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Estimating the impact of climate change on the potential distribution of Indo-Pacific humpback dolphins with species distribution models

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As an IUCN critically endangered species, the Indo-Pacific humpback dolphin, *Sousa chinensis*, has attracted great public attention in recent years. The threats of human disturbance and environmental pollution to this population have been documented extensively. However, to our knowledge, research on the sensitivity of this species to climate change is lacking. To understand the effect of climate change on the potential distribution of *Sousa chinensis*, we developed a weighted ensemble model based on 83 occurrence records and six predictor variables (e.g., ocean depth, distance to shore, mean temperature, salinity, ice thickness and current velocity). The ensemble model exhibited higher prediction accuracy than the single-algorithm model, according to the TSS and AUC values and indicated that ocean depth and distance to shore were the most important predictors in shaping the distribution patterns. The projections from our model indicated a severe adverse impact of climate change on the *Sousa chinensis* habitat, and over 80% of the suitable habitat in the present day will be lost in all RCP scenarios in the future. With the increased numbers of records of stranding and deaths of *Sousa chinensis* in recent years, strict management regulations and conservation plans are urgent to safeguard the current suitable habitats. Due to habitat contraction and poleward shifts in the future, adaptive management strategies, including adjusting the current reserves and designing new reserves, should be formulated to minimize the impacts of climate change on *Sousa chinensis*.

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Abstract: As an IUCN critically endangered species, the Indo-Pacific humpback dolphin, *Sousa chinensis*, has attracted great public attention in recent years. The threats of human disturbance and environmental pollution to this population have been documented extensively. However, to our knowledge, research on the sensitivity of this species to climate change is lacking. To understand the effect of climate change on the potential distribution of *Sousa chinensis*, we developed a weighted ensemble model based on 83 occurrence records and six predictor variables (e.g., ocean depth, distance to shore, mean temperature, salinity, ice thickness and current velocity). The ensemble model exhibited higher prediction accuracy than the single-algorithm model, according to the TSS and AUC values and indicated that ocean depth and distance to shore were the most important predictors in shaping the distribution patterns. The projections from our model indicated a severe adverse impact of climate change on the *Sousa chinensis* habitat, and over 80% of the suitable habitat in the present day will be lost in all RCP scenarios in the future. With the increased numbers of records of stranding and deaths of *Sousa chinensis* in recent years, strict management regulations and conservation plans are urgent to safeguard the current suitable habitats. Due to habitat contraction and poleward shifts in the future, adaptive management strategies, including adjusting the current reserves and designing new reserves, should be formulated to minimize the impacts of climate change on *Sousa chinensis*.

Key words: *Sousa chinensis*, Species distribution models; Ensemble model; Potential distribution, Habitat contraction

1. Introduction

Indo-Pacific humpback dolphins (IPHD), *Sousa chinensis,* belong to the porpoise family of cetaceans and are also known as "mermaids" and "water pandas". Due to their preferred inshore and estuarine habitats, IPHD are typically found in the shallow, coastal waters of the Indian and western Pacific oceans (Jefferson and Rosenbaum, 2014; Jefferson and Smith, 2016; Parra and Jefferson, 2018). These areas, which have intensive commercial fisheries, are usually rapidly developing and are easily polluted by industrial production and the lives of local residents; the corresponding consequences of habitat degradation may lead to population declines or even put this species at risk of extinction (Li, 2020). In recent years, the numbers of records on strandings or deaths of IPHD have increased in China. This species has already been classified as “vulnerable” by the International Union for Conservation of Nature (IUCN, 2019). Consequently, formulating a conservation plan for IPHD is urgent under current and future environmental scenarios, and understanding the species distribution is a prerequisite for plan formulation.

A species lives in a certain environmental niche space, so environmental changes have a great influence on the species distribution. The distribution of top marine predators is related to a variety of environmental determinants, such as ocean depth, salinity, distance to the shore and sea surface temperatures (Nøttestad et al., 2015; Chen et al., 2020). Global climate change has caused significant changes in marine environmental conditions over the past decades. For instance, the assessment that was made for the coastal China seas over the 21st century shows that the East China Sea will be simultaneously exposed to enhanced warming, deoxygenation, acidification, and decreasing net primary productivity (NPP) as a consequence of increasing greenhouse gas emissions (Tan et al., 2020). According to these facts, understanding how future climate change will influence IPHD distributions is vital for better protection of this species.

Species distribution models (SDMs) build species-environment relationships that are typically based on species location data (e.g., abundance and occurrence) and environmental variables that are thought to influence species distributions and can provide a useful framework for identifying and evaluating the habitat suitability for a given species (Guisan and Thuiller, 2005). Currently, SDMs are applied broadly in the life and environmental science fields. A variety of algorithms are available to predict the impacts of climate change on species distributions (Zhang et al., 2019), to understand biological invasions (Zhang et al., 2020a) and to site aquaculture farms (Dong et al., 2020). Accordingly, the use of SDMs in conservation biology and biodiversity assessments is ever increasing (Araújo et al., 2019).

In this study, we developed SDMs and built an ensemble model, which has not, to our knowledge, been used to identify suitable habitats for IPHD or to estimate the potential distributions of IPHD under present-day and future climate scenarios. Our ensemble model, which integrates the advantages of multiple modeling algorithms, can help us to 1) determine the important environmental variables that affect IPHD distributions, 2) map the environmental suitability for IPHD under present-day and future climate scenarios, and 3) assess the impacts of climate change on IPHD habitat distributions. Our study can provide important implications for formulating current and future protection strategies for IPHD and provides guidance for research on the potential distributions of other protected species under future climate change scenarios. In addition, it provides an essential reference to solve marine conservation planning problems.

2. Materials and methods

2.1 Study area and IPHD data collection

IPHD are mainly distributed in the Western Pacific and Indian Ocean, so our research is located in these areas (e.g., 50°E to 180°E, 50°S to 50°N) (Fig. 1). Georeferenced species data (presence/absence) were obtained from the online database: Global Biodiversity Information Facility (GBIF, https://www.gbif.org) and Ocean Biogeographic Information System (OBIS, https://obis.org). The cluster samples in a 5 × 5 arc-minute grid that are consistent with the spatial resolution of environmental data are removed, and only one record per grid unit is used to avoid overrepresentation of environmental conditions (sampling bias) in densely sampled areas. A total of 124 incidents were retrieved, 82 of which were within our study area.

