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

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As IUCN critically vulnerable species, the Indo-Pacific humpback dolphins (*Sousa chinensis*) have attracted great public attention in recent years. The threats of human disturbance and environmental pollution to this population have been documented extensively. However, 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 82 occurrence records and six predictor variables (e.g., ocean depth, distance to shore, mean temperature, salinity, ice thickness, and current velocity). According to the TSS and AUC values, our ensemble model presented higher prediction precision than most of the single-algorithm models. It also indicated that ocean depth and distance to shore were the most important predictors in shaping the distribution patterns. The projections for the 2050s and 2100s from our ensemble model indicated a severe adverse impact of climate change on the *Sousa chinensis* habitat. Over 75% and 80% of the suitable habitat in the present day will be lost in all RCP scenarios in the 2050s and 2100s, respectively. 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 shift in the future, adaptive management strategies, including designing new reserves and adjusting the location and range of reserves according to the geographical distribution of *Sousa chinensis*, should be formulated to minimize the impacts of climate change on this species.

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27 **Abstract:** As IUCN critically vulnerable species, the Indo-Pacific humpback dolphins (*Sousa*

28 *chinensis*) have attracted great public attention in recent years. The threats of human disturbance

29 and environmental pollution to this population have been documented extensively. However,

30 research on the sensitivity of this species to climate change is lacking. To understand the effect

31 of climate change on the potential distribution of *Sousa chinensis*, we developed a weighted

32 ensemble model based on 82 occurrence records and six predictor variables (e.g., ocean depth,

33 distance to shore, mean temperature, salinity, ice thickness, and current velocity). According to

34 the TSS and AUC values, our ensemble model presented higher prediction precision than most

35 of the single-algorithm models. It also indicated that ocean depth and distance to shore were the

36 most important predictors in shaping the distribution patterns. The projections for the 2050s and

37 2100s from our ensemble model indicated a severe adverse impact of climate change on the

38 *Sousa chinensis* habitat. Over 75% and 80% of the suitable habitat in the present day will be lost

39 in all RCP scenarios in the 2050s and 2100s, respectively. With the increased numbers of records

40 of stranding and deaths of *Sousa chinensis* in recent years, strict management regulations and

41 conservation plans are urgent to safeguard the current suitable habitats. Due to habitat

42 contraction and poleward shift in the future, adaptive management strategies, including

43 designing new reserves and adjusting the location and range of reserves according to the

44 geographical distribution of *Sousa chinensis*, should be formulated to minimize the impacts of

45 climate change on this species.

46 **Keywords:** *Sousa chinensis*, Marine fauna, Greenhouse gas emissions, Climate impact, Future

47 projections

1. Introduction

48

49   As the most concerning environmental issue, global climate change has caused significant

50   changes in marine environmental conditions over the past decades (Belkin, 2009; Cheung et al.,

51   2013; Wu, 2020). For instance, the assessment that was made for the coastal China seas over the

52   21st century shows that the East China Sea (ECS) will be simultaneously exposed to enhanced

53   warming, deoxygenation, acidification, and decreasing net primary productivity (NPP) as a

54   consequence of increasing greenhouse gas emissions (Tan et al., 2020). A species lives on a

55   certain environmental niche space, so the change of the dependent environment conditions may

56   change the distribution of this species (Bellard et al., 2012; Faleiro et al., 2018). The distributions

57   of marine mammals have been impacted significantly by the environmental change over the past

58   decades (Nøttestad et al., 2015; Chen et al., 2020). According to these facts, understanding how

59   future climate change will influence species distributions is vital for the better protection of

60   species.

61   Species distribution models (SDMs) build species-environment relationships that are

62   typically based on species location data (e.g., abundance and occurrence) and environmental

63   variables that are thought to influence species distributions and can provide a useful framework

64   for identifying and evaluating the habitat suitability for a given species (Guisan & Thuiller,

65   2005). Currently, SDMs are applied broadly in the life and environmental science fields (Cheung

66   et al., 2009; Robinson et al., 2011). For example, multiple types of SDM are available to predict

67   the impacts of climate change on species distributions (Zhang et al., 2019), to assess how habitat

68   loss restricts large-scale species distribution (Vasconcelos & Doro, 2016), to understand

69   biological invasions (Zhang et al., 2020) and to site aquaculture farms (Dong et al., 2020).

