Using species distribution model to predict the impact of climate change on the potential distribution of Japanese whiting *Sillago japonica*

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ABSTRACT

Climate change is one of the most serious global environmental problems and it is of great importance to understand how species respond to climate change. Species distribution models (SDMs) have been regarded as an effective tool to examine the impacts of climate change on species' potential distribution. In this study, we developed a SDM for a marine fish, the Japanese whiting *Sillago japonica* by using records of its occurrence and five predictor variables (ocean depth, distance to shore, mean sea surface temperature, salinity, and currents velocity) and predicted its habitat suitability for current conditions and under scenarios of future climates. The SDM suggests that ocean depth, distance to shore, and temperature are the three most important predictor variables determining the distribution of *S. japonica*. Our SDM accurately predicted the current distribution of the species, with values of true skill statistics and area under the receiver operating characteristic curve above 0.95. Under future climate scenarios, the suitable habitat of *S. japonica* is predicted to become smaller in size and to shift northward. Differences between climate change scenarios for 2040–2050 and 2090–2100 showed that this species will lose more suitable habitat as climate change progresses over time. Future fisheries management strategies should take this range contraction and associated northward shift into account.

1. Introduction

A large number of studies have provided evidence of strong environmental changes taking place in oceans, likely driven by global climate change (Lin et al., 2005; Belkin, 2009; Cheung et al., 2013). For instance, sea surface temperatures in the Yellow Sea and the East China Sea have increased by 1.0 °C and 1.6 °C, respectively, from 1957 to 2006 (Belkin, 2009). These changes in marine environments are expected to lead to significant alterations in the distribution of marine species, likely resulting in biodiversity losses (Sorte et al., 2010; Chen et al., 2011; Bellard et al., 2012; Cheung et al., 2013; Faleiro et al., 2018). Accordingly, it is important to gain a better understanding of how marine species will respond to changes in climatic conditions.

Species distribution models (SDMs), are considered a powerful tool to predict the potential distribution of species (Araújo et al., 2005a,b; Elith and Leathwick, 2009; Capinha et al., 2011; Guisan et al., 2017; Cianfrani et al., 2018; Dyderski et al., 2018). In SDMs the distributions of species are modelled against a set of spatial environmental factors in

order to estimate a geographical delimitation of suitable environments. The application of SDMs in the terrestrial realm has been common, and their use for marine organisms has received increasingly more attention in recent years (Cheung et al., 2009; Robinson et al., 2011; Marshall et al., 2014). SDMs for marine species are typically used for conservation planning (Robinson et al., 2011). For example, Zanardo et al. (2017) predicted suitable habitats for the southern Australian bottlenose dolphin (*Tursiops* sp.) along Adelaide's metropolitan coast, South Australia, providing essential information for the conservation of this species. Although less common, SDMs have also been used to investigate the impact of climate change or species invasions in the marine environment (Robinson et al., 2011). For example, Weinmann et al. (2013) investigated the effect of climate change on the potential distribution of invasive foraminifera *Amphistegina* spp. in the Mediterranean Sea. They found that *Amphistegina* spp. are likely to expand their distribution ranges under future climate conditions.

The Japanese whiting *Sillago japonica* (family Sillaginidae) is a benthic fish widely distributed along the coasts of China, Korea and

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Japan (Oozeki et al., 1992; Sulistiono et al., 1999a,b; Wang et al., 2014; Gao et al., 2019). This species is commonly found along sandy beaches and its reproductive season is from June to October (Khan et al., 1991; Sulistiono et al., 1999a). As a carnivorous species, *S. japonica* feed on a variety of prey organisms such as small crustacean gammaridean amphipods and mysids (Nakane et al., 2011; Kwak et al., 2004; Inoue et al., 2005). *S. japonica* is of great commercial and recreational value, and as a likely result of environmental changes and overfishing, their catches have declined in Japan (Sulistiono et al., 1999a). In order to appropriately preserve and utilize *S. japonica* as a natural resource, it is of great importance to understand its potential distribution. Thus far, however, no study has provided predictions of the potential distribution of Japanese whiting. In addition, the potential impacts of climate change on the distribution of this species also remain unevaluated. Previous studies have demonstrated that climate change can result in shifts in the distribution of marine species (Perry et al., 2005; Dulvy et al., 2008; Sorte et al., 2010; Cheung et al., 2013; Poloczanska et al., 2013). In particular, Yona et al. (2016) experimentally demonstrated a causal link between increasing water temperature and a reduction of hatching success and survival of *S. japonica* larvae. Accordingly, we hypothesize that the distribution of *S. japonica* might shift northward, accompanying the shift expected for the Kuroshio current, a north-flowing ocean current that transports warm ocean water along the east Asian coast (Yang et al., 2016). In this study, we developed SDMs for *S. japonica* to (1) identify the key environmental variables that determine its distribution, and (2) map the environmental suitability for this species under current conditions and future climate scenarios. This study represents the first attempt to study climate change impacts on the distribution of *S. japonica* and provides important implications for developing future climate adaptation management strategies.

