CLIMATE ENVELOPE MODELLING OF HARD CORALS

by

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DECLARATION

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ABBREVIATIONS

3D	Three Dimensional
ASCII	American Standard Code for Information Interchange
AUC	Area under the Curve
BIOCLIM	Bioclimatic variables
BODC	British Oceanographic Data Centre
BRT	Boosting Regression Trees
DK-GARP	Desktop Genetic Algorithm for Rule-set Production
ENFA	Ecological Niche Factor Analysis
ENM	environmental niche modelling
GAM	Generalised Additive Models
GARP	Genetic Algorithm for Rule-set Prediction
GBIF	Global Biodiversity Information Facility
GDM	Generalized Dissimilarity Models
GEBCO	General Bathymetric Chart of the Ocean
GHG	Green House Gas
GIS	Geographic Information System
GLM	Generalised Linear Models
GMED	Global Marine Environment Datasets
HYCOM	Hybrid Coordinate Ocean Model
IDW	Inverse distance weighting
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
MARS	Multivariate Adaptive Regression Splines
MaxEnt	Maximum Entropy Modelling
MODIS-aqua	Moderate Resolution Imaging Spectro radiometer-aqua
OBIS	Ocean Biogeographic Information System
PAR	Photo synthetically active radiation
RCP	Representative Concentration Pathway
ROC	Receiver Operating Characteristic
SDM	Species Distribution Modelling
SODA	Simple Ocean Data Assimilation
SSS	sea surface salinity
SST	Sea Surface Temperature
TED	Turtle Exclusion Devices

CHAPTER 1
INTRODUCTION

During 1992, the United Nations Convention on Biological Diversity defined the term "biodiversity" as "the variability among living organisms from all sources including, *inter alia*, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species and of ecosystems". At present, the biodiversity of the world stands close to about 1.75 million species, without taking into consideration the microbial species (Heywood and Watson, 1995). Reaka-Kudla (1997) estimated it as around 5 to 120 million. A side by side comparison between terrestrial and marine species reveals that, while about 1.5 million terrestrial species are known to humans the number of known marine species stands at a mere 0.3 million (Groombridge and Jenkins, 2002). This draws our attention to the fact that there is a huge gap when it comes to the knowledge about marine species and their distribution, as 90% of all taxonomic classes are marine.

Corals are important marine species which form highly productive ecosystem in the marine realm called coral reefs (Birkeland, 1997). By supporting a large number of species, the reefs give a tight competition to the tropical rainforests in terms of biodiversity. Their presence is one of the reasons for the settlement of people in tropical coastal areas and reef islands (Ferrario *et al.*, 2014). They are a source of livelihood to millions of people and they also function as a major base of income in some of the developing countries. They are also considered as a future refuge of the pharmaceutical industry (Spalding *et al.*, 2001). They play a vital role in providing protection to the coastal region from the waves by acting as a natural barrier (Hearn 1999; Monismith *et al.*, 2015; Harris *et al.*, 2018). It is our duty to conserve and protect this treasure. But the changing climate act as hurdle to our conservation strategies. It affects every single coral badly which leads to the reduction of the reef complexity (Harris *et al.*, 2018).

Climate change can be defined as the change in regional or global patterns of climate, especially the changes after the mid or late 20th century, mainly due to the release of excessive amounts of carbon dioxide to the atmosphere by fossil fuels (Lineman *et al., 2015).* Within the past 100 years itself, the temperature of the Earth elevated at a rate of 0.2 °C per decade (IPCC, 2017). During 1961 and 2003, the average warming of ocean layers to the depths of 0 - 700 m was 0.1^0 C (Bindoff *et al.*, 2007). The impacts of climate change can be observed in different spheres such as agricultural field, coastal areas, *etc*. It can increase the intensity of natural disasters, can cause the extinction of species, the spread of vector-borne diseases, etc. (Pandve, 2009). Climate change can also result in the redistribution of species. Many marine species are changing their habitat due to climate change and it is predicted that it may lead to an increase in the rate of extinction of species (Cheung *et al.*, 2010; Pereira *et al.*, 2010; Cahill *et al.*, 2013).

Coral reefs are not an exception since they are very sensitive to global climate change effects (Riegl *et al.*, 2009). Any slight variation in environmental parameters will adversely affect the reef ecosystem. The major climatic factors which control the reef ecosystem include sea temperature, sea level rise, salinity, extreme climatic events, etc. The rate and extent of climate change along with the resilience capacity of the reefs will dictate the future health of the reef and its associated fauna. (Hoegh-guldberg, 2011). The rise in atmospheric temperature can disrupt the symbiotic relationship between reef-building corals and their zooxanthellae (*Symbiodinium* spp.) on which the former depends for energy. When the relationship is broken it paves way for coral bleaching. The global climate change leads to an alteration in the physical and chemical characteristics of oceans and it results in the shift in a geographic range of the suitable habitat of coral reefs (Freeman *et al.*, 2013). The El Nino Southern Oscillation (ENSO) events have a greater impact on coral reefs and such an event that occurred in 1998 caused a massive coral bleaching and destruction of corals across the globe (Baker *et al.*, 2008). Temperature and light are two important physical factors that trigger coral bleaching (Coles & Jokiel, 1978).

In order to conserve species, knowledge on their distributions is very important. Species Distribution Modelling (SDM) acts as a tool for predicting the range of a particular species. Through SDM, one can understand the environmental conditions required for an organism's survival, the likelihood of the existence of a particular species and its abundance in a region. It also helps in getting an insight into the effects of climate change in their range. SDM emerged as an important instrument used in the field of ecology and conservation (Miller, 2010). Easier access to georeferenced species records and environmental data played a vital role in the growth of SDM in the research fields of ecology and conservation. Along with that, the user-friendly approach of various models also helped in the growth of SDM (Gomes *et al.*, 2018).

The common strategy which is used in the modeling of species' distribution is to identify the suitable environmental conditions of the species and then to locate those conditions in space (Robinson *et al.,* 2017, Gomes *et al.,* 2018). There are mainly three approaches to know the suitable environmental conditions and they are 1) Mechanistic, 2) Correlative and 3) Hybrid. In the mechanistic approach, the relationship between the environment of a species and its fitness is determined. Then map that data onto a location. In the correlative method, the map is illustrated using the data obtained by correlating the presence or abundance of a species with the spatial habitat. A hybrid approach is a mixture of both the two methods (Robinson *et al.,* 2017).

There are different kinds of SDMs such as Generalized Dissimilarity Models (GDM), Multivariate Adaptive Regression Splines (MARS), Genetic Algorithm for Rule-set Prediction (GARP), Boosted Regression Trees (BRT), Maximum Entropy Modelling (MaxEnt) etc. Various marine organisms have been subjected to SDMs for studying the impact of climate change on these organisms, for their conservation, etc. Some examples for SDMs done on marine organisms are: *Stenella* dolphins for knowing their distribution across southwestern Atlantic (Do Amaral *et al.,* 2015), by taking the mean values of environmental variables such as sea surface temperature; Copepod species in North Atlantic for understanding their abundance and distribution (Melle *et al.,* 2014); Asian kelp (*Undaria pinnatifida)* for identifying their macro environmental determinants for the successful establishment in the northern Iberian coast (Báez *et al.,* 2010); marine benthos in the North sea (Reiss *et al.* 2011); distribution of benthic marine invertebrates at northern latitudes (Meißner *et al.,* 2014), etc.; Franklin *et al.,* (2013), did predictive modeling of 6 coral species in the Hawaiian Islands using BRT models.

The study aims to develop a multivariate statistical model to delineate the relationship of remotely sensed climatic variables with the spatial distribution of hard corals in the northern Indian Ocean. The study also aims to evaluate the habitat suitability of hard corals in selected future climate scenarios. *Acropora muricata (*Linnaeus, 1758*), Favia pallida* (Dana, 1846), *Platygyra daedalea* (Ellis & Solander, 1786), *Pocillopora damicornis* (Linnaeus, 1758) and *Porites lutea* (Milne Edwards & Haime, 1851) were selected for the study.

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CHAPTER 2
REVIEW OF LITERATURE

2.1 Climate Change and its influence on the distribution of different species

The chronicles of Earth's history reveal the alteration in the distribution of species in response to various factors that includes environmental tolerance, constraints in dispersion, interaction with other biotic and abiotic factors and climatic events (Peterson *et al.*, 2011; Pecl *et al.*, 2017; Rosen, 1984). At present, the Earth is encountering dramatic climate change. Within the past 100 years itself, the temperature of the Earth elevated at a rate of 0.2 °C per decade and the global mean temperature may extend further by 4.3 ± 0.7 °C. Globally, the Earth is getting warmed by 0.85^0 C from 1880 onwards (IPCC, 2017).

Since climate is an influential aspect in the geographic distribution of species, climate change has a profound effect on it, and this is evinced from the fossil records and from the well-documented research lines which provide insight on shifts across latitudes, elevations and with the depths of the oceans (Pearson & Dawson, 2003, Pecl *et al.*, 2017). Due to climate change, the species of marine, freshwater and terrestrial environments are changing their distribution to stick on to suitable habitats. There is a positive relationship between warming and the distance moved by the species. It is predicted that climate change may shift the residence of species more towards higher latitudes and elevations (Parmesan *et al.*, 1999, Parmesan & Yohe, 2003, Hickling *et al.*, 2006, Parry *et al.*, 2007, Thomas, 2010, Chen *et al.*, 2011). In comparison with terrestrial organisms, marine species exhibits a higher rate of species distribution (Poloczanska *et al.*, 2013). The meta-analysis done by Chen *et al.*, 2011 on terrestrial species showed that the distribution of terrestrial organisms is shifting to higher latitudes at a median rate of 16. 9 km per decade (or an average of 17.9 km per decade) and to higher elevations at a median rate of 11m per decade and the meta-analysis done by Poloczanska *et al.* (2013) on marine species revealed that marine species move polewards at a mean rate of 72 km per decade. The terrestrial organisms are moving upwards in order to escape from the warming lowlands whereas the marine organisms shift from hotter sea surfaces to deeper regions (Chen *et al.*, 2009; Dulvy *et al.*, 2008). The species mainly in temperate regions are changing their geographic distributions between glacial and interglacial cycles. All these forced shifts will have a pervasive effect on their speciation, range size, latitudinal patterns, minute changes in the timing of their activity and microhabitat use (Dynesius & Jansson, 2000; Williams *et al.*, 2008; Bates *et al.*, 2014). In certain species, there might be a lag in distributional response towards climate change which may be influenced by various factors (Poloczanska *et al.*, 2013; Lenoir & Svenning, 2015; Williams *et al.*, 2008).

The redistribution of species can have impacts of varying degrees. The influence of redistribution of species is reflected in the quality of freshwater systems, marine community assemblages, the productivity of terrestrial regions, functional traits within a community etc. (Weed *et al.*, 2013; Fossheim *et al.*, 2015; Paerl & Paul, 2012; Buisson *et al.*, 2013). It also affects the alpha, beta and gamma diversity of a species (Ochoa-Ochoa *et al.*, 2012). In severe cases, it may even lead to the alteration of the productivity of the ecosystem and cause havoc in the carbon sequestration (Cavanaugh *et al.*, 2014). The research world is in general agreement that, in future, the redistribution of species due to climate change may become a prominent reason for the extinction of species which may occur mainly due to the lack of suitable habitat and limitations in dispersal abilities (Pease *et al.*, 1989; Thomas *et al.*, 2004).

2.2 Distribution of Hard coral species across the world with an emphasize to those in the Indian Ocean

Corals are a bizarre group of invertebrate animals belonging to the phylum Cnidaria. Coral reef communities are widely distributed and spread over distances of thousands of kilometres. They are known as the architects of sea literally building cities underwater with their hard calcium carbonate skeleton (Bermert & Ormond, 1981). Warm-water coral reefs are found in tropical and subtropical waters within the coastal areas of the Pacific, Indian, and Atlantic oceans typically between 30°S to 30°N latitudes where the ocean is warm, sunlit, alkaline, clear, and relatively nutrient deficient (Kleypas *et al.*, 1999b.). Globally there are three major coral reef ecosystems recognized. They are the Indo-pacific, the wider Caribbean and the Red Sea. In addition to these, there are certain minor areas too, such as in the tropical eastern Atlantic, along with the east coast of southern Brazil and around the island of

Bermuda. There is also some pockets of coral development at eastern Pacific, off the coast of southern Japan and Western Australia.

2.2.1 Global Distribution

It is estimated that coral reefs cover only 0.1% of the surface of the earth which is about 250,000 sq. km (McAllister, 1995). The Carribean reefs are home to 9% of the total coral reefs in the world covering about 20000 square miles. Most of these corals are located in the Carribean Sea and Central American coast (Spalding & Bunting, 2004). In the Pacific Ocean, it covers almost 110,493 sq km (Chin *et al.,* 2011). Australia's Great Barrier Reef covers more than 3000000 square kilometres.

India is a biodiversity-rich country and has a coastline extending over 8,000 km with many regions are ideal for reef formation. All three major types.of the reef (atoll, fringing, and barrier) can be seen in the Indian subcontinent. According to Muley *et al.* (2002), the total area of coral reefs in India is estimated at 2,374.9 sq. km. Lakshadweep islands are the only Atoll types, while others are fringing reefs. Barrier reefs are present in the Andaman, and patchy reefs are found in Malvan area as well as the Kanyakumari district of Tamil Nadu. Remote sensing survey of Indian coral reefs shows that the areal extent of Gulf of Kutch is 148.4km^2 and that of Tamil Nadu coast as 64.9 km^2, Lakshadweep with 140.1 km^2 and Andaman and Nicobar with 813.2 km^2. In addition, knolls and lagoon reefs roughly constitute an area of 50 km^2 (Pillai, 1996).

2.3 Chagos

Chagos archipelago is a pristine marine ecosystem in central Indian ocean consisting of a large group of atolls and submerged banks. Its central 200 X 300 km area consists of five atolls with islands. It is surprisingly one of the world's largest atoll areas with only eight islands on its western and northern rim forming a total area of about 550000 km2 (Sheppard *et al.,* 2012). The sublittoral substrate in the photic zone is calculated to be approximately 60000 km^2 (Dumbraveanu and Sheppard, 1999) which is a suitable habitat for coral reef formation. But how much of this huge area actively support coral reef formation is not yet understood because more than 95% of the territory has never been studied (Sheppard *et al.,* 2012). Reef area estimation is a herculean task and has been subject to wide variations. According to Spalding *et al.,* (2001), the Indian Ocean has 32 000 km2 of reefs, in which the Red Sea region and the Gulf region forms 17 400 and 4200 km2 respectively while Chagos has 3770 km^2 of reefs (Rajasuriya *et al.*, 2004). Sheppard *et al.*, (2012) mentioned the lagoons of Chagos has a higher hard coral coverage (63.04 ± 3.19%) than the ocean facing slopes (39.69 ± 2.03%).

2.3.1 Maldives

The Maldives constitute the most extensive area of coral reefs in the Indian ocean, comprised of 27 atolls with 1200 coral reef islands from the central part of the Chagos-Maldives-Laccadive ridge stretching in the north-south direction (Risk and Sluka, 2000; Gischler *et al.*, 2014). Before the mass coral bleaching in 1998 Maldives was reported to have the highest coral cover in the western Indian ocean with 56% to 65% (Davies *et al.*, 1971; Scheer, 1971). But after the 1998 incident, the hard-coral cover declined to < 10% (McClanahan, 2000; Edwards *et al.*, 2001; Morri *et al.*, 2010). Lasagna *et al.* (2008) undertook a detailed coral study in 2006 in the middle of South Male Atoll and Felidhoo atolls and reported hard coral cover between 12% and 37%. A study conducted in 2010 at Ihavandippolo atoll, which is the northernmost Maldive atoll, shows a high variability of coral cover between 1.7% and 50% (Tkachenko, 2012). Similar studies conducted in the other Maldivian atolls such as southern Addu, Ari and Rasdhoo atoll in 2006 also found variability but some higher coral cover between 5% and 95% (Wallace and Zahir, 2007).

