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# Influence of environmental data of different sources on marine species habitat modeling: A case study for *Ommastrephes bartramii* in the Northwest Pacific Ocean

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**Abstract**

The quality of environmental data and its possible impact on the marine species habitat modelling are often overlooked while the sources for these data are increasing. This study selected sea surface temperature (SST) from two commonly used sources, the NOAA OceanWatch and IRI/LDEO Climate Data Library, and then constructed habitat suitability index model to evaluate the influences of SST from the two sources on the outcomes of *Ommastrephes bartramii* habitat models for the months of July–October in the Northwest Pacific Ocean during 1996–2012. This study examined the differences in the amount of estimated unfavourable/favourable habitat area when the SST used for model building and inference were the same or different. Dynamics in suitable habitat area calculated from SST was insensitive to the two different SST products. In the fishing season of *O.bartramii*, the changes of magnitude and trend of monthly suitable habitat area in August and September were similar over time, whereas there were large differences for July and October. Importantly, there is a substantial lack of consistency in the *O.bartramii* habitat distribution based on SST of two sources. This study considered the sources of environmental data for habitat modelling and then inferred species habitat distribution whether by the same or different data source.

**Key words:** habitat suitability index model, environmental data, *Ommastrephes bartramii*, Northwest Pacific Ocean

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## 1 Introduction

An accurate and precise description and understanding of processes regulating the distribution of marine species are fundamental to the conservation of biodiversity and sustainable fisheries management. Due to the complexity of ecological processes and difficulties in developing a mechanistic framework to quantify dynamic interactions of marine organisms and environmental variables, statistical analyses are often used to describe these interactions (Valavanis et al., 2008). Habitat modelling is commonly used to identify the relationships between species distribution patterns and abiotic/biotic variables (Brooks, 1997). The habitat suitable index (HSI) model, one of the most used empirical models, has been applied in ecological restoration research and exploitation of fisheries resources (Gore and Hamilton, 1996; Maddock, 1999; Lee et al., 2005; Feng et al., 2007). In contemporary fisheries management, HSI models are often used to characterize fish habitat preference, availability and quality (Morris and Ball, 2006).

Environmental data are important and necessary components in species habitat modelling. Many types of marine environmental data, such as sea surface temperature (SST), chlorophyll *a* (Chl *a*), sea surface height (SSH), sea level anomaly (SLA) and sea surface currents (SSC) at high or low resolution at a global scale, can be derived from satellite images or oceanic dynamics models and used to establish species habitat models (Valavanis et al., 2008; Klemas, 2013). However, marine environmental data may have biased values when retrieved using different algorithms or satellite sensors and released by different agencies and websites (Reynolds et al., 2002; Huang et al., 2017). This may be confusing for some fisheries scientists who may not have a good under-

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standing of how data are derived from satellite remote sensing.

The results from HSI models in combination with GIS can provide an effective tool to evaluate spatiotemporal variability in habitat conditions of a target species and produce habitat maps that can be used by managers to make informed decisions (Morris and Ball, 2006; Eveson et al., 2015; Brodie et al., 2017). For example, near-term predictions of high-density fish areas could help fishers save fuel and ship time, produce fisheries forecasts, and develop strategies for sustainable fisheries management (Klemas, 2013). Keeping the continuity and consistency of environmental data is one of the essential requirements to use this tool validity (Welch et al., 2019, 2020). However, many factors including cloud coverage, website crash, and delayed release of environmental data make it not always possible to obtain data timely and the data from other sources would be alternatives to make inferences or decisions biased. Thus, the influences of environmental data from different sources, especially when the same type of environmental data from different sources, used in species habitat modeling need to be examined.

Remote sensing techniques are being useful and effective tools for monitoring and managing fish resources, especially for pelagic fish which are hardly accessed by at-sea observation. Neon flying squid, *Ommastrephes bartramii*, is a large oceanic squid distributed in temperate and subtropical waters of the Pacific, Indian and Atlantic Oceans (Roper et al., 1984). Abundance of *O. bartramii* is high in the Northwest Pacific Ocean. The Japanese squid-jigging fleet has exploited this species since 1974, and it was later exploited by South Korea and China (Wang and Chen, 2005). The *O. bartramii* population is composed of four stocks: the central stock and eastern stock of the autumn cohorts, the western stock and central-eastern stock of the winter-spring cohorts (Yatsu et al., 1997). The western winter-spring cohort has become a traditional fishing target for Chinese squid-jigging fleets in waters between 35°–50°N and 150°–175°E (Wang and Chen, 2005). The total annual catch of *O. bartramii* by Chinese mainland fleets ranged from 36 764 t to 132 000 t during 1996–2012.