2. Material and methods

2.1. Study area and species occurrence data

This study area is located in East Asia, starting from the Philippine Sea in the south and the Sea of Okhotsk in the north to the Pacific Ocean in the East to the South China Sea in the west (15˚N to 60˚N, 105˚E to 150˚E) (Fig. 1). Occurrence records of *S. japonica* (ranging from the year 1995 to 2018) were obtained through field sampling (from 2009 to 2017), from online data repositories: the Global Biodiversity Information Facility (http://www.gbif.org), the Ocean Biogeographic Information System (http://iobis.org), the Taiwan Biodiversity Information Facility (www.taibif.tw), and from published literature (Kato and Yoshida, 1996; Kashiwagi et al., 2000; Kwak et al., 2004; Inoue et al., 2005; Nakane et al., 2011; Niu et al., 2016; Sulistiono et al., 1999b; Teishima et al., 2017; Gao et al., 2019). In order to match with the resolution of available environmental data, only records allowing a spatial precision of a 5×5 arc-minute grid cell (approximately 9.2 km $\times$ 9.2 km), or better were considered. We removed clustered samples and used only one record per grid cell in order to avoid over-representation of environmental conditions in densely sampled areas (sampling bias). In total, 90 occurrence records of *S. japonica* were retrieved, of which 56 records were included in the study.

2.2. Environmental predictor variables

Distribution of marine species can be influenced by a number of environmental variables, but previous studies have demonstrated that a few predictor variables can accurately predict marine species distributions (Belanger et al., 2012; Bosch et al., 2018; Goldsmit et al., 2018). Considering the biological relevance and data availability under present-day and future climate scenarios, five predictor variables were used in this study (Supplementary Material, Table S1). From Bio-ORACLE (http://www.bio-oracle.org) (Assis et al., 2018), we retrieved spatial data referring to three benthic marine environmental factors at
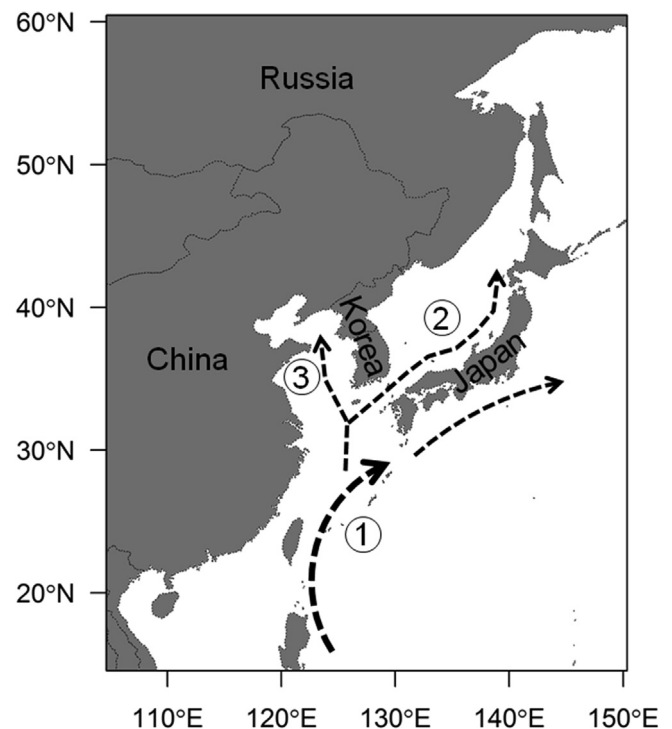
Fig. 1. Map showing the study area. White area is ocean and grey area is land. Dashed arrows indicate main warm currents in this area: the Kuroshio Warm Current (1), the Tsushima Warm Current (2) and the Yellow Sea Warm Current (3).

average depths: mean temperature, salinity, and currents velocity. Ocean depth and distance to the shore were retrieved from the Global Marine Environment Datasets (http://gmed.auckland.ac.nz) (Basher et al., 2014). The five marine layers had a spatial resolution of 5×5 arc-minutes or higher. No prohibitive levels of redundancy existed between these layers, i.e., all pairwise Pearson's correlation coefficients were less than $|0.7|$ (Dormann et al., 2013) (Supplementary Material, Fig. S1).