2.3.2 Thailand

As elsewhere in the world coral reefs are one of the most productive marine systems in Thai waters, both in the Andaman Sea and the Gulf of Thailand. There are approximately 700 km coastline, 545 islands span the distance between near-shore and off-shore areas. Thailand has a total of 153 km2 area of coral reefs in that almost 78 km^2 is in the Andaman Sea and 75 km^2 is in the Gulf of Thailand (Yeemin *et al.*, 2006). A study by Yeemin *et al.*, (2009) observed live coral cover of two islands that ranged from 5.2% at Koh Samui to 64.3% at Koh Lan, with *P. lutea* as the dominant coral species. Various bleaching episodes severely affected the coral reefs of Thailand. In the 2010 bleaching event, there was a loss of 45% coral cover and the most affected species are *P. damicornis* and *Acropora millepora* (Sutthacheep *et al.*, 2012).

2.3.3 Madagascar

In the western Indian Ocean, mainly between the waters of Madagascar and mainland Africa, is located one among the world's most biodiverse area which supports diverse coral species.369 coral species are identified in the western Indian Ocean and there may be nearly another 100 (Obura, 2012; Obura *et al.*, 2012), this makes the western Indian ocean as biodiverse as the Great Barrier reef, and behind the Coral Triangle which has almost 600 species.

2.4 Mauritius

Mauritius has a coastline of 322 km and it has 150 km of protective coral reefs covering a lagoon area of around 243 km^2. Coral diversity of Mauritius is around 159 species of scleractinian corals (Moothien Pillay *et al.*, 2002). The coral reefs of Mauritius are facing threat from climate change and ocean warming and they have lost more than 50%- 60% of their coral cover (McClanahan *et al.*, 2005, Moothien Pillay *et al.*, 2012).

2.4.1 Sri Lanka

Sri Lanka, situated in the south of Indian sub-continent, has a coastline of about 1585 km of which 300 km are beaches and sand dunes (Lowry and Wickremaratne, 1989, Olsen et al., 1992). Fringing and offshore reefs are mainly seen in Sri Lanka and these have been categorized into three main habitat types; the first one is true coral habitat consisting of life coral reefs, then sandstone habitat and rocky habitats (Rajasuriya & De Silva, 1988; De Silva & Rajasuriya, 1989). About 2% of the coastline contains nearshore fringing reefs (Swan, 1983). Almost 183 species of stony corals have been recorded from Sri Lanka. Growth of coral is highly influenced by monsoons that have a major impact on the level of turbidity and freshwater input to the sea, as a result, the extensive coral habitat is limited to areas with lower sedimentation, which is found in the north-western and eastern coastal areas. Excess of 50% of reef building coral cover found in some of the offshore reefs. The live coral cover on most inshore coral reefs is less than 50% while the rocky and sandstone habitats support a percentage of live coral less than the true coral reefs (Rajasuriya and De Silva, 1988). Almost all of Sri Lanka's reefs are located within 40 km from the coast and they contribute significantly to the marine fish production (Rajasuriya and White, 1995).

2.5 Tanzania

Tanzania has a coastline of over 800 km and the coral reefs are located along around two thirds (600 km) of Tanzania's continental shelf (Wagner, 2004). Most common reef formations are fringing reefs and patch reefs, found on the continental shelf which is 8-10 km wide along most of the coast (IUCN Conservation Monitoring Center, 1988). But in some areas, it reaches a width of 35 km (Darwall & Guard, 2000). Fringing reefs of Tanzania are often narrow and consist primarily of a reef flat, which is broken by numerous, often extensive mangrove stands (IUCN Conservation Monitoring Center, 1988). Coral reefs are typically found close to land due to the narrowness of the shelf of most of Tanzania. There are well-developed barrier reefs present on the ocean-facing eastern coastline of the islands. There are also coral outcrops and reefs along the leeward side of the islands. 1501 species of hard corals have been reported from Tanzanian reefs (Hamilton and Brakel, 1984).

2.6 Ecological Forecasting Methods, their uses, and advantages

The rapid change in the climate coupled with anthropogenic stresses are posing severe threats to the ecosystems such as shifting of natural habitats, invasion of new species and the emergence of new diseases. So the modeling of the environmental dynamics with parameters as species distribution and abundance, ecosystem variability and the community composition contributes to the better prediction of the ecosystem movements and thereby facilitates better management decisions, conservation, and sustainability. During earlier days' ecologists developed management decisions utilizing the model from mean and variances of the observed environmental parameters. But faster reformations which occur in the ecosystem as a consequence of climatic variations cannot be quantified precisely by mere historic observations (Smith *et al.*, 2009; Milly *et al.*, 2008; Craig, 2010). Ecological forecasting makes an attempt to derive a clue about how the environment will behave in the future, based on the current trends and the past data. This includes forecasts of agricultural yield (Cane *et al.*, 1994), species distributions (Guisan & Thuiller, 2005), species invasions (Levine & Antonio, 2003), pollinator performance (Corbet *et al.*, 1995), extinction risk (Gotelli & Ellison, 2006), fishery dynamics (Hare *et al.*, 2010); disease dynamics (Ollerenshaw & Smith, 1969) and population size (Ward *et al.*, 2014).

There are mainly two methods for measuring the structural and physical changes occurring in the ecosystem and for better forecasting, namely population models and species distribution models.

2.6.1 Population Models

Models of population dynamics or the ecological population models provide a proper perception about the dynamics and persistence of a population. This model maps the size of population and age distribution within a population to its decline or extensive growth and produces a better prediction regarding the status of a population. The environmental, as well as interactions with other and similar species, may also be a deciding factor (Uyenoyama , 2004). Crowder *et al.*,1994; Crouse *et al.*, 1987; Caswell, 2001 developed a population model which helps to reverse the population diminishing of the loggerhead sea turtle. The model discloses that the mortality of adults and subadults are the major cause of population decline of these species. So an alternate management action had been taken by installing the TED (Turtle Exclusion Devices) in shrimp trawls and was favorable to the growth of population size of the turtle. Population dynamics models also link the interaction of the environmental variation and the population growth such as the influence of the sea level rise on the extinction of polar bears (Hunter et al., 2010). The overabundant species population is also managed by the help of the population dynamics. Govindarajulu *et al.* (2005) propose the measures for controlling the population of harmful bullfrog of Vancouver Island. Elk population reduction (Bradford and Hobbs, 2008) and potency control of the white-tailed deer (Merrill *et al.* 2003) was also achieved from the results of the population model.

Even though this model is used extensively for predicting the behavior of a population, the amount of uncertainty in the data leads to error in prediction. The complicated biological interactions are not flawlessly implemented by this model unless a sufficient amount of data is supplied.

2.6.2 Species Distribution Models (SDMs)

Species distribution models (SDMs), otherwise called environmental (or ecological) niche modeling (ENM), habitat modeling, predictive habitat distribution modeling, and range mapping (Elith and Leathwick, 2009) are widely used in ecological and biodiversity conservation research for modeling how the species are distributed globally over the geographical area. This model accommodates the tools that incorporate known species occurrences with environmental data (Phillips *et al.*, 2006).

2.6.2.1 Correlative SDMs

Correlative SDMs forecasts the influence of climatic variations on the geographical distribution of data. (Thomas *et al.* 2004). In European diadromous fishes the linear combination of predictor attributes best suited for the propagation of the species are developed by Mennesson-Boisneau *et al.* (2006). The statistical records of association of environment to the species abundance and occurrence are analyzed in this SDMs for identifying the hindering processes to the spread of the species. As per Moilanen & Wintle (2007) the ease of implementation of the Correlative SDMs because of simplicity and the capability to model complex interactions of the environment with less data requirement provides supremacy over other SDMs.

2.6.2.2 Mechanistic SDMs

This model otherwise called biophysical models or process-based models because it aims at mapping the relationship between the physiology of the species and the surroundings which has an influence on their abundance and distribution. (Kearney & Porter., 2009). Other than the current radius of the species, the model utilizes the processes or physiological changes within the body of organisms with respect to climate variations and vegetation which helps in the prediction of the future extension possibilities of species range towards a great extent of the ecosystem levels (Porter *et al.*, 2002; Kearney & Porter, 2009). For the complex analysis of interactions between the environment and climatic influences in large scales, the mechanistic SDMs will not be suitable because it requires a large quantity of variables to be considered which makes the model computationally and time constrained to carry out both train and validation phases.

2.6.3 Methods used in the Species Distribution Modelling

The species-specific interaction had to be studied in conservation planning measures and the best tool available for this is species bioclimatic envelope models. They shared the same principle of biome envelope models, in which the current distribution of species is used to 'train' a model for the future incorporation of predicted climatic conditions (Hannah *et al.*, 2002). Envelopes were constructed using the Geographic Information System (GIS) software or by genetic algorithms or general additive modeling (Peterson *et al.*, 2001; Berry *et al.*, 2002; Midgley *et al.*, 2002). But these models could not model dynamic transitions, interspecific competition, herbivory, dispersal or other factors. By coupling with land-use projection models, application of the results of bioclimatic envelope models could be used in real-world conservation (Hannah *et al.*, 2002). Forecasting the geographic ranges of different species with the use of occurrence records (presence or absence) and data of environmental variables from the same locality is the focus of Species distribution modeling (Phillips *et al.*, 2006; Elith and Leathwick, 2009).

2.6.4 Generalized Dissimilarity Models (GDM)

For the modeling of spatial turnover in community composition among pairs of sites as functions of environmental differences between these sites, Generalized Dissimilarity Models (GDM) were used (Ferrier *et al.*, 2007). For the estimation of the probability of occurrence of distribution of a given species, kernel regression algorithm was used within the transformed environmental space produced by GDM (Lowe, 1995). Elements of matrix regression and generalized linear modeling were combined which allowed the user to model non-linear responses of the environment which captured the ecologically realistic relationships between dissimilarity and ecological distance (Ferrier, 2002; Ferrier *et.al.*, 2002).

2.6.5 GLM and GAM models

Non-parametric and non-linear functions were used by Generalised Linear Models (GLM) whereas Generalised Additive Models (GAM) use parametric and combinations of linear, quadratic or cubic terms. GAMS can model complex ecological response shapes than GLM because of greater flexibility (Yee and Mitchell, 1991). GLM and GAM were widely used in species distribution modeling because ecological relationships were modelled realistically and they have strong statistical foundations (Jowett *et al.*, 2008; Alexander, 2016; Rezaei and Sengül, 2018).

2.6.6 Multivariate Adaptive Regression Splines (MARS)

For fitting non-linear responses, an alternative regression-based method called Multivariate Adaptive Regression Splines (MARS) was used. It used piecewise linear fits rather than smooth functions. It was very easy to use in GIS applications for making prediction maps, faster to implement compared to GAMs and had the ability to analyze community data (MARS-COMM) which helped in relating the variation in occurrence of species to the environmental predictors in one analysis, and later estimating the individual model coefficients for each species simultaneously (Leathwick *et al.,* 2005).

2.6.7 Genetic Algorithm for Rule-set Prediction (GARP)

For the approximation of bioclim species' fundamental ecological niches, several approaches had been used such as BIOCLIM (Booth *et al.,* 2014), logistic multiple regression (Peeters and Gardeniers, 1998) and Genetic Algorithm for Rule-set Prediction (GARP). GARP was defined by heterogeneous rules that defined the polyhedrons in the ecological niche spaces that were assumed to be liveable by a particular species. The model quality was assessed by dividing the occurrence points into 'training data' used for training and 'test data' used for testing models (Fielding and Bell, 1997). GARP has two versions: DK-GARP used widely for the modeling data from natural history collections and OM-GARP, a new open implementation, where a group of rules for adaptations of regression and range specifications are chosen with the use of a genetic algorithm for both these versions and hence predicted as the best species distribution (Stockwell and Peters, 1999). GARP is a machine-learning approach and also linked the occurrence records to the environment variables using envelope (variables are bounded to lower and upper bounds), atomic (values are assigned to each variable) and logistic regression rules. The algorithm used pseudo-absence localities since the model works on presence-absence data (Stockwell and Peters, 1999). GARP included the properties of both BIOCLIM and logistic multiple regression and it was based upon artificial intelligence (Stockwell and Noble, 1992; Stockwell and Peters, 1999). The extensive testing done on the GARP model showed that it has high predictive ability for species geographic distributions (Peterson and Cohoon, 1999; Peterson *et al.,* 2001).

2.6.8 Boosted Regression Trees (BRT)

Boosting Regression Trees were developed in a forward stage-wise manner, where small modifications were done in the model at each step for better fitness of data (Friedman *et al.*, 2000). BRT used the combination of two algorithms: regression-tree algorithm also called as the boosting algorithm to construct a combination or "ensemble" of trees. The use of regression-trees helped in the good selection of relevant variables and it could model interactions. It was upon the weighted versions of data set where the observation that was poorly fitted in the preceding model and they were accounted by adjusting the weights (Elith *et al.*, 2006). Overfitting of data were avoided by using cross-validation in BRT, to grow the models progressively during the predictive accuracy testing on withheld portions of the data (Elith *et al.*, 2006). The correlation between the distribution of adult stage of copepod Oithona similis was established using the Boosted Regression tree method (Pinkerton *et al.*, 2010).

2.6.9 Maximum Entropy Modelling (MaxEnt)

According to Phillips *et al.*, 2006, MaxEnt uses the distribution of maximum entropy. This data was subjected to the constraint that the expected value of each environment parameter (interactions) in the estimated distribution matched its empirical average for estimating the distribution of species. Using the background locations and data derived constraints, it approximated the most uniform distribution (Philips *et al.*, 2004; Philips *et al.*, 2006). In this model the complexity of the fitted functions could be chosen, if presence-only species data were used. It was observed that Maximum entropy modeling (MaxEnt) had done better or as well than other modeling techniques (Elith *et al.*, 2006; Hernandez *et al.*, 2006; Philips *et al.*, 2006). Compared to other algorithms, MaxEnt achieved higher success rate and it marked the differences even at low sample sizes (Pearson *et al.*, 2007). MaxEnt models predicted the broader area of suitable conditions and the MaxEnt projection had the ability to predict excluded areas also, but the model performance felt a negative impact when sample sizes were reduced artificially (Pearson *et al.*, 2007). However, it is observed that species-specific model parameter tuning can enhance Maxent models efficiency (Radosavljevic and Anderson, 2014.).

MaxEnt can create very complicated, extremely nonlinear response curves that is possible due to the usage of various feature classes like linear, quadratic, threshold, hinge, product, and categorical that in turn is decided by the number of presences by default (Syfert *et al.*, 2013). Other than the feature class, the MaxEnt has another modifiable parameter called the Regularization Multiplier. It is a parameter that adds new restrictions, i.e. a penalty imposed on the model. The main objective is to avoid overcomplexity and/or overfitting by controlling the intensity of the selected feature classes used to create the model (Morales *et al.*, 2017). Several studies have recorded the variability in predictions that may arise from distinct MaxEnt background samples, with a specific focus on the extent of the location from which they are chosen (Baasch *et al.*, 2010; Giovanelli *et al.*, 2010; Barve *et al.*, 2011). The outputs obtained from MaxEnt models fall into three categories namely, the raw output that is interpreted in terms occurrence rate, Cumulative output interpreted as omission rate and then the logistic output. But the difference in the scaling of these three types of outputs plays a crucial role in providing differently appearing prediction maps (Merow *et al.*, 2013). Maxent has recently been shown to be associated mathematically to log-linear modeling and differ only in intercept terms (Renner & Warton, 2013). An attempt to test the effect of bias types, bias intensity, and correction method on MAXENT model performance the ability of methods to correct the originally sampling bias varied greatly depending on bias, bias intensity and species (Fourcade *et al.*, 2014). Reliability on small sample size, non-essentiality of absence data and methods to compensate the spatial bias in sampling are the reason for the recent popularity of MaxEnt in modeling of habitat suitability and distribution of various open sea species (Peavey, 2010).

