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ORIGINAL ARTICLE

Habitat suitability projections for the Black Pomfret (*Parastromateus niger*) under climate change: an ensemble modeling approach

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Abstract
Marine ecosystems are under serious threat from climate change, which can alter species distributions, biodiversity patterns, community structure, and ecosystem functioning by affecting temperature, acidification, and current patterns. Species distribution models (SDMs) are a useful tool for ecologists to link species' fundamental niches with environmental conditions and project potential distribution shifts under climate change scenarios. This study modeled current and future habitat suitability for the black pomfret (*Parastromateus niger*) using an ensemble SDM with 1,396 occurrence records and environmental data layers (depth, temperature, salinity, currents). Six algorithms (MAXENT, GAM, GLM, RF, ANN, MARS) with ensemble approach modeled species distribution under current and future semi-optimistic (RCP 4.5) and pessimistic (RCP 8.5) scenarios for both 2050s and 2100s. Models were evaluated by AUC, TSS and Cohen's Kappa indices. According to the results, future range changes under all optimistic and pessimistic scenarios were negative. These results reveal prospective climate change impacts on the geographic range of *P. niger*, providing a valuable basis for science-based adaptation initiatives aimed at ensuring long-term sustainability of populations. Localized conservation and global mitigation policies are urgently needed to sustain *P. niger* and reliant human communities into the future. Habitat modeling supports climate-resilient management strategies for threatened marine species.

Keywords: Aquatic biodiversity, Species distribution Modeling, Climate change, Range change, Conservation.

INTRODUCTION

Marine biodiversity is under increasing threat from climate change, which can alter the distribution of species by affecting ocean temperature, oxygen, acidity, and currents (Doney et al. 2012; Gattuso et al. 2015). This has significant implications for fish populations that are commercially exploited and provide food and income for millions of people worldwide (FAO 2018). However, the impact of climate change on the distribution of individual species is poorly understood for many ecosystems (Mostafavi et al. 2021).

One of the most climate-sensitive regions is the Persian Gulf and Oman Sea, which have unique oceanographic and ecological features (Sheppard et al. 2010). The black pomfret (*Parastromateus niger*) is a key reef fish in this region, both ecologically and economically, as it supports the livelihoods and food security of local fishers (Al-Abdulrazzak et al. 2015). Yet, the effect of climate change on the distribution of *P. niger* has not been investigated before. Therefore, it is essential to model how this species might respond to climate change, given its importance for the region and the high climate exposure of the Persian Gulf.

This research aims to fill this knowledge gap by using predictive modeling to assess the impact of climate change on *P. niger*. The results will inform adaptation strategies to maintain *P. niger* populations and their benefits for the region. We used species distribution modeling (SDM) to link species occurrence records with environmental data and project potential range shifts under climate change scenarios (Elith & Leathwick 2009; Makki et al. 2023 a, b). In fact, understanding how species will adapt to climate change and how they will be distributed in future climate change scenarios is crucial for effective biodiversity management and conservation (Hosseini et al. 2024 a, b). Therefore, our objectives were to 1) Predict the distribution of *P. niger* under the current climatic and environmental conditions. 2) Estimate the currently suitable distribution areas of the mentioned species within Iran. 3) Forecast the potential distribution variations under proposed future climate change scenarios.

MATERIAL AND METHODS

Species occurrence data: To understand the distribution of *Parastromateus niger* across various locations, occurrence data was collected from several sources. The Global