From Bio-ORACLE we also retrieved spatial layers with projections of future temperature, salinity, and the velocity of currents under four representative concentration pathway emission scenarios (RCP) (RCP26, RCP45, RCP60, and RCP85). The Bio-ORACLE dataset provides projections of two future time periods 2050s (average for 2040–2050) and 2100s (average for 2090–2100). These two future time periods are representative of mid and long-term future climate conditions. The four RCPs represent distinct pathways for greenhouse gas and aerosol concentrations: RCP26 is an optimistic scenario with lower concentrations, RCP45 and RCP60 are intermediate emission scenarios, and RCP85 is a pessimistic scenario, with the higher concentrations. Under future climate scenarios, sea surface temperature and currents velocity in the study area are predicted to increase (Supplementary Material, Figs. S2 and S3) while salinity is predicted to decrease (Supplementary Material, Fig. S4). Predicting the impacts of climate change on species distribution represents a great challenge, and one major uncertainty comes from the choice of general circulation models (Goberville et al., 2015; Tang et al., 2018). Therefore, it is common practice to investigate the effects of climate change on the distribution of terrestrial species by using several general circulation models (Cianfrani et al., 2018; Dyderski et al., 2018; Faleiro et al., 2018). According to Assis et al. (2018), projections of future temperature, salinity, and velocity of currents from Bio-ORACLE were generated based on the average simulation results of three atmosphere-ocean general circulation models (AOGCMs: CCSM4, HadGEM2-ES, MIROC5) from the Coupled Model Intercomparison Project 5, which is believed to be capable of reducing
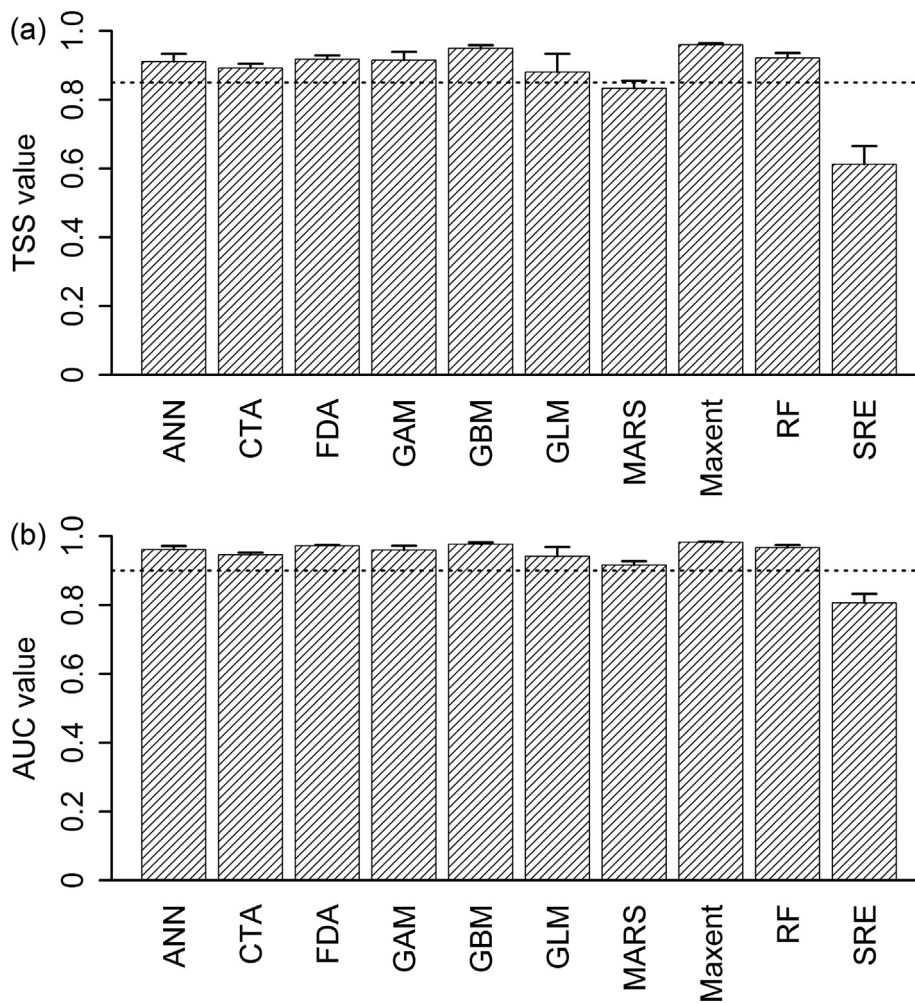
Fig. 2. The true skill statistics (TSS) (a) and area under the receiver operating characteristic curve (AUC) (b) values of ten modelling algorithms used in this study. Dotted lines represent cut-off levels (TSS = 0.85 and AUC = 0.90). Data are expressed as mean ± standard error.
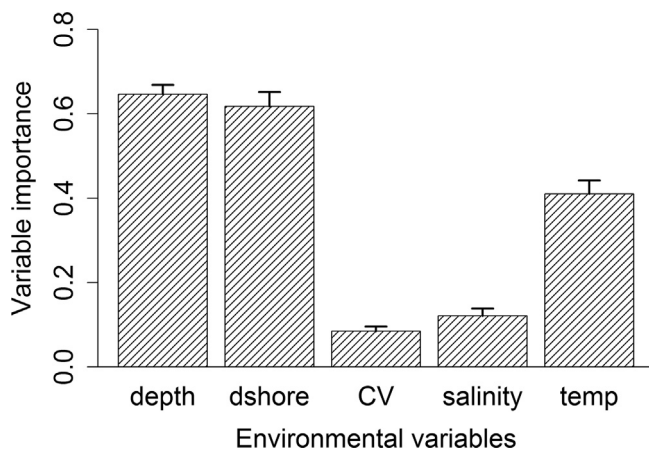

