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Predicting current and future global distribution of black rockfish (*Sebastes schlegelii*) under changing climate

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ABSTRACT

Changes in the marine environment, particularly climate change, can have large effects on the distribution patterns of various marine species, and alter the biodiversity, structure and functions of the affected ecosystems. Species distribution models (SDM) are tools often used to link species' ecological niches with their environment. We applied SDM to investigate the effects of five biologically relevant climatic variables from multiple databases, including bottom temperature, bottom salinity, current velocity, depth and primary productivity, on habitat suitability of *Sebastes schlegelii* in the marine waters of China, Korea and Japan. Nine individual SDM and an ensemble model were used to predict the current and future distribution of *S. schlegelii* under alternative climate change scenarios (Representative Concentration Pathways, RCP). Results indicated that the ensemble model produced more accurate projections than any individual model. Among the environmental variables investigated, bottom temperature was the most important in determining the range of *S. schlegelii*. Its current distribution demonstrated that suitable habitat for *S. schlegelii* was mostly concentrated in the Bohai Sea, coastal areas of the central and northern Yellow Sea, and in the Sea of Japan. Negative effects from climate change on the distribution patterns of *S. schlegelii* were predicted to lead to varying degrees of habitat reduction, with highest estimate of 45% occurring under RCP8.5 at the end of 2100. Our results illustrate the potential effects of climate change on the future distribution of *S. schlegelii* populations and can assist with implementing adaptive management measures of this species.

1. Introduction

Changes in the marine environment, particularly climate change, are expected to affect the distribution patterns of many marine species, and to alter the biodiversity, structure and functions of their ecosystems. (Hazen et al., 2013; Becker et al., 2019). Marine species are expected to shift their spatial and temporal distributions in response to changing environmental conditions (Hollowed et al., 2013). Tropical regions, semi-enclosed seas, and sub-polar areas may experience more loss of local populations, whilst polar areas may have more species invasion issues (Cheung et al., 2009). Acquiring a comprehensive and accurate understanding of current species distributions and providing reliable predictions under future environmental change scenarios, are important to implementing effective conservation and resource management strategies (Melo-Merino et al., 2020).

Species distribution models (SDM) provide an approach to assess climatically generated impacts by linking species occurrence records with environmental variables and estimating the potential effects under plausible future scenarios (Briscoe et al., 2019). SDM have been constructed from bioclimatic envelope models, generalized linear models (GLM) and machine learning methods such as generalized boosting models (GBM) and random forests (RF, Hao et al., 2019). SDM can help with understanding species population distributions and provide valuable implications due to their potential applicability to different spatial resolutions, and available data sources, even for seldom studied species (Melo-Merino et al., 2020). Ensemble modeling has been increasingly

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explored as a way to integrate the strengths of different individual SDM (Bevan et al., 2019; Hao et al., 2020). By combining models with different assumptions and algorithms, ensemble models are capable of providing more robust results than individual models (Zhang et al., 2019).

At present, SDM studies on marine species influenced by climate change are mostly focused on pelagic species, especially in tropical and polar areas (Wisz et al., 2015; Erauskin-Extramiana et al., 2019; Schickele et al., 2020). The extent to which demersal species inhabiting temperate regions are affected by climate changes is less commonly considered (Fredston-Hermann et al., 2020). The black rockfish *Sebastes schlegelii* (class Actinopterygii, order Scorpaeniformes, family Scorpaenidae) provides a typical example for exploring such issues. It is a demersal fish widely distributed in the northwest Pacific along the coast of China, Japan and the Korean Peninsula (Wang et al., 2017), and characterized by strong adult site fidelity and a preference for rocky reef, silt and sand habitat (Zhang et al., 2015). The species usually matures at the of age 3 years with an ovoviviparous reproduction mode (Chin et al., 2013; Xu et al., 2019). *S. schlegelii* is carnivorous, mainly feeding on shrimps and fishes and has strong initiative in prey selectivity (Chin et al., 2013; Zhang et al., 2014). As to the status of the *S. schlegelii* resource in the Yellow Sea, mean individual weight and catch per unit of effort were both reported to have declined during the last thirty years (Xu and Jin, 2005; Chen et al., 2018). Due to its high economic and recreational value, *S. schlegelii* has been considered as an important target species for stock enhancement programs in China, Japan and Korea (Kim et al., 2001; Chin et al., 2013; Wang et al., 2017). Current studies of *S. schlegelii* largely focus on growth, behavior, physiology, immunity and population genetics (Zhang et al., 2015; Kim and Kang, 2016; Wang et al., 2017; Yin et al., 2018), however, a large scale study focusing on availability of suitable habitat and associated future population distributions under changing climatic conditions is lacking for *S. schlegelii*. Research on demersal fish like *S. schlegelii* can help to identify and more comprehensively understand the potential impacts of climate change on fish communities and their ecosystems.

Here, using data sourced from multiple databases, our study presents the first large scale biogeographic study of *S. schlegelii* analyzed by SDM, with an aim to identify the main environmental variables affecting its distribution, and to evaluate the expected changes in suitable habitat over mid-term (2050) and long-term (2100) periods situated under four Representative Concentration Pathways (RCP, van Vuuren et al., 2011). This study provides insights about the potential effects of climate change on the distribution of *S. schlegelii* populations and can assist the development of adaptive strategies for managing this resource.

2. Materials and methods

2.1. Study areas and data sources

2.1.1. Study areas

Our study area spans the coastal waters adjacent to Japan, Korea, China and Russia, encompassing the Sea of Japan, the Bohai Sea, the Yellow Sea and the northern region of the East China Sea (28° to 50°N; 115° to 150°E, Fig. 1).