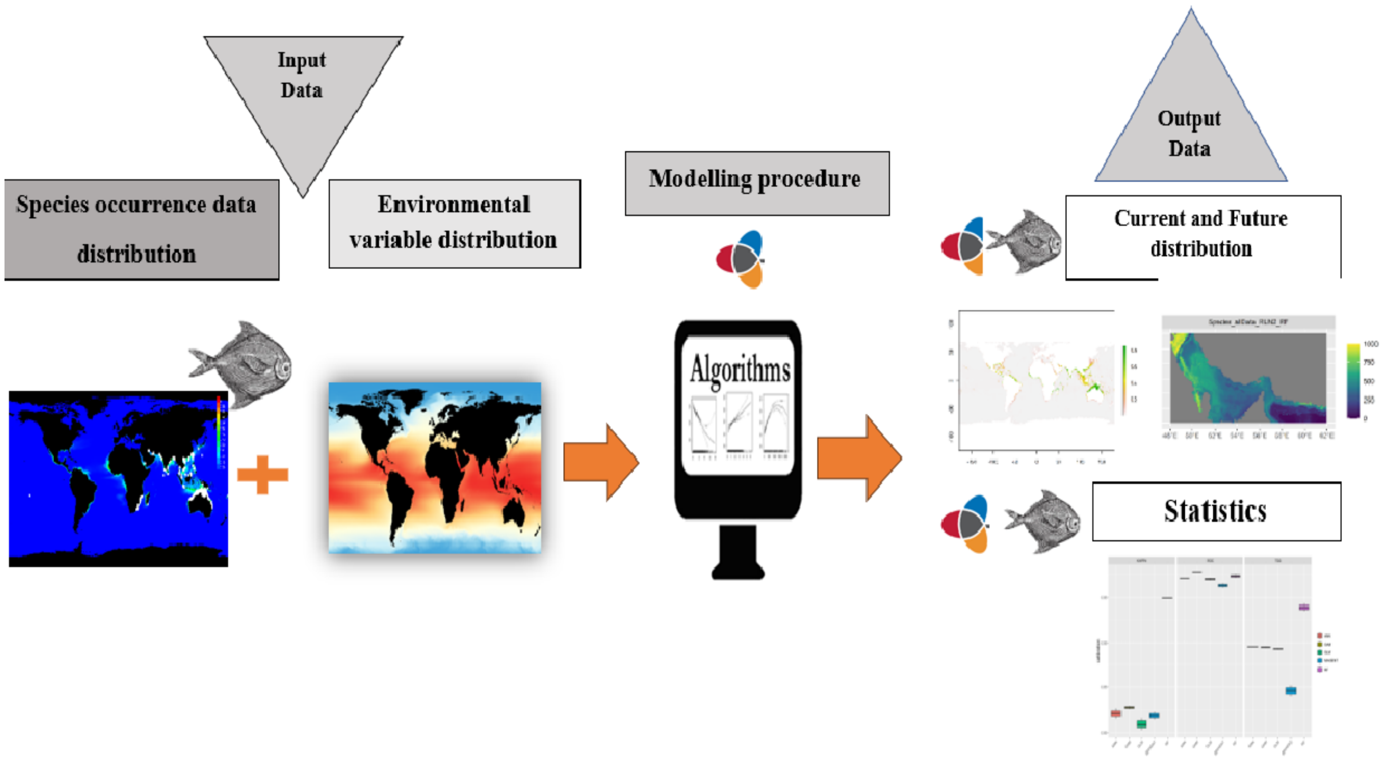

Fig.1. Schematic diagram of study process.

Biodiversity Information Facility (GBIF) and Ocean Biogeographic Information System (OBIS) online databases furnished the majority of records, providing 78.1% and 14.47% of the total data, respectively. These records were accessed via the "rgbif" and "robis" of R packages (Chamberlain et al. 2022; Provoost & Bosch 2022). An additional 4.89% of occurrence points were obtained through meticulous review of published scientific literature reporting geo-referenced *P. niger* observations. To enrich the dataset, field data collected from Moshta and fishing sites along the Persian Gulf coastline (November 2022-August 2023) following proper informed consent procedures, contributed 2.5%. All records underwent thorough quality control for accuracy, removing duplicates, and excluding errors like missing data or land-based points. This resulted in a final, reliable dataset of 1396 *P. niger* occurrence records for further analysis.

Environmental Predictors/Variables: The selection of ecologically relevant Environmental variables for modeling the current and future environmental suitability of *P. niger* was guided by two key factors: data availability and established biological knowledge. Four variables were chosen: sea surface temperature (°C), salinity (PSS), current velocity (m/s), and depth (m). These variables have documented influences on marine species distributions and possess compatible data availability within the study area.

Data Source and Resolution: Environmental layers for all four variables were retrieved at a high spatial resolution of 5 arc-minutes from Bio-ORACLE, a comprehensive global dataset extensively used for species distribution modeling (Tyberghein et al. 2012; Assis et al. 2018). This choice ensures robust representation of environmental conditions across the study area, essential for accurate model development.