70   Accordingly, the use of SDMs in conservation biology and biodiversity assessments is ever-

71   increasing (Pereira et al., 2018; Araújo et al., 2019; Zhang et al., 2020b).

72   Indo-Pacific humpback dolphins (*Sousa chinensis*), also known as "mermaids" and "water

73   pandas", belong to the porpoise family of cetaceans (Jefferson & Karczmarski, 2001). Due to

74   their preferred inshore and estuarine habitats, *Sousa chinensis* are typically found in the shallow,

75   coastal waters of the Indian and western Pacific oceans (Jefferson & Rosenbaum, 2014; Jefferson

76   & Smith, 2016; Parra & Jefferson, 2018). These areas, which have intensive commercial

77   fisheries, are usually rapidly developing and are easily polluted by industrial production and

78   daily activities of residents (Karczmarski, 2000; Chen et al., 2008; Wu & Chen, 2014;

79   Karczmarski et al., 2016; Guo et al., 2020; Li, 2020); the corresponding consequences of habitat

80   degradation may lead to population declines of *Sousa chinensis* or even put this species at risk of

81   extinction. In recent years, the numbers of records on strandings or deaths of *Sousa chinensis*

82   have increased in China (Chen et al., 2008; Guo et al., 2020). This species has already been

83   classified as "vulnerable" by the International Union for Conservation of Nature (Jefferson et al.,

84   2017). Consequently, formulating a conservation plan for *Sousa chinensis* is urgent under current

85   and future environmental scenarios. Predicting the geographical distribution for the present and

86   future is a prerequisite for plan formulation (Schickele et al., 2020).

87   In this study, we developed ten individual SDMs. We then built a weighted average

88   ensemble model, which has not been used to identify the potential distributions of *Sousa*

89   *chinensis* under present-day and future climate scenarios. Our ensemble model was expected to

90   present a better performance in predictive accuracy and uncertainty reduction than each

91   individual model. We hypothesize the suitable habitats of *Sousa chinensis* will contract and shift

92   poleward because of climate change in the future. Our ensemble model can help us to 1)

93   determine the important environmental variables that affect *Sousa chinensis* distributions, 2) map

94   the environmental suitability for *Sousa chinensis* under present-day and future climate scenarios,

95   and 3) assess the impacts of climate change on *Sousa chinensis* habitat distributions. Our study

96   can provide important implications for formulating adaptive management strategies, including

97   designing new reserves and adjusting the location and range of reserves according to the

98   geographical distribution of *Sousa chinensis* under current and future scenarios and an important

99   reference to solve marine conservation planning problems. It also provides guidance for research

100 on the potential distributions of other protected species under future climate change scenarios.

101 **2. Materials and methods**

102 2.1 Study area and *Sousa chinensis* data collection

103   Indo-Pacific humpback dolphins (*Sousa chinensis*) are mainly distributed in the Western

104 Pacific and the Indian Ocean, so our research is located in these areas (i.e., 50°E to 180°E, 50°S

105 to 50°N; Fig. 1). Georeferenced species data (presence) were obtained from the online database:

106 Global Biodiversity Information Facility (GBIF, https://www.gbif.org) and Ocean Biogeographic

107 Information System (OBIS, https://obis.org). The cluster samples in a 5 × 5 arc-minute grid

108 consistent with the spatial resolution of environmental data are removed; only one record per

109 grid unit is used to avoid over-representation of environmental conditions (sampling bias) in

110 densely sampled areas. A total of 124 incidents were retrieved, 82 of which were within our

111   study area.

