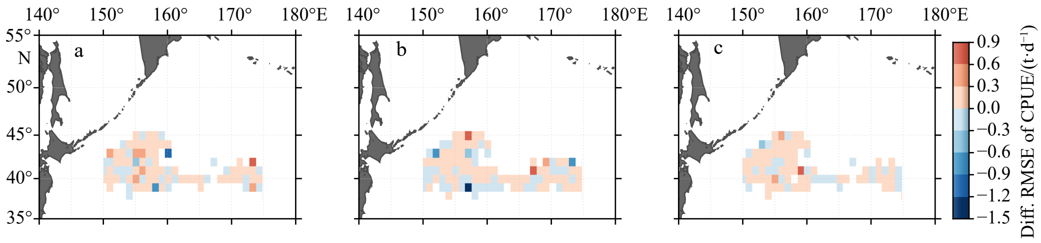

Fig. 2. Spatial distribution of the differential (diff.) root mean square error (RMSE) of the artificial neural network (ANN)-simulated catch per unit effort (CPUE) of *Ommastrephes bartramii* from July to December during 2004–2013. a. Scheme I minus Ⅳ; b. Scheme Ⅱ minus Ⅴ; c. Scheme Ⅲ minus Ⅵ.

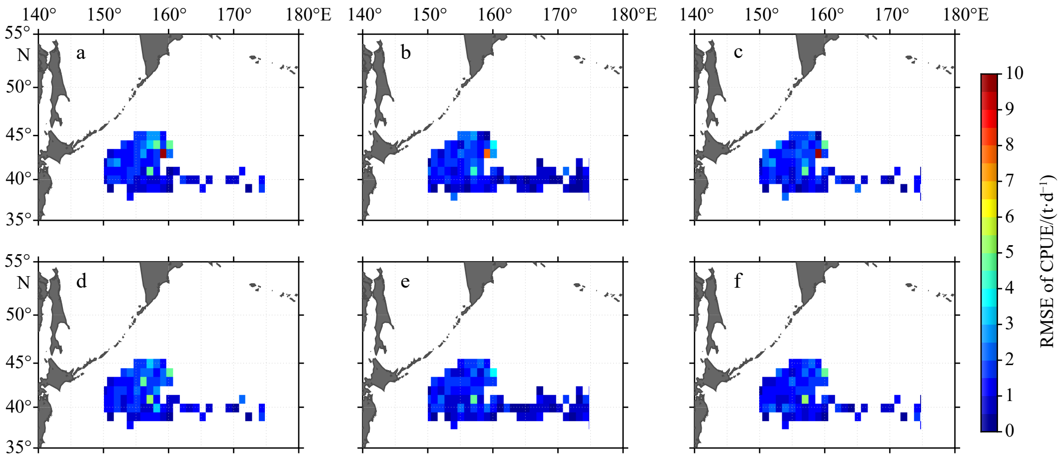

Fig. 3. Distribution of root mean square error (RMSE) of artificial neural network (ANN)-predicted catch per unit effort (CPUE) of *Ommastrephes bartramii* from July to December during 2014–2018. a. Scheme I with chlorophyll *a* concentration (Chl *a*) as input; b. Scheme Ⅱ with SST as input; c. Scheme Ⅲ with Chl *a* and SST as input; d. Scheme Ⅳ with remote sensing reflectance (Rrs) as input; e. Scheme Ⅴ with brightness temperature (BT) as input; f. Scheme Ⅵ with Rrs and BT as input.

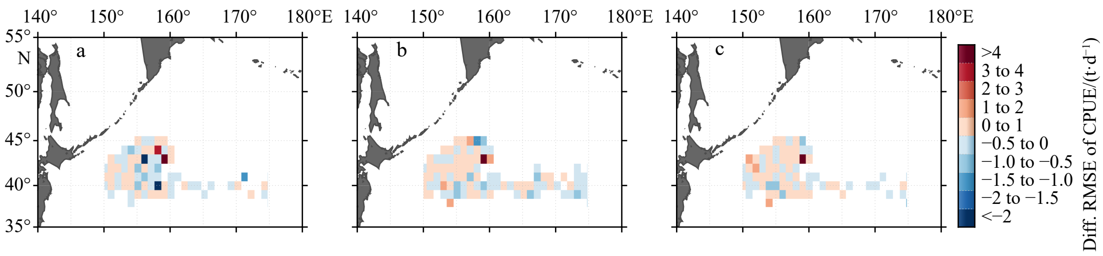

Fig. 4. Spatial distribution of the differential (diff.) root mean square error (RMSE) of the artificial neural network (ANN)-predicted catch per unit effort (CPUE) of *Ommastrephes bartramii* from July to December during 2014–2018. a. Scheme I minus Ⅳ; b. Scheme Ⅱ minus Ⅴ; c. Scheme Ⅲ minus Ⅵ.