2.2 Environmental variables and future projections

The raster data of environmental variable projections in this study were retrieved from the Bio-ORACLE v2.1 dataset (http://www.bio-oracle.org) (Assis et al., 2018) and Global Marine Environment Datasets (http://gmed.auckland.ac.nz) (Basheret al., 2014). The mean chlorophyll, velocity, salinity, temperature, dissolved oxygen content, ice thickness and pH data were obtained from Bio-ORACLE. The distance to shore and mean ocean depth data were obtained from GMED. In addition, the annual ranges of chlorophyll, flow rate, salinity, temperature, dissolved oxygen, and ice thickness were also obtained from Bio-ORACLE. There were a total of 15 environmental variables with a spatial resolution of 5 × 5 arc-minutes (e.g., 9.2*9.2 km at the equator). Pearson correlation analysis was conducted for these 15 environmental variables to reduce the influence of collinearity on the precision of model predictions. By comprehensive consideration of the availability of current and future environmental data, six low-correlation (pairwise Pearson's correlation coefficients were less than |0.7|) (Dormann et al., 2013) environmental variables, including mean current velocity, mean salinity, mean temperature, mean ice thickness, mean ocean depth and distance to shore, were finally selected for the modeling analysis (Fig. 2).

Meanwhile, the projections of the first four environmental variables for the future (e.g., 2040–2050 (2050s) and 2090–2100 (2100s)) under four representative concentration pathway emission scenarios (RCPS) were also retrieved from the Bio ORACLE v2.1 dataset. RCPs (e.g., RCP26, RCP45, RCP65, and RCP85) and are new climate change scenarios on radiation forcing at the end of the 20th century that were published in the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC). RCP26, which is a peak-and-decline scenario ending in very low greenhouse gas concentration levels by the end of the 21st century; RCP45 and RCP60, in which these levels stabilize; and RCP85, which is a scenario of increasing emissions over time, which leads to high levels of greenhouse gas concentrations (Moss et al., 2010). We assumed that distance to shore and ocean depth remain constant in the future. Projections of future temperature, salinity, and current velocity from Bio-ORACLE were generated based on the mean simulation results of three atmosphere-ocean general circulation models (e.g., AOGCMs: CCSM4, HadGEM2-ES, MIROC5) from the Coupled Model Intercomparison Project 5 (CMIP 5), which is believed to be capable of reducing the uncertainties among different AOGCMs (Assis et al., 2018). The changes in the four predictor variables in the future (e.g., 2050s and 2100s) under different scenarios are shown in Table 1.

2.3 Modeling procedures

We conducted the model analysis on the R platform based on the biomod2 package, and ten species distribution models were available in this package (Thuiller et al., 2020). The ten models include the generalized linear model (GLM) (McCullagh and Nelder, 1989), generalized additive model (GAM) (Hastie and Tibshirani, 1990), classification tree analysis (CTA) (Breiman et al., 1984), generalized enhanced regression model (GBM) (Ridgeway, 1999), artificial neural network (ANN) (Lek and Guégan, 1999), surface range envelope (SRE) (Breiman, 2001a), flexible discriminant analysis (FDA) (Hastie et al.,1994), multiple adaptive regression splines (MARS) (Friedman, 1991), random forest (RF) (Breiman, 2001b), and maximum entropy model (Maxent) (Phillips et al., 2006).

Due to the small number of true absence records, we simulated 5000 pseudoabsence points randomly in contrasting environmental conditions with the true presence points (Guisan et al., 2017; Thuiller et al., 2020). A fivefold cross-validation technique with 10 repetitions was used to assess the model prediction accuracy (Guisan et al., 2017; Thuiller et al., 2020). Based on this approach, 80% of the dataset was randomly selected for calibration and testing of the models, and 20% was withheld for evaluation of the model predictions. Two indicators were used to evaluate the predictive ability of each model: the true skill statistic (TSS) (Allouche et al., 2006) and the area under the receiver operating characteristic curve (AUC) (Swets, 1988). To ensure sufficient prediction accuracy, the models with mean TSS values above 0.80 and mean AUC values above 0.85 were reserved for further analyses (Zhang et al., 2019).

To integrate the advantage of each model, we built an ensemble model that was based on the weighted average of the predictions from the selected models and used this ensemble model to predict IPHD distributions under present and future climate conditions. For a better interpretation of model outcomes, continuous habitat suitability projections were converted into binary maps (e.g., suitable/unsuitable) by using a threshold that maximized the TSS value (Guisan et al., 2017; Liu et al., 2013; Zhang et al., 2020b).

The relative importance of each environmental variable in predicting the IPHD distributions was determined by a randomized approach. This approach computes the Pearson correlations among predictions using all predictor variables and predictions in which the predictor variable being evaluated was randomly permutated (Guisan et al., 2017; Thuiller et al., 2020). Low correlations between the standard predictions and those using the permuted variable indicate the high importance of a predictor variable(Zhang et al., 2019). A response curve, which describes the variations in species occurrence probability along the gradient of each important predictor variable, was plotted.

3. Result

3.1 Model performances and predictive accuracy of SDMs

The different AUC and TSS values indicated the different predictive performances among all 10 modeling algorithms. All of the models except SRE, MAXENT and FDA exhibited good predictive capacity and were selected to construct the ensemble model (Figs. 3, 4). The AUC and TSS values of any individual model were lower than those of the ensemble model (AUC: 0.993 ± 0.002, TSS: 0.963 ± 0.001), which demonstrated the superior predictive performance of the ensemble model.

3.2 Response curve and variable importance

The six predictor variables made different contributions to the IPHD distributions. Among the six predictor variables, depth (0.435 ± 0.029) and distance to shore (0.473 ± 0.031) were the two most important variables for the model predictions. The contributions of temperature (0.234 ± 0.018), salinity (0.135 ± 0.013) and current velocity (0.080 ± 0.011) were moderate, while ice thickness (0.003 ± 0.0007) was considered to be nearly irrelevant (Fig. 5). The response curves of IPHD to the three most important variables from the ten models (except SRE) are shown in Fig. 6. The response curves indicated that the environmental requirements of IPHD in the different models were generally similar.

3.3 Potential distributions under present and future climate scenarios

Our prediction of suitable habitat for IPHD under present climate conditions is shown in Fig. 7. All of the occurrence records were within the predicted suitable range. The predictions show that a large part of the coastal areas of the Southeast Asian countries and northern Australia are suitable habitats for IPHD. Some of the occurrence records were located in the coastal areas of the Indian Peninsula.

As the model results show, the suitable area for IPHD will decrease under all four assumed future climate change scenarios. Future habitat projections under different RCP scenarios show different distribution patterns and consistently suitable range contraction for IPHD (Table 2). The model projections indicate that the contraction of the suitable range of this species could be from 81.95% (under the RCP2.6 scenario in the 2050s) to 94.10% (under the RCP8.5 scenario in the 2100s). Future predictions for the 2100s show that environmental conditions suitable for IPHD will shift northward to the East China Sea and south coast of Japan. The equatorial sea area and coastal area of northern Australia are predicted to be less suitable for this species (Fig. 8).

4. Discussion

4.1 Model performance

Utilizing georeferenced presence/pseudoabsence data and the corresponding environmental data, we innovatively developed an ensemble model for IPHD to predict the present and future potential distributions of this rare species. The results demonstrate that our ensemble model performed well in predicting the habitat suitability for IPHD under the present environmental conditions. The model predictions indicated that the potential distribution of IPHD will contract in the future under different RCP scenarios and that the suitable habitat in the Indo-Pacific Mid-Seas will shift to higher latitudes.