*Ommastrephes bartramii* is a short-lived ecological opportunist with distribution and abundance largely driven by the surrounding environment, especially SST (Wang et al, 2017). For example, Chen et al. (2007) found that when the feeding area of *O. bartramii* was affected by a La Niña event, the SST generally increased, the subarctic front moved north, and the high-yield fishing grounds were located farther north; if the feeding grounds were influenced by an El Niño event, the SST generally decreased, the subarctic front moved south, and the fishing grounds moved southward and were also more aggregated. This shift in the distribution of fishing ground for *O. bartramii* was closely related to SST. Wang et al. (2015) suggested that the SST was the most important environmental factor in the formation of fishing ground by the neural network method. Since its distribution is sensitive to the SST, *O. bartramii* would be a suitable case species for evaluating the influences of SST from different sources on habitat modelling.

This study described the background of two SST sources (NOAA OceanWatch and IRI/LDEO Climate Data Library) and evaluated their spatio-temporal differences. This study developed HSI models using these two datasets to evaluate the influence of environmental data on estimated *O. bartramii* habitat in the Northwest Pacific Ocean, compared the *O. bartramii* habitat distribution maps and analyzed the trends in unfavourable or favourable habitat area resulting from different SST based habitat models. This study can help improve our understanding of potential impacts of selection of data sources on marine species habitat modelling and potential implications.

## 2 Materials and methods

### 2.1 *Background of SST*

Two sources of environmental data were selected from a myriad of options to obtain SST. One source is NOAA OceanWatch website (http://oceanwatch.pifsc.noaa.gov/, hereafter referred to OW), which has a dataset called the Extended Reconstructed Sea Surface Temperature with Version 5 currently. The newest version of SST uses new data sets from ICOADS Release 3.0 SST; SST comes from Argo floats above 5 m (from the sea bottom), Hadley Centre Ice-SST version 2 (HadISST2) ice concentration. It has improved SST spatial and temporal variability by several methods, such as reducing spatial filtering in training the reconstruction functions Empirical Orthogonal Teleconnections. After 1880, the strength of the remote sensor signal is more consistent over time, and the SST is suitable for long-term global and basin-wide studies (Huang et al., 2017).

The other source is IRI/LDEO Climate Data Library (http://iridl.ldeo.columbia.edu/, hereafter referred to IRI), which is a powerful and free tool that offers various marine and climate data, including SST. The SST from IRI had been produced from *in situ* and satellite data using optimum interpolation version 2 (OI. v2) algorithm from November 1981 to the present. The OI. v2 has a modest improvement in the bias correction to produce more accurate weekly and monthly SST with 1° spatial resolution for various studies (Reynolds et al., 2002).

### 2.2 *Fishery data*

*Ommastrephes bartramii* fishery data, for the Northwest Pacific Ocean between 35°–45°N and 150°–170°E during the months of July to October from 1996 to 2012, were digitized from logbooks collected by Sustainable Development Centre of Distant-water Fishery (SD-DWF) in Shanghai Ocean University (Chinese Squid-jigging Science and Technology Group of Shanghai Ocean University), covering more than 90% of the total squid catch. The data consisted of daily catch (tons), fishing effort (days fished), fishing locations (latitude and longitude) and fishing dates (year and month). This study split the fishing grounds for *O. bartramii* into 200, 1° (longitude)×1° (latitude) cells. The monthly nominal catch per unit effort (CPUE) in a cell was calculated as:

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

where $\mathrm{CPUE}_{y,m,i}$, $C_{y,m,i}$ and $F_{y,m,i}$ are the monthly nominal CPUE, the total catch for all the fishing vessels within a cell, and the number of fishing vessels within a cell for cell $i$ during month $m$ of year $y$. The monthly CPUE was a good indicator of local abundance for *O. bartramii* in the Northwest Pacific Ocean (Chen et al., 2008)

### 2.3 *Merging SST and O. bartramii fishery data*

The SST data for the modelled region were downloaded with temporal resolution of monthly and spatial resolution of 0.1°×0.1° and 1°×1° for OW and IRI, respectively. The SST data from OW were converted into 1°×1° using the mean function for the same with IRI (Wang et al., 2015). The differences in space were calculated:

$$\mathrm{DSST}_{y,m,i} = \mathrm{OSST}_{y,m,i} - \mathrm{ISST}_{y,m,i,} \tag{2}$$

where $DSST_{y,m,i}$, $OSST_{y,m,i}$ and $ISST_{y,m,i}$ are the differences in SST between OW and IRI, the SST from OW, and the SST from IRI, respectively, for cell $i$ for month $m$ of year $y$. Each monthly DSST map from July to October during 1996–2012 in the Northwest Pacific Ocean was compared. Then the *O. bartramii* fishery data and SST of OW and IRI were merged according to the same time (year and month) and fishing cells.