MaxEnt had used to investigate the distributional patterns of Geckos (*Uroplatus* spp.) for predicting the species distribution (Pearson *et al.*, 2007), American black bear (*Ursus americanus*) for the assessment of denning habitat (Baldwin and Bender, 2008), Bush dog (*Speothos venaticus*) to appraise the excellence of protection (DeMatteo and Loiselle, 2008), Little bastard (*Tetrax tetrax*) for modelling the seasonal distribution changes (Suárez-Seoane *et al.*, 2008), predicting and mapping of Sage grouse's (*Centrocercus urophasianus*) nesting habitat, Asian slow lorises (*Nycticebus* spp.) was assessed to threats and species distribution analyzed to find conservation urgencies (Thorn *et al.*, 2009). MaxEnt can precisely build the model even if there is less number of location points and it was an advantageous feature since frequently there is a deficiency of dependable locations obtainable for mapping the spreading of species (Baldwin, 2009).

2.7 SDM in marine animals

Species distribution models (SDMs) has been done for a variety of organisms in the marine environment, for effective marine biodiversity management, which includes correlative, mechanistic and hybrid models (Robinson *et al.*, 2011). For example, the correlative model for the distribution of *Stenella* dolphins across southwestern Atlantic was done by Do Amaral *et al.* (2015), mechanistic model for the distribution and abundance of a copepod species in the North Atlantic by Melle *et al.* (2014) and the hybrid model for the abundance pattern of two abalone species by Fordham *et al.* (2013). Many other SDMs done on various marine lives includes those on Asian kelp *Undaria pinnatifida* to identify its macro environmental determinants for the successful establishment in the northern Iberian coast (Báez *et al.*, 2010); marine benthos in the North Sea (Reiss, 2011); distribution of benthic marine invertebrates at northern latitudes (Meißner *et al.*, 2014); the foraging habitats of grey-headed albatross in southern Atlantic (Scales *et al.*, 2016) to list out a few. SDMs for marine species have especially focused on developing conservation and management plans, assessing climate change impacts and spread of invasive species on marine ecosystems and to study the relationship between organisms and their environment (Robinson *et al.*, 2017). Among these objectives proposing marine protected, areas and essential fishing habitats are the focus of the majority of marine SDMs while a less number of works targeted the invasive species and climate change impact in the marine realm. A different group of marine animals came under SDMs till date with those on fishes is the most common possibly due to their commercial value and data availability followed by marine mammals due to their declining population trends (Robinson *et al.*, 2011). A systematic review of marine-based SDMs by Robinson *et al.* (2017) found 236 SDMs having applications in the intertidal, pelagic and deep ocean environment. More than a hundred of these studies were conducted in the northern Atlantic Ocean followed by temperate northern Pacific and central Indo-Pacific. The least number of SDMs (2-3) were done in temperate South America and Southern Africa. Western Indo-Pacific that includes the marine areas of India, together with tropical Eastern Pacific and the Arctic witnessed only 4-7 SDMs (Robinson *et al.*, 2017).

A major issue associated with SDMs is the quality of data through the occurrence and ecology of thousands of fish and other marine animals are available databases such as FishBase (http://www.fishbase.org/search.php) or OBIS (OBIS: http://www.iobis.org/)

(Robinson *et al.*, 2011). For rare marine species, occurrence data are very few making the prediction of their distribution quite challenging. The testing of the robustness of predictive performance of models with decreasing occurrence data found that the thinning of occurrence data for a species with small habitat is less undesirable to the predictive performance than a species having larger habitats (Virgili *et al.*, 2018). Another problem associated with marine species modeling is the use of environmental variables having an impact on the sea surface only is coupled with bathymetric occurrence to predict the distribution despite the striking disparity in the environmental conditions (Duffy & Chown, 2017)

Different types of distribution modeling methods used in the marine environment are presence-only algorithms, algorithm comparisons, 3D modeling, rare species, joint SDMs, ensemble modeling, scale effects, null models, model selection, pseudo-absence generation and predictor datasets (Bosch *et al.*, 2018). Bosch *et al.* (2018) studied the most suitable predictors of marine species distribution and the part of the SDM process which has the most influence on the suitability of the predictors. They noted that the methods of marine SDMs are highly biased towards terrestrial studies in spite of the remarkable variations in the ecological factors existing in the marine environment that determine the spatiotemporal differences in the distribution of animals. Recently, in contrast to the single models used in earlier studies, a method of using multiple models and then ensemble them to reduce model uncertainty is adopted by some modelers, for example, Jones and Cheung (2015).

2.8 Species Distribution Modelling of Hard Corals

Species Distribution Models that is used to identify vulnerable marine ecosystems and to predict the distribution of biological functional group have been less frequently applied on the coral reef species (Garza-Pérez *et al.*, 2004). Different computer models are now increasingly used to pretend the aspects of coral reef (Aigner *et al.*, 1989). Different species of scleractinian coral display intraspecific variation in colony architecture among habitats (Kaniewska *et al.*, 2008)

The statistical modeling of species distributions needed components such as an ecological model concerning the ecological theory, a data model concerning the collection of the data, and a statistical model concerning the statistical theory (Austin, 2002). MaxEnt is a statistical model, and to apply it to model species distributions successfully must consider how it relates to the two other modeling components (the data model and ecological model (Philips *et al.,* 2006). (Leathwick *et al.,* 2008) suggested that Data from coral SDMs can be incorporated into spatial optimization exercises for marine conservation) or for geographically explicit threat assessments to reefs (Selkoe *et al.,* 2009; Burke *et al.,* 2011). Modeled probabilities of species occurrence can easily be adjusted to projected changes in environmental conditions on a species-by-species basis (*e.g.* changes in distributions of corals with increased sediment levels owing to major coastal deforestation)

Tittensor *et al.* (2010) conducted studies on predicting habitat suitability for stony corals on seamounts using MAXENT and ENFA, showed the influence of variables relating to the chemical environment e.g. levels of nitrate, silicate, phosphate, aragonite saturation, dissolved oxygen, and percent oxygen saturation on model predictions. Higher resolution environmental parameters should also improve model predictions (Anderson *et al.*, 2013) and may also contribute to more local-scale models of coral-distribution (Dolan *et al.,* 2008). From SDMs, coral species can be characterized on regional scale. This characterization will lay the foundation for spatially explicit ecosystem modelling of coral reefs along with its marine spatial planning (Franklin *et al.,* 2013). Regional-scale characterization of coral species from SDMs provides the framework for spatially explicit ecosystem modeling and marine spatial planning of coral reefs.

CHAPTER 3
MATERIAL AND METHODS

3.1 Study area

The area chosen for the present study is the Northern Indian Ocean. This study area comprises of Arabian Sea, Bay of Bengal, Red Sea, the Persian Gulf, the Andaman Sea, Gulf of Thailand, Gulf of Aden, Malacca strait etc. The Indian Ocean includes nearly 20% of the water in the world (Fatima and Jamshed, 2015). The unique feature of the Indian ocean is that it is a closed ocean unlike the Atlantic and Pacific Ocean, it is land-locked in the north and does not extend to the northern hemisphere's cold climate areas. (Bouchard and Crumplin, 2010) The area of the Indian ocean selected for this study comes under the jurisdiction of different nations.

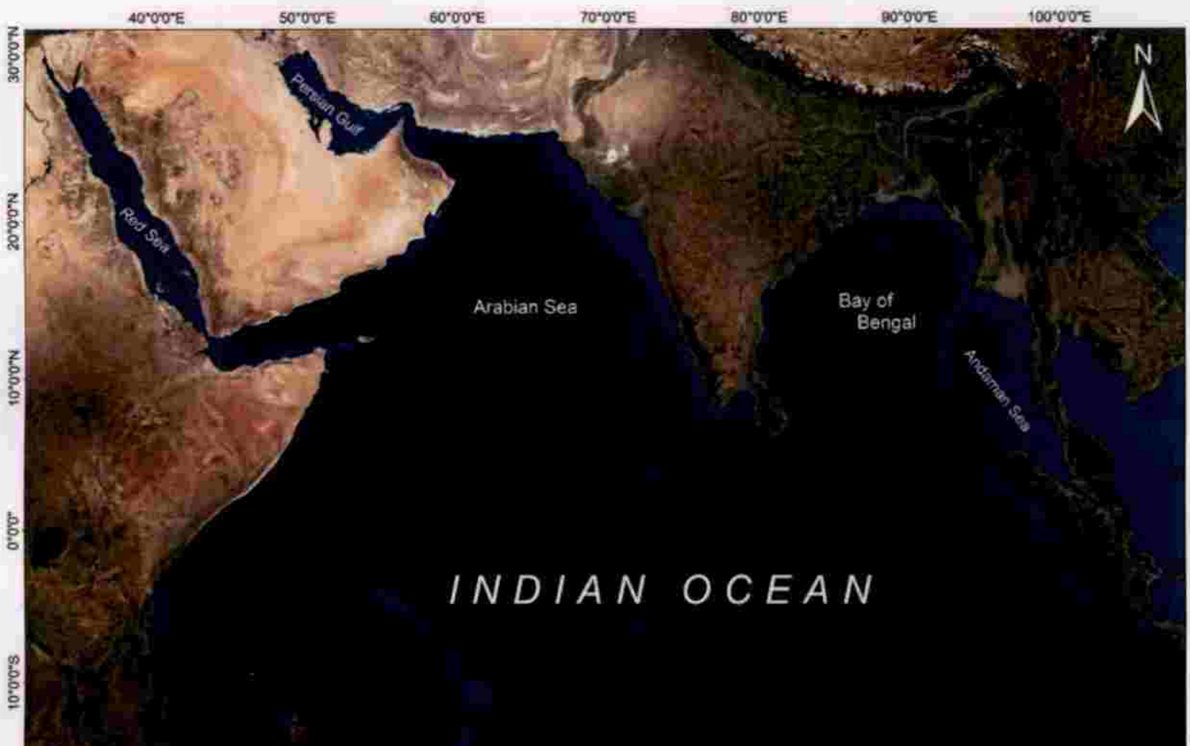

Fig. 1 Map of the study site - The Northern Indian Ocean

3.2 Species Occurrence Data

The corals selected for the study are:

Acropora muricata: They are considered as 'Nearly threatened' species (Carpenter *et al.*, 2008). They can be found in tropical to subtropical regions and also in Indo – Pacific regions (Veron, 2000). They grow at a rate of 3.7–7.6 cm per year. (Yamano *et al.*, 2011). According to the studies, they are the architects of the reefs of Indopacific regions (Hongo & Kayanne, 2011).

Pocillopora damicornis: It is also known by the common name 'Cauliflower Coral'. It is a cosmopolitan species and it is widely distributed in the Indo – Pacific region (Veron, 2000; Torres & Ravago-Gotanco, 2018). It is characterized by the absence of a true verruca (Veron and Pichon, 1976).

Favia pallida: One of the most common faviids, it is widely distributed in its own range. It can be seen in shallower and deeper parts of the reefs of the tropical region (DeVantier *et al.*, 2014)

Platygyra daedalea: The common name of *P. daedalea* is 'Brain Coral'. This species is very common and can be found in various reef environments. They may form colonies of diameter of about one meter or more (DeVantier *et al.*, 2014)

Porites lutea: It belongs to the family 'Poritidae'. It is a common species and can be seen in large numbers in the Red Sea. It forms huge colonies with diameters of 3 to 5m (Sheppard *et al.*, 2014).

The occurrence records of these five different coral species were collected from open source databases like GBIF, OBIS and other published literature. The distribution points of the species were plotted using ArcGIS software

3.3 Selection of environmental layers

The environmental predictors were obtained from the Bio-oracle and GMED which are available online. This study used 13 potential predictors that are capable of influencing the occurrence of the selected coral species. These include Mean Sea Surface Temperature (Mean temperature), Maximum Sea Surface Temperature (Max temperature), Sea Surface Salinity (SSS), Bathymetry, Chlorophyll-a, Ocean current, Photosynthetically Active Radiation (PAR), pH, Calcite, Phosphate, Nitrate, Diffusion attenuation coefficient and Dissolved oxygen.

Distance from the shore was avoided to achieve the lowest collinearity among predictors. The climatology data of mean and maximum SST were collected from MODIS-Aqua (Moderate Resolution Imaging Spectroradiometer (EOS PM) satellite) with a spatial resolution of 4x4 km and were downloaded from ocean color web database maintained by NASA (Feldman & McClain, 2010). SSS data of Simple Ocean Data Assimilation ocean/sea ice reanalysis (SODA) (Carton *et al.,* 2008) of 1/4 x 1/4-degree resolution were utilized. The gridded bathymetric data of 30 arc-second was obtained from GEBCO (General Bathymetric Chart of the Ocean) Global ocean & land terrain models hosted by the British Oceanographic Data Centre (BODC). The chlorophyll-a data with 4 km x 4 km Spatial resolution was taken from the Ocean color web database (Feldman & McClain, 2010). Ocean current data was taken from HYCOM Global with 1/12-degree spatial resolution (Bleck, 2002). The monthly climatology data of PAR (5 arc-minute spatial resolution) was taken from Bio-Oracle (Feldman & McClain, 2010). The Calcite, Phosphate, Nitrate, pH, Dissolved oxygen and Diffusion attenuation coefficient with a spatial resolution of 5 arc-minute were gathered from GMED (Global Marine Environment Datasets, version 2.0) (Basher *et al.,* 2014). Using ArcGIS version each variable was reprojected to GCS_WGS_1984 coordinate system and clipped to the same extent. The variables of coarse resolution were interpolated using Inverse Distance Weighting (IDW) with a mask polygon, which covers the occurrence data. All the covariate rasters were resampled to get the same extent and resolution (9 x 9 km). The rasters were finally converted into ASCII using conversion tools in ArcMap.

The environmental variables used for the prediction of coral occurrence under the three different RCP scenarios (RCP 4.5, RCP 6 and RCP 8.5) were Maximum SST, Mean SST, SSS and ocean currents. Bio-oracle also offers future variables based on predictions produced by the Intergovernmental Panel on Climate Change (IPCC) for 2100 with different levels of RCP scenarios. These variables have been trimmed to our research area and re-sampled for a resolution of 5 arc minute (~ 9 km). The predicted concentration scenarios for greenhouse gas (GHG) such as RCP 4.5, 6.0, and 8.5 were chosen for the expected periods 2040-50 and 2090-2100.

3.4 Predicting Hard Coral Distributions

Maximum Entropy modeling is a machine learning strategy that involves the correlative modeling of a species ' spatial distribution relative to the environmental factors that determine the species ' niche. MaxEnt is a technique for modeling geographic distributions of species on a grid as a function of that grid's environmental predictors and species occurrence. It estimates the probability of species existence by establishing the connection between variables and species occurrence. Although there is no need for absence data as a modeling input for a species, this method utilizes other independent background variables for the entire study region. We developed background rasters for each species to enhance the model's precision as well as prevent the sampling bias. A regularization feature is used to prevent model overfitting (Philips, 2006) and value (ß) was set as one so that the model will give the highest test AUCs (Area Under the Curve) among various trials (Warren and Seifert, 2011). The data should be entered in the necessary format in the software. Species data have been transformed into '.csv ' format and the bioclimatic layers should be '. asc' format. The software was programmed to a suitable level in accordance with our requisites for a run under settings options. The recommended default values were used for the convergence threshold (10-5) and maximum iterations (1000). The random test percentage has been set as 30%, which decreases the bias from the entire model outcomes when using the single set of points. Sub-sampling has been chosen for replication because it does not encourage the incorporation of noise variables and has been shown to create a stable model (Meinshausen and Buhlmann, 2006). This utilizes all thresholds to discriminate between appropriate and noise variables. A background raster of coral occurrence was developed using ArcGIS and used in the model to decrease bias and uncertainty in the samples.