Fig. 3. Contribution of the five predictor variables used to construct the species distribution model for the Japanese whiting *Sillago japonica*. dshore: distance to shore, CV: currents velocity, temp: temperature. The horizontal dotted line indicates the mean contribution of each variable. Data are expressed as mean ± standard error.

the uncertainties among different AOGCMs.

2.3. Modelling procedure

We used ten modelling techniques to relate the distribution of *S. japonica* with benthic environmental conditions: artificial neural network (ANN), classification tree analysis (CTA), flexible discriminant analysis (FDA), generalized additive model (GAM), generalized boosting model (GBM), generalized linear model (GLM), multiple adaptive regression splines (MARS), maximum entropy (Maxent), random forest (RF), and surface range envelop (SRE) as implemented in the biomod2 package (Thuiller et al., 2014) for R 3.4.3 (R Development Core Team, 2014). We randomly generated 10,000 pseudo-absence records within the study area, because some of these techniques require a set of environmental conditions to contrast with the ones where the species was found (Elith and Leathwick, 2009; Elith and Graham, 2009; Thuiller et al., 2014; Guisan et al., 2017). All modelling algorithms were performed using the default settings of biomod2 package.

To evaluate the predictive performance of each modelling technique, we used a five-fold cross-validation approach with 10 repetitions. In this approach, the dataset was randomly divided into five groups with an equivalent number of distribution records, of which four groups are used to train the model and the one is withheld for comparison with the predictions (Thuiller et al., 2014; Guisan et al., 2017). The accuracy was assessed using the true skill statistics (TSS) and the area under the receiver operating characteristic curve (AUC). The TSS
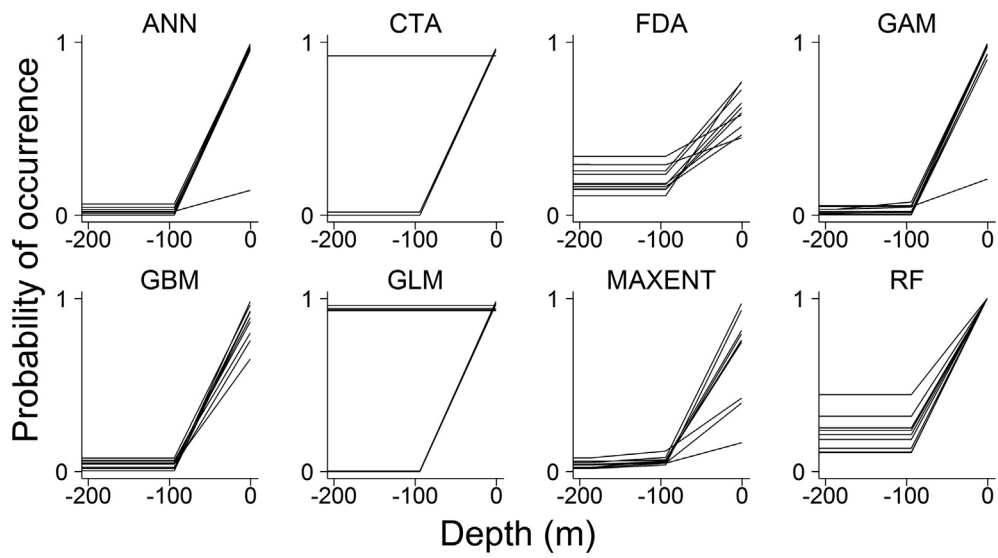
Fig. 4. Response curves of predicted occurrence probability of Japanese whiting *Sillago japonica* against ocean depth.
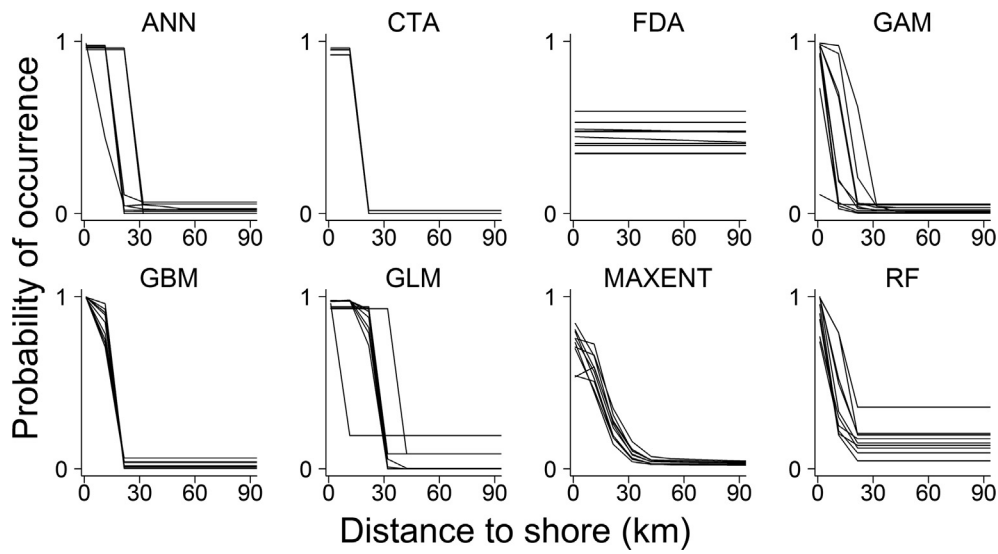