Future Scenarios: To elucidate potential climate change impacts on *P. niger* distribution, future environmental conditions were modeled using two contrasting Representative Concentration Pathway (RCP) emission scenarios: RCP4.5 (intermediate greenhouse gas concentration) and RCP8.5 (higher concentration). These scenarios represent divergent pathways for future greenhouse gas emissions, enabling exploration of a range of potential climate futures and their subsequent effects on species distribution. Furthermore, two time periods were considered for each scenario: the 2050s (2040-2050 average) and the 2100s (2090-2100 average). This temporal scope allows for evaluation of both medium-term and long-term climate change impacts.

Modeling Procedure: Figure 1 presents a schematic overview of the study design and its key components. Six

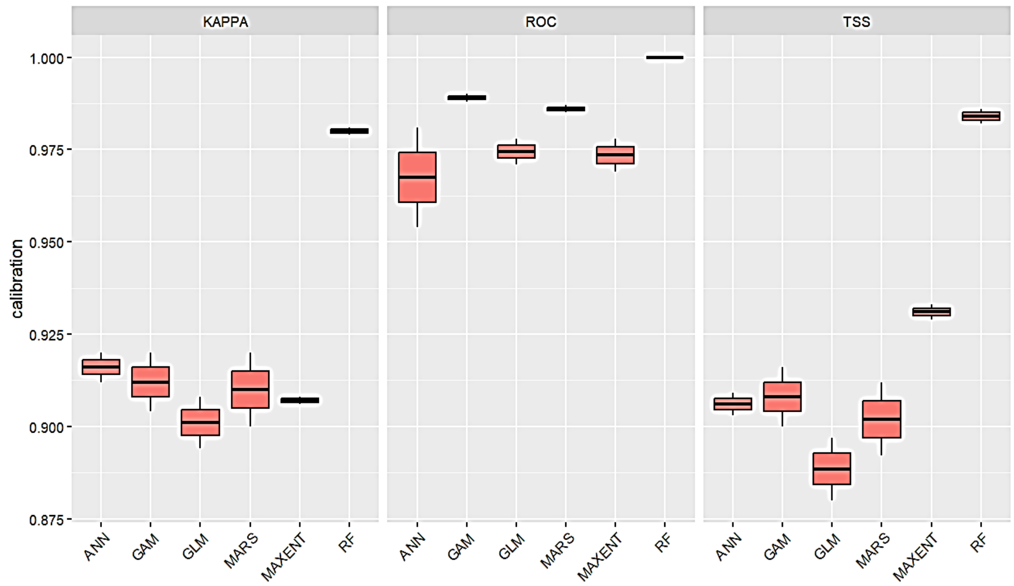

Fig.2. Distributions of overall accuracy of different individual SDM. Box plots showing the estimated median (horizontal lines). The true skill statistics (TSS) the receiver operating characteristic curve (AUC) and the Cohen's kappa values of five modelling algorithms used in this study

individual Species Distribution Models (SDMs) available in the biomod2 package were employed in R 4.1.3 (Thuiller et al. 2016) to model and map the current and future distribution of *P. niger*. These models included: Artificial Neural Network (ANN),Generalized Additive Models (GAM),Generalized Linear Models (GLM),Maximum Entropy (MaxEnt),Random Forest (RF),Multivariate Adaptive Regression Splines (MARS).Following established practices (Elith & Leathwick 2009; Elith & Graham 2009; Thuiller et al. 2014; Guisan et al. 2017; Makki et al. 2022), 10,000 pseudo-absence records were randomly generated within the study area, as certain techniques require environmental conditions contrasting with species occurrence locations. Modeling algorithms were executed using the default settings of the biomod2 package.

Model Evaluation: The predictive performance of each SDM was assessed using a five-fold cross-validation approach with 10 repetitions (Tabasinezhad et al. 2023). This involved randomly splitting the occurrence dataset into five groups with equal numbers of records, using four groups for training and the remaining group for testing predictions (Thuiller et al. 2014; Guisan et al. 2017; Mostafavi et al. 2018; Makki et al. 2022). Additionally, the occurrence dataset was partitioned into training (70%) and testing (30%) subsets for further cross-validation with 10-fold repetitions, facilitating a comprehensive assessment of overall model accuracy (Fielding & Bell 1997; Mostafavi et al. 2018; Makki et al. 2022). Three commonly employed indices were used to quantify model performance: Area Under the Receiver Operating Characteristic Curve (AUC; Hanley & McNeil 1982), True Skill Statistic (TSS; Allouche et al. 2006) and Cohen's Kappa (Kappa; Cohen 1960).