2.1.2. Presence/absence data of S. Schlegelii

Global presence/absence data of *S. schlegelii* were collected and merged from three sources: the Global Biodiversity Information Facility (GBIF, https://www.gbif.org/), the Ocean Biodiversity Information System (OBIS, https://obis.org/) and systematic fishery surveys conducted by the Yellow Sea Fisheries Research Institute, Chinese Academy of Fishery Sciences in 2016. A total of 563 occurrence records (presence-only) were obtained from GBIF and OBIS, and 438 high-quality site-occupancy data (presence and absence) were obtained from fishery surveys during all four seasons in 2016. Sites in which *S. schlegelii* occurred at least once were regarded as present, whereas those with no recorded observations were treated as absent. Overall, occurrence data of *S. schlegelii* retrieved from the data sources for our study ranged from the years 1883 to 2018, recent records (since 1990) accounted for 74.5% (746) of the total observations compared with past (1883–1990) records representing 9.9%, and undated observations 15.6%. Eighty-eight per cent of the records among past and undated observations did not have longitude and latitude recorded. Due to these limitations, we took a precautionary approach to narrow down the number of presence/absence sites to guaranteed data quality by the following selection steps: (1) records prior to 1990 and any undated were removed; (2) unreliable

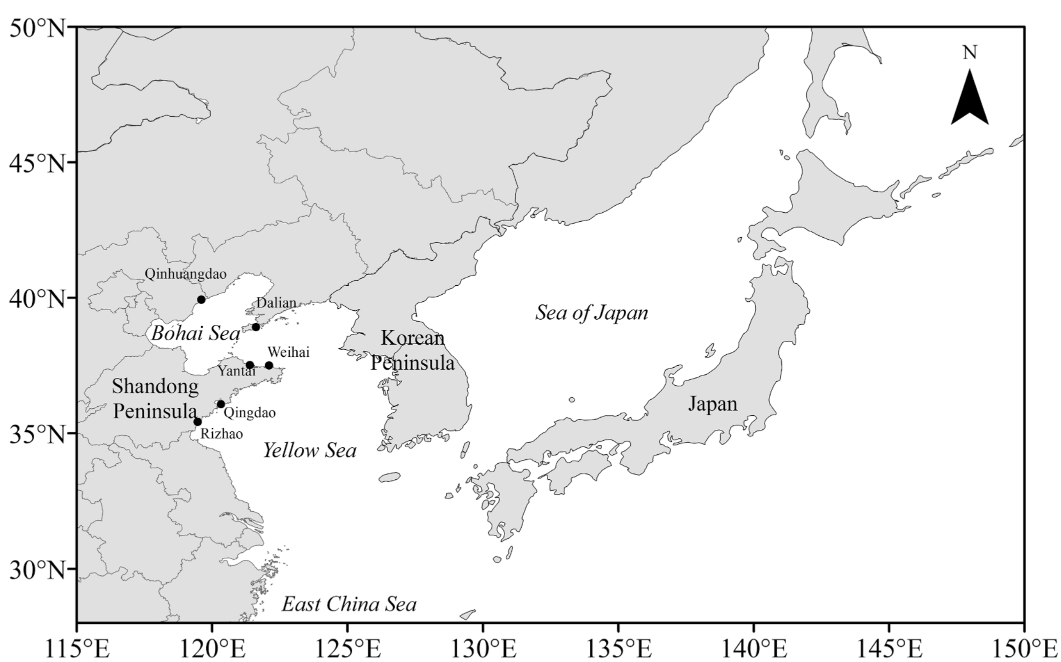

Fig. 1. Study area from which data were sourced. Black solid circles represent important stock enhancement sites of *S. schlegelii* along the Bohai Sea and the Yellow Sea.

records due to typographical or other errors evident in the longitude or latitude were removed; (3) records with only specific locality descriptions but no coordinates were georeferenced; (4) occurrence records were aggregated on a spatial grid with a resolution of 5 arcmin corresponding to that of the environmental data, and any duplicate records within same grid were removed to avoid the risk of sampling bias. Finally, 215 records (87 presences and 128 absences) were reserved for further analysis (Supplementary Material, Fig. S1).

2.1.3. Environmental data

Considering both biological relevance and data availability, we chose eight environmental factors (bottom temperature, bottom salinity, current velocity, depth, distance to shore, primary productivity, phytoplankton and chlorophyll) which were averaged over the year as the predictive variables. Depth and distance to shore at 5 arcmin resolution were downloaded from Global Marine Environment Datasets (GMED, http://gmed.auckland.ac.nz/index.html). Data for the remaining six variables were obtained from the Bio-ORACLE database (http://www.bio-oracle.org/) at a resolution of 5 arcmin (Tyberghein et al. 2012; Assis et al., 2017). Pearson's correlation among environmental factors was examined initially and an absolute value of correlation coefficient $r = 0.7$ was defined as a threshold to avoid the possible multicollinearity which could lead to biased model estimation (Schickele et al., 2020). Five environmental variables (bottom temperature, bottom salinity, current velocity, depth and primary productivity) were finally selected (Supplementary Material, Fig. S2). Considering the strong site fidelity of *S. schlegelii*, we assumed that it is reasonable to combine annual environmental data with presence/absence data in the study area. All environmental data were cropped to the geographical distribution range of *S. schlegelii* (28° N − 50° N, 115° E − 150° E) before developing the SDM.