Fig. 5. Response curves of predicted occurrence probability of Japanese whiting *Sillago japonica* against distance to the shore.
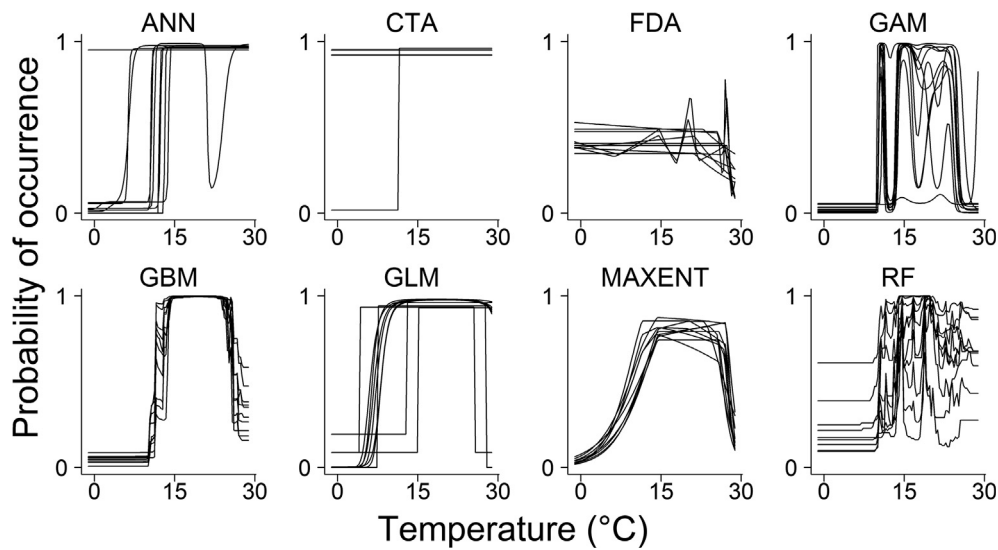