Ensemble Modeling: In order to reduce the uncertainty of modeling, an ensemble modeling framework was incorporated due to its proven ability to enhance predictive performance compared to individual models (Araújo & New 2007; Mostafavi et al. 2014; Mostafavi et al. 2018). Adhering to best practices outlined in the literature (Barbet-Massin et al. 2012), individual SDMs exceeding performance thresholds of AUC ≥ 0.7, TSS ≥ 0.5, and Kappa ≥ 0.4 were included in the ensemble. This ensemble approach was then utilized to model and map the potential distribution of *P. niger*.

RESULTS AND DISCUSSION

Model Performance: The employed ensemble modeling framework yielded robust and reliable predictions with high inter-model consistency. True Skill Statistic (TSS), Area Under the Receiver Operating Characteristic Curve (AUC), and Cohen's Kappa values indicated strong predictive accuracy across all models (Fig. 2). Notably, Random Forest (RF) achieved the highest overall accuracy (TSS = 0.984, AUC = 1, Kappa = 0.98), demonstrating its exceptional suitability for this application. Other models, including Generalized Linear Models (GLM), Generalized Additive Models (GAM), Artificial Neural Networks

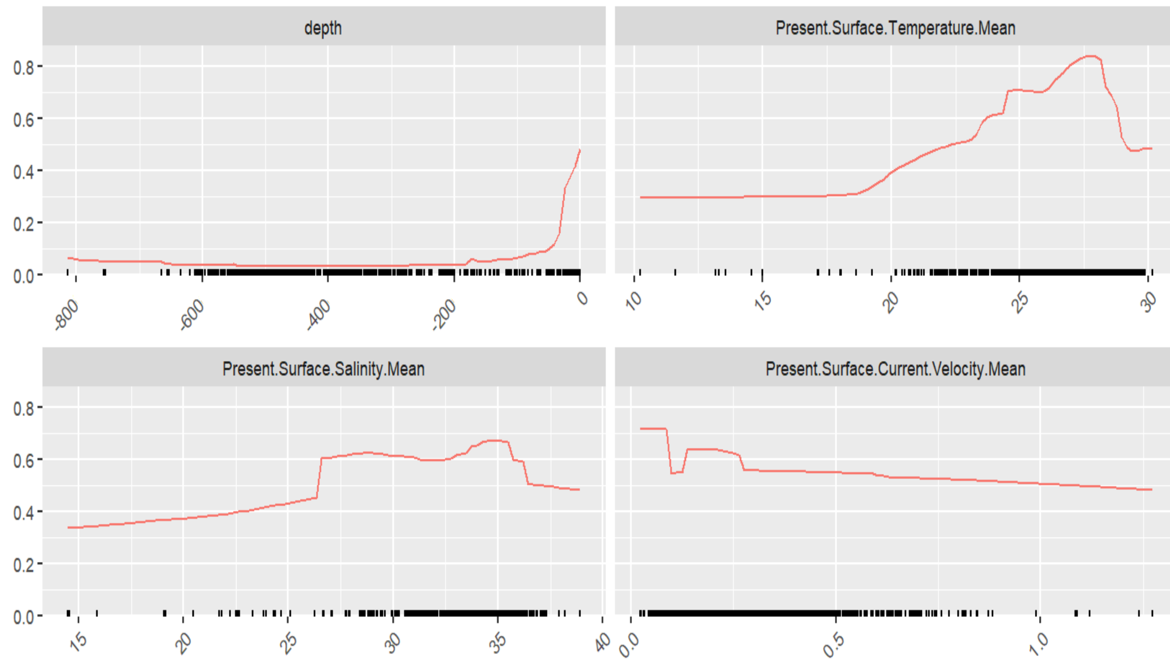

Fig.3. response curves indicating the relationship between environmental variables and the probability of predicted occurrence for black pomfret. Four environmental variables include Depth, sea surface temperature, salinity and currents velocity.

(ANN), MAXENT, and Multivariate Adaptive Regression Splines (MARS), also exhibited commendable performance (TSS > 0.9, AUC > 0.97, Kappa > 0.9). The final ensemble model further affirmed this reliability, achieving a high TSS score (0.923) and Kappa value (0.913), along with an excellent ROC value (0.994) indicating superior model fit. These results align with similar ensemble applications in previous studies (Zhang et al. 2019; Baer & Maron 2020; Chen et al. 2021; Yunlong et al. 2021), solidifying the ensemble approach as a reliable method for species distribution and abundance prediction.