### 2.4 *Model development*

HSI models were used to evaluate the influence of uncertainty in environmental variables by comparing SST data of different sources. HSI is a numerical index as a function of key habitat variables based on suitability indices (SI) that can quantify habitat conditions from 0 (least suitable habitat) to 1 (most suitable habitat) (Franklin, 2010). Development of a HSI model requires: (1) selection of habitat variables to be included in the model, (2) development of SI for each habitat variable, and (3) combination of those SI to produce a composite HSI. It has been shown that SST is the most important environmental variable affecting the distribution of pelagic species, such as *O. bartramii*, and it should be used exclusively (Tian et al., 2009; Chen et al., 2010; Wang et al., 2015). Consequently, this study only used one habitat variable, SST, to compute SI. Thus, two models (OW-HSI and IRI-HSI) were constructed based on SST from OW and IRI, respectively.

The monthly relationship between CPUE and SST was determined as follows: (1) SST was divided into ten classes using Fisher's natural breaks classification method (Bivand, 2013), and (2) SI was estimated using the common histogram method (Chen et al., 2010; Vinagre et al., 2006; Tanaka and Chen, 2015). The SI value for class $k$ in month $m$, $SI_{m,k}$ was calculated on a scale of 0–1.0 as

$$SI_{m,k} = \frac{CPUE_{m,k} - CPUE_{m,\min}}{CPUE_{m,\max} - CPUE_{m,\min}}, \tag{3}$$

where $CPUE_{m,\min}$ and $CPUE_{m,\max}$ are the minimum and maximum values of the CPUEs over all classes in month $m$, and $CPUE_{m,k}$ is the average CPUE over all the sampling stations falling within class $k$. The $k$ was set as 10, and the SI value was assigned to every class of SST for each month. In result, four SI of SST for four months (July–October) were calculated, respectively.

Cross-validation was used to evaluate the performance of accuracy and robustness for HSI models. All samples during 1996 to 2012 were randomly divided into groups of 80% and 20% for use as training and validation data, respectively. Linear regressions were performed on predicted versus observed HSI values by month, where the observed values were calculated from CPUE values in the validation data set, and the regression intercept, slope, and $R^2$ value were used to evaluate the predictive performance of the HSI model (Tanaka and Chen, 2015). A model with good predictive performance should have an intercept not significantly different from 0, a slope not significantly different from 1, and a high $R^2$. This study ran cross validation 1 000 times based on random selection to obtain 1 000 sets of regression parameters. The validation process was implemented for both OW-HSI and IRI-HSI models in each month.

### 2.5 *Evaluating habitat dynamics in reality*

This study constructed two scenarios: one in which the data for model building and projection/inference came from the same source ("data-model matched"), and one in which the data for model building and projection/inference came from a different source ("data-model mismatched"). The spatiotemporal variability of species habitat preference area is important for fishery management. Thus, the areas with HSI<0.2 and HSI>0.5 were defined are the unfavourable and favourable habitat areas, respectively. The monthly proportions of unfavourable/favourable habitat from 1996 to 2012 were calculated for four cases: (1) OW SST based on the OW-HSI model; (2) IRI SST based on the IRI-HSI model; (3) OW SST based on the IRI-HSI model; and (4) IRI SST based on the OW-HSI model. The first two cases pertain to "data-model matched" scenario, and the last two pertain to the "data-model mismatched" scenario. Combined with above, the flowchart for this study is shown below (Fig. 1).

## 3 Results

### 3.1 *Differences between SSTs from OW and IRI*

The differences of monthly mean SST on the fishing grounds of *O. bartramii* from OW and IRI are obvious, especially in July and August. The DSST of July had reached to 1.5°C in 2005 and 2010 and the highest DSST of August was close to 1.2°C in 2006 (Fig. 2). Only 20% of monthly mean DSSTs were close to zero (Figs 2 and 3, Fig. S1). Moreover, the monthly DSST maps exhibited irregular spatial patterns, with values ranging from –3.0°C to