Fig. 6. Response curves of predicted occurrence probability of Japanese whiting *Sillago japonica* against temperature.
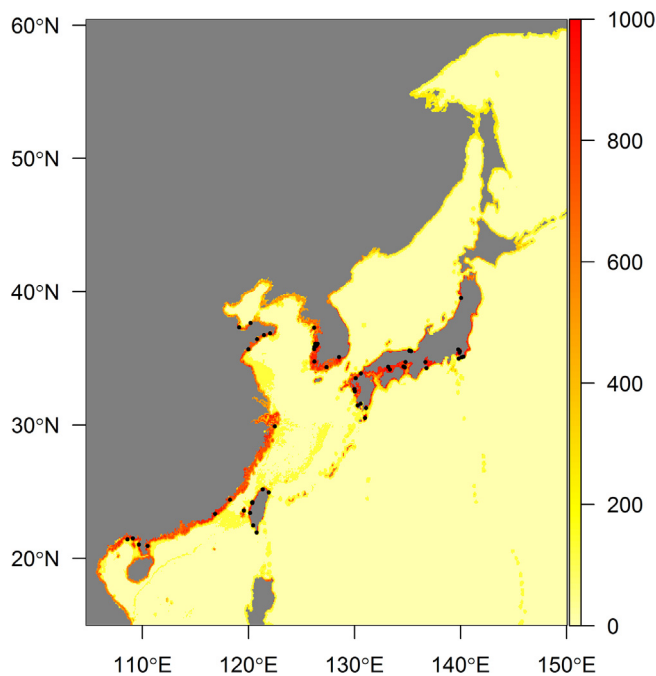
Fig. 7. Predicted current potential distribution of Japanese whiting *Sillago japonica*. Black dots represent the occurrence records used to build the species distribution model. Color gradient indicates variation in habitat suitability (red = highest, yellow = lowest).

Table 1
Range size change (%) of Japanese whiting *Sillago japonica* under future climate scenarios. RCP: representative concentration pathway.

	2050s (2040–2050)	2100s (2090–2100)
RCP26	− 26.1	− 53.2
RCP45	− 36.6	− 38.9
RCP60	− 21.3	− 63.7
RCP85	− 19.4	− 79.6

can range from − 1 to 1 and the AUC ranges from 0 to 1. Similar to previous studies, model algorithms with mean TSS value below 0.85 and mean AUC value below 0.90 were excluded from further analyses (Araújo et al., 2005a,b; Zhang et al., 2019).

We also evaluated the relative importance of each variable in predicting the distribution of the species. This was measured by using a randomisation approach, which computes the Pearson correlations between predictions using all predictor variables and predictions where the predictor variable being evaluated was randomly permutated (Thuiller et al., 2014; Guisan et al., 2017). A predictor variable is considered unimportant if the correlation between the standard predictions and those using the permuted variable is high. Response curves of important predictor variables, which describe variation of the species occurrence probability along the gradient of each predictor variable, were also determined and plotted.

All occurrence and pseudo-absence data were used to build a committee averaging ensemble model predicting the distribution of *S. japonica* under current conditions and projections of future climates. For the latter, we trained the model using variables for current conditions and projected it using the layers of projected mean temperature, projected salinity, projected velocity of currents and present-day ocean depth and present-day distance to coast. By this we assume that there will be no significant changes in ocean depth and distance to the shore within the time span of the projections.

3. Results

3.1. Model performance

TSS and AUC values showed high inter-model variability (Fig. 2). The TSS values varied from 0.612 (± 0.053) (SRE) to 0.960 (± 0.004) (Maxent) and the AUC values ranged from 0.806 (± 0.026) (SRE) to 0.983 (± 0.001) (Maxent) (Fig. 2). Both TSS and AUC results suggest that the Maxent algorithm provides the best predictive performance, while SRE the worst. Based on cutoff values of TSS and AUC, eight modelling algorithms were selected for ensemble modelling and descriptive analysis (i.e. ANN, CTA, FDA, GAM, GBM, GLM, Maxent, and RF; Fig. 2). The TSS and AUC values of the ensemble model were 0.967 (± 0.002) and 0.990 (± 0.001), respectively, exceeding the predictive performance of all individual models.

3.2. Variable contribution and response curves

Among the five predictor variables, depth (0.647 ± 0.022) contributed most to the model predictions, followed by distance to shore (0.618 ± 0.034) and temperature (0.410 ± 0.032) (Fig. 3). Salinity contributed little to the predictive performance of the model (0.121 ± 0.018) while currents velocity was considered nearly irrelevant (0.085 ± 0.011) (Fig. 3). Response curves of *S. japonica* to ocean depth and distance to the shore suggest that this species prefers habitats that are shallow (< 93 m) and near to the shore (< 22 km) (Figs. 4 and 5). Response curves of temperature showed important variation among different algorithms, but in general, these suggest that the suitable temperature range for this fish species is between 12 °C and 25 °C (Fig. 6).

3.3. Current and future potential distributions

The predicted suitable habitat for Japanese whiting under current climate conditions is shown in Fig. 7. All the occurrence records we collected were within the predicted suitable range. The predictions show that a large part of coastal areas of China, Japan, and Korea are suitable for *S. japonica*. Our SDM results consistently suggest that the suitable environments for *S. japonica* under future climate scenarios will decrease in spatial extent (Table 1). This loss of potential distribution will be more aggravated by the end of the century than in the 2050s (Table 1). The predicted distributions of this species under the distinct RCP scenarios showed similar patterns; therefore, we only presented the results under an intermediate RCP4.5 scenario. Future predictions under this scenario show that environmental condition suitable to *S. japonica* will shift northward encompassing coastal areas such as Bohai Bay, the Yellow Sea, and North Hokkaido (Fig. 8). On the other hand, the south coast of China is predicted to become less suitable for this species (Fig. 8).