112   2.2 Environmental variables and future projections

113   The raster data of environmental variable projections in this study were retrieved from the

114   Bio-ORACLE v2.1 dataset (http://www.bio-oracle.org) (Assis et al., 2018) and Global Marine

115   Environment Datasets (http://gmed.auckland.ac.nz) (Basher et al., 2014). The mean chlorophyll,

116   velocity, salinity, temperature, dissolved oxygen content, ice thickness, and pH data were

117   obtained from Bio-ORACLE. The distance to shore and mean ocean depth data were obtained

118   from GMED. In addition, the annual ranges of chlorophyll, flow rate, salinity, temperature,

119   dissolved oxygen, and ice thickness were also obtained from Bio-ORACLE. There were a total

120   of 15 environmental variables with a spatial resolution of 5×5 arc-minutes (i.e., 9.2*9.2 km at

121   the equator). Pearson correlation analysis was conducted for these 15 environmental variables to

122   reduce the influence of collinearity on the precision of model predictions. By comprehensive

123   consideration of the availability of current and future environmental data, six low-correlation

124   (pairwise Pearson's correlation coefficients were less than |0.7|) (Dormann et al., 2013)

125   environmental variables, including mean current velocity, mean salinity, mean temperature,

126   mean ice thickness, mean ocean depth and distance to shore, were finally selected for the

127   modeling analysis (Fig. S1).

128   Meanwhile, the projections of the first four environmental variables for the future (i.e.,

129   2040–2050 (the 2050s) and 2090–2100 (the 2100s)) under four representative concentration

130   pathway emission scenarios (RCPS) were also retrieved from the Bio ORACLE v2.1 dataset.

131   RCPs (i.e., RCP26, RCP45, RCP65, and RCP85) are new climate change scenarios on radiation

132 forcing at the end of the 20th century that were published in the fifth assessment report of the

133 Intergovernmental Panel on Climate Change (IPCC). RCP26 indicates an optimistic emission

134 level resulting in low greenhouse gas concentration; RCP45 and RCP60 represent the moderate

135 emission level; and RCP85 indicates an pessimistic emission level leading to the highest

136 greenhouse gas concentration (Moss et al., 2010). We assumed that distance to shore and ocean

137 depth remain constant in the future. Future temperature, salinity, ice thickness, and current

138 velocity) in Bio-ORACLE were predicted based on the mean simulation results of three

139 Atmosphere-Ocean General Circulation Models (AOGCMs), i.e., Community Climate System

140 Model (CCSM4, National Center for Atmospheric Research), Hadley Center Global

141 Environment Model, version 2 (HadGEM2-ES, Met Office Hadley Centre) and Model for

142 Interdisciplinary Research on Climate, version 5 (MIROC5, Atmosphere and Ocean Research

143 Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth

144 Science and Technology) from the Coupled Model Intercomparison Project 5 (CMIP 5) (Assis et

145 al., 2018; Sharma et al., 2021). We believed the mean results of three different AOGCMs can

146 reduce the uncertainties effectively. The changes in the four predictor variables in the future (i.e.,

147 the 2050s and the 2100s) under different scenarios are shown in Table 1.

148 2.3 Modeling procedures

149   We conducted the model analysis on the R platform based on the "biomod2" package, and

150 ten SDMs were available in this package (Thuiller et al., 2020). The ten models include the

151 generalized linear model (GLM) (McCullagh & Nelder, 1989), generalized additive model

152 (GAM) (Hastie & Tibshirani, 1990), classification tree analysis (CTA) (Breiman et al., 1984),

153 generalized enhanced regression model (GBM) (Ridgeway, 1999), artificial neural network

154 (ANN) (Lek & Guégan, 1999), surface range envelope (SRE) (Breiman, 2001a), flexible

155 discriminant analysis (FDA) (Hastie et al.,1994), multiple adaptive regression splines (MARS)

156 (Friedman, 1991), random forest (RF) (Breiman, 2001b), and maximum entropy model (Maxent)

157 (Phillips et al., 2006).