2.2. SDM construction and evaluation

2.2.1. SDM

Nine individual SDM available in the biomod2 package in R (Thuiller et al., 2016) were used to model and map the current and future distribution of *S. schlegelii*. Specifically, these were: (1) artificial neural network (ANN), (2) classification tree analysis (CTA), (3) flexible discriminant analysis (FDA), (4) generalized additive models (GAM), (5) GBM, (6) GLM, (7) multivariate adaptive regression splines (MARS), (8) RF and (9) surface range envelop (SRE). SRE requires presence-only data and the other eight SDM require both presence and absence information as contrast in order to model responses to different environmental variables (Hao et al., 2019). Parameter settings of the nine individual SDM were determined based on default settings recommended by Ruiz-Navarro et al. (2016) and Thuiller et al. (2016), Supplementary Material, Table S1).

2.2.2. Model evaluation

The occurrence dataset was randomly split into two subsets, 80 percent were used to train the models and the remaining 20 percent were used for testing. A cross-validation procedure with 10 evaluation repetitions was conducted to represent the overall accuracy. Model performance was quantified using three commonly used evaluation metrics: (1) the area under the curve (AUC) of the receiver operating characteristic (ROC; Hanley and McNeil, 1982), (2) the true skill statistic (TSS; Allouche et al., 2006) and (3) the Cohen's Kappa (Kappa; Cohen, 1960). An ensemble modeling approach was used to model and map the distribution of *S. schlegelii* due to its potential ability to outperform predictions of individual models (Zhang et al., 2019). Individual models with AUC $\geq$ 0.7, TSS $\geq$ 0.5 and Kappa $\geq$ 0.4 were included in the ensemble model construction based on a range of published work (Silva et al., 2016; Ruiz-Navarro et al., 2016; Phillips et al., 2017). Then, the ensemble model was built by weighting the individual models according to their calculated AUC values. Variable importance was evaluated by using a randomization procedure that compared reference predictions with those using the same model but with one variable randomized (Thuiller et al., 2016). Then Pearson correlations between reference predictions and the 'permuted variable' were computed. Variable importance is defined as one minus the correlation and the higher this value, the more influence the variable has on the model. Response plots were used to reflect how important the predictive variable across its range was in explaining the observed species distribution (Bouska et al., 2015).

2.3. Current and future distribution of *S. schlegelii*

The current and future occurrence probabilities of *S. schlegelii* were estimated for each 5 arcmin geographic grid by the ensemble model with values ranging from 0 to 1, where 1 indicated the highest probability of occurrence and 0 represented the lowest. Four climate change scenario-RCP projected by the Intergovernmental Panel on Climate Change (IPCC) were applied to predict the future distribution of *S. schlegelii.* Among them, RCP2.6 was considered as the best case for limiting anthropogenic climate change under a low emission scenario, RCP4.5 and RCP6.0 were selected as two intermediate stabilization scenarios, and RCP8.5 was generally regarded as a high emission scenario. Future distributions of *S. schlegelii* in mid-term (2050) and long-term (2100) situations were projected under the four RCP. In future prediction, environmental variables depth and primary productivity were static while bottom temperature, bottom salinity and current velocity would change according to different RCP scenarios. The information required by the RCP scenarios was obtained from the Bio-ORACLE database (http://www.bio-oracle.org/) at a resolution of 5 arcmin (Tyberghein et al. 2012; Assis et al., 2017) and then cropped to the study area (Supplementary Material, Fig. S3). To assess the change in range extent of *S. schlegelii* under current and predicted future climatic conditions, the predicted number of grids with probability was calculated. Species' probability of occurrence was converted into binary presence and absence data according to the cut-off value that maximized the true skills statistic (Guisan et al., 2017). A grid could have four different situations under future scenarios: (1)"lost" represents the grid is predicted to be lost by the species in the future, (2)"gain" represents grid was not occupied currently, and is predicted to be into the future, (3)"pres" represents the grid is occupied both now and in the future, (4)"abs" represents the grid is not occupied both now or in the future.

3. Results

3.1. Model performance evaluation

Results based on the cross validation (Fig. 2) demonstrated that predictive performance varied among models, with GAM, GLM, RF, ANN, GBM, MARS, FDA performing well across all three evaluation metrics, CTA ranked second last, and SRE was the poorest fitting model falling below the specified minimum performance criteria for all three measures (AUC, TSS, and Kappa). The ensemble model with AUC, TSS and Kappa values of 0.945, 0.791 and 0.781 produced highly accurate projections in comparison to the less performant individual models. In light of its superior performance, the ensemble model was selected to model and map the current and future habitat suitability of *S. schlegelii.*

3.2. Importance and response curve of environmental predictor factors

Among the five environmental factors, bottom temperature was the most important variable influencing the distribution of *S. schlegelii* with an importance value of 0.77 ± 0.19 across the nine models tested (Fig. 3). Response curves for the predicted occurrence probability of *S. schlegelii* against bottom temperature showed consistent results across different individual SDM, indicating *S. schlegelii* prefers to inhabit areas with bottom temperature ranging from 3 °C to 13 °C (Fig. 4). Depth was