4. Discussion

4.1. Model accuracy and current distribution

In this study, we developed an ensemble species distribution model for Japanese whiting *Sillago japonica*, to predict potential distribution of this species under current condition and projected future climates for the first time. Our ensemble SDM not only successfully predicted the habitat suitability of Japanese whiting under current conditions, but also indicate that the suitable habitat of this species will become smaller in size and shift northward under future climate scenarios.

Considering the availability of current and future marine environmental data, five environmental factors were used for building the model. The relative importance of each predictor variable and the form of the relationships identified suggests that the models are biologically plausible. *S. japonica* is commonly distributed in shallow coastal waters
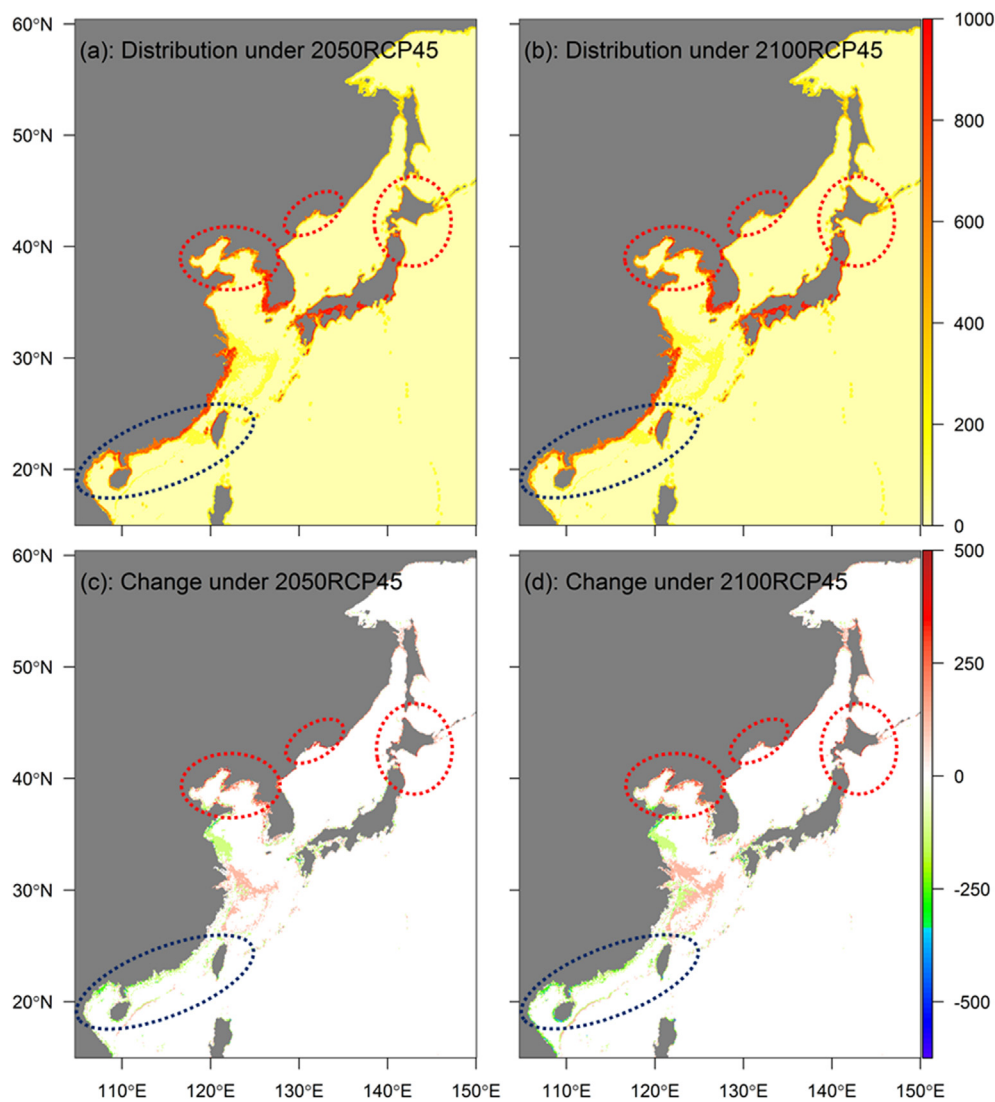
Fig. 8. The predicted potential distribution (a, b) and changes in habitat suitability (c, d) of *Sillago japonica* under RCP45 scenarios. (a) potential distribution under RCP45 in 2050s, (b) potential distribution under RCP45 in 2100s, (c) change in habitat suitability between current and future distribution under RCP45 in 2050s, and (d) change in habitat suitability between current and future distribution under RCP45 in 2100s. The blue ellipses represent areas where suitable habitat is predicted to decrease in the future, the red ellipses identify areas where suitable habitat should increase in future. RCP: representative concentration pathway.