Importance Analysis of Environmental Variables: Among the four examined environmental predictors, depth and temperature emerged as the dominant factors influencing the model projections, collectively contributing over 90% of the mean algorithmic influence. Depth held the strongest sway, accounting for a mean contribution of 0.89±0.06, followed by temperature with a significant but lesser influence (mean contribution 0.06±0.04). Salinity and current velocity exerted minimal impacts, each contributing less than 0.03 on average. Response curves (Figure 3) provide further insights into these environmental preferences. The depth curve reveals a preference for shallow neritic habitats, evidenced by the rapid decline in occurrence probability below 81 meters. Similarly, the temperature response curve indicates an optimal thermal range centered around 30°C, with high suitability between 25-35°C. The salinity curve demonstrates a peak preference at approximately 35 psu, while tolerating a broad range from 30-40 psu. These findings align with previous studies, highlighting the critical roles of depth and temperature in shaping the distribution of black pomfret (Basher & Costello 2016; Saeedi et al. 2017; Sharifian et al. 2023, 2021a, 2021b; Zhang et al. 2019). Likewise, temperature has been identified as a key driver for distribution changes in various marine species, including sea squirts (Park et al., 2020), octopuses (Ángeles-González et al. 2021), Japanese whiting (Zhang et al. 2019), black rockfish (Chen et al. 2021), and fishes in a Norwegian fjord (Freitas et al. 2021).

While depth and temperature appear as the primary drivers for many marine taxa, it is crucial to recognize the complexity and diversity of species responses. Additional factors such as food availability, ocean currents, sea ice cover, and biotic interactions can significantly influence future range shifts (Poloczanska et al. 2013, 2016). Therefore, incorporating these factors into future studies could provide a more comprehensive understanding of species responses to climate change and inform effective conservation strategies.

Present and Future Spatial Distribution Patterns of Black Pomfret

Present Distribution: The ensemble model effectively predicted the present suitable habitat for black pomfret, aligning closely with known occurrence records (Fig. 4). The model identifies highly suitable areas in the northwest

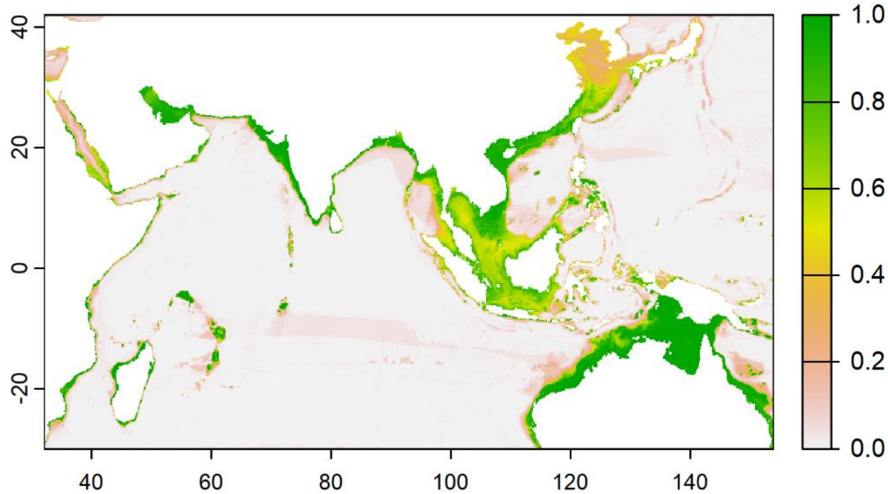

Fig.4. Present spatial distribution of *P.niger* predicted by the ensemble model. Colors represent the occurrence probability (0 to 1).

Table 1. Range size change (%) in the occupied area by of *P. niger* under future climate scenarios.

Scenarios	Years	Change	Years	Change
RCP45	2050	-28.4165	2100	-29.737
RCP85	2050	-27.342	2100	-64.853

Indian Ocean, encompassing the Persian Gulf, Oman Sea, southern Papua New Guinea, southern and western Japan, eastern and southern China, Philippines, and eastern and northern coasts of Australia.