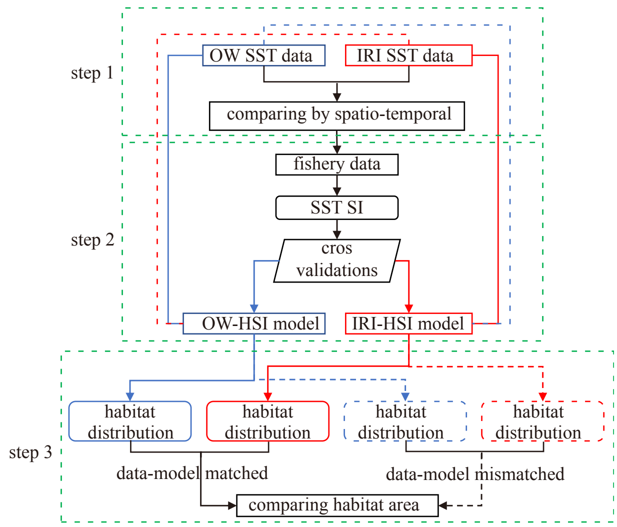


**Fig. 1.** Flowchart of modelling procedures for "data-model matched" (solid line) and "data-model mismatched" (dashed line) scenarios.

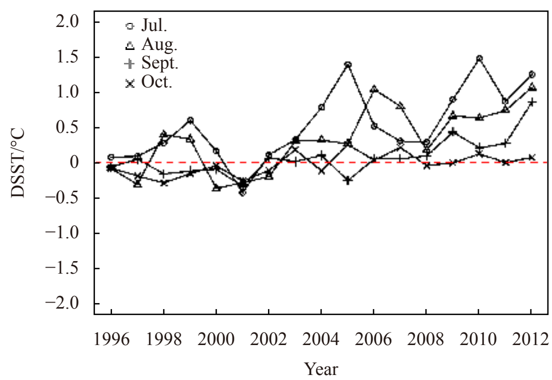


**Fig. 2.** Monthly mean DSSTs for the months of July–October in the Northwest Pacific Ocean during 1996–2012.

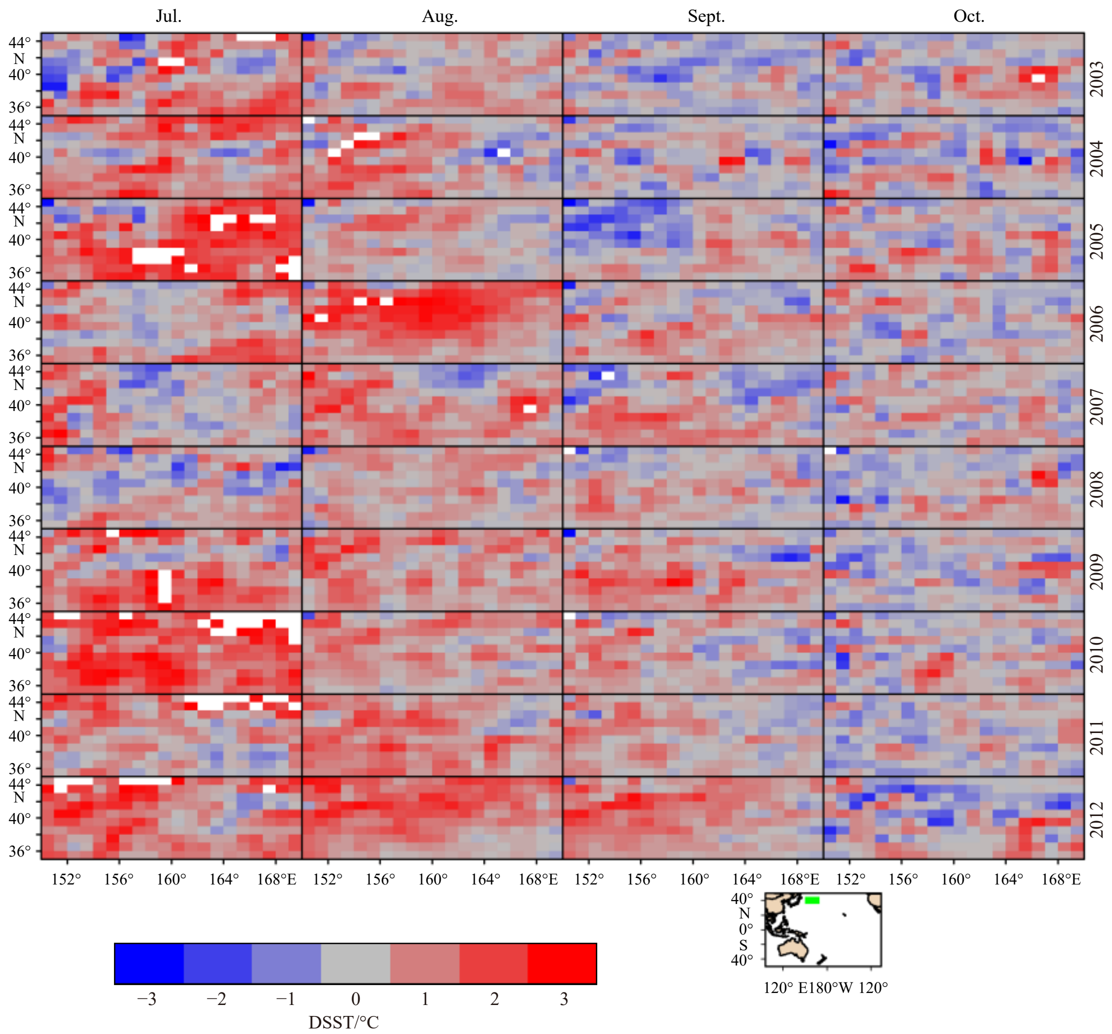


**Fig. 3.** Spatial distribution of DSST for months of July–October in the Northwest Pacific Ocean during 2003–2012. The green area on inset map is our study area.

3.0°C (Fig. 3, Fig. S1), indicating different spatial variation in the SST data from the two data sources caused by various reasons, such as processing algorithms.

### 3.2 *Suitability indices*

The SI for SST differed by month, and the ranges of suitable SST (SI>0.5) based on OW and IRI. With the OW data, the favourable SSTs were 9.58–14.80°C (July), 9.8–19.3°C (August), 13.9–21.7°C (September), and 11.9–15.8°C (October), while those for IRI were 8.99–11.10°C, 12.4–19.4°C, 15.3–20.0°C, and 10.1–16.7°C (Fig. 4). The ranges of unfavourable monthly SST calculated from OW and IRI also differed (Fig. 4).