(Oozeki et al., 1992; Kwak et al., 2004; Wang et al., 2014), this was also reflected by response curves for ocean depth and distance to shore. According to our results, water temperature also plays an important role in controlling the potential distribution of *S. japonica*. Water temperature can affect various physiological processes in *S. japonica* including hatching success and egg development (Oozeki and Hirano, 1985; Khan et al., 1991; Kashiwagi et al., 2000; Hotta et al., 2001). For instance, Hotta et al. (2001) found that the upper thermal limit of normal spawning for this species is approximately 28 to 29 °C. Exceeding this temperature leads to decreases in fecundity and hatching rate. Khan et al. (1991) reported that *S. japonica* eggs failed to hatch below 20 °C. These thermal tolerance limits would certainly influence geographical distribution of this species.

Our ensemble SDM for the Japanese whiting showed excellent predictive performance and accurately predict the current known distribution of this species. The most northward occurrence record of *S. japonica* used in this study was located in Akita Prefecture, Japan (39°32′ N, 140°3′ E). Our ensemble predictions suggest that environmental conditions further north of Japan, including Aomori and Hokkaido Prefectures, are also suitable for this fish. Our predictions were supported by the reports of this species in these areas. Several

records from these regions were not included in our study due to the absence of accurate geographical data. For instance, Yamazaki et al. (2015) confirmed the occurrence of *S. japonica* in the Shimokita Peninsula, Aomori Prefecture, Japan in September 2012. In addition, according to sportfishing reports (FishingLabo, https://www.fishing-labo.net), this species can be caught in Hokkaido during the summer seasons. These records provide circumstantial support to the accuracy of predictions made for current conditions. The predictions of suitable habitat for *S. japonica* along the coast of China is wider than its known distribution; further investigations are required to verify the presence of the species in these areas. Despite its potential importance for management strategies, the present model has some limitations. Previous studies suggest *S. japonica* prefers sandy substrate (Oozeki et al., 1992; Wang et al., 2014; Gao et al., 2019). Due to the lack of sediment data in the study area, our model did not consider sediment layer as a predictor variable. Further studies are needed to address this issue.

4.2. Range shift in response to climate change

Our SDM predictions suggests that the potential distribution of *S. japonica* could become smaller in size and move further north under

future climate scenarios, which supports our initial expectation. Range shifts in response to climate change have been reported in both terrestrial and marine species (Parmesan et al., 1999; Sorte et al., 2010; Chen et al., 2011; Cheung et al., 2009, 2013; Poloczanska et al., 2013). For instance, La Sorte et al. (2010) reviewed the range shifts in 129 marine species and they found 75% of the range shifts were in a poleward direction. Previous studies have reported that in addition to latitudinal range shifts, marine species may also move to deeper waters in response to climate change (Perry et al., 2005; Dulvy et al., 2008). In our SDM for *S. japonica*, that sort of biological response cannot be predicted as it represents a shift from the species current niche. Therefore, a deepening movement could not be detected in our study.

4.3. Management implications

Our SDM results indicate that the Japanese whiting is likely to change its distribution in response to future climatic changes. It is quite possible that in addition to *S. japonica*, other fish species in the study area also shift their geographic distributions as a result of climate change. The distribution range shifts of marine species may lead to the changes in the species composition of fisheries catches and ultimately influence the fisheries activities. The impacts of ocean warming on the composition of fisheries catch have recently been addressed (Cheung et al., 2013; Kleisner et al., 2017). For instance, Cheung et al. (2013) proposed an index called mean temperature of the catch (MTC), which measures the temperature preference of the exploited species. They found that between 1970 and 2006, the MTC in 52 large marine ecosystems increased by about 0.19 °C per decade. Further studies are required to investigate the effects of climate change on fisheries catches in our study area. In addition to range shifts, climate change can cause changes to the timing of life–history events (i.e., phenology) (Edwards and Richardson, 2004; Doney et al., 2012). In order to minimize the impacts of phenological and distributional changes of marine species on fishing activities, adaptation management strategies on fisheries, such as changing fishing season and fishing grounds, should be considered in advance.

Acknowledgements

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2019.05.023.

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