158   Due to the lack of true absence records, we simulated 5000 pseudo-absence points randomly

159 in contrasting environmental conditions with the true presence points (Guisan et al., 2017;

160 Thuiller et al., 2020). A fivefold cross-validation technique with 10 repetitions was used to

161 assess the model prediction accuracy (Guisan et al., 2017; Thuiller et al., 2020). Based on this

162 approach, 80% of the dataset was randomly selected for calibration and testing of the models,

163 and 20% was withheld for evaluation of the model predictions. Two indicators were used to

164 evaluate the predictive capability of each model: the true skill statistic (TSS) (Allouche et al.,

165 2006) and the area under the receiver operating characteristic curve (AUC) (Swets, 1988). To

166 ensure sufficient prediction accuracy, the models with mean TSS value above 0.80 and mean

167 AUC value above 0.85 were reserved for further analyses (Zhang et al., 2019).

168   According to the cutoff values of TSS and AUC, the retained individual SDMs were used to

169 build a weighted average ensemble model predicting the *Sousa chinensis* distributions under

170 present and future climate conditions based on the "biomod2" package (Zurell et al., 2020). For a

171 better interpretation of model outcomes, continuous habitat suitability projections were

172 converted into binary maps (e.g., suitable/unsuitable) by using an automatically generated

173 threshold that maximized the TSS value of the ensemble model (Liu et al., 2013; Guisan et al.,

174   2017; Zhang et al., 2020b).

175   The relative importance of each environmental variable in predicting the *Sousa chinensis*

176   distributions was determined by a randomized approach. This approach computes the Pearson

177   correlations among predictions using all predictor variables and predictions in which the

178   predictor variable being evaluated was randomly permutated (Guisan et al., 2017; Thuiller et al.,

179   2020). Low correlations between the standard predictions and those using the permuted variable

180   indicate the high importance of a predictor variable (Zhang et al., 2019). A response curve,

181   which describes the variations in species occurrence probability along the gradient of each

182   important predictor variable, was plotted.

183   **3. Result**

184   3.1 Model performances and predictive accuracy of SDMs

185   The different AUC and TSS values indicated the different predictive performances among

186   all 10 modeling algorithms. All the models except SRE, MAXENT and FDA exhibited good

187   predictive capacity and were selected to construct the ensemble model (Figs. S2 and S3). The

188   AUC and TSS values of all the individual models except GBM and RF were lower than those of

189   the ensemble model (AUC: 0.993, TSS: 0.963), which demonstrated the superior predictive

190   performance of the ensemble model.

191   3.2 Response curve and variable importance

192   The six predictor variables made different contributions to the *Sousa chinensis* distributions.

193   Among the six predictor variables, depth (0.435 ± 0.029) and distance to shore (0.473 ± 0.031)

194   were the two most important variables for the model predictions. The contributions of

195   temperature (0.234 ± 0.018), salinity (0.135 ± 0.013), and current velocity (0.080 ± 0.011) were

196   moderate, while ice thickness (0.003 ± 0.0007) was considered to be nearly irrelevant (Fig. S4).

197   The response curves of *Sousa chinensis* to the three most important variables from the ten

198   models (except SRE) are shown in Fig. S5. The response curves indicated that the environmental

199   requirements of *Sousa chinensis* in the different models were generally similar.

200   3.3 Potential distributions under present and future climate scenarios

201   Our prediction of suitable habitat for *Sousa chinensis* under present climate conditions is

202   shown in Fig. 1. All of the occurrence records were within the predicted suitable range. The

203   predictions show that a large part of the coastal areas of the Southeast Asian countries and

204   northern Australia are suitable habitats for *Sousa chinensis*. Some of the occurrence records were

205   located in the coastal areas of the Indian Peninsula.

206   As the model results show, the suitable area for *Sousa chinensis* will decrease under all four

207   assumed future climate change scenarios. Future habitat projections under different RCP

208   scenarios show different distribution patterns and consistently suitable range contraction for

209   *Sousa chinensis* (Table 2). The model projections indicate that the contraction of the suitable

210   range of this species could be from 75.626% (under the RCP2.6 scenario in the 2050s) to

211   95.815% (under the RCP8.5 scenario in the 2100s). Future predictions for the 2100s show that

212   environmental conditions suitable for *Sousa chinensis* will shift northward to the East China Sea

213   and south coast of Japan. The equatorial sea area and coastal area of northern Australia are

214   predicted to be less suitable for this species (Fig. 2).