Future Projections: Under future climate change scenarios (Figs. 5 and 6), the highly suitable area for *P. niger* exhibits a decline across both representative concentration pathway (RCP) emissions scenarios (4.5 and 8.5) for both 2050 and 2100 (Table 1). Both scenarios display a similar downward trend in suitable habitat range compared to the present. By 2050, the projected area of occupancy is likely to decrease by approximately 28% under the moderate RCP4.5 scenario and 27% under the high RCP8.5 scenario, relative to the present-day suitable range. By 2100, the projections diverge between the two scenarios. Under RCP4.5, the species is estimated to lose roughly 30% of its current occupied area. Conversely, the high-emissions RCP8.5 scenario indicates a more substantial decrease, reaching 64% of currently occupied area by 2100 (Table 1). Future reductions in *P. niger* habitat are projected to occur primarily in three regions: eastern and southern Africa, southern and southeastern Asia, and northern Australia.

The northernmost occurrence of *P. niger* is projected to shift northward from northern Libya and the South China Sea, Philippine Sea, and East China Sea by 2100 under the RCP8.5 scenario (Fig. 6). Notably, the substantial projected loss of suitable habitat under high emissions (RCP8.5), reaching 64% by 2100 compared to just 27% by 2050, highlights the need for adaptive fisheries management strategies that account for potential inconsistencies between mid-term and long-term climate scenarios to sustain *P. niger* populations over time. Research has documented shifts in marine species distributions in response to climate change, including poleward expansions in the Arctic, subpolar and tropical regions, and semi-enclosed seas (Doney et al. 2012; Cheung et al. 2009; Pinsky et al. 2013; Sharifian et al. 2023). Numerous studies across fish taxa have documented poleward range shifts as waters warm (e.g., Rijnsdorp et al. 2009; Poloczanska et al. 2013; Jones & Cheung 2014).

Persian Gulf: Model projections indicate expanded habitat suitability for *P. niger* in the northern Persian Gulf by 2050 under both emissions scenarios (Fig. 5). However, divergent trends emerge by 2100 between RCP4.5 and RCP8.5 (Fig. 6). While the moderate emissions scenario continues to show habitat gains in the northern Gulf in 2100, the high emissions scenario conversely projects substantial loss of suitability, particularly in the southwestern region encompassing Saudi Arabia, Bahrain, Qatar, and UAE. Only northern and northwestern Persian Gulf areas may remain suitable. However, the enclosed nature of the Persian Gulf and lack of adjacent warmer areas with potential colonists limit northward shifting

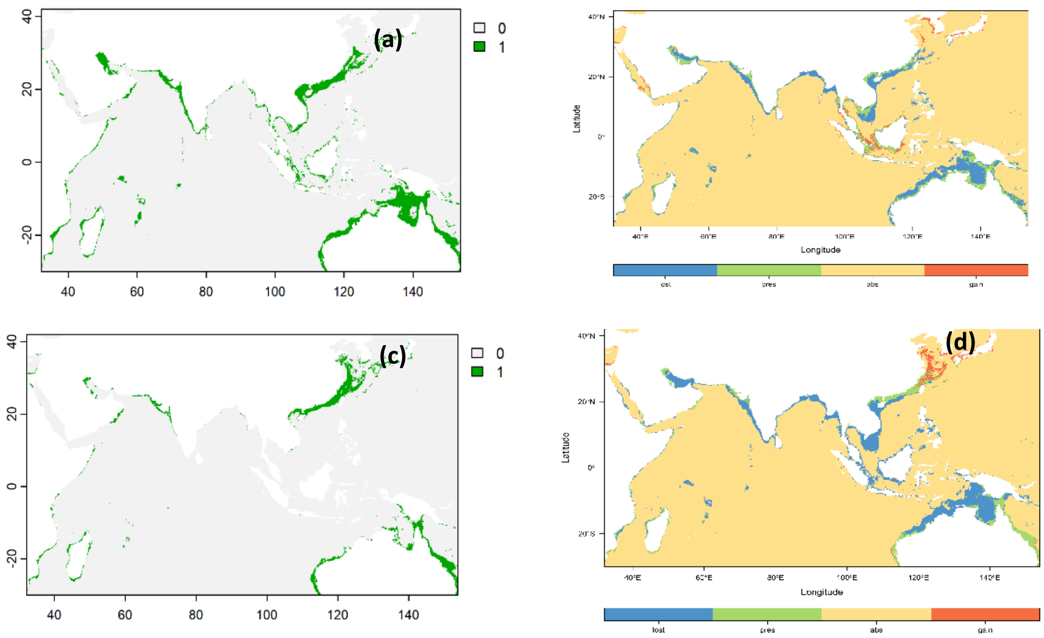

Fig.5. Predicted future distribution of *p.niger* under Representative Concentration Pathway (RCP) 4.5 scenario and 8.5 scenario 2050. (a) Predicted spatial distribution of *p.niger* in 2050 (RCP 4.5), (b) Occupied area change of *p.niger* in 2050, (c) Predicted spatial distribution of *p.niger* in 2050(RCP 8.5), (d) Occupied area change of *p.niger* in 2050. Colors represent the occurrence probability (0 to 1)