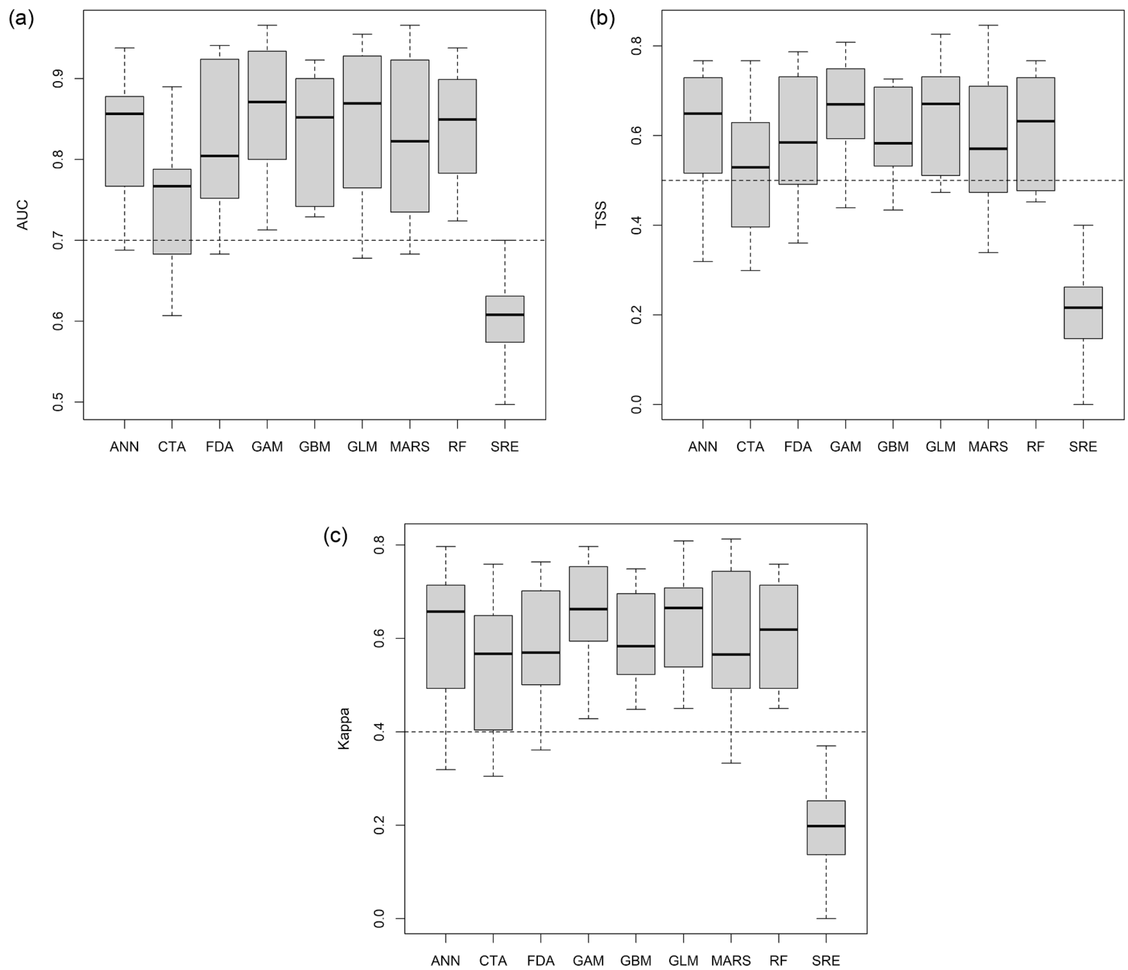

Fig. 2. Distributions of overall accuracy of different individual SDM. Box plots showing the estimated median (horizontal lines), 25th–75th percentiles (boxes) and the range (whiskers) of AUC (a), TSS (b) and Kappa (c). Dotted horizontal line represents the selecting criterion (AUC = 0.7, TSS = 0.5, Kappa = 0.4) of individual models for inclusion in the ensemble model.

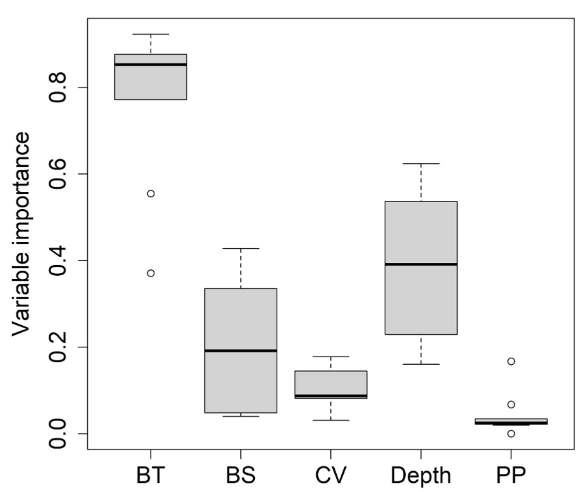

Fig. 3. Variable importance of five environmental variables (BT: bottom temperature; BS: bottom salinity; CV: current velocity; PP: Primary productivity).

the second ranking variable with an importance value of 0.38 ± 0.16. The observed depth range for *S. schlegelii* was 5–111 m and a high probability of occurrence was predicted for depths less than 70 m (Fig. 5). Bottom salinity, current velocity and primary productivity were only weakly associated with the distribution of *S. schlegelii* with importance values below 0.20.

3.3. Current and future global distribution

Our study indicates that the current distribution map of predictions from the ensemble model is highly consistent with the known occurrence records from the three databases (Fig. 6). Areas with higher occurrence probability were mostly concentrated on the Bohai Sea, and coastal areas of the central and northern Yellow Sea. In addition, coastal waters around the Sea of Japan, such as the eastern Korean Peninsula and Hokkaido coastal areas, also have high habitat suitability for *S. schlegelii*.