### 3.3 *Performance of HSI model*

The HSI models based on OW and IRI both performed well, with intercepts ($\alpha$) close to 0 and slopes ($\beta$) close to 1 in the regression between cross-validation for predicted and observed HSI values (Table 1). The performances of models for August and September were higher with $R^2$ ranged in 0.71–0.76, $\alpha$ 0.12–0.19 and $\beta$ 0.73–0.79. The $R^2$, $\alpha$, $\beta$ of models for July and October were 0.59–0.64, 0.17–0.23, 0.65–0.68, respectively (Table 1). The monthly HSI models based on OW and IRI are satisfactory for further analysis based on the criteria developed by Tanaka and Chen (2015).

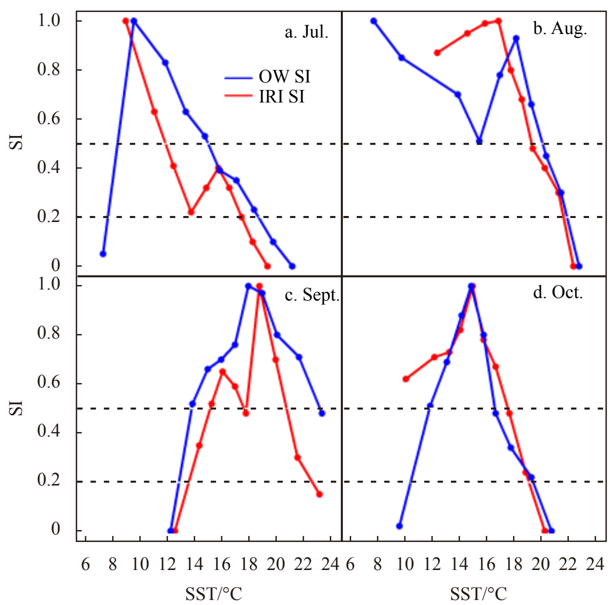


**Fig. 4.** Suitability indices (SI) based on OW (blue) and IRI (red) for July (a), August (b), September (c), and October (d).

**Table 1.** Model parameters for linear regression between the predicted and observed habitat suitable index (HSI) values, summarized regression analyses from 1 000 runs of cross validation