Based on the ROC curve, the different models predicted under different settings were analyzed and high AUC values were used to measure the model's capacity for discrimination (Philips *et al.*, 2006). An AUC value of 0.5 showed that the output of the model was no better than random, while values close to 1.0 showed the better output of the model. Twenty-five percent of the occurrence data were used as test data and the rest were used for training the model. To quantify the contribution of each environmental parameter to the model and its efficiency, the Jackknife analysis (Pearson *et al.*, 2007) and in order to analyse the contribution of each environmental parameter to the model and its efficiency, single variable response curves were used. AUC's Jackknife helps to know the largest contribution of the environmental predictor and the least influence on hard coral distribution in the present research region. The most appropriate is the expected maps with pixel values of 1 and the least suitable are cells with values near to 0. Appropriate habitats were then split into 2 classifications to demonstrate appropriate habitat gradation. The area of suitable habitat predicted was estimated in the GIS environment.

3.5 Prediction of Future Distribution

In MaxEnt model, the trained environment layers are projected to another available set of environmental layers containing the future climatic data in order to predict the species distribution of the five selected hard coral species in the future. The projection layers should have trained layers which were mutually compatible but the conditions will be different. The name of the layers and the map projection should be the same as that of the trained data. A model was trained on the environmental variables which corresponded to the current climatic conditions and was projected into a separate layer based on the future environmental data. Models of different RCPs *i.e.*, RCP 4.5, RCP 6.0 and RCP 8.5 were done for the years 2040-50 and 2090-2100 using ten replicates and test percentage of 30. The projection was done using subsampling method of replication.

CHAPTER 4
RESULTS

We predicted the current spatial distribution of five major hard coral species viz., *A. muricata, F. pallida, P. daedalea, P. damicornis* and *P. lutea* in the Northern Indian Ocean. The environmental suitability is indicated on the map by the legend from yellow to red. Red represents highly suitable habitat whereas yellow represents the least. The predicted habitat suitability of each species for different climatic scenarios was represented as maps using a legend from blue, green to red according to the increasing order of species habitat suitability.

4.1 *Acropora muricata*

4.1.1 Prediction of the current distribution

4.1.1.1 The Model Performance and variable contributions

The model performance is assessed by using the average test AUC value for 10 replicates was 0.943 (SD= 0.014). The sensitivity *vs.* 1-specificity graph shows the area under the Receiver Operating Characteristic (ROC) curve or AUC. The test omission rate and AUC curve (Fig. 2 & Fig.3) was found fit in this model. The Fig.3 shows that the mean omission line on the test data was passing through the predicted omission line. In the Fig. 2 the AUC line was passing through the left top of the random prediction.

4.1.1.2 Contribution of predictor variables

The relative contribution of each predictor variable is given by the MaxEnt output and it is shown in Table 1. Among all the variables, bathymetry showed a significantly higher contribution of 70.2 %, followed by Nitrate (7.6%) and Phosphate (5.6%). The dissolved oxygen is the only variable with no contribution in this particular model developed for *A. muricata.* For the Permutation importance, for each environmental variable, the values of that variable in training presence as well as in background data were randomly permuted. The variable having high permutation importance (83.9) were bathymetry and the diffusion attenuation coefficient by 4.3 percent.

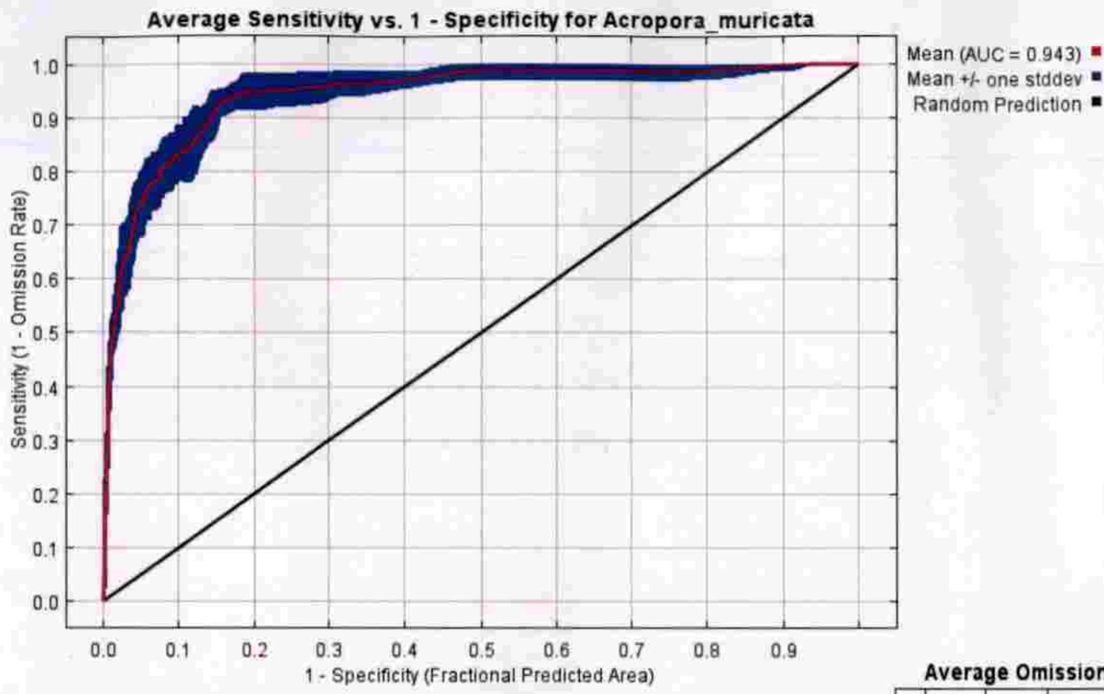

Fig. 2 The ROC curve of variable optimization of the model for *A. muricata*

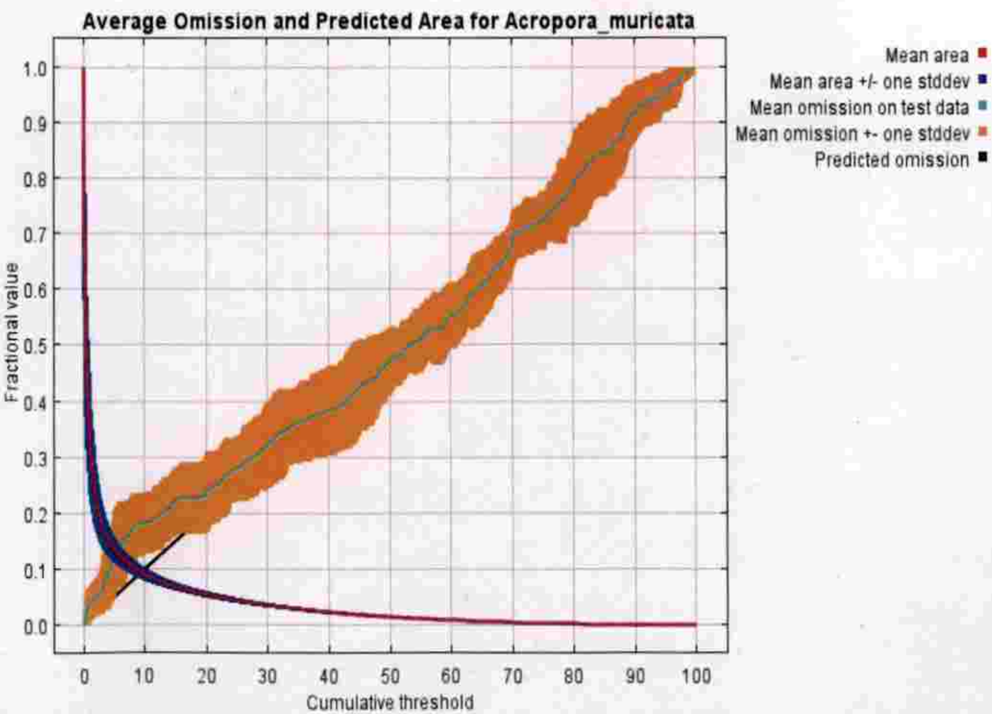

Fig. 3 Test omission rate and predicted area as a function of the cumulative threshold, averaged over the replicate runs for *A. muricata*

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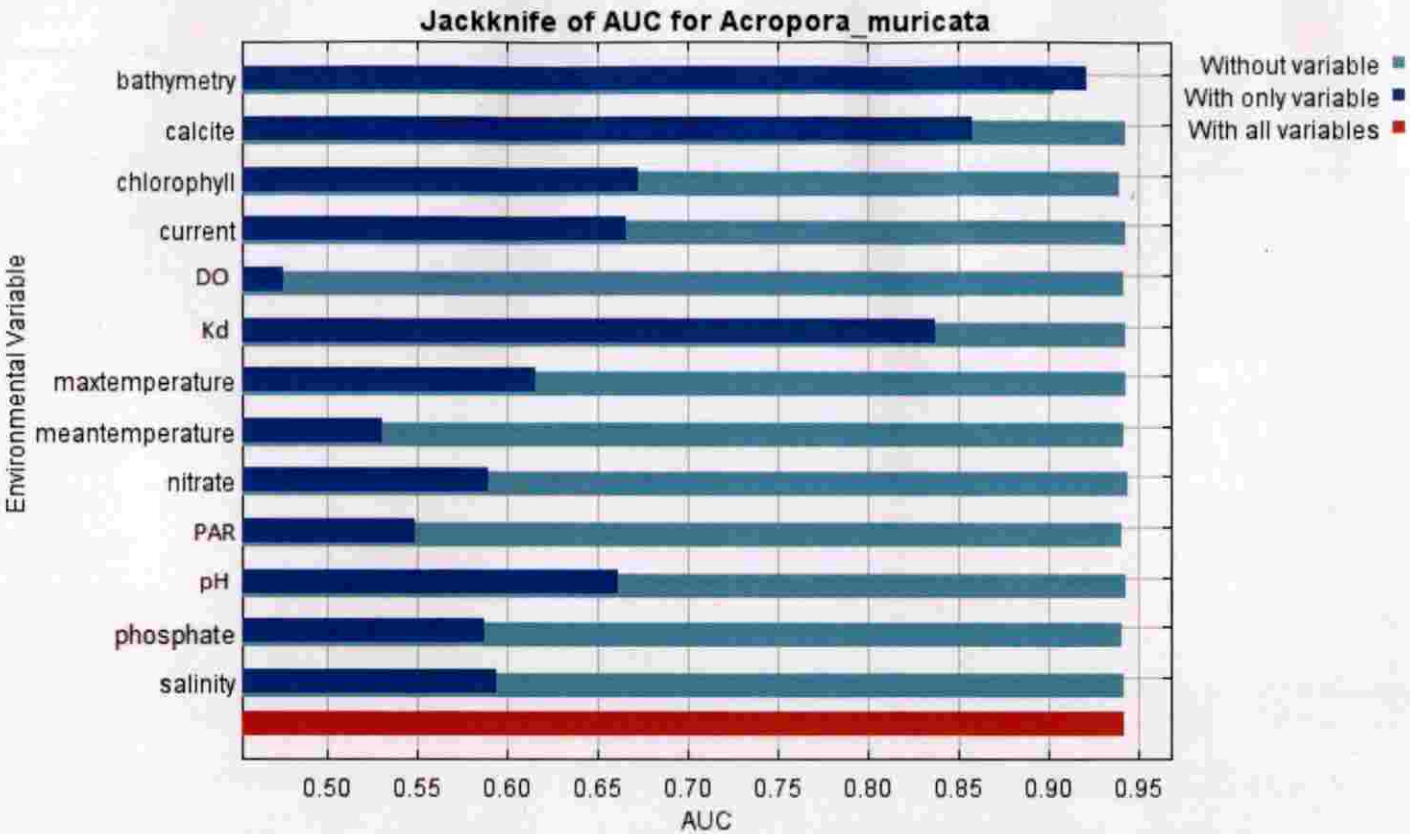

Fig. 4 Jackknife analysis of AUC for the *A. muricata* using all the variables

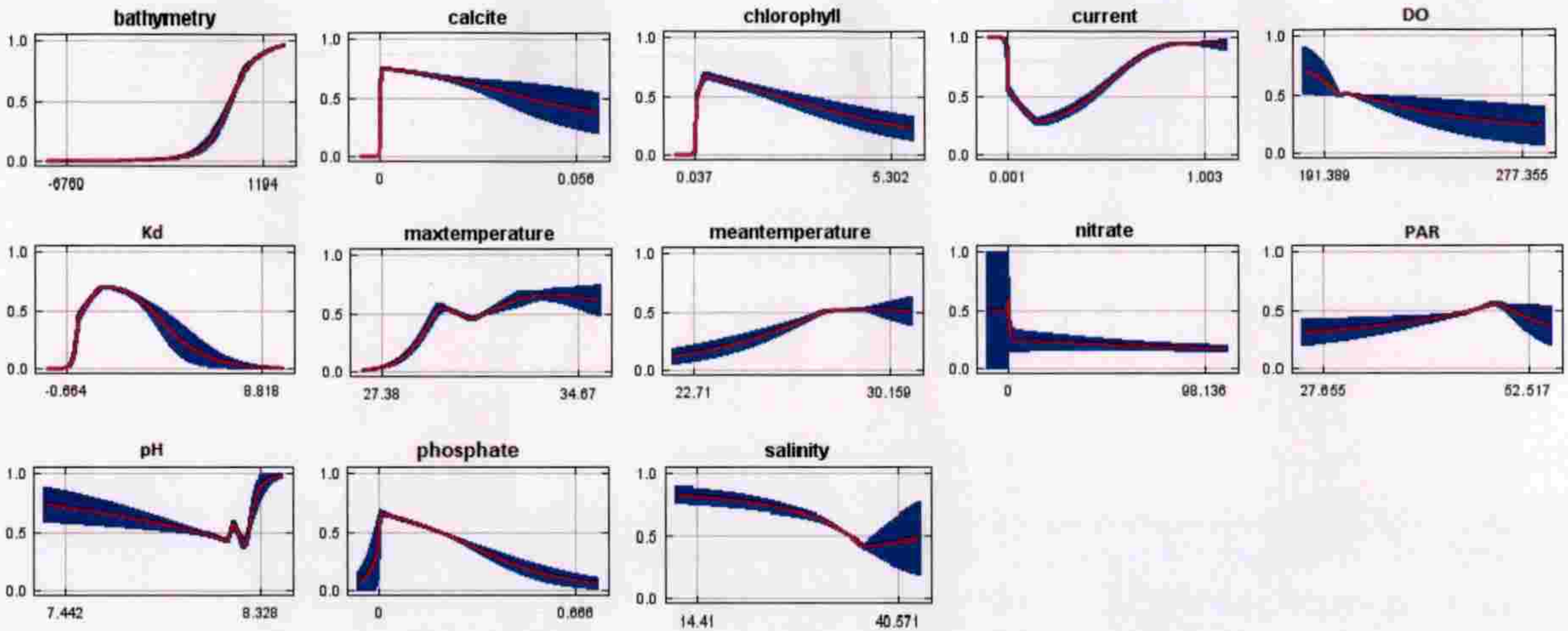

Fig. 5 The response curves for the *A. muricata* model

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Table 1 Percent contribution and permutation importance of all environmental variables to the model for *A. muricata*