In order to consider the potential impacts of climate change on the distribution of *S. schlegelii*, we converted the occurrence probability into a binary presence/absence value. The associated cut-off value used for transforming fitted probability into binary form was 38.8% with a 90.8% sensitivity (true positive rate) and 88.3% specificity (true negative rate). Results from future climate change scenarios tended to have similar trends compared with the current situation in the mid-term (2050), with the area of occupancy decreasing by 12%–21%. At the end of 2100, the distribution patterns are projected to differ across the four scenarios, with RCP4.5 experiencing the least decrease of 10% of the currently occupied area, whereas RCP8.5 would experience the most impact with a decrease of 45% (Table1). Future habitat reduction of *S. schlegelii* is projected mainly occur in three areas: the coastal waters in the northeast Bohai Sea, northern and southern Shandong Peninsula,

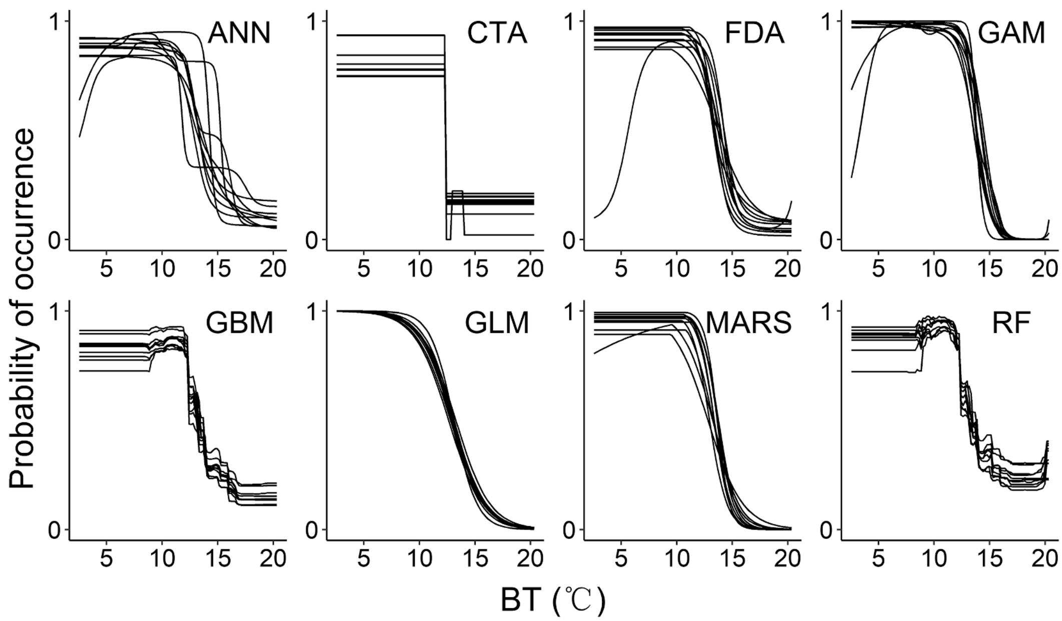

Fig. 4. Response curves of predicted occurrence probability of *S. schlegelii* against bottom temperature.

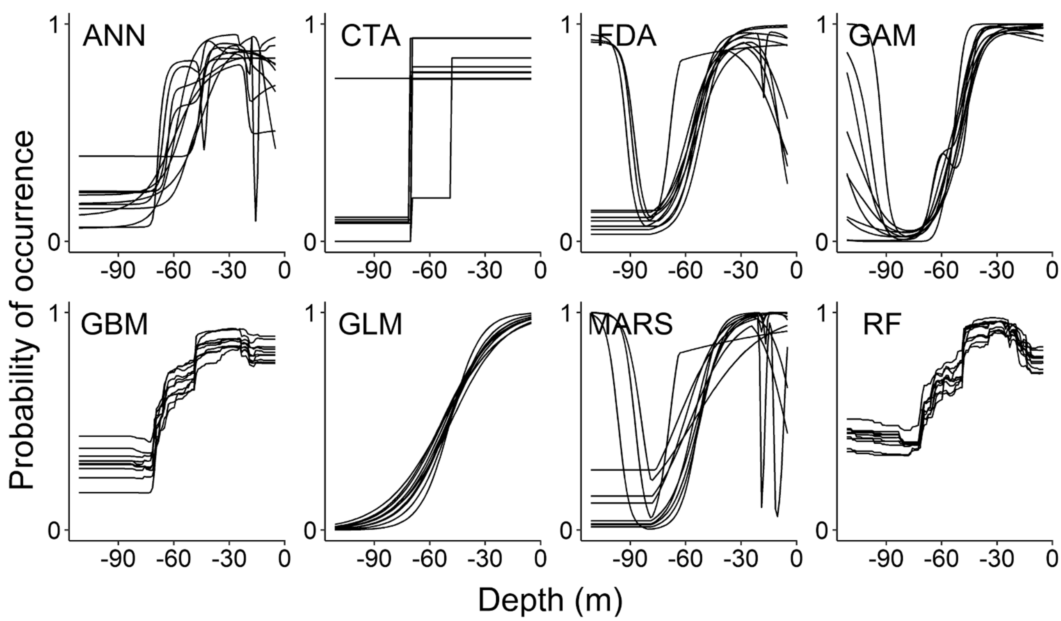

Fig. 5. Response curves of predicted occurrence probability of *S. schlegelii* against depth.

and sporadic areas along the coast of the Korean Peninsula and Japan (Fig. 7).