There are many mature models that can be used to predict species distributions. The most commonly used method is to select the best model based on performance indicators such as TSS and AUC and then use the single best model to predict species distributions. In this study, ten single-algorithm models exhibited different performances and provided slightly different results. However, our weighted ensemble model, which integrated the advantages of seven single models with higher performances, proved to be optimal for predicting IPHD distributions. Due to the higher accuracy and reliability compared to a single model, we recommend using an ensemble model to predict potential species distributions and habitat suitabilities (Araújo and New, 2007; Thuiller et al., 2009; César and Pedro, 2011; Shabani et al., 2016).

4.2 Climate change and associated distribution shift

The predicted suitable habitats of IPHD include their known distribution range as expected, for example, the coast of Malaysia, which is also a suitable habitat for white dolphins. Suitable habitats were also found beyond where the species have been recorded, and this phenomenon can be caused by many factors, such as biotic interactions, dispersal limitation of species, niche size (Pulliam 2000) and sampling bias (Goldsmit et al., 2018). Published studies have reached similar conclusions in predicting species distributions using SDM (Goldsmit et al., 2018; Zhang et al., 2020a). As shown in the binary output of habitat prediction, the main IPHD habitat in China is located in the Pearl River Estuary in Guangdong Province. The Pearl River Estuary is an intersection area of brackish and fresh water that results in fertile water quality and high primary productivity. The suitable temperatures and salinities as well as the low pollution, high biodiversity and unexploited natural shorelines all make this area a favorite for IPHD.

According to the projected layer of future climate that was produced from 3 distinct AOGCMs provided by CMIP 5, we determined the changes in four available environmental variables. As shown in Table 1, temperatures will increase with different amplitudes under different RCPs. This tendency of global warming will severely affect IPHD distributions in terms of range size, i.e., will probably lead to a reduction of more than four-fifths of its range. Meanwhile, the suitable IPHD habitat in the future will shift northward. In China, the suitable habitat on the southern coast will shift to the east Yellow Sea and even to the coastal areas of Bohai Bay. Tan et al. (2020) assessed the East China Sea and found that climate change caused by increasing greenhouse gas emissions will induce considerable biological and ecological responses and cause the East China Sea to be among the ocean areas that are most vulnerable to future climate change. On the other hand, the habitat in areas around Australia will shift southward, and the areas off the coast of Malaysia will no longer be suitable for IPHD. This trend toward higher latitudes is similar that described in the formal research (i.e., Ruiz-Navarro et al., 2016; Zhang et al., 2020c, 2019). Regardless of the dispersal scenario, our results highlight the high vulnerability of this critically endangered species to climate change.

4.3 Impact factors of IPHD distribution

Due to the intricate relationships among survival, growth and environmental conditions, many factors may affect the habitat distributions of IPHD. The basic niche that is suitable for the growth of IPHD, such as water temperature, water depth, and distance from shore, was considered in this study. The distribution of IPHD is negatively correlated with distance from shore and distance from the main estuary (Chen et al., 2020); hence, estuaries have been identified as their preferred habitat (Jefferson and Karczmarski, 2001; Wang et al., 2007; Chen et al., 2008; Jefferson and Smith, 2016). Because of the data availability, the realized niche of IPHD, such as human activities and dietary structure, was not considered in this study. Stomach content analyses in previous studies have found that humpback dolphins consume a wide variety of pelagic and demersal fishes (Ning et al., 2020). Environmental change induced by climate change may affect the distributions of these bait fishes and will indirectly affect IPHD distributions (Schickele et al., 2020).

Human activities have a great impact on IPHD habitats. The coastal areas of the China Sea, with many estuaries, bays, coral reefs and fisheries, are not only suitable habitats for IPHD but are also the most active areas for developing the maritime economy. Fishing behavior and boat travel have been determined to cause stranding deaths of IPHD (Guo et al. 2020). IPHD proved to be more acoustically active and prefer locations with lower noise levels (Caruso et al., 2020a, 2020b). However, human activities often generate underwater noise, which interferes with information exchange with conspecifics and interaction with the surrounding environment and can even lead to behavioral disorders(Xu et al., 2020). Meanwhile, IPHD prefer waters near the natural coastline, while human activities such as sea reclamation would change the type of coastline and reduce the length of the natural coastline. Since the middle of the last century, the proportion of natural coastlines in China has continued to decline (Hou et al., 2016), which makes it more difficult for IPHD to find their preferred habitats and makes this sensitive species more vulnerable to extinction.

4.4 Conservation suggestions

Protected areas have been considered to be an effective in situ strategy for conserving biodiversity and ecosystem services. As a vulnerable species with great public concern, conservation attention has been given to IPHD, and seven natural reserves have been set up for this species (Indo-Pacific Humpback Dolphins Conservation Program (2017-2026)) in China. The adverse effects of climate change on the protected areas of other animals have been elucidated (D'Amen et al., 2011; Zhang et al., 2020b). The same situation will possibly occur in the protected areas for marine mammals such as IPHD. For instance, Hunt et al. (2020) used SDMs to predict the IPHD distribution in the marine reserve in Australia and evaluated the effect in the established reserve. The results showed that the projected decline of suitable ranges for IPHD will possibly diminish the efficacy of these existing nature reserves. The habitat changes induced by climate change may require adjustment of current reserves, and the results from this study can be used as references for adjusting the present natural reserves and establishing new reserves. Meanwhile, implementing biodiversity conservation plans and fishery management strategies in coastal waters will be beneficial for the protection of IPHD.

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Figure 1

Study area.