215   **4. Discussion**

216   4.1 Model performance

217   Utilizing georeferenced presence/pseudo-absence data and the corresponding environmental

218   data, we developed an ensemble model for *Sousa chinensis* to predict the present and future

219   potential distributions of this rare species. The results demonstrate that our ensemble model

220   performed well in predicting the habitat suitability for *Sousa chinensis* under the present

221   environmental conditions. The model predictions indicated that the potential distribution of

222   *Sousa chinensis* will contract in the future under all the RCP scenarios and that the suitable

223   habitat in the Indo-Pacific Mid-Seas will shift to higher latitudes.

224   Many mature models can be used to predict species distributions. The most commonly used

225   method is to select the best model based on performance indicators such as TSS and AUC and

226   then use the single best model to predict species distributions. Due to the higher accuracy and

227   reliability compared to individual models, several published studies recommended using

228   ensemble model to predict potential species distribution and habitat suitability (Araújo & New,

229   2007; Thuiller et al., 2009; César & Pedro, 2011; Shabani et al., 2016). In this study, the

230   weighted ensemble model performed better than most of the individual models but was not the

231   best in predictive performance, and this finding was consistent with the previous study (Hao et

232   al., 2020). The ensemble model is built based on the weighted average of individual models, so

233   this model will present an advantage over individual models in reducing the uncertainties of

234   model results.

235   4.2 Climate change and associated distribution shift

236   The predicted suitable habitats of *Sousa chinensis* include their known distribution range as

237   expected (e.g., the coast of Malaysia). Suitable habitats were also found beyond where the

238   species have been recorded, and this phenomenon can be caused by many factors, such as biotic

239   interactions, dispersal limitation of species, niche size, and sampling bias (Pulliam, 2000;

240   Goldsmit et al., 2018). Published studies have reached similar conclusions in predicting species

241   distributions using SDM (Goldsmit et al., 2018; Zhang et al., 2020a). As shown in the binary

242   output of habitat prediction, the main *Sousa chinensis* habitat in China is located in the Pearl

243   River Estuary in Guangdong Province. The Pearl River Estuary is an intersection area of

244   brackish and freshwater that results in fertile water quality and high primary productivity. The

245   suitable temperatures and salinities, as well as the low pollution, high biodiversity, and

246   unexploited natural shorelines, all make this area a favorite for *Sousa chinensis*.

247   According to the projected layer of future climate that was produced from 3 distinct

248   AOGCMs provided by CMIP 5, we determined the changes in four available environmental

249   variables. As shown in Table 1, temperatures will increase with different amplitudes under

250   different RCPs. This tendency of global warming will severely affect *Sousa chinensis*

251   distributions in terms of range size, e.g., it will probably lead to a reduction of more than four-

252   fifths of its range in the 2100s. Meanwhile, the suitable *Sousa chinensis* habitat in the future will

253   shift northward. In China, the suitable habitat on the southern coast will shift to the east Yellow

254   Sea and even to the coastal areas of Bohai Bay. Tan et al. (2020) assessed the East China Sea

255   (ECS). They found that climate change caused by increasing greenhouse gas emissions will

256   induce considerable biological and ecological responses and cause the ECS to be among the

257   ocean areas that are most vulnerable to future climate change. For example, the rising sea

258   temperature and the change of dissolved oxygen content in the ECS affected the metabolic

259   process of marine organisms and brought significant changes in the abundance and geographical

260   distribution of marine life (Stenseth et al., 2002; Walther et al., 2002). On the other hand, the

261   habitat in areas around Australia will shift southward in the future. The areas off the coast of

262   Malaysia will no longer be suitable for *Sousa chinensis*. This trend toward higher latitudes is

263   similar to that described in the formal research (e.g., Ruiz-Navarro et al., 2016; Zhang et al.,

264   2019, 2020c). Regardless of the dispersal scenario, our results highlight the high vulnerability of

265   this critically vulnerable species to climate change.

266   4.3 Impact factors of *Sousa chinensis* distribution

267   Due to the intricate relationships among survival, growth and environmental conditions,

268   many factors may affect the habitat distributions of *Sousa chinensis*. The basic niche that is

269   suitable for the growth of *Sousa chinensis*, such as water temperature, water depth, and distance

270   from shore, was considered in this study. The distribution of *Sousa chinensis* is negatively

271   correlated with distance from shore and distance from the main estuary (Chen et al., 2020);

272   hence, estuaries have been identified as their preferred habitat (Jefferson & Karczmarski, 2001;

273   Wang et al., 2007; Chen et al., 2008; Jefferson & Smith, 2016). Environmental change induced

274   by climate change may also affect the distributions of bait fishes and will indirectly affect *Sousa*

275   *chinensis* distributions (Schickele et al., 2020).