4. Discussion

4.1. Model performance

We developed individual SDM which were aggregated into an ensemble model for *S. schlegelii* by integrating presence-only data from online databases and site-occupancy data from systematic fishery surveys to produce satisfactory results, suggesting these data sources are valuable for predicting the distributions of *S. schlegelii*. We assumed the absence data from fishery surveys were real asbences although species activity and variation in catchability mean that some of these are likely to be false absences. SDM have been applied extensively in order to solve various ecological issues including predicting the current and future geographic range of species, evaluating biological invasion impacts, and developing conservation strategies (Elith et al., 2006; Zhang and Vincent, 2017; Eberhard et al., 2020; Zhang et al., 2020). Most SDM require both presence and absence data to map the species distribution except for few presence-only models such as SRE (Hao et al., 2019). Presence data are commonly available from multiple online databases, whereas the absence data are usually difficult to obtain. However, absence data can be of great importance in helping to identify the favorable environmental conditions compared to the presence data (Brotons et al., 2004). Here our study also highlighted that presence/absence dependent SDM, such as GAM, GLM and RF, out-performed presence-only models such as SRE based on all three evaluation metrics. Although AUC, TSS and Kappa values for individual SDM had a wide range indicating there exist differences produced by each evaluation repetition in

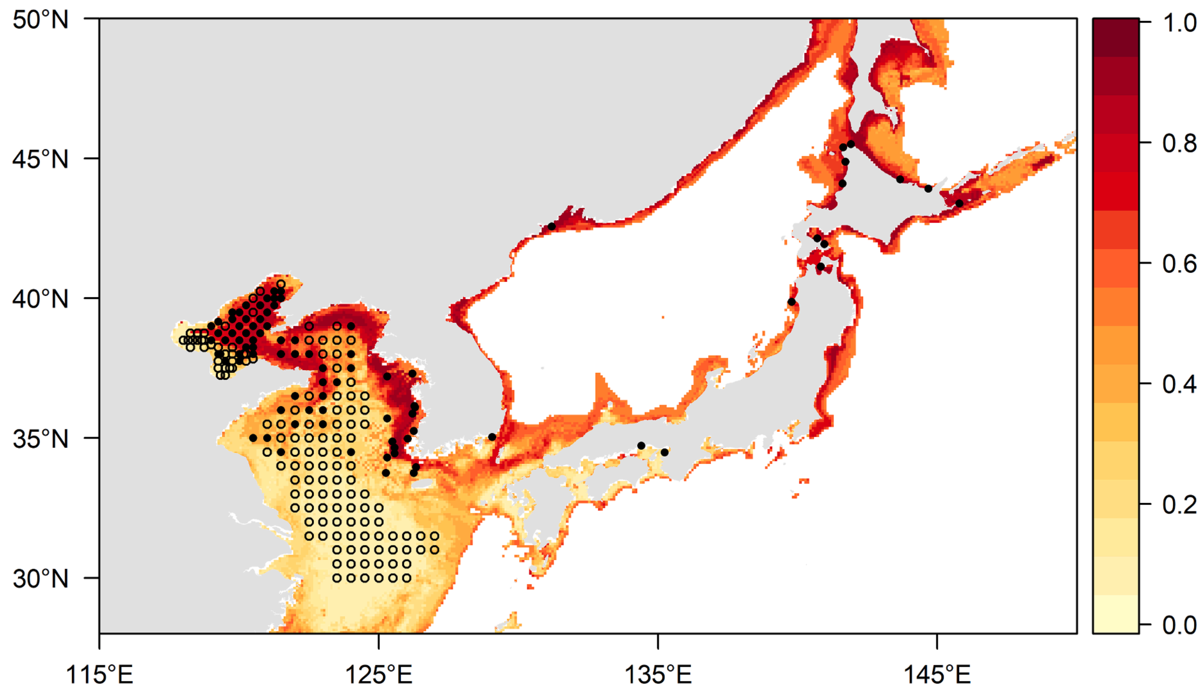

Fig. 6. Current spatial distribution of *S. schlegelii* predicted by the ensemble model. Black solid circles represent the presence and hollow circles represent the absence of *S. schlegelii*. Colors represent the occurrence probability (0 to 1).

Table 1
Grade of change (%) in the occupied area by *S. schlegelii* under climate change scenarios.

Scenarios	Year	Change (%)	Year	Change (%)
RCP2.6	2050	−18.77	2100	−19.36
RCP4.5	2050	−16.08	2100	−9.65
RCP6.0	2050	−11.61	2100	−13.62
RCP8.5	2050	−20.59	2100	−45.30

the cross-validation procedure, the overall accuracy of most models was high (AUC $\geq$ 0.7, TSS $\geq$ 0.5 and Kappa $\geq$ 0.4).

We found that the ensemble model yielded projections with greater accuracy than any individual model that we tested. Nevertheless, it should be noted that single models such as GAM, GLM and RF also achieved high values for the evaluation metrics. Since we used the default tuning choices of biomod2 package followed the previous studies (Ruiz-Navarro et al., 2016), it is worthwhile to compare the performance between the ensemble model and the improved individual models in future studies and examine the consistency of the ensemble model's performance among different species.