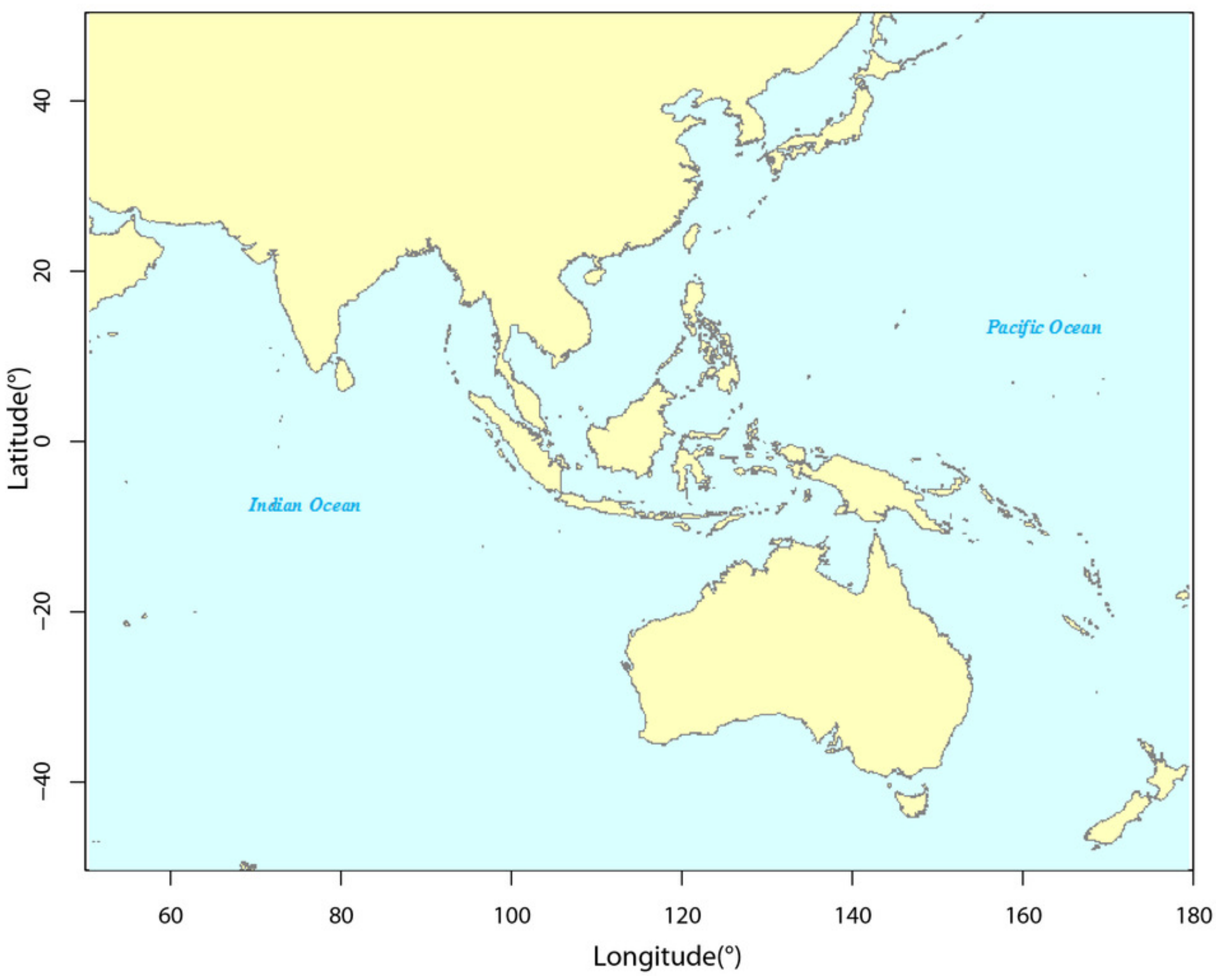


Figure 2

The six environmental variables selected for building species distribution models.

(A) mean temperature, (B) mean ocean depth, (C) distance to shore, (D) mean current velocity, (E) mean ice thickness, and (F) mean salinity.

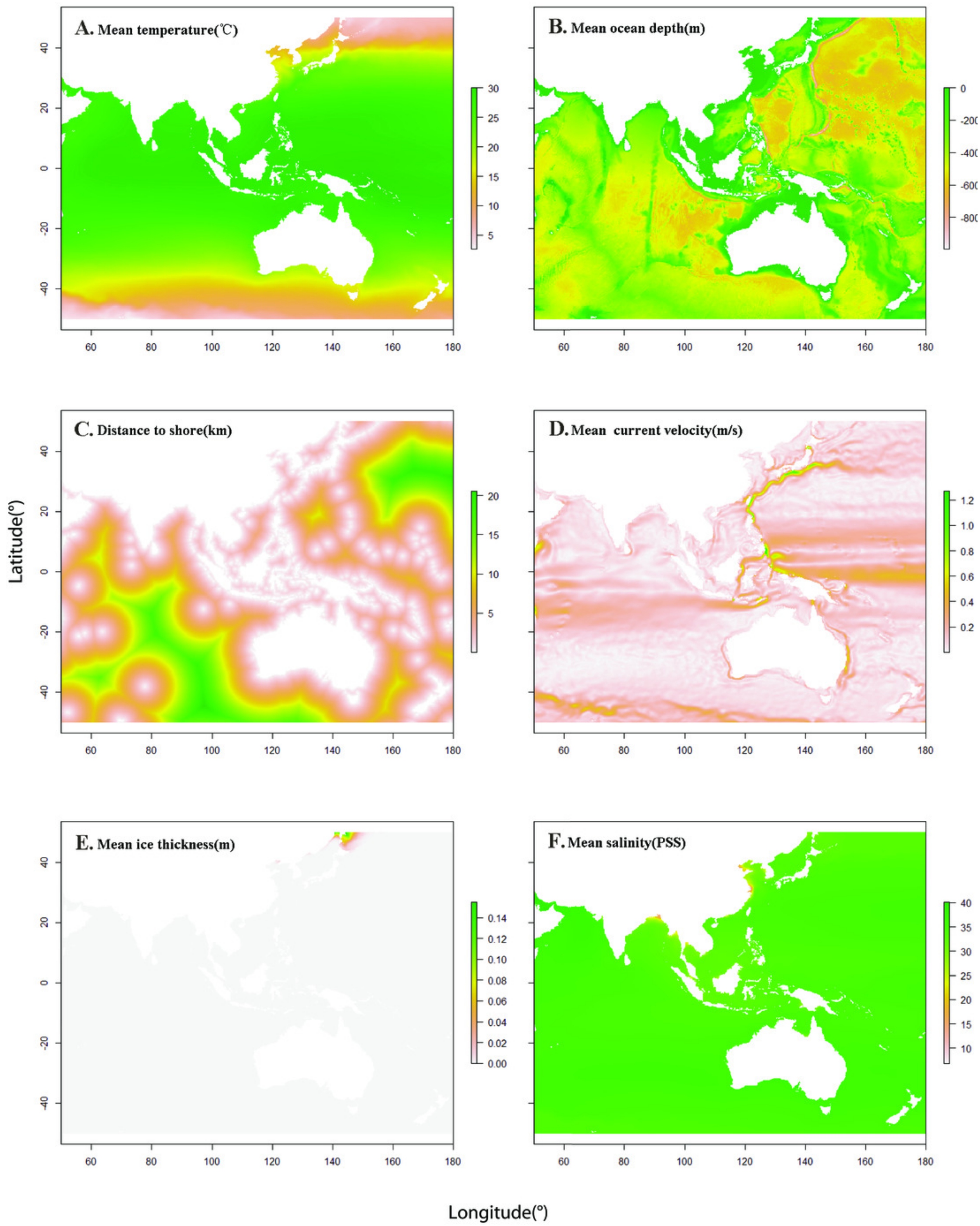

A. Mean temperature(℃)
B. Mean ocean depth(m)
C. Distance to shore(km)
D. Mean current velocity(m/s)
E. Mean ice thickness(m)
F. Mean salinity(PSS)
Latitude(°)
Longitude(°)

Figure 3

The area under the receiver operating characteristic curves (AUC) of 10 modeling algorithms that were used to estimate the habitat suitability of *Sousa chinensis*.