276   Human activities have great impacts on *Sousa chinensis* habitats. The coastal areas of the

277   China Sea, with many estuaries, bays, coral reefs and fisheries, are not only suitable habitats for

278   *Sousa chinensis* but are also the most active areas for developing the maritime economy. Fishing

279   behavior and boat travel have been determined to cause stranding deaths of *Sousa chinensis* (Guo

280   et al. 2020). *Sousa chinensis* proved to be more acoustically active and prefer locations with

281   lower noise levels (Caruso et al., 2020a; Caruso et al., 2020b). However, human activities often

282   generate underwater noise, which interferes with information exchange with conspecifics and

283   interaction with the surrounding environment and can even lead to behavioral disorders (Xu et

284   al., 2020). Meanwhile, *Sousa chinensis* prefer waters near the natural coastline, while human

285   activities such as sea reclamation would change the type of coastline and reduce the length of the

286   natural coastline. Since the middle of the last century, the proportion of natural coastlines in

287   China has continued to decline (Hou et al., 2016), which makes it more difficult for *Sousa*

288   *chinensis* to find their preferred habitats and makes this sensitive species more vulnerable to

289   extinction.

290   4.4 Conservation suggestions

291   Our results indicated that over 75% and 80% of the suitable habitat for *Sousa chinensis* in

292   the present-day would be lost in all RCP scenarios in the 2050s and 2100s, respectively. The

293   results may be inflated by the high over prediction of the models due to the few environmental

294   variables used and not accounting for the biotic variables influencing *Sousa chinensis*

295   distribution. Meanwhile, areas, where the species have never been observed in the current

296   climate conditions and were lost in the future climate scenarios may also inflate the results.

297   However, the change of marine environment induced by climate change will undoubtedly cause

298   habitat reduction and poleward in the future. Therefore, adaptive management strategies are

299   important for minimizing the impact of climate change on this vulnerable species.

300   Protected areas have been considered to be effective in situ strategy for conserving

301   biodiversity and ecosystem services (Wang & Li, 2021). As a vulnerable species with great

302   public concern, conservation attention has been given to *Sousa chinensis*. Seven natural reserves

303   have been set up for this species (Indo-Pacific Humpback Dolphins Conservation Program

304   (2017-2026)) in China. The adverse effects of climate change on the protected areas of many

305   amphibian species and Chinese giant salamander (*Andrias davidianus*) have been elucidated

306   (e.g., D'Amen et al., 2011; Zhang et al., 2020b). The same situation will possibly occur in the

307   protected areas for marine mammals such as *Sousa chinensis*. For instance, Hunt et al. (2020)

308   used SDMs to predict the *Sousa chinensis* distribution in the marine reserve in Australia and

309   evaluated that the effect in the established reserve will be reduced. Based on the present

310   prediction of *Sousa chinensis* distribution in this study, we suggest establishing new reserves and

311   limiting human and industrial activities in the important habitats in the short term. Based on the

312   predicted distribution for future, we suggest formulating adaptive management strategies,

313   including restoring the damaged habitats, adjusting the reserve range and location according to

314   the change of distribution, and pre-establishing conservation areas in the long term. For example,

315   the coastal areas of the East Yellow Sea in China should be protected to prepare for the possible

316   poleward shift of *Sousa chinensis* distribution.

317   **5. Conclusion**

318   In this study, we developed a weighted average ensemble model based on 82 occurrence

319   records and six predictor variables to predicted the potential distribution of *Sousa chinensis*

320   under current and future climate scenarios. Our results indicated that over 75% and 80% of the

321   suitable habitats in the present-day would be lost in all RCP scenarios in the 2050s and 2100s,

322   respectively. The contraction and shift poleward of suitable habitats in the future imply that

323   adaptive management strategies are important for minimizing the impact of climate change on

324   *Sousa chinensis*. The results from our study can be used as references to formulate specific

325   protection plans, such as designing new reserves and adjusting the current reserves.