| Model | Month | Intercept ($\alpha$) | | | | Slope ($\beta$) | | | | $R^2$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Median | (95% confidence interval) | | Mean | Median | (95% confidence interval) | | Mean | Median |
| OW-HSI | Jul. | 0.18 | 0.17 | 0.023 | 0.231 | 0.65 | 0.64 | 0.561 | 0.781 | 0.62 | 0.61 |
| | Aug. | 0.13 | 0.13 | 0.031 | 0.217 | 0.73 | 0.74 | 0.642 | 0.901 | 0.75 | 0.74 |
| | Sept. | 0.11 | 0.14 | 0.011 | 0.223 | 0.78 | 0.77 | 0.625 | 0.898 | 0.71 | 0.72 |
| | Oct. | 0.18 | 0.19 | 0.009 | 0.211 | 0.68 | 0.67 | 0.524 | 0.745 | 0.61 | 0.59 |
| IRI-HSI | Jul. | 0.20 | 0.22 | 0.021 | 0.261 | 0.69 | 0.70 | 0.498 | 0.863 | 0.63 | 0.65 |
| | Aug. | 0.15 | 0.16 | 0.008 | 0.245 | 0.75 | 0.74 | 0.652 | 0872 | 0.76 | 0.72 |
| | Sept. | 0.17 | 0.19 | 0.004 | 0.247 | 0.78 | 0.79 | 0.694 | 0.923 | 0.73 | 0.75 |
| | Oct. | 0.21 | 0.23 | 0.014 | 0.245 | 0.69 | 0.68 | 0.598 | 0.865 | 0.59 | 0.60 |

### 3.4 *Dynamics of habitat under different scenarios*

The ranges of the monthly proportions of suitable habitat area differed greatly depending on the data used for model building, except for August (Fig. 5). Almost half of the combinations of data for calibration and forecasting led to non-significant relationships by correlation analysis (Table 2). Similar situations occurred in the results of the monthly proportions of unsuitable habitat area (Fig. S2, Table S1). The proportion of unfavourable/favourable habitat area is more consistent on annual level (i.e., when indices are averaged over July, August, September and October; Fig. 6). Spatially distribution of HSI values showed different patterns for the four cases during 1996–2012. Generally, the most suitable habitat calculated from OW-SST was located between 41°–43°N and 150°–161°E in July, whereas the location of the most suitable habitat calculated from IRI-SST was further to the north (Fig 7, Fig. S3).

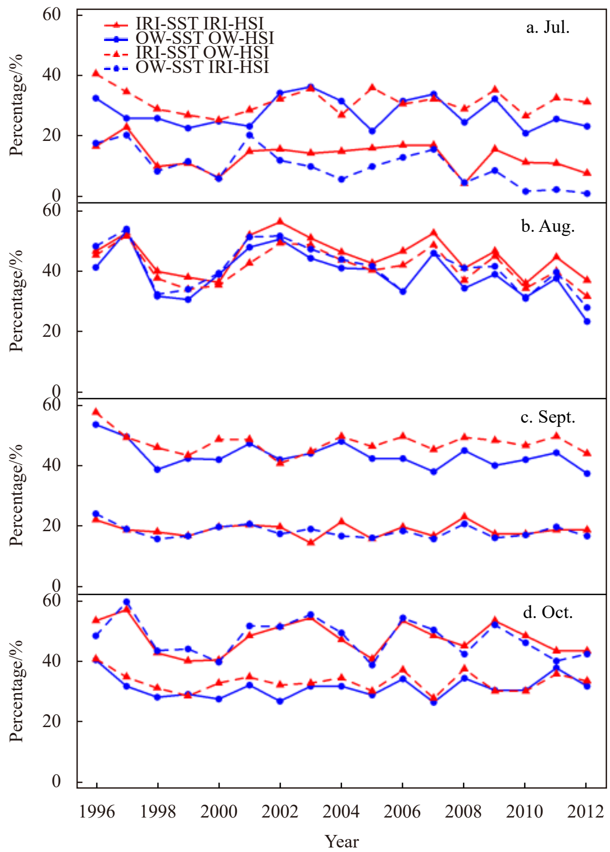


**Fig. 5.** Time series of the percentage of suitable habitat area under "data-model matched" and "data-model mismatched" scenarios for July (a), August (b), September (c), and October (d) during 1996–2012. The red line with solid triangles corresponds to the IRI data applied to the model based on the IRI data; the blue line with solid circles to the OW data applied to the model based on the OW data; the red dotted line with solid triangles to the IRI data applied to the model based on the OW data; and the blue dotted line with solid circles to the OW data applied to the model based on the IRI data.

## 4 Discussion

With the data of Chinese squid-jigging fishery and SST from two sources (i.e., the NOAA OceanWatch website and the IRI/LDEO Climate Data Library) during 1996–2012, we developed HSI models and evaluated the influence of different SSTs on HSI models. This study observed the different trends of monthly mean CPUE, and the different distribution patterns in spatial HSI maps in "data-model matched" and "data-model mismatched" scenarios. The results remind that caution of the uncertainties in environmental data should be used for species habitat modelling.