Variable	***Percent contribution***	***Permutation importance***
Bathymetry	70.2	83.9
Nitrate	7.6	2.3
Phosphate	5.6	2.5
Kd	4.1	4.3
Calcite	3.1	0.5
pH	2.5	1.3
Current	1.5	0.3
Chlorophyll	1.3	2.6
Mean Temperature	1.2	0.9
Salinity	1.1	0
PAR	1	1
Max. Temperature	0.9	0.1
DO	0	0.1

The Jackknife of AUC for *A. muricata* shows the environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most

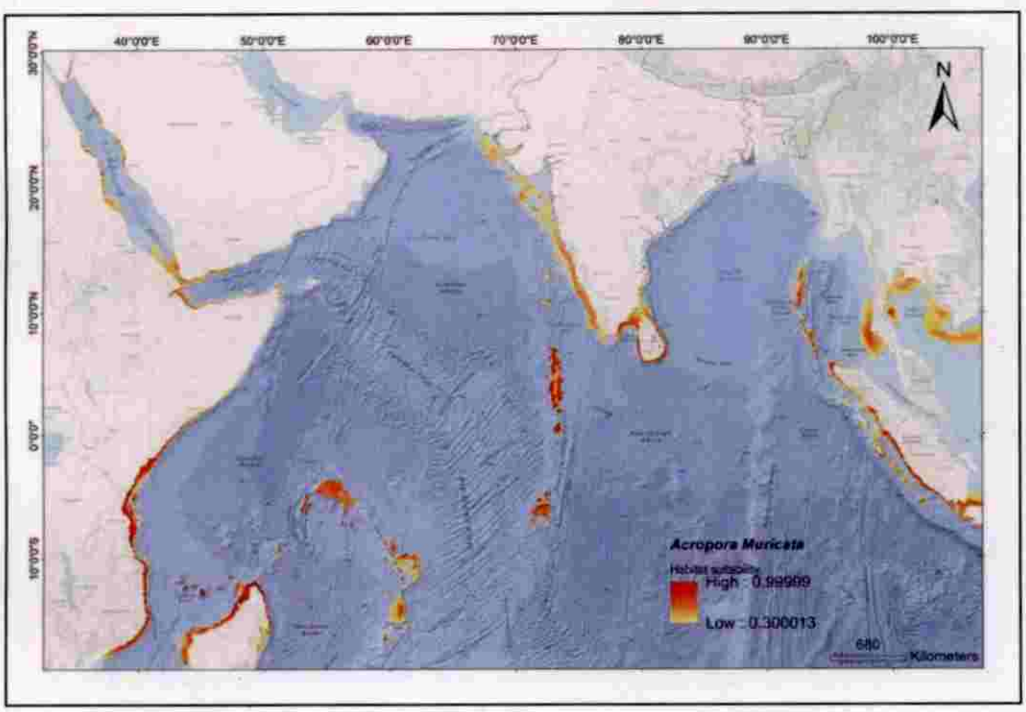


Fig. 6 The predicted distribution of *A. muricata* in the Northern Indian ocean

information that isn't present in the other variables. Also dissolved oxygen shows a lesser gain, lower than 0.50.

The response curves for the *A. muricata* model (Fig. 5) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates. These plots demonstrate the dependence of predicted suitability on the selected variables as well as on the dependencies induced by correlations between each variable and other variables.

4.1.1.3 Prediction of the present distribution of the *A. muricata*

Fig. 6 shows that the predicted distribution of *A. muricata* in the Northern Indian ocean with suitability ranging from 0.30 to 0.99, low to high indicated by a legend of yellow to red. The *A. muricata* shows higher environmental suitability (80-99%) along the Maldives, Chagos, Gulf of Mannar, Andaman & Nicobar Islands, Southwestern boundary of Northern Indian Ocean, Northwestern boundary of Madagascar Island as well as in the islands and seamounts (which lies in between), the Western islands and boundaries of Sumatra. A medium to high suitability (50-80%) was predicted in Lakshadweep Islands, Gulf of Kutch, Gulf of Thailand, Malacca Strait, boundaries of Red Sea, along the Seychelles-Mauritius Plateau and along the South-western coast of India.

4.1.2 The Future distribution of *A. muricata* under different Climate Scenarios

Models prepared using the optimized variables under three different Representative Concentration Pathways (RCP) such as RCP4.5, RCP6 and RCP8.5 gave the prediction for future distribution of the *A. muricata* in the Northern Indian Ocean for the years 2040-2050 and 2090-2100.

4.1.2.1 Future distribution of *A. muricata* under RCP 4.5 for years 2040-50 and 2090-2100

4.1.2.1.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.922, (SD= 0.059) and 0.97(SD=0.053) respectively (Fig. 7).

4.1.2.1.2 Contribution of predictor variables

Table 2 Percentage contribution and permutation importance of all environmental variables to the model for *A. muricata* under RCP 4.5 for the decades of 2040-2050 and 2090-2100.

Variable	*Percent contribution RCP4.5 (2040-2050)*	*Permutation importance RCP 4.5 (2040-2050)*	*Percent contribution RCP4.5 (2090-2100)*	*Permutation importance RCP 4.5 (2090-2100)*
Bathymetry	57.9	76.3	62.5	67.8
Mean Temperature	24	17.1	23.6	27
Salinity	9.4	3.3	7.6	1.4
Current	8.5	3.3	5.9	3.7
Max Temperature	0.2	0	0.5	0

Among these variables, bathymetry showed a significantly higher contribution of 57.9 % and 62.5% for the years 2040-50 and 2090-2100 respectively under RCP 4.5, followed by Mean Temperature (24% & 23.6%) (Table 2). The Maximum Temperature has the least contribution in this particular model developed for *A. muricata.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 76.3% & 67.8% and the Maximum temperature shows no contribution to this scenario.

The Jackknife of AUC for *A. muricata* shows environmental variable with the highest gain when used in isolation is Mean Temperature followed by bathymetry for both periods under the RCP 4.5 (Fig. 8). The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is mean temperature, which therefore appears to have the most information that isn't present in the other variables, whereas salinity shows a lesser gain, lower than 0.55.

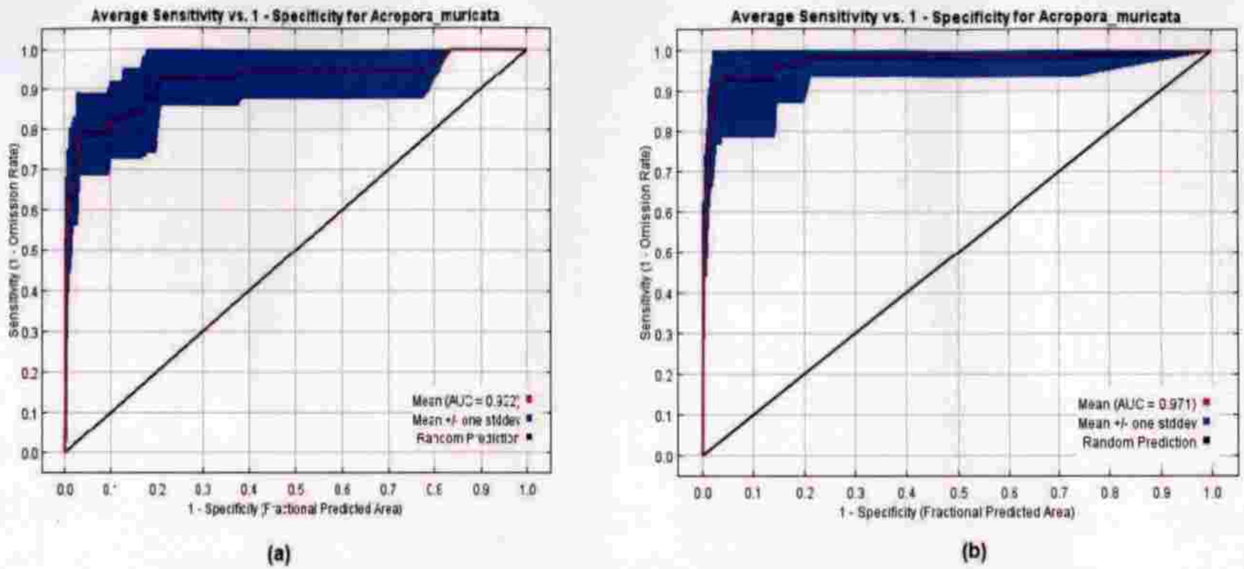


Fig. 7 ROC curve of variable optimization of the *A. muricata* under RCP 4.5 for the years 2040-50 (a) and 2090-2100 (b)

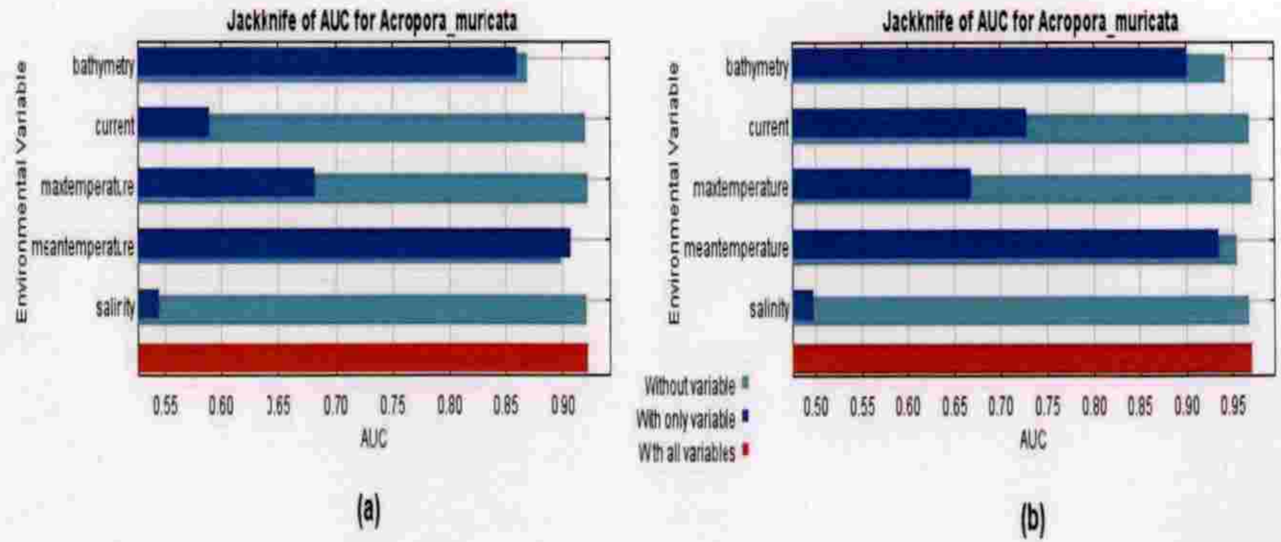


Fig. 8 Jackknife analysis of AUC for the *A. muricata* using variables according to RCP 4.5 for years 2040-2050 (a) and 2090-2100 (b)

4.1.2.1.3 Response curves of variables used in both models

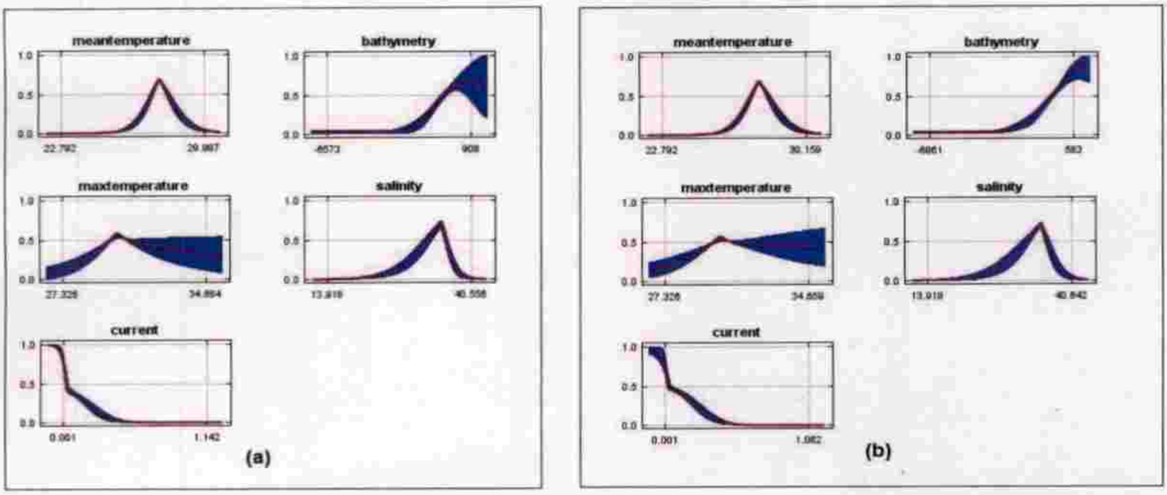


Fig. 9 The Response curve of each variable for 2040-50 and 2090-2100

The response curves for the *A. muricata* model under the RCP 4.5 for the years 2040-50 (Fig. 9a) and 2090-2100 (Fig. 9b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

4.1.2.1.4 The predicted habitat suitability of *A. muricata* under RCP 4.5

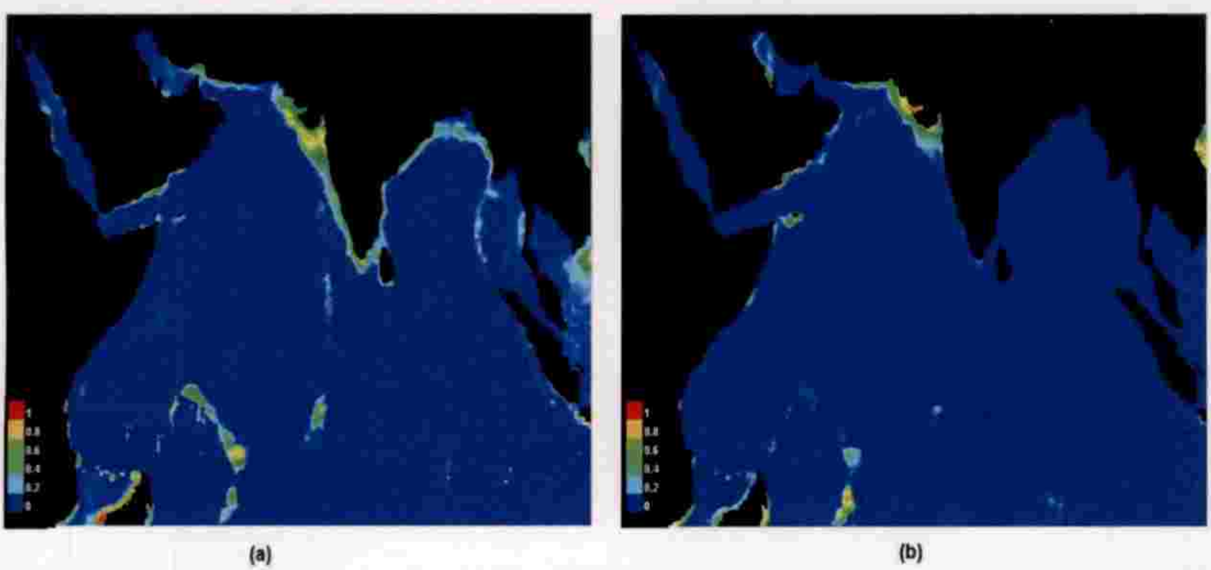


Fig. 10 Map showing the predicted habitat suitability of *A. muricata* in the northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 4.5

Based on current environmental variables the model predicted maximum distribution in regions such as the Gulf of Kutch, Western coast of Madagascar, the entire stretch of Seychelles - Mauritius Ridge (SMR) and the Chagos Archipelago. Other regions of low plausibility of occurrence include south-eastern Africa, coast of Arabian Peninsula, western central and eastern coast of India, the islands of Andaman & Nicobar and the Gulf of Thailand. However, the occurrence of corals predicted as per the RCP 4.5 for 2040-2050 shows the disappearance of reef ecosystems from all the above-mentioned regions except the southern part of SMR, Gulf of Kutch and north-eastern Madagascar.