Dashed line represents the threshold for AUC (0.85) to build the ensemble model. Data are expressed as means ± standard error.

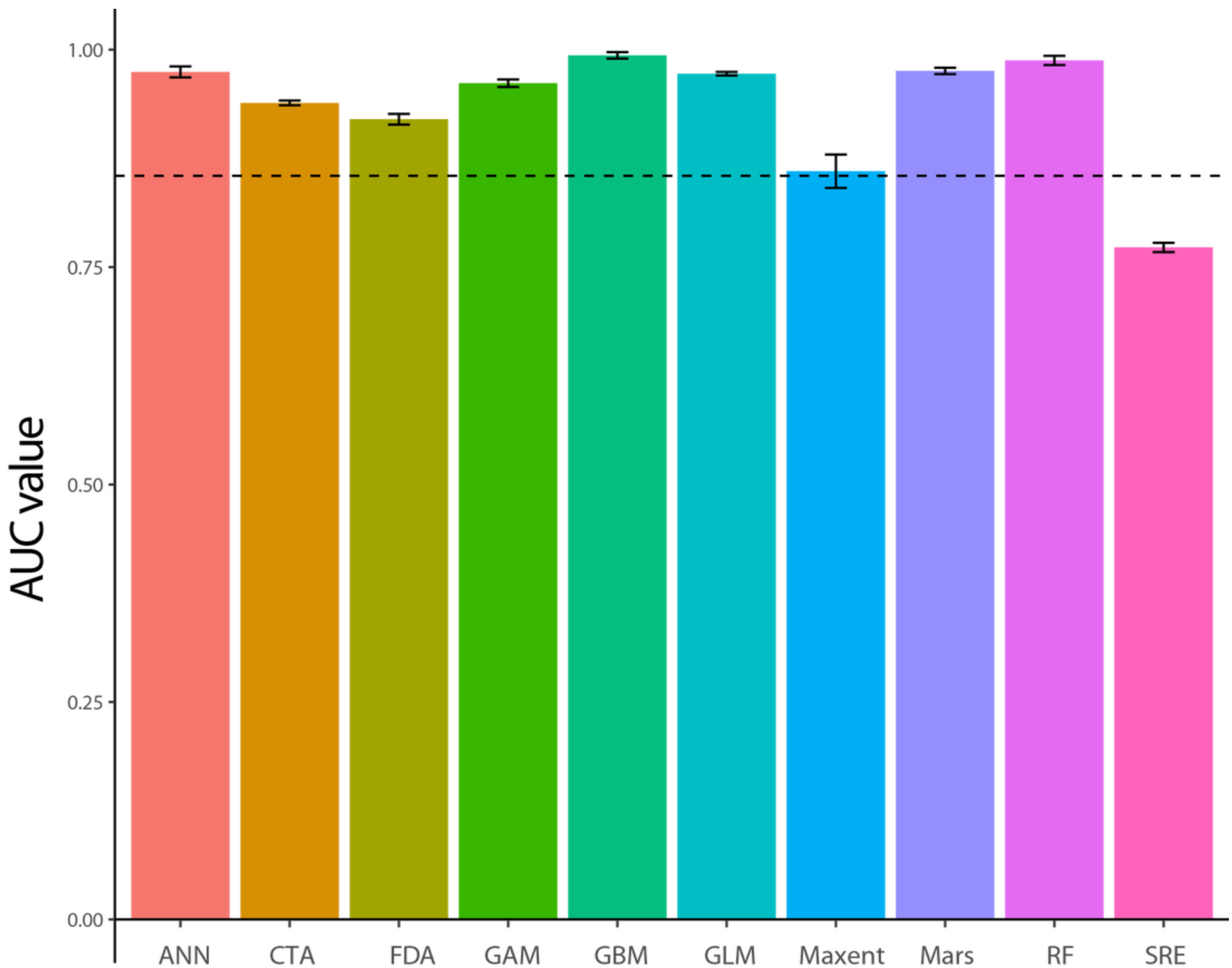


Figure 4

The true skill statistics (TSS) of 10 modeling algorithms that were used to estimate the habitat suitability of *Sousa chinensis*.

Dashed line represents the threshold for TSS (0.8) to build the ensemble model. Data are expressed as means ± standard error.