4.2. Current and future distribution of S. schlegelii

Our work produced reliable species distribution projections for *S. schlegelii* within its geographic range using annual environmental and occurrence data. The performance of these models may be benefit from the semi-sedentary reef-dwelling behavior of *S. schlegelii* with a lack of long-distance migration among its life history traits (Zhang et al., 2015). Current range projections from our analyses are supported by known distributions of *S. schlegelii* (Chin et al., 2013). Further, Wan et al. (2014) reported that larvae of *S. schlegelii* have been found in the coastal waters of the East China Sea in May 2008 but not in May 2007 nor in three other seasons. Its index of relative importance (IRI) showed that *S. schlegelii* was not the dominant species in this area (Wan et al., 2014). This is also be reflected in our results which show that the coastal waters adjacent to the Yangtze River Estuary were predicted to be moderately suitable for *S. schlegelii.* Collectively, the explicit spatial distribution information in this work can provides a more substantial body of data in support of further habitat quality evaluation and population dynamics investigations of *S. schlegelii.*

Our study indicates that bottom temperature was the most important variable affecting the distribution of *S. schlegelii*, with its thermal tolerance ranging from 3 °C to 20 °C, and 3 °C to 13 °C predicted as its thermal preference. This is consistent with the results from previous studies. Physiological and feeding ecology experiments under *in vitro* culture conditions have demonstrated that *S. schlegelii* can survive at a much wider range of water temperatures, from 5 °C to 28 °C, than our prediction with its upper bound of 8 °C lower (Kim et al., 2001; Lyu et al., 2018). Our study also showed that *S. schlegelii* usually inhabits relatively shallow water less than 70 m deep. Especially in highly suitable habitats, the average depth inhabited in the Bohai Sea and the Yellow Sea is 21 m and 44 m with the maximum depth of 70 m and 140 m respectively. Previous studies have also indicated that *S. schlegelii* prefers to inhabit reef terrain of high rugosity (Zhang et al., 2015). Unfortunately, the substrate type was not included in our analysis due to a lack of suitable data availability. Further studies could explore more biological and abiotic factors to potentially provide greater insight into factors governing the spatial distribution dynamics of *S. schlegelii.*

Given the predicted loss in occupied habitat of *S. schlegelii* projected by our model as a result of climate change, it is important to consider the inconsistencies in projected distributions between mid-term and long-term scenarios when designing future fisheries management strategies aimed sustaining stocks. In the high emission scenario RCP8.5, habitat loss is projected to reach 45% in 2100 compared with 21% in 2050. In contrast, in the low (RCP2.6) and the intermediate (RCP6.0) stabilization scenarios, the distribution of *S. schlegelii* is projected to be roughly the same in 2100 compared to projected values in 2050. Significantly, our model predicts that suitable habitat would be more abundant at the end of 2100 than in 2050 in the RCP4.5 scenario, mainly due to the "gain" regions in the southern coastal waters adjacent to the Yangtze River Estuary and in the East China Sea (28° to 32°N; 125° to 127°E, Fig. 4d). We notice that these areas are projected to experience changes in future salinity and current velocity (Supplementary Material, Fig. S2).