The prediction of coral distribution for 2090-2100 based on the RCP 4.5 (Fig. 11) is somewhat similar to that for 2040-2050. The reason can be inferred from the similarity in the temperature range for decadal periods.

4.1.2.2 Future distribution of *A. muricata* under RCP 6.0 for years 2040-50 and 2090-2100

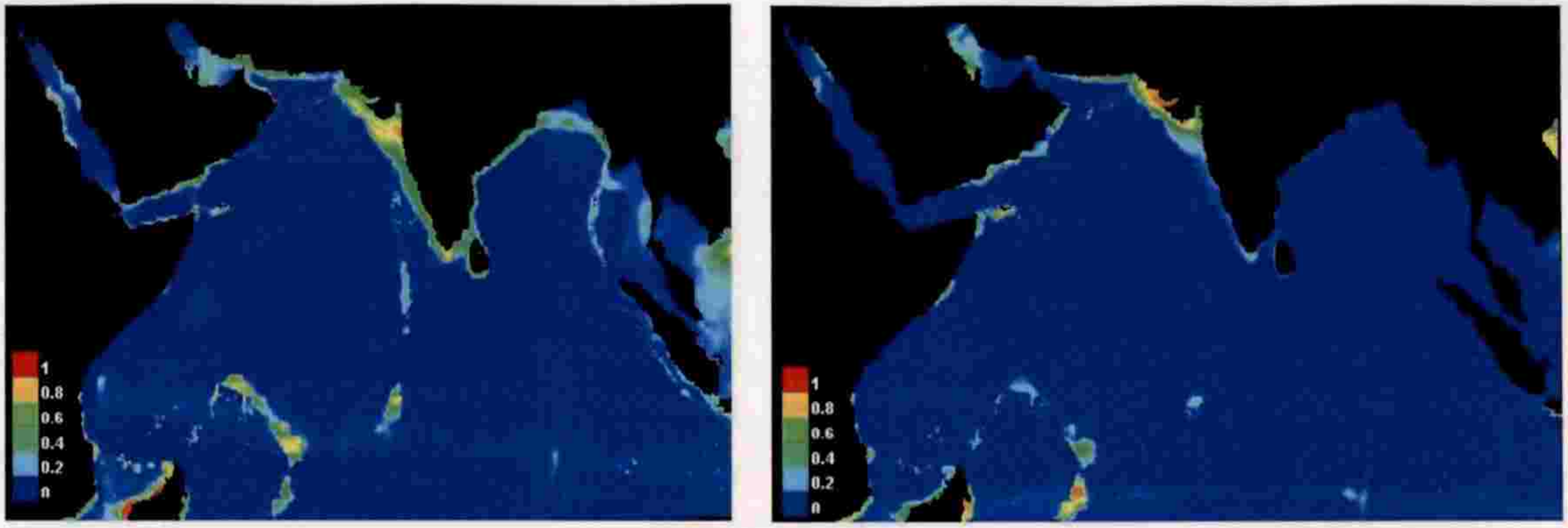
4.1.2.2.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.917, (SD= 0.047) and 0.941 (SD= 0.050) respectively (Fig. 12).

4.1.2.2.2 Contribution of predictor variables

Table 3 Percentage contribution and permutation importance of all environmental variables to the model for *A. muricata* under RCP 6.0 for the decades of 2040-2050 and 2090-2100.

Variable	*Percent contribution (RCP 6.0 2040-50)*	*Permutation importance (RCP 6.0 2040-50)*	*Percent contribution (RCP 6.0 2090-2100)*	*Permutation importance (RCP 6.0 2090-2100)*
Bathymetry	56.4	59.4	56.6	75.7
Mean temperature	27.9	26.7	27.5	19.3
Salinity	8.5	3.9	8.2	1.9
Current	6.5	9.9	7.4	3.1
Max temperature	0.6	0.1	0.2	0



(a)

(b)

Fig. 11 Map showing the predicted habitat suitability of *A. muricata* in the northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 4.5.

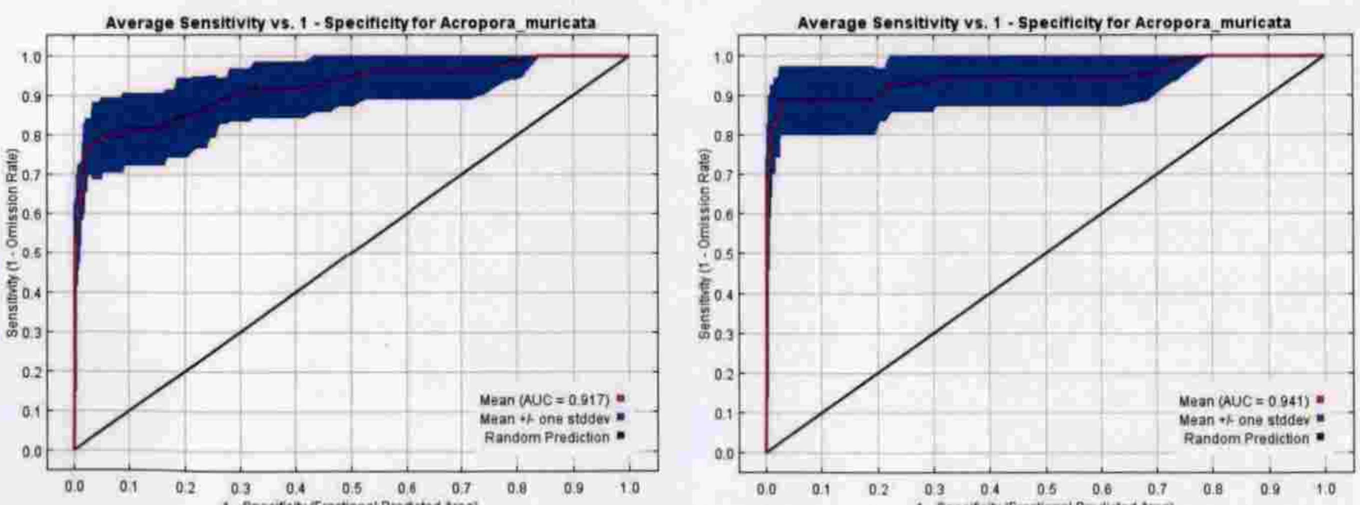


Fig. 12 ROC curve of variable optimization of the *A. muricata* under RCP 6.0 for the years 2040-50 (a) and 2090-2100 (b)

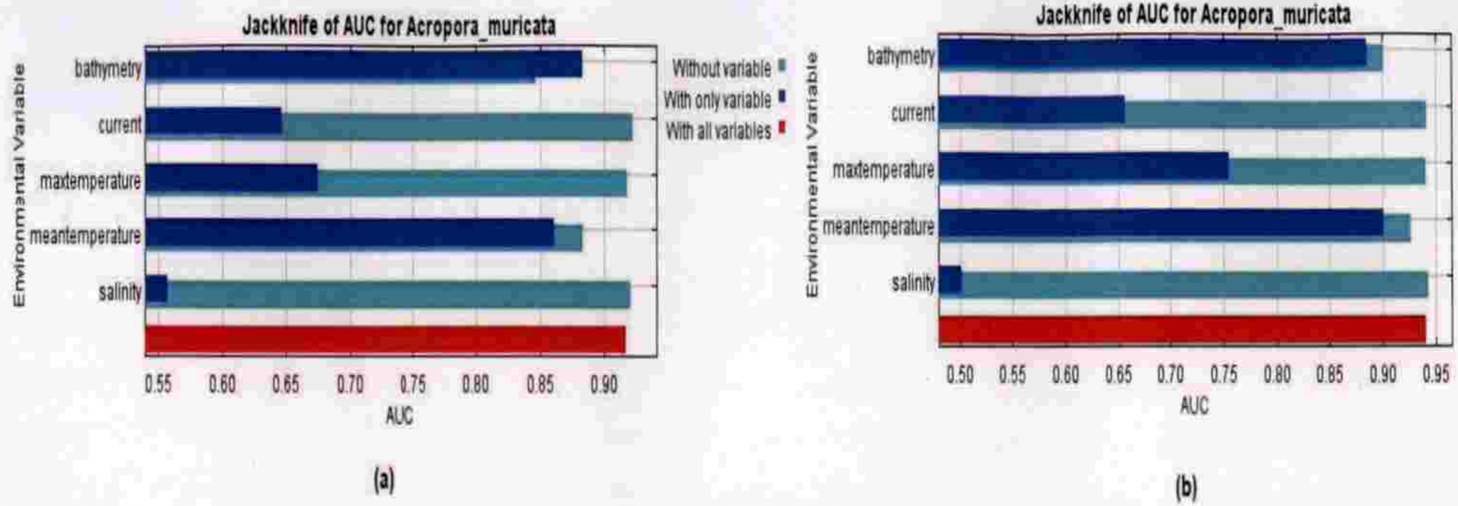


Fig. 13 Jackknife analysis of AUC for the *A. muricata* using variables according to RCP 6.0 for years 2040-2050 (a) and 2090-2100 (b)

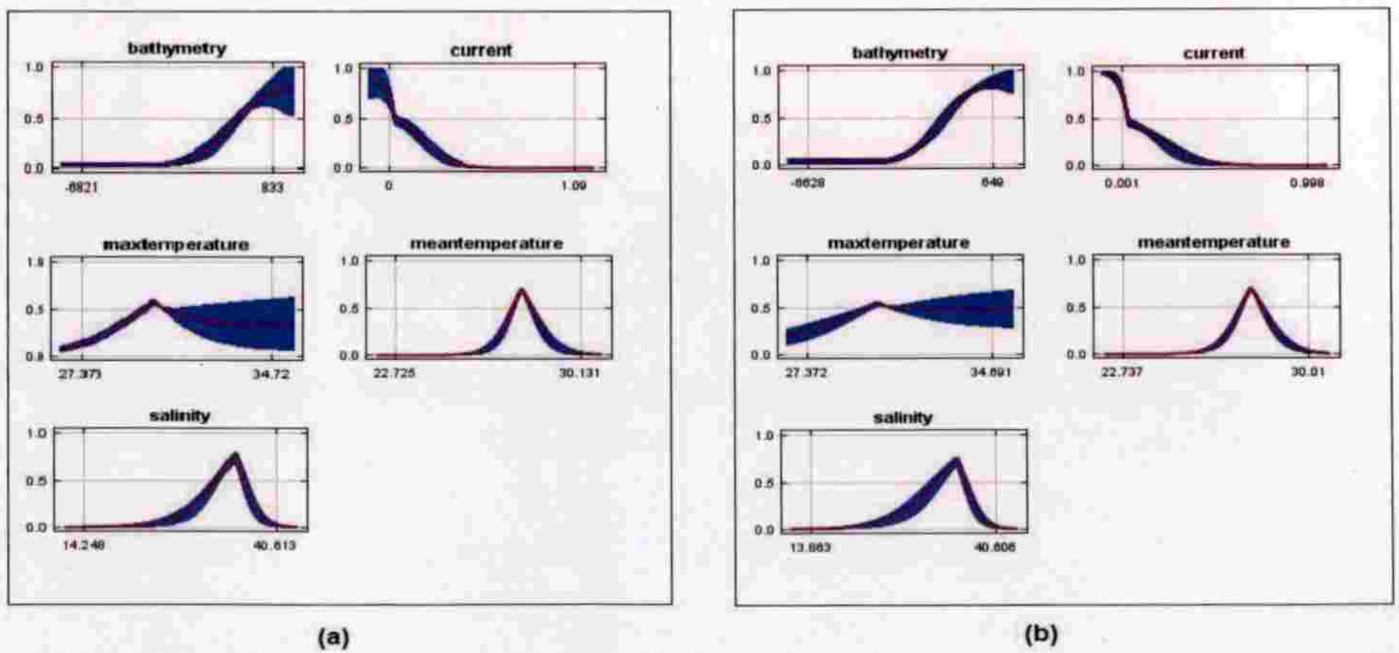


Fig. 14 The Response curve of each variable for 2040-50 and 2090-2100.

Among these variables, bathymetry showed a significantly higher contribution of 56.4 % and 56.6 % for the years 2040-50 and 2090-2100 respectively under RCP 6.0, followed by Mean Temperature (27.9 & 27.5%) (Table 3). The Maximum Temperature has the least contribution in this particular model developed for *A. muricata.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 59.4% & 75.7% and the Maximum temperature shows the least contribution (0.1 & 0%) for this scenario in both periods.

The Jackknife of AUC for *A. muricata* shows environmental variable with the highest gain when used in isolation is bathymetry followed by mean temperature for the first decadal period whereas the Jackknife analysis for 2090-2100 shows that the mean temperature exceeds bathymetry under the RCP 6.0 (

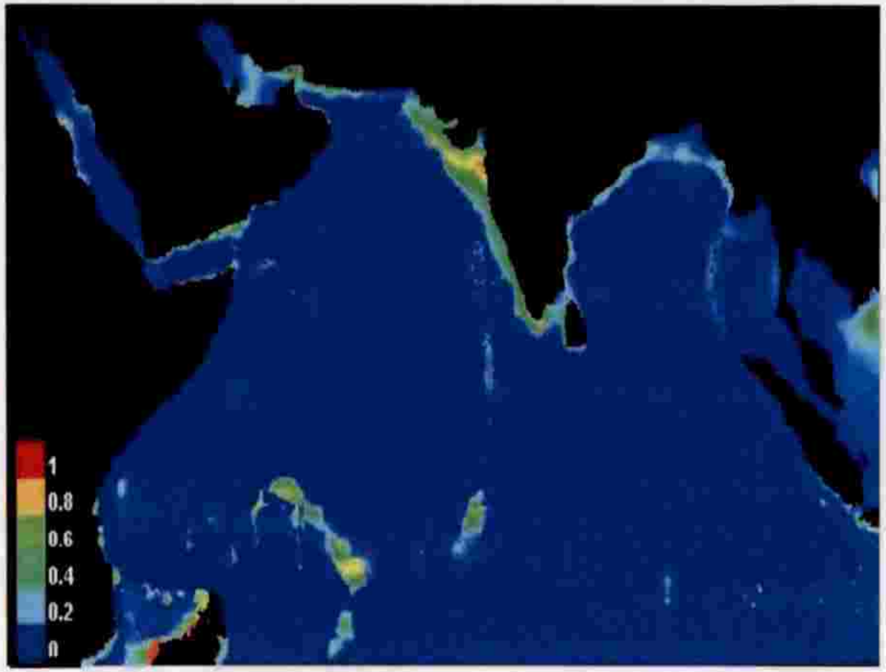
Fig. 13). The values shown are averages over 10 replicate runs. The salinity shows a lesser gain in both cases that just above 0.55 and about 0.50 for the period 2040-50& 2090-2100 respectively.