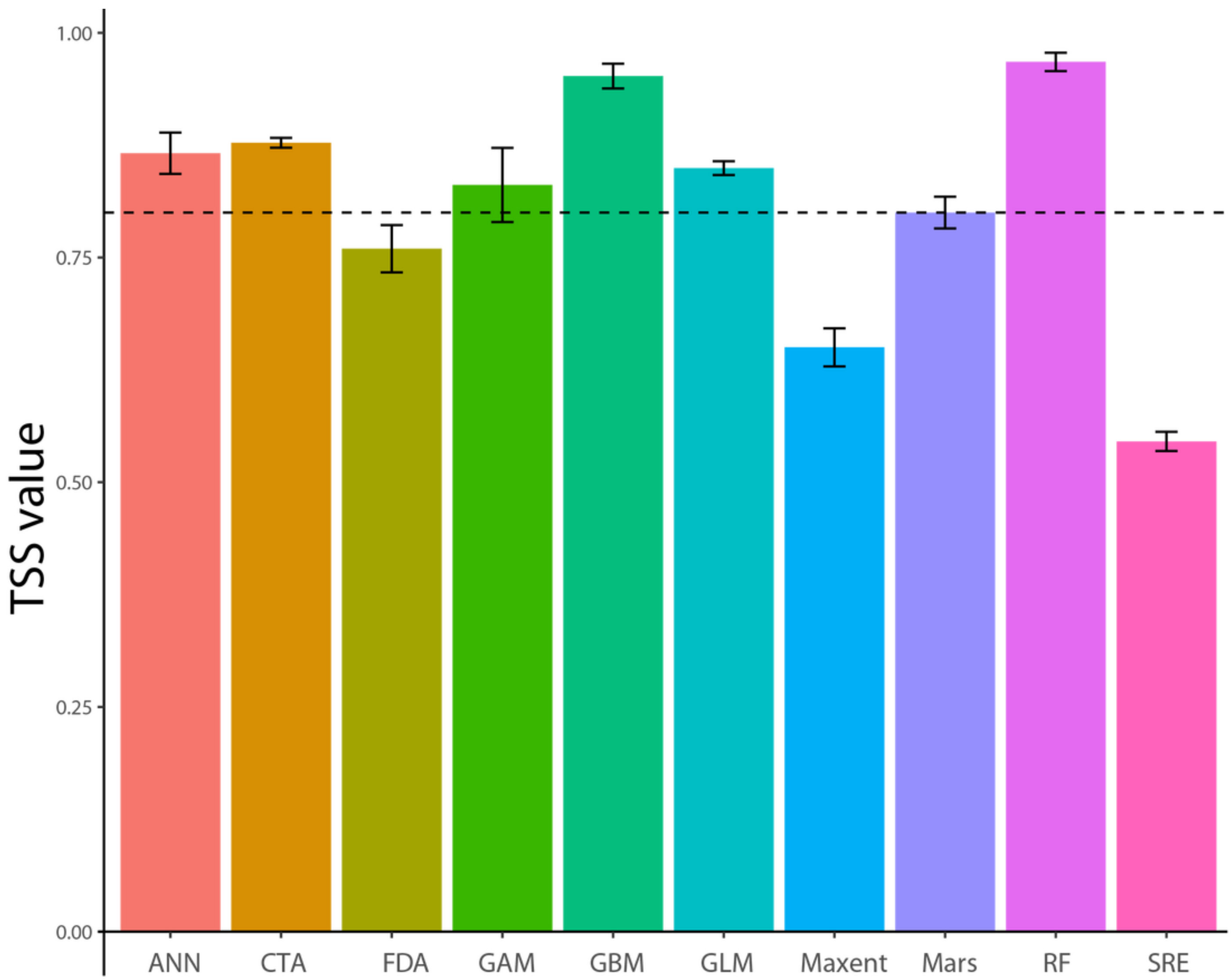


Figure 5

Variable importance of the six predictor variables from the 10 species distribution models for *Sousa chinensis*.

T: temperature, Depth: ocean depth, Dshore: distance to shore, CV: current velocity, Ice: ice thickness and Sal: salinity. Data are expressed as means ± standard error.

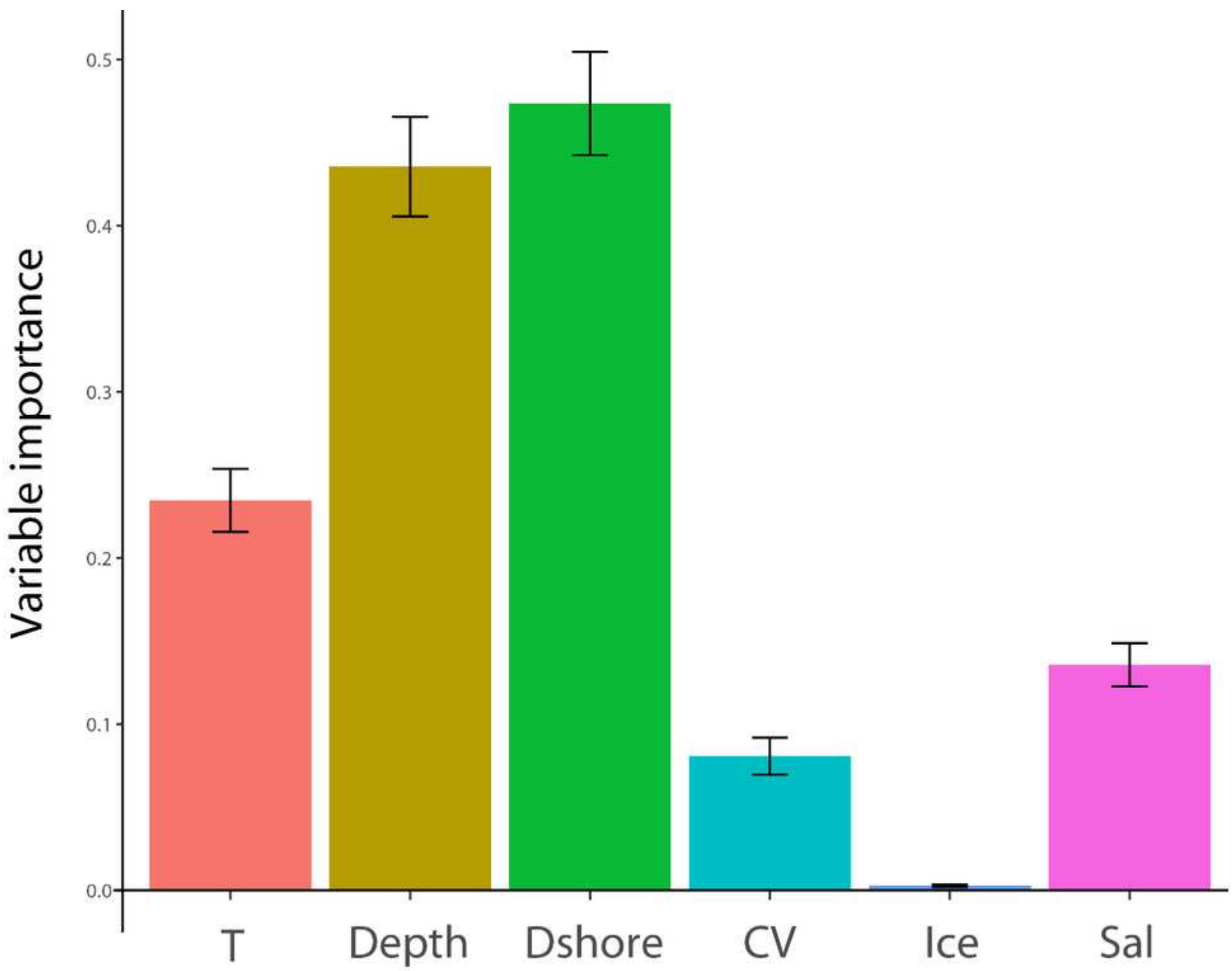
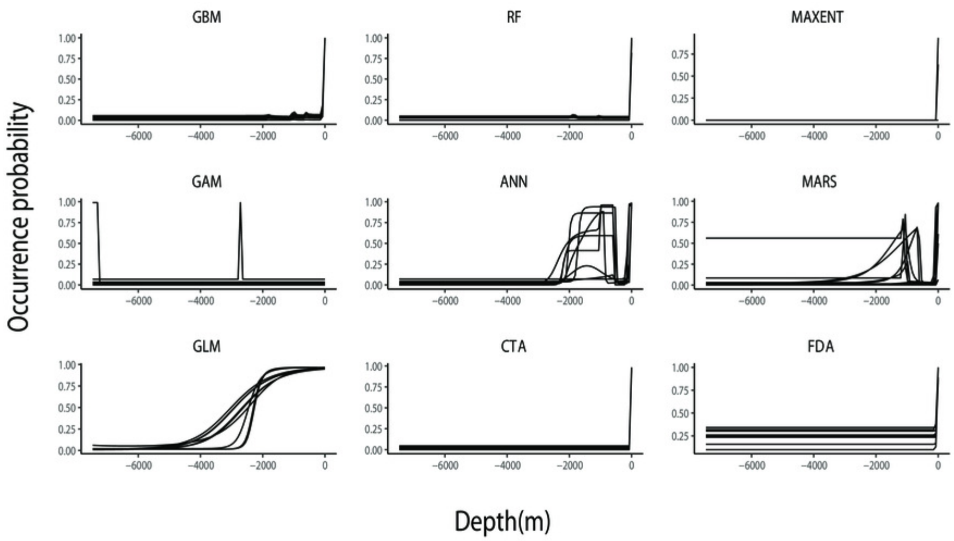
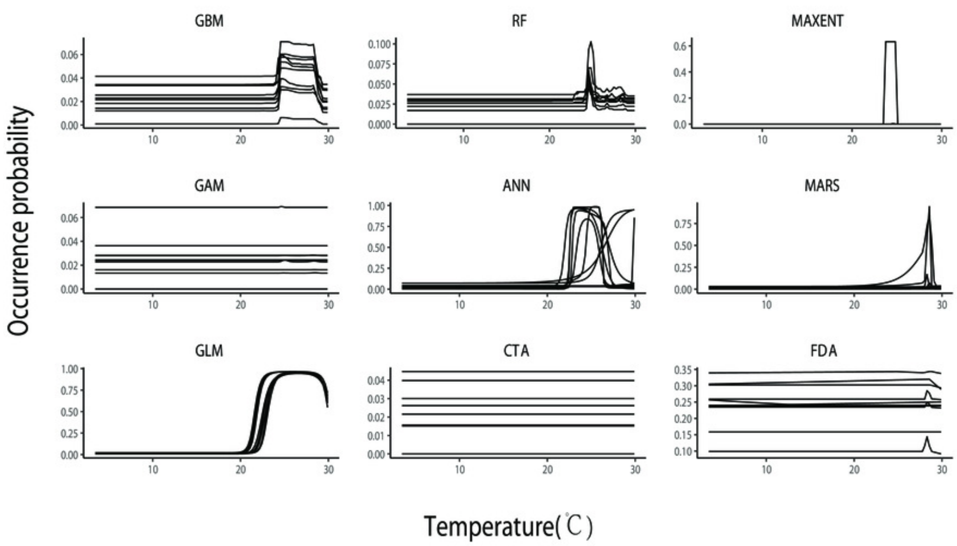