326   **Acknowledgments**

327   We thank Global Biodiversity Information Facility (GBIF, https://www.gbif.org), Ocean

328   Biogeographic Information System (OBIS, https://obis.org), Bio-ORACLE v2.1 dataset

329   (http://www.bio-oracle.org) and Global Marine Environment Datasets

330   (http://gmed.auckland.ac.nz) for providing the data to us.

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Figure 1

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

(A) Binary output 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 purple dots show the occurrence points that were used to develop the species distribution model.

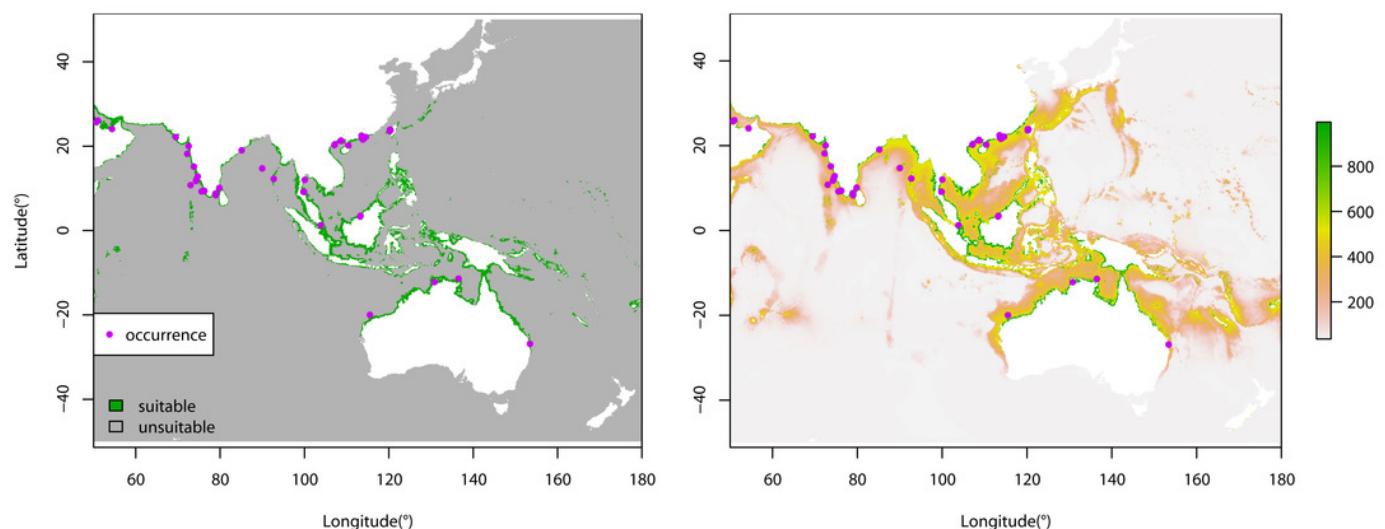
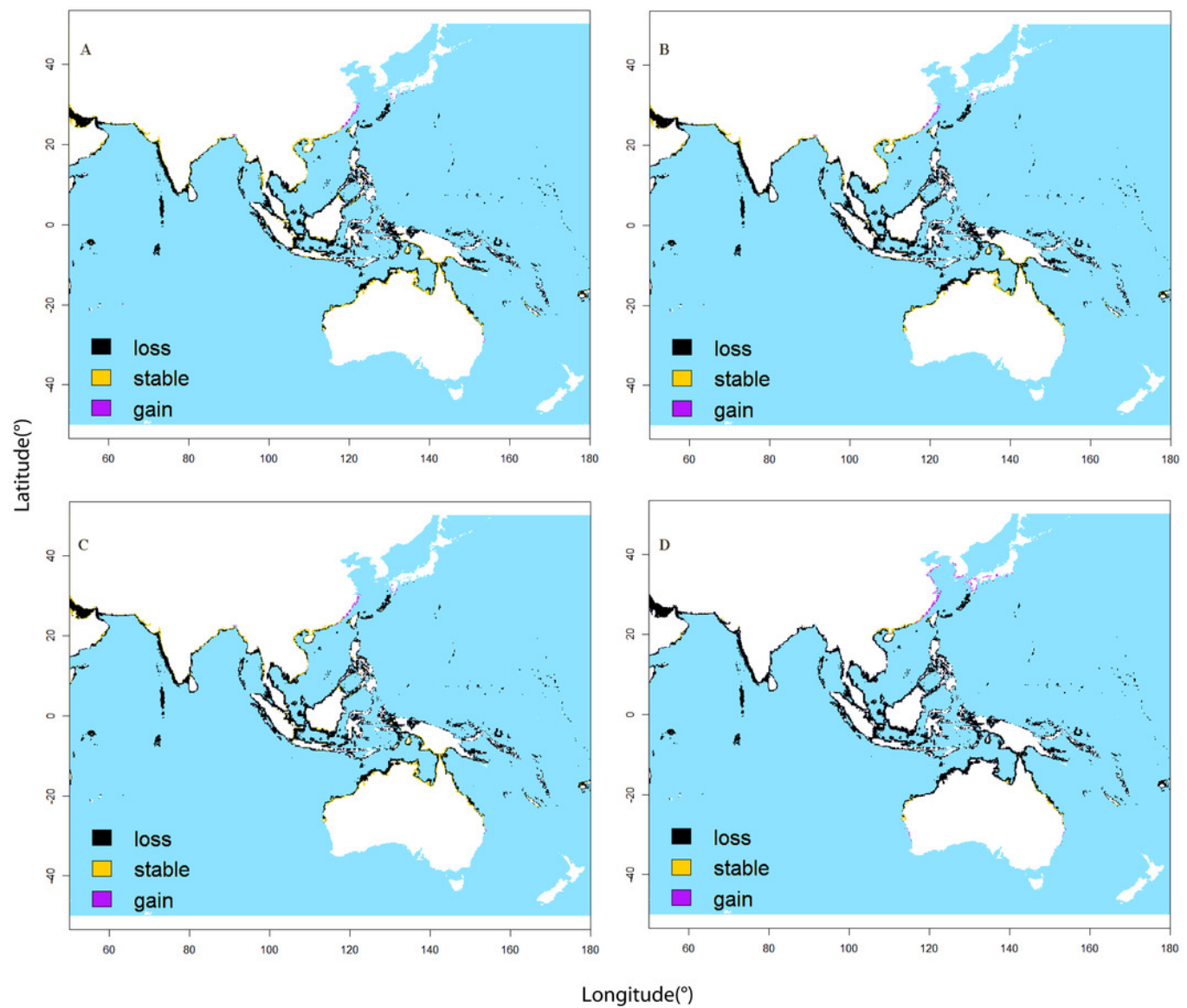