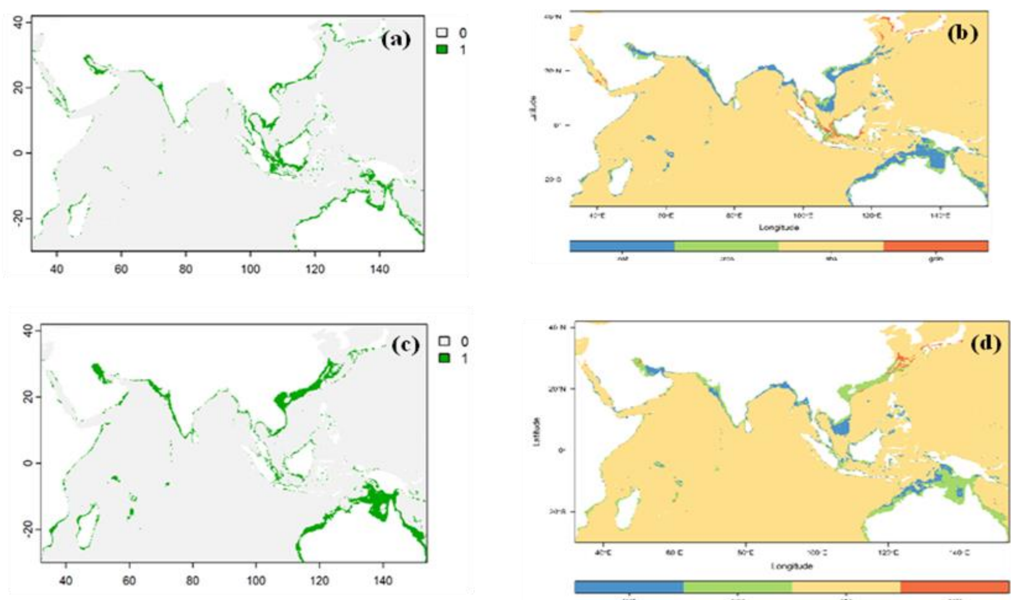

Fig.6. Predicted future distribution of *p.niger* under Representative Concentration Pathway (RCP) 4.5 scenario and 8.5 scenario 2100. (a) Predicted spatial distribution of *p.niger* in 2010 (RCP 4.5), (b) Occupied area change of *p.niger* in 2100, (c) Predicted spatial distribution of *p.niger* in 2100 (RCP 8.5), (d) Occupied area change of *p.niger* in 2100. Colors represent the occurrence probability (0 to 1).

possibilities in response to regional warming. These findings align with Wabnitz et al. (2018), which projected highest species losses along UAE and Bahrain coasts by 2050 under RCP8.5, expanding nearly everywhere by 2090, especially in southern areas. Using IUCN criteria, Buchanan et al. (2019) found most Persian Gulf fish diversity faces high extinction risk, particularly coral-associated and commercially targeted species, due to climate change and extreme events projected to intensify.

Climate change poses significant threats to *P. niger*, particularly under high emissions by 2100. These results offer valuable insights into the climatic impacts on this vulnerable marine ecosystem. The findings underscore the urgent need for regional conservation policies to mitigate biodiversity declines from climate change and protect shared marine resources within the northwest Indian Ocean. This modeling study serves as an important first step towards evidence-based, climate-resilient management strategies that strengthen the resilience of *P. niger*, an ecologically and commercially vital species, to mounting climate pressures. Further research can build upon these projections to support localized adaptation initiatives fostering persistence.

Implications for Management: Projections from the species distribution models suggest that the range of *P. niger* will likely experience significant distributional shifts due to ongoing climate change. These shifts are not limited to *P. niger*, as numerous other fish species within the study area are also anticipated to undergo alterations in their geographic ranges as climatic conditions evolve. Such multi-species distributional changes could fundamentally reshape the composition of fisheries catches, potentially impacting fishing practices and activities across the region.