4.1.2.2.3 <u>Response curves of variables used in both models</u>

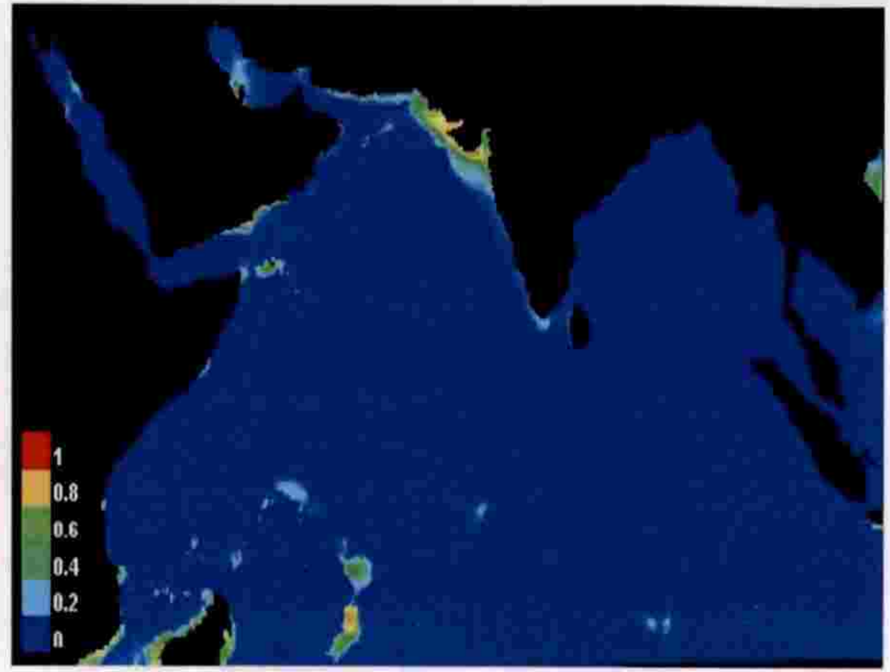
The response curves for the *A. muricata* model under the RCP 6.0 for the years 2040-50(Fig. 14a) and 2090-2100 (Fig. 14b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged over 10 replicates.

4.1.2.2.4 <u>The predicted habitat suitability of *A. muricata* under RCP 6.0</u>

Based on RCP 6.0 the distribution of *A. muricata* in the present condition is predicted in the entire Indian coast with a higher probability of presence on the northern coast of Maharashtra and the nearby regions of Gujarat coast followed by north-western Madagascar; the SMR and the Chagos Lakshadweep ridges, and also on the southern cape regions of Indian peninsula. However, the Andaman Nicobar Islands and the surrounding regions are predicted poorly for the presence of this species. The distribution becomes more reduced for the decade of 2040-2050 under RCP 6.0 in which the entire Andaman and Nicobar Islands, Lakshadweep islands and the east and west coast of India are predicted with no *A. muricata*. Its distribution is also diminished on the SMR, the Red Sea and the Persian Gulf regions. An increase in the coral population density is predicted for the southern part of SMR and south-eastern Africa.



(a)



(b)

Fig. 15 Map showing the predicted habitat suitability of *A. muricata* in the Northern Indian Ocean in present condition (a) and for 2040-2050 (b) under RCP 6.0.

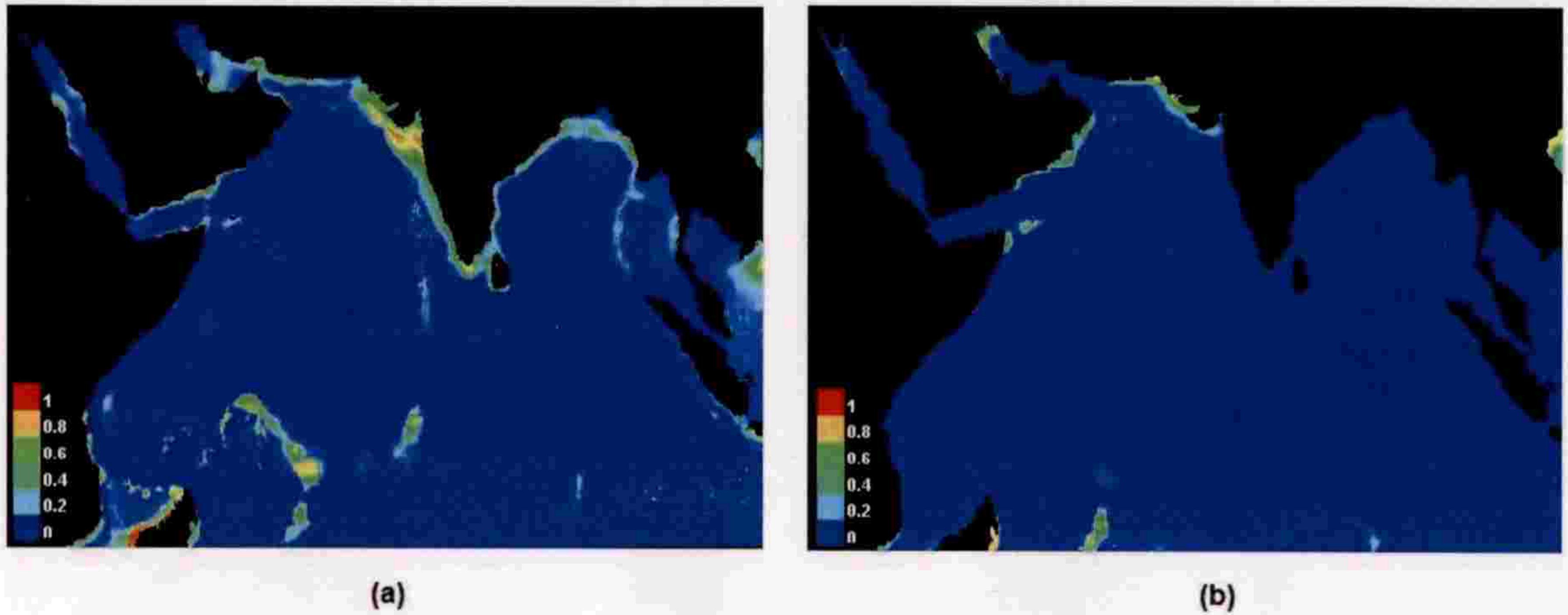
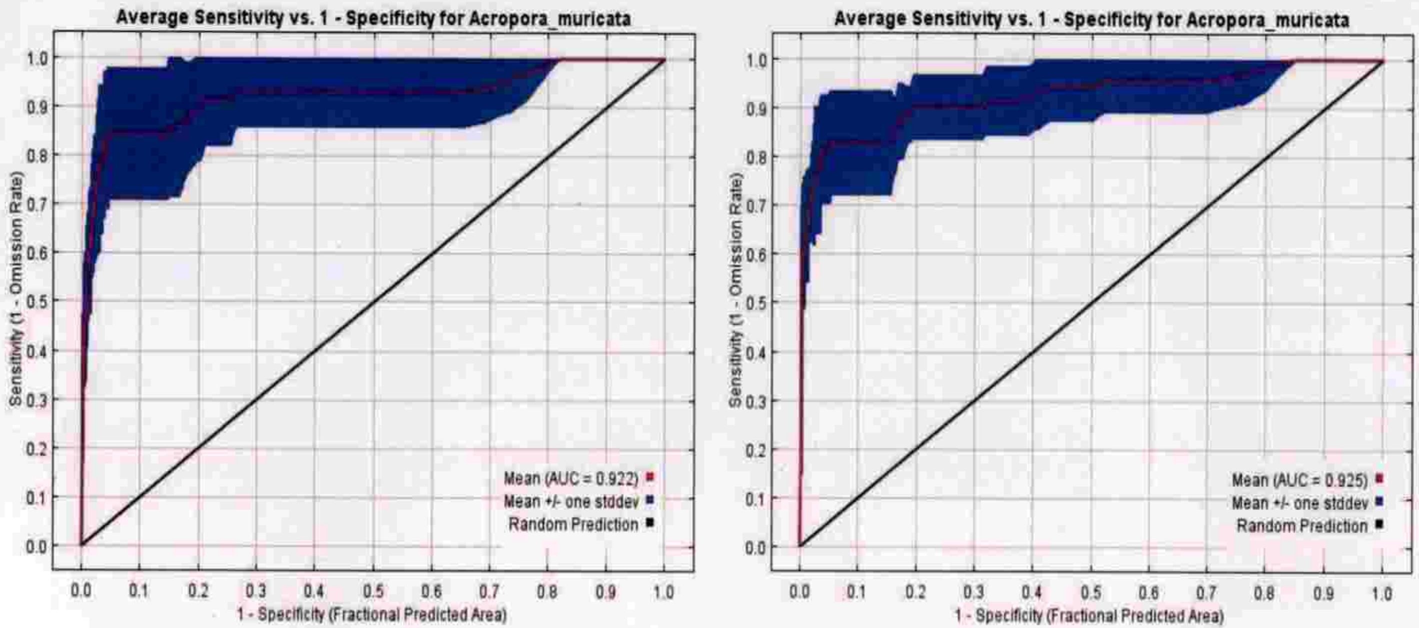
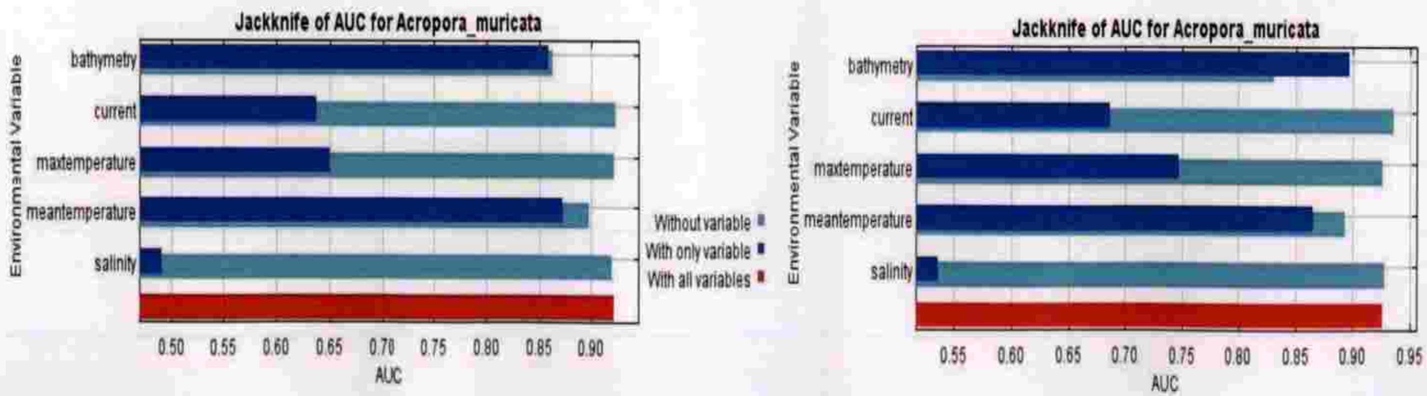


Fig. 16 Map showing the predicted habitat suitability of *A. muricata* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 6.0.



(a) (b)

Fig. 17 The AUC curve of variable optimization of the *A. muricata* under RCP 8.5 for the years 2040-50 (a) and 2090-2100 (b)



(a) (b)

Fig. 18 Jackknife analysis of AUC for the *A. muricata* using variables according to RCP 8.5 for years 2040-2050 (a) and 2090-2100 (b)

When compared with the prediction given for 2040-2050 under RCP 6.0 remarkable differences can be seen in the predicted distribution for this species in 2090-2100 (Fig. 16). Here it is completely absent in two island groups of India and its entire coast expect Gujarat. The population vanished in the north-western parts of Madagascar and the SMR while a comparatively good presence is retained in the eastern coast of Madagascar and southern part of SMR. Distribution is predicted but in new regions along the coast of the Arabian Peninsula. A notable feature is the almost complete absence of the species in the Red Sea.

4.1.2.3 Future distribution of *A. muricata* under RCP 8.5 for years 2040-50 and 2090-2100

4.1.2.3.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.922 (SD= 0.061) and 0.925 (SD= 0. 046) respectively (Fig. 17).

4.1.2.3.2 Contribution of predictor variables

Table 4 Percentage contribution and permutation importance of all environmental variables to the model for *A. muricata* under RCP 8.5 for the period of 2040-2050 and 2090-2100.

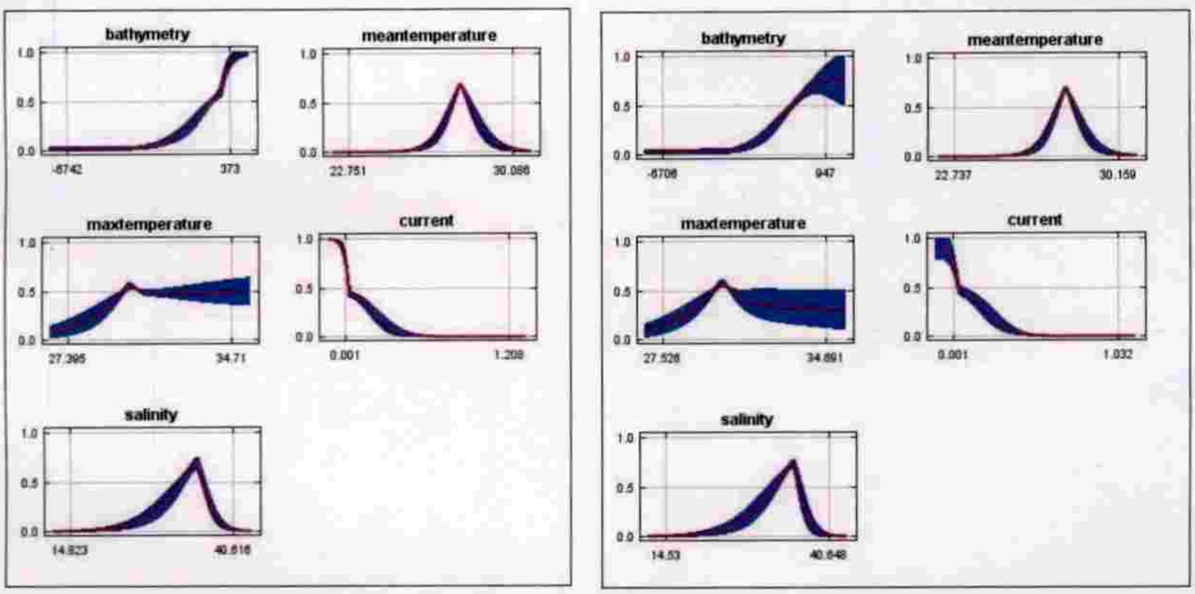
Variable	*Percent contribution RCP 8.5 (2040-2050)*	*Permutation importance RCP 8.5 (2040-2050)*	*Percent contribution RCP 8.5 (2090-2100)*	*Permutation importance RCP. 8.5 (2090-2100)*
Bathymetry	59.1	71.1	54.6	65.6
Mean Temperature	25.2	20.2	28.2	24.8
Salinity	8.5	5.1	9.2	6.2
Current	7.1	3.7	7.5	3.3
Max Temperature	0.1	0	0.5	0.1

Among these variables, bathymetry showed a significantly higher contribution of 59.1 % and 54.6% followed by Mean Temperature (25.2 & 28.2%) for the years 2040-50 and 2090-2100 respectively (Table 4). The Maximum Temperature has the least contribution in this particular model developed for *A. muricata.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 71.1% & 65.6% and the

Maximum temperature shows the least contribution for the year 2040-2050 and has no contribution for 2090-2100 during this scenario.

The Jackknife of AUC for *A. muricata* (Fig. 18) shows environmental variable with the highest gain is bathymetry when used in isolation, followed by mean temperature for both periods under the scenario RCP 8.5. The values shown are averaged over 10 replicates. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas salinity shows a lesser gain in both periods similar to the other scenarios.