Figure 2

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

(A) under the RCP2.6 scenario in the 2050s, (B) under the RCP8.5 scenario in the 2050s, (C)under the RCP2.6 scenario in the 2100s, and (D) under the RCP8.5 scenario in the 2100s. Purple indicates areas that will become suitable in the future, dark yellow areas are projected to besuitable under both present-day and future climates, and black represents suitable areas that will become unsuitable in the future.

Current environmental conditions and the averages and ranges of climatic changes for the future (i.e., the 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(℃)	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)

Variation of distribution range (%) of *Sousa chinensis* under future climate scenarios.

RCP: representative concentration pathway; PercLoss: percentage of loss; PercGain: percentage of gain; PerStable: percentage of stability. Species range changes were calculated as (suitable range under future climate scenarios – present-day suitable range)/present-day suitable range.

	2050s				2100s			
	RCP26	RCP45	RCP60	RCP85	RCP26	RCP45	RCP60	RCP85
PercLoss	75.626	84.197	81.133	81.493	80.566	86.451	90.72	95.815
PercGain	3.995	3.507	3.595	3.86	3.595	3.562	3.653	5.083
PercStable	24.374	15.803	18.867	18.507	19.434	13.549	9.28	4.185
SpeciesRangeChange	-71.631	-80.69	-77.538	-77.633	-76.971	-82.889	-87.067	-90.732