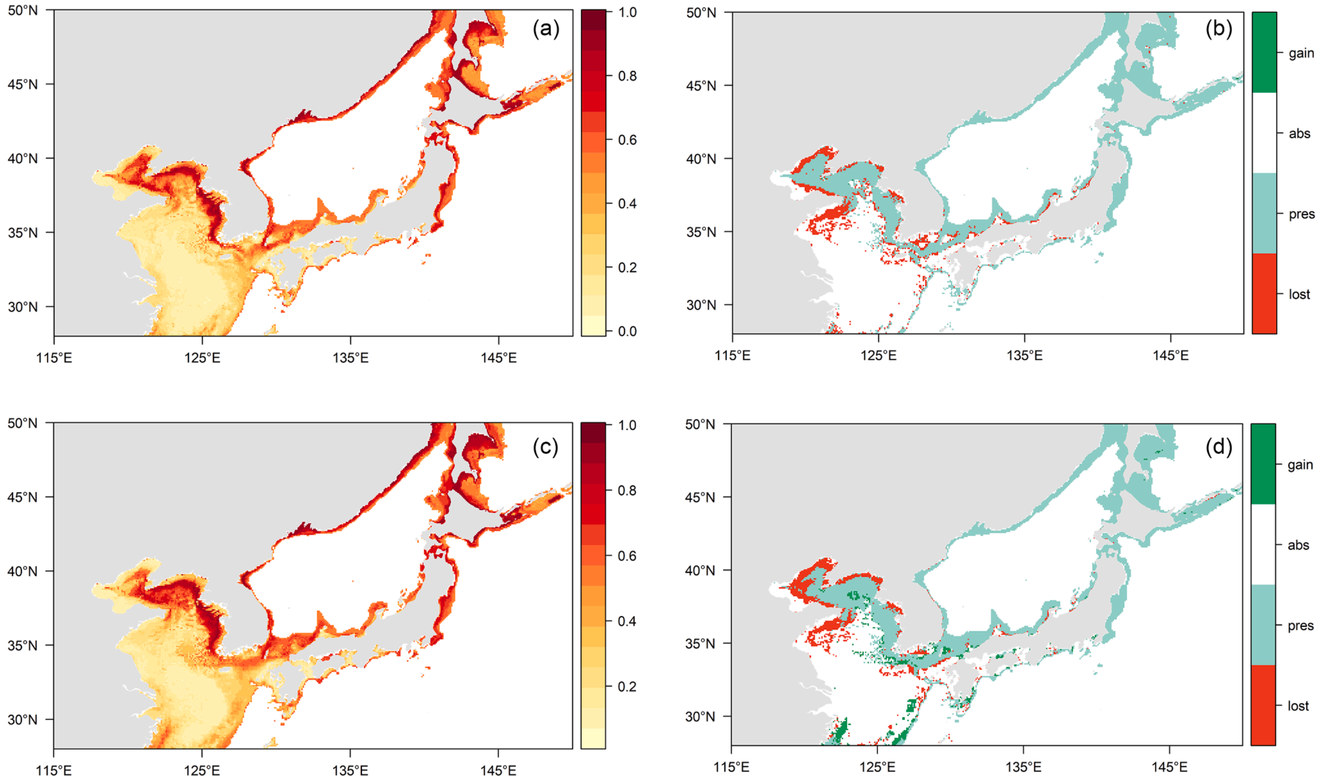

Fig. 7. Predicted future distribution of *S. schlegelii* under Representative Concentration Pathway (RCP) 4.5 scenario. (a) Predicted spatial distribution of *S. schlegelii* in 2050, (b) Occupied area change of *S. schlegelii* in 2050, (c) Predicted spatial distribution of *S. schlegelii* in 2100, (d) Occupied area change of *S. schlegelii* in 2100. Colors represent the occurrence probability (0 to 1).

Moreover, the substrates in these areas are dominated by silt and sand, which are both favorable for *S. schlegelii* (Wu and Wen, 2021). Similar negative impacts of climate change have been reported for species in the northwest Pacific such as Japanese whiting *Sillago japonica* and other species in the northeast Pacific and north Atlantic (Lenior et al., 2011; Hazen et al., 2013; Erauskin-Extramiana et al., 2019; Zhang et al., 2019).

4.3. Limitations

To project current and future distributions of *S. schlegelii*, we made a number of approximations and assumptions. Firstly, the current distribution map may have uncertainties arising from false absence data recorded during surveys of the fishing grounds. *S. schlegelii* is demersal and the catchability of bottom trawls cannot be one hundred percent, especially in rocky rugose habitats where nets are prone to snagging. The degree to which false absence data can impact the accuracy of habitat suitability assessments should be further evaluated. Secondly, the distribution pattern will almost certainly be impacted by effects between species and anthropogenic activities (e.g. fishing) that were not considered in our analysis. Thirdly, *S. schlegelii*'s adaptability to changing or new environment conditions may influence the accuracy of forecasts. Overall, our work illustrates potential climate change-induced impacts on the distribution of *S. schlegelii*, but researchers, fishery managers and policy makers should be cautious when developing suitable strategies for conservation and fishery management due to the acknowledged limitations of our study and the need for further research on *S. schlegelii*.

4.4. Conservation and management implications of S. Schlegelii

Our spatially-explicit maps of *S. schlegelii* can be useful in several aspects of management of this species. Firstly, *S. schlegelii* is an important target species for stock enhancement in Japan, Korea and China (Kim et al., 2001; Chin et al., 2013; Wang et al., 2017). The projected maps produced by our model can be used to guide local authorities and researchers to determine whether locations are appropriate and identify whether there exists more suitable potential locations to implement stock enhancing activities when considering new or revised resource conservation plans. Secondly, since climate change has been attributed through empirical research as a vital factor influencing the distribution of marine species (Perry et al., 2005; Hollowed et al., 2013), our predicted distributions of *S. schlegelii* under future climate change scenarios should be of great help when developing adaptive conservation and management strategies. For instance, it is noteworthy that our model predicts that many important stock enhancement localities in China, such as Qingdao, Rizhao and Qinhuangdao (Fig. 1) would likely to be impacted significantly under the scenarios we investigated. In view of the increasing scale of stock enhancement activities, especially in China, we recommend a strengthening of the monitoring of exploited fish populations and the species with which they interact, and evaluations of habitat suitability when striving to continually improve the effectiveness of fisheries management. Thirdly, our work can provide scientific support in incorporating climate change into future marine policies among nations, societies and stakeholders. Every contribution counts, no matter how modest, as the impacts of climate change become increasingly significant, and formulating more appropriate climate-related fishery policies and management measures is the future pathway for sustainable fisheries. From the present study, we predict that the future suitability of habitats for *S. schlegelii* will decrease, so areas that are highly sensitive to climate change warrant more attention when developing long-term policy initiatives. In summary, we caveat that our findings provide potential niches for *S. schlegelii* persistence that might not be realized, yet the results nevertheless provide an important roadmap for developing future conservation and management strategies of *S. schlegelii* in this region.

5. Conclusion

This study utilized multiple datasets to construct a large-scale SDM of *S. schlegelii*. Our results indicated that the ensemble model we formulated produced more accurate projections than any individual model. Bottom temperature was the most important environmental variables in determining the range of *S. schlegelii*. The potential changes in suitable habitat in mid-term and long-term periods under four RCP demonstrated that climate change would have negative effects on the total amount of suitable habitat for *S. schlegelii*. Both the climate-induced spatial distribution and inconsistencies among alternative scenarios should be considered when designing future conservation and management strategies. We caution that the projected results of our study are indicative not a reality, and may be subject to the following limitations: uncertainties in the absence data, effects between species and anthropogenic activities (e.g. fishing) and species' adaptability to the changing or new environment conditions. Future studies are necessary to address these issues. The current and future distributions of *S. schlegelii* presented in this paper serve as a first step towards developing a marine policy to cope with the impact of climate change on this species.

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CRediT authorship contribution statement

Yunlong Chen: Conceptualization, Methodology, Formal analysis, Software, Writing - original draft, Writing - review & editing. **Xiujuan Shan:** Conceptualization, Supervision, Formal analysis. **Daniel Ovando:** Conceptualization, Methodology, Formal analysis, Writing - review & editing. **Tao Yang:** Investigation. **Fangqun Dai:** Investigation. **Xianshi Jin:** Conceptualization, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2021.107799.

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