Figure 6

Sousa chinensis response curves for the nine spatial distribution modeling techniques against depth, temperature, and distance to shore.

(A) Response curves against depth, (B) Response curves against temperature, (C) Response curves against distance to shore.


GBM
RF
MAXENT
GAM
ANN
MARS
GLM
CTA
FDA
Occurrence probability
Depth(m)


GBM
RF
MAXENT
GAM
ANN
MARS
GLM
CTA
FDA
Occurrence probability
Temperature(℃)

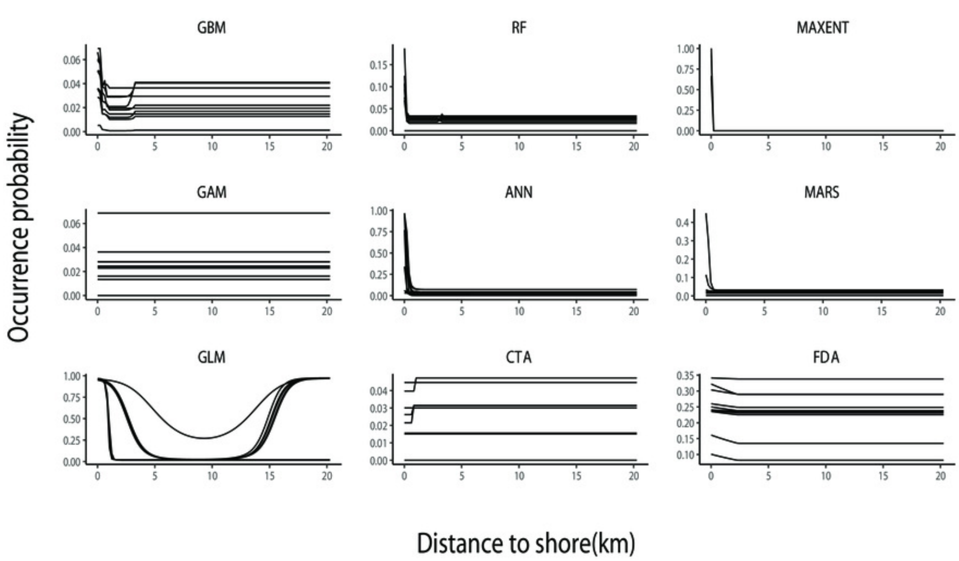

GBM
RF
MAXENT
GAM
ANN
MARS
GLM
CTA
FDA
Occurrence probability
Distance to shore(km)

Figure 7

Binary outputs of habitat suitability and predicted potential distribution under current climate conditions of Sousa chinensis.

(A) Binary outputs of habitat suitability under current climate conditions. (B) Predicted current potential distribution. Green colors indicate suitable areas, and gray colors represent unsuitable ranges on the left; the color gradient indicates variations in habitat suitability on the right (green = highest and pink = lowest); the red dots show the occurrence points that were used to develop the species distribution model.

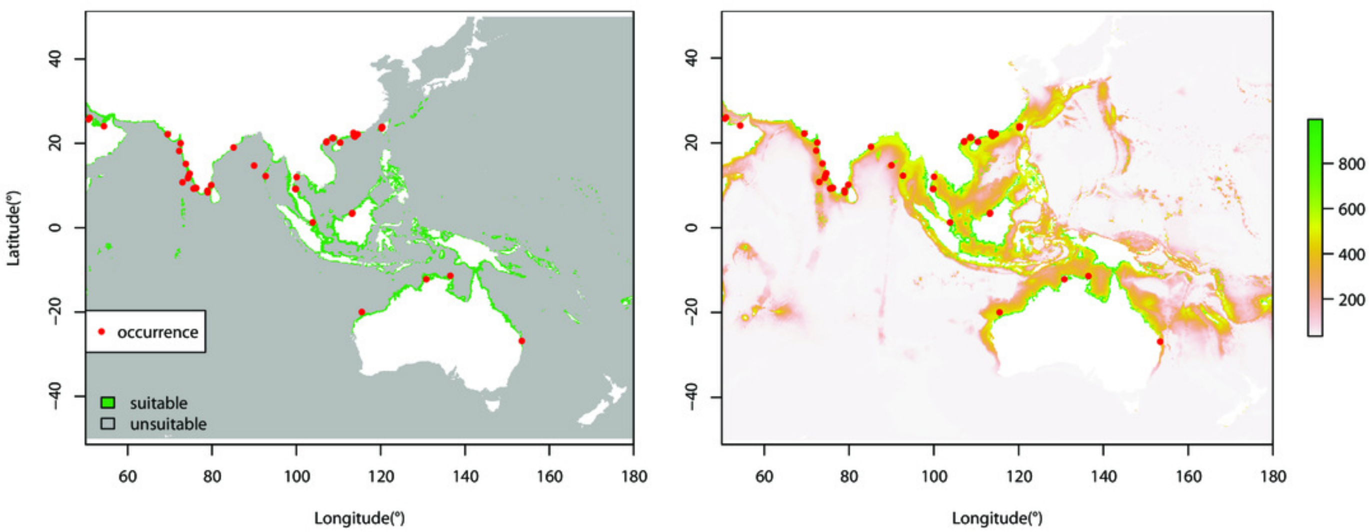


Figure 8

Range shifts in habitat suitability of Sousa chinensis as projected by the ensemble species distribution model between current and future climate conditions.