Because satellite remote sensing provides synoptic ocean measurements for evaluating environmental influences on the abundance and distribution of fish populations, it has been an important technique in fishery search, management and harvesting (Klelmas, 2013). Usually, fishery scientists and management, as high-level user, rarely focus on the differences existed in mass of data from more and more easily accessible remote sensing sources, which blurred our choice. The "data-model matched"

**Table 2.** Correlation analysis between the suitable habitat areas calculated from different SST in different models

| Data model | Month | $r$ | $p$ | Month | Data model |
|---|---|---|---|---|---|
| IRI-SST IRI-HSI | Jul. | 0.431 | 0.082 | Jul. | OW-SST OW-HSI |
| | Aug. | 0.863 | <0.010 | Aug. | |
| | Sept. | 0.517 | 0.037 | Sept. | |
| | Oct. | 0.276 | 0.283 | Oct. | |
| | Average | 0.846 | <0.010 | Average | |
| OW-SST IRI-HSI | Jul. | 0.294 | 0.251 | July | OW-SST OW-HSI |
| | Aug. | 0.959 | <0.010 | Aug. | |
| | Sept. | 0.768 | 0.010 | Sept. | |
| | Oct. | 0.035 | 0.893 | Oct. | |
| | Average | 0.869 | <0.010 | Average | |
| IRI-SST IRI-HSI | Jul. | 0.500 | 0.062 | Jul. | IRI-SST OW-HSI |
| | Aug. | 0.935 | <0.010 | Aug. | |
| | Sept. | 0.559 | 0.019 | Sept. | |
| | Oct. | 0.326 | 0.200 | Oct. | |
| | Average | 0.775 | <0.010 | Average | |

and "data-model mismatched" scenarios often occurred when some data sources do not work timely as various reasons. However, the conclusion from our case study showed that this type of error would cause biases in species habitat modelling.

On the one hand, dynamic ocean management (DOM) as an efficient and effective tool has become more practical in recent years (Maxwell et al., 2015). The consistent long-term datasets, such as remote sensing and the advanced processing and modelling techniques for predicting species distribution are key ingredients in DOM (Welch et al., 2020). This study found that the projected *O. bartramii* habitat distribution differed greatly and the subsequent TACs may be inappropriate if the "model-data mismatched" scenario occurred in the Northwest Pacific Ocean. This study suggested that more species habitat models should be established based on different datasets and the influences in habitat metrics derived from "data-model" scenario should be evaluated to implement DOM smoothly in case of some disappeared data sources.

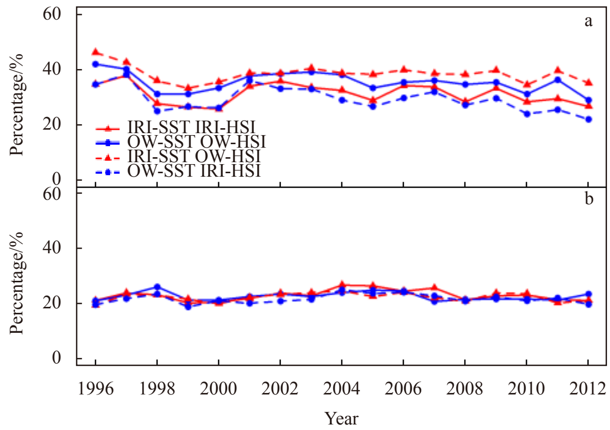


**Fig. 6.** Average (annual) percentages of favourable habitat area (a)/unfavourable habitat area (b) under "data-model matched" and "data-model mismatched" scenarios.

The medium- and long-term relationships between the fishery stock size and preferred habitat area are influenced by oceanic and climate factors such as the Pacific Decadal Oscillation, and the El Niño-Southern Oscillation (Perry et al., 2005; Meng et al., 2016; Yu et al., 2017). Fortunately, the annual average and overall trends in *O. bartramii* unfavourable/favourable habitat area were consistent irrespective of the data set used for model building and that used for inference (Fig. 6). Thus, the conclusions would be safe if annual environment-related stock abundance in surplus production model for *O. bartramii* assessment is used in the Northwest Pacific Ocean.