tional oceanographic variables are not representative of the oceanic environment. In this study, the neglected Rrs and/or BT data were firstly proposed to simulate and predict the spatio-temporal distributions of *O. bartramii* in the Northwest Pacific Ocean based on the feed-forward BP ANN model.

The robust connections between the distributions of *O. bartramii* and SST have also been demonstrated by previous studies (e.g., Chen and Tian, 2005; Chen et al., 2007, 2008). Wang et al. (2015) also suggested that the favourable range of SST for *O. bartramii* was 11–18°C in the Northwest Pacific Ocean based on the BP ANN model. This article further demonstrated that the neglected BTs have consistent effects with SST on simulating the CPUE of *O. bartramii* with the feed-forward BP ANN in the Northwest Pacific Ocean (Figs 1b, e and 2b; Table 2). Moreover, we also found that BT was better than SST in predicting the distribution of *O. bartramii*, since the RMSE of the CPUE of *O. bartramii* is decreased by approximately 9% for the former (Figs 3b, e and 4b; Table 2).

Considering that the Chl *a* is a good indicator of the food availability for squid (Nishikawa et al., 2014), it is an important environmental variables that significantly affects the distribution of *O. bartramii* (Xu et al., 2004). This study confirmed the importance of Chl *a* during the simulation and prediction of the CPUE of *O. bartramii* in the Northwest Pacific Ocean with the BP ANN (Figs 1a and 3a). Additionally, we also found that the Rrs measurements at 465 nm, 555 nm and 645 nm were more suitable than the Chl *a* to simulate and predict the distribution of *O. bartramii* (Figs 1d, 2a, 3d and 4a; Table 2). As such, the neglected Rrs (and BT) could be a prefer data source than the conventional Chl *a* (and SST) in studying the habitat suitability of *O. bartramii* in the Northwest Pacific Ocean.

While the RMSEs of the simulated and predicted CPUE of *O. bartramii* with the combined Chl *a* and SST (Rrs and BT) as the model input were less than those with Chl *a* (Rrs) as the model input, they were greater than those with SST (BT) as the model input (Table 2). Moreover, the uncertainties in the simulated and predicted CPUE of *O. bartramii* with the Chl *a* (Rrs) as model input were remarkably larger than those with the SST (BT) as model input (Table 2). This indicated that the RMSE improvements with the combined parameters as input were mainly owe to the SST (BT), and that the SST (BT) was better than the Chl *a* (Rrs) in simulating and predicting the CPUE of *O. bartramii* in the Northwest Pacific Ocean. The results were also consistent with Wang et al. (2015), who found that the SST was the most important environmental factor in the formation of fishing grounds and it had the greatest influence on the prediction model.

It is also worth mentioning that despite only the CPUE of *O. bartramii* in the Northwest Pacific Ocean is simulated and predicted in this paper, the neglected Rrs (and BT) data could be further popularized to build the prediction model of other marine species over other sea areas. Furthermore, the corresponding neglected remote sensing information to other conventional oceanographic variables (e.g., SSH, sea surface salinity and wind stress curl) can be also further explored for studying the habitat suitability of the marine species.

Table 2. The overall mean root mean square (RMS) of artificial neural network (ANN)-derived CPUE of *Ommastrephes bartramii* with different schemes (Unit: t/d)

Scheme	Overall mean RMS	
	ANN-simulated CPUE	ANN-predicted CPUE
Ⅰ	0.492	1.547
Ⅱ	0.447	1.294
Ⅲ	0.457	1.514
Ⅳ	0.473	1.481
Ⅴ	0.446	1.180
Ⅵ	0.480	1.304

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