(A) under the RCP2.6 scenario in 2050, (B) under the RCP8.5 scenario in 2050, (C) under the RCP2.6 scenario in 2100, and (D) under the RCP8.5 scenario in 2100. Red indicates areas that will become suitable in the future, green areas are projected to be suitable under both present-day and future climates, and blue represents suitable areas that will become unsuitable in the future.

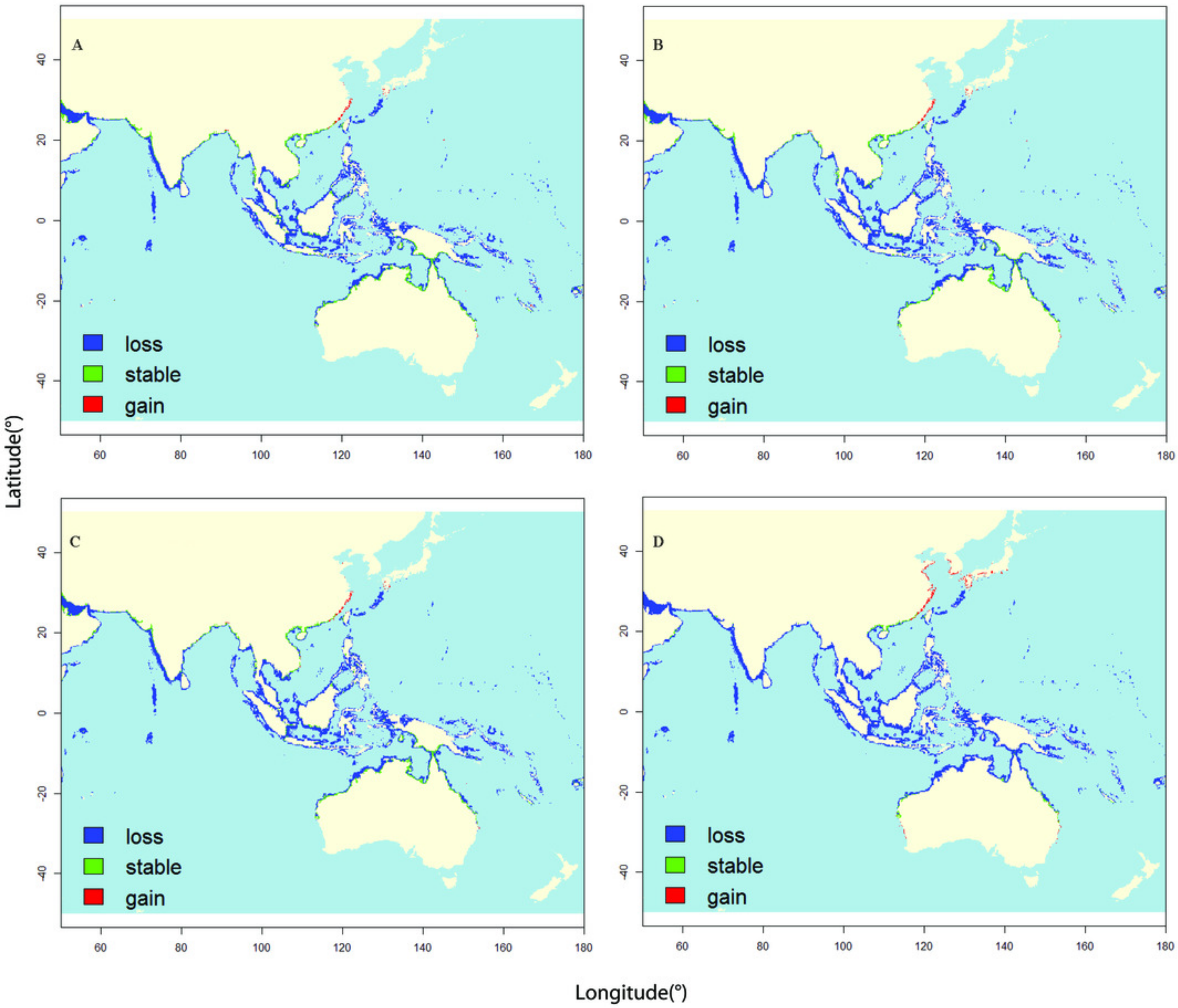

A
B
C
D
loss
stable
gain
Latitude(°)
Longitude(°)
40
20
0
-20
-40
60
80
100
120
140
160
180

Table 1(on next page)

Current environmental conditions and the averages and ranges of climatic changes for the future (e.g., 2050s and 2100s) under different scenarios in the study area.

T: temperature, Sal: salinity, CV: current velocity and Ice: ice thickness.

Environment Variable	Current value	Changes in 2050s				Changes in 2100s			
		RCP26	RCP45	RCP60	RCP85	RCP26	RCP45	RCP60	RCP85
T(°C)	22.72	0.72 (0.19,1.89)	0.96 (0.06,2.35)	0.77 (0.81,1.76)	1.10 (0.50,2.30)	0.63 (0.80,1.87)	1.21 (0.24,2.67)	1.68 (0.47,3.42)	2.87 (1.56,5.53)
Sal(PSS)	34.51	-0.061 (-0.12,0.09)	-0.07 (-0.70,0.45)	-0.07 (-0.91,0.23)	-0.07 (-0.88,0.33)	-0.09 (0.88,1.15)	-0.13 (-1.03,0.40)	-0.16 (-1.64,0.42)	-0.26 (-1.97,0.53)
CV(m/s)	0.10	0.00 (-0.06,0.09)	0.24 (-0.84,1.68)	0.25 (-0.84,1.66)	0.00 (-0.12,0.09)	0.24 (-0.85,1.68)	0.13 (-0.84,1.67)	0.13 (-0.84,1.67)	0.23 (-0.84,1.68)
Ice(m)	0.00	0.00 (-0.10,0.00)	0.00 (-0.12,0.00)	0.00 (-0.10,0.00)	0.00 (-0.13,0.00)	0.00 (-0.12,0.00)	0.00 (-0.17,0.00)	0.00 (-0.17,0.00)	0.00 (-0.17,0.00)

Table 2(on next page)

Range size changes (%) of *Sousa chinensis* under future climate scenarios.

RCP: representative concentration pathway. Range size changes were calculated as (suitable range under future climate scenarios – present-day suitable range)/present-day suitable range.

	RCP26	RCP45	RCP60	RCP85
2050s	-81.952	-87.725	-85.709	-85.77
2100s	-85.349	-89.144	-91.772	-94.104