The generated modeled distribution maps offer valuable tools for local managers and researchers. Specifically, identifying optimal areas for stock enhancement initiatives can be facilitated through these maps, informing crucial updates to conservation plans (Mostafavi et al. 2018). Considering the well-established influence of climate change on marine species distributions (Cheung et al. 2009; Poloczanska et al. 2013; Hiddink et al. 2015), our projections for *P. niger* under future scenarios provide essential information for adapting management strategies proactively. Notably, our models predict substantial impacts on current stock sites in the Persian Gulf and Oman Sea, further underlining the value of these projections for proactive planning. These spatially explicit predictions offer crucial insights for stakeholders seeking to sustain *P. niger* populations despite the anticipated climate shifts.

Declining habitat suitability for *P. niger* due to climate change is evident in the model projections, highlighting regions that require prioritized conservation efforts. While uncertainties concerning realized niches, biotic interactions, anthropogenic impacts, and adaptive capacity remain, the predicted distributions provide valuable guidance for management strategies. It is crucial to emphasize that these projections represent potential outcomes, not guarantees. Addressing limitations through further research and monitoring will enhance the strength and effectiveness of adaptive initiatives supporting the persistence of *P. niger* in the face of climate change. Ultimately, these present and predicted distributions serve as an initial step towards developing evidence-based policies that solidify the resilience of this species.

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مقاله کامل

مدل‌سازی مطلوبیت زیستگاه و پیش‌بینی پراکنش مکانی ماهی حلوا سیاه (*Parasteromateus niger*) تحت تأثیر تغییرات اقلیمی جهانی با استفاده از روش Ensemble

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چکیده: افزایش دما، اسیدی‌شدن آب و تغییر الگوهای موجود در اکوسیستم‌های آبی به‌طور چشم‌گیری پراکنش گونه‌ها، الگوهای تنوع زیستی و ساختار و عملکرد بخش زنده این اکوسیستم‌ها را دست خوش تغییر کرده است. بنابراین استفاده از مدل‌های توزیع گونه‌ها (SDMs) یک ابزار مؤثر برای برقرای پیوند میان جایگاه اصلی گونه‌ها با شرایط محیطی آن‌ها است و تحت سناریوهای تغییرات آب و هوایی می‌توان تغییرات بالقوه در پراکنش آن‌ها را پیش‌بینی کرد. این مطالعه به بررسی اثر تغییر اقلیم بر مطلوبیت زیستگاه حلوا سیاه (*Parasteromateus niger*) در مقیاس جهانی و منطقه‌ای با استفاده از روش مدل‌سازی پراکنش گونه‌ها پرداخته است. شش الگوریتمMAXENT، GAM، GLM، RF، ANN و MARS توزیع‌ها را تحت شرایط فعلی و سناریوهای اقلیمی آینده (۲۰۵۰، ۲۱۰۰) پیش‌بینی کردند نتایج نشان داد که عملکرد کلی مدل‌ها در سطح عالی بوده و عمق و دمای آب به‌عنوان مهم‌ترین عوامل مؤثر بر توزیع این ماهی شناسایی شدند در حال حاضر، زیستگاه مناسب برای این ماهی در منطقه شمال غربی اقیانوس هند متمرکز شده است که شامل خلیج فارس، دریای عمان و بخش‌هایی از پاپوآ گینه نو، ژاپن، چین، فیلیپین و استرالیا می‌شود. پیش‌بینی‌ها تحت سناریوهای تغییر اقلیم، حاکی از اثرات منفی بالقوه بر توزیع این ماهی هستند، به‌طوری که براساس سناریوی انتشار بالای RCP8.5، حداکثر ۶۴ درصد کاهش در زیستگاه مناسب تا سال ۲۱۰۰ پیش‌بینی می‌شود. پیش‌بینی تغییرات آتی توزیع گونه‌ها براساس عوامل کلیدی محیطی می‌تواند در مدیریت شیلات و آمادگی جوامع ساحلی در برابر پیامدهای تغییر اقلیم، کاربرد داشته باشد. البته باید توجه داشت که واکنش گونه‌ها به تغییرات پیچیده بوده و عوامل دیگری نیز می‌توانند بر آن مؤثر باشند.

کلمات‌کلیدی: خلیج فارس، دریای عمان، مدل‌سازی توزیع گونه‌ها، تغییر محدوده.