However, the values and trends in the percentage of monthly suitable habitat area differed depending on which data set was used for inference, except for August (Fig. 5). Simultaneously, there is a substantial lack of consistency when the model outputs are summarized spatially (Fig. 7, Fig. S3). For example, the area of the most suitable habitat was much larger from the OW-HSI model than from the IRI-HSI model when the IRI data were used for inference (Figs 7e and m). Similarly, the area of the most suitable habitat predicted using IRI data and the OW-HSI model was

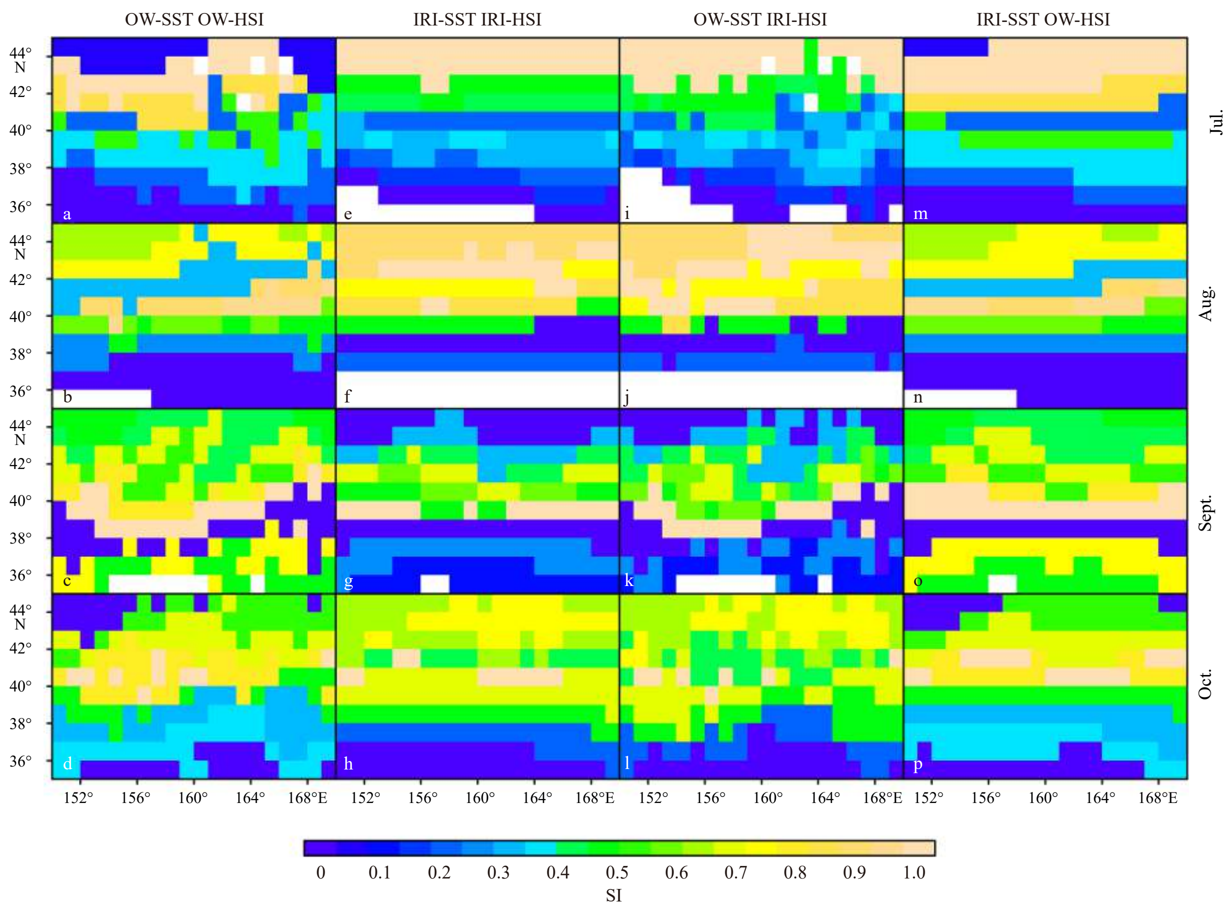


**Fig. 7.** Suitability indices (SI) for *O. bartramii* under "data-model matched" and "data-model mismatched" scenarios for 1996.

much larger and wider in latitude than the area of the most suitable habitat when the OW data formed the basis for inference using the IRI-HSI model (Figs 7i and m). Thus, the conclusions should be prudent if monthly or spatially environment-related stock abundance in complex stock assessment models (such as age-structured model or spatial surplus production model) is used for *O. bartramii* management.

In summary, it is important to consider the source of environmental data and their consistency when developing and applying habitat suitability models.

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# Supplementary information:

**Fig. S1.** Spatial distribution of DSST for months of July–October in the Northwest Pacific Ocean during 1996–2002. The green area on inset map is our study area.

**Fig. S2.** Time series of the percentage of unsuitable habitat area under “data-model matched” and “data-model mismatched” scenarios for July (a), August (b), September (c), and October (d) during 1996–2012.

**Fig. S3.** Suitability indices for *O. bartramii* under “data-model matched” and “data-model mismatched” scenarios for 1997–2012.

**Table S1.** Correlation analysis between the unfavorable habitat area calculated from different data and different models

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