4.1.2.3.3 <u>Response curves of variables used in both models</u>

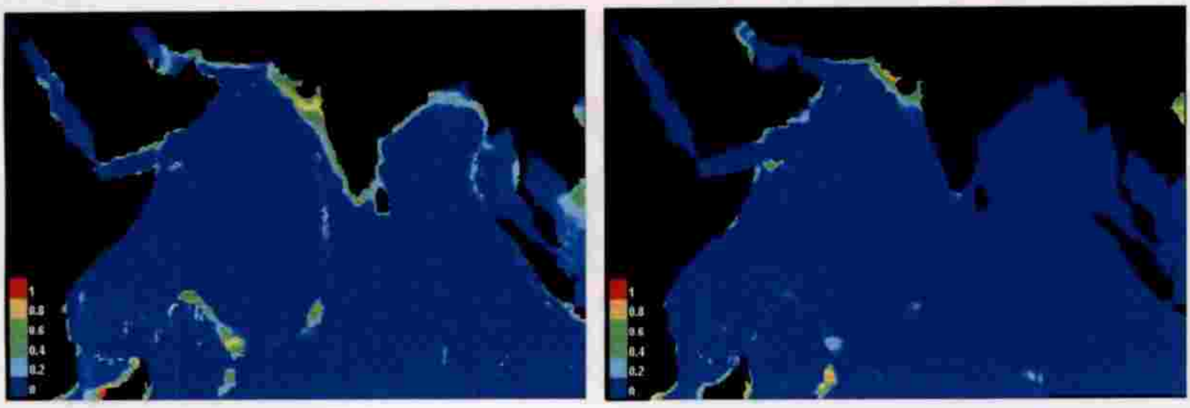


(a) (b)

Fig. 19 The Response curve of each variable for 2040-50 and 2090-2100.

The response curves for the *A. muricata* model under the RCP 8.5 for the period of 2040-50 (Fig. 19a) and 2090-2100 (Fig. 19b) showed the response of each variable in determining the distribution of the species created using only the corresponding variable, averaged for 10 replicates.

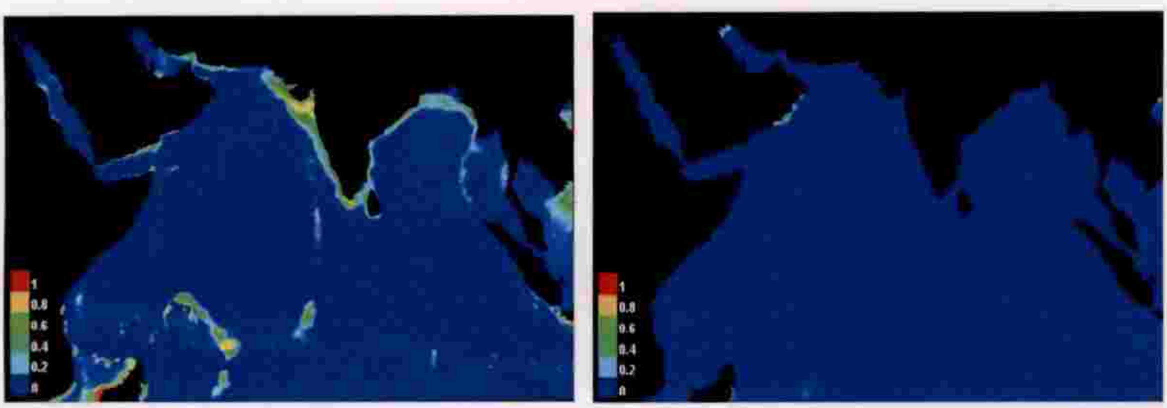
4.1.2.3.4 <u>The predicted habitat suitability of *A. muricata* under RCP 8.5</u>



(a) (b)

Fig. 20 Map showing the predicted habitat suitability of *A. muricata* in the Northern Indian Ocean in present condition (a) and for 2040-2050 (b) under RCP 8.5.

Under RCP 8.5 the predicted distribution of *A. muricata* (Fig. 20) for the present condition is almost similar to that under RCP 4.5 and 6.0. For the 2040-2050 decade, the prediction is more similar to that under RCP 4.5.



(a) (b)

Fig. 21 Map showing the predicted habitat suitability of *A. muricata* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 8.5.

Here the range of *A. muricata* for 2090-2100 (Fig. 21) is just confined to the northernmost coast of the Persian Gulf, the coast of Oman, eastern Madagascar and southern SMR, however to a lesser degree.

4.2 *F. pallida*

4.2.1 Prediction of the current distribution

4.2.1.1 The Model Performance and variable contributions

The model performance assessed by using the average test AUC value for 10 replicates was 0.933 (SD= 0.025). The sensitivity *vs.* 1-specificity graph shows the area under the Receiver Operating Characteristic (ROC) curve or AUC. The test omission rate and AUC curve (Fig. 22 & Fig 23) was found fit in this model. The Fig. 22 shows that the mean omission line on the test data was passing through the predicted omission line. In theFig. 22, the AUC line was passing through the left top of the random prediction.

4.2.1.2 Contribution of predictor variables

Table 5 Percentage contribution and permutation importance of all environmental variables to the model for *F. pallida*

Variable	***Percent contribution***	***Permutation importance***
Bathymetry	62.3	80.7
Calcite	7.9	0.9
pH	6.3	3
Nitrate	6.1	3.9
Current	4.9	0.5
Kd	3.2	2.3
Phosphate	2.1	1.1
PAR	1.9	2.5
Mean temperature	1.7	1.7
Chlorophyll	1.3	1.4
Salinity	1.2	1.3
Max temperature	0.6	0.3
DO	0.5	0.1

The relative contribution of each predictor variable is given by the MaxEnt output and it is shown in Table 5. Among all the variables, bathymetry showed a significantly higher contribution of 62.3 %, followed by Calcite (7.9%) and pH (6.3%). The dissolved oxygen shows the least contribution of 0.5 % in this model developed for *F. pallida.* For the Permutation importance, for each environmental variable, in turn, the values of that variable in training presence as well as in background data were randomly permuted. The variable

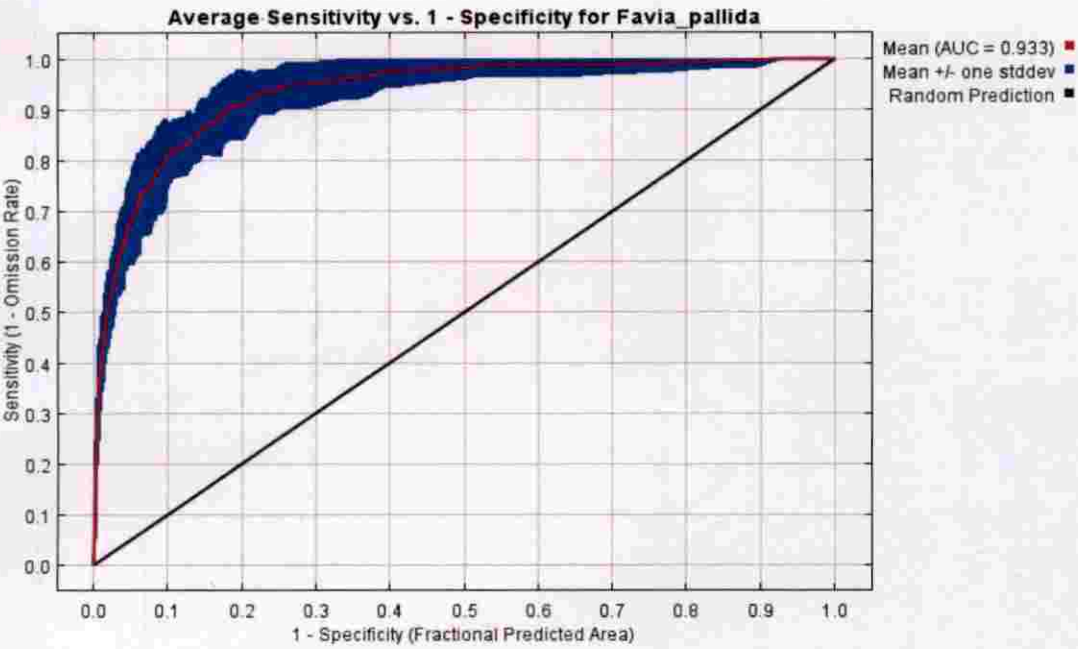


Fig. 22 ROC curve of variable optimization model of the *F. pallida*

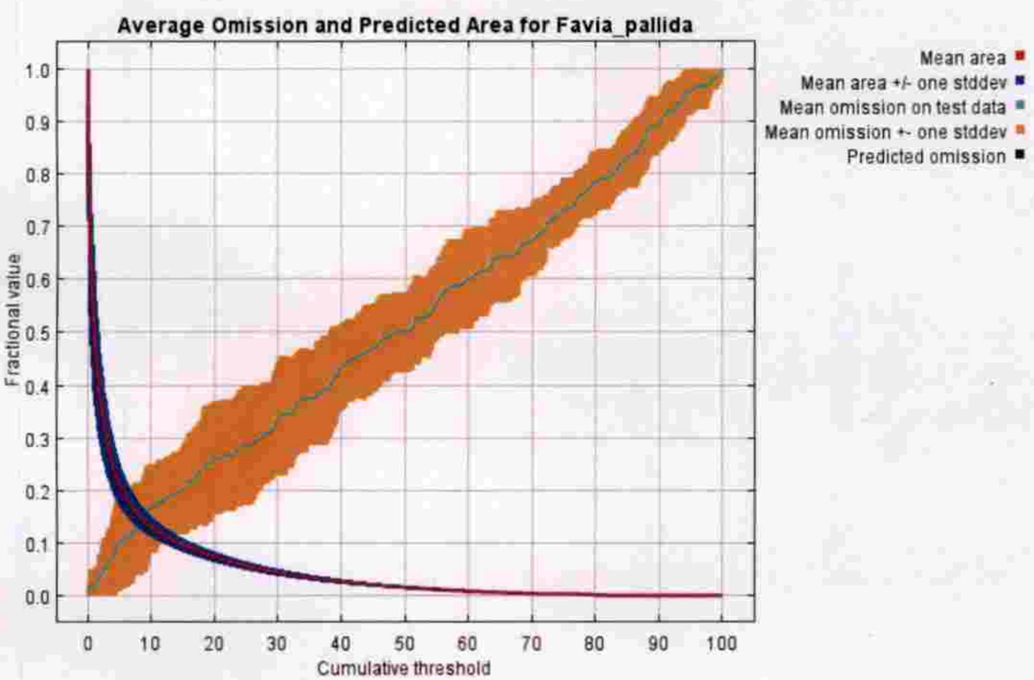


Fig. 23 Test omission rate and predicted area as a function of the cumulative threshold, averaged over the replicate runs for *F. pallida*

having high permutation importance (80.7%) were bathymetry and the nitrate by 3.9 percentage.

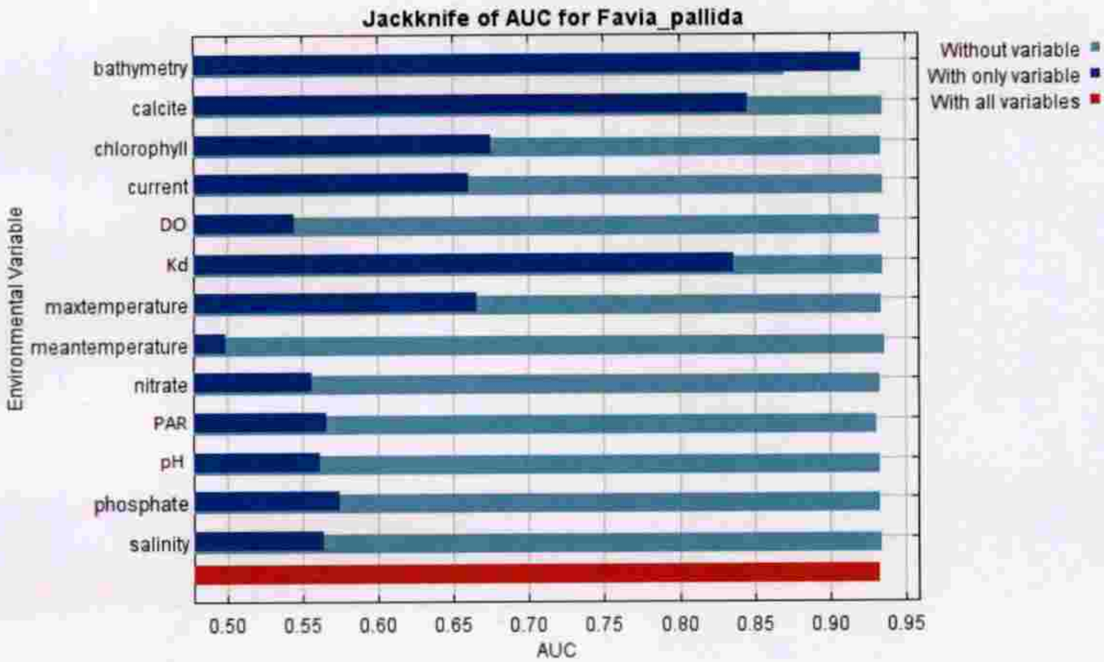


Fig. 24 Jackknife analysis of AUC for the *F. pallida* using all the variables

The Jackknife of AUC for *F. pallida* (Fig. 24) shows environmental variable with the highest gain when used in isolation is bathymetry, followed by calcite and diffusion attenuation coefficient (Kd), which therefore appears to have the most useful information by itself. The values shown are averages over replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Also, the mean temperature showed the least gain

The response curves for the *F. pallida* model (Fig. 25) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates. These plots demonstrate the dependence of predicted suitability on the selected variables as well as on the dependencies induced by correlations between each variable and other variables.

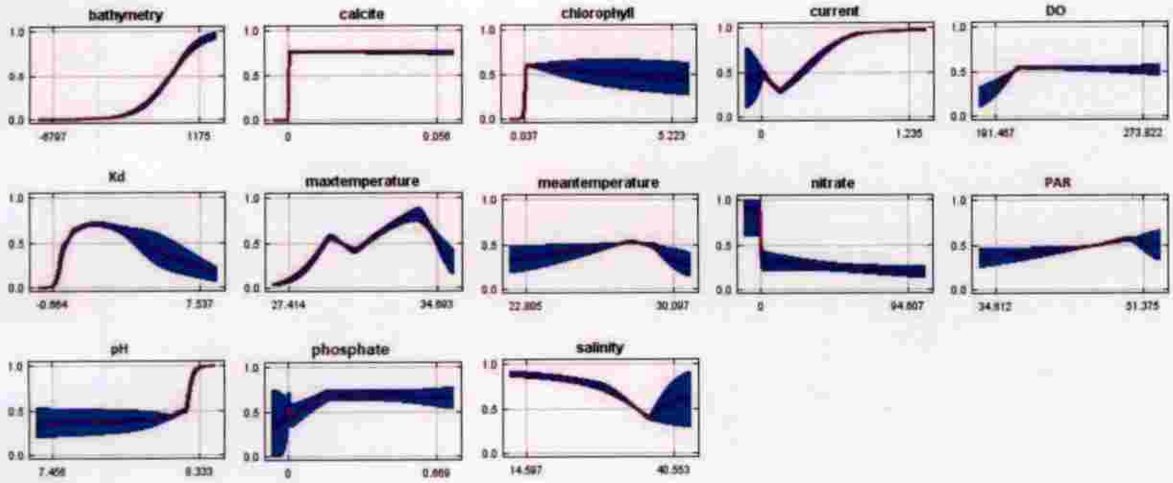


Fig. 25 The response curves of each variable for the F. *pallida* model

4.2.1.3 Prediction of the present distribution of the *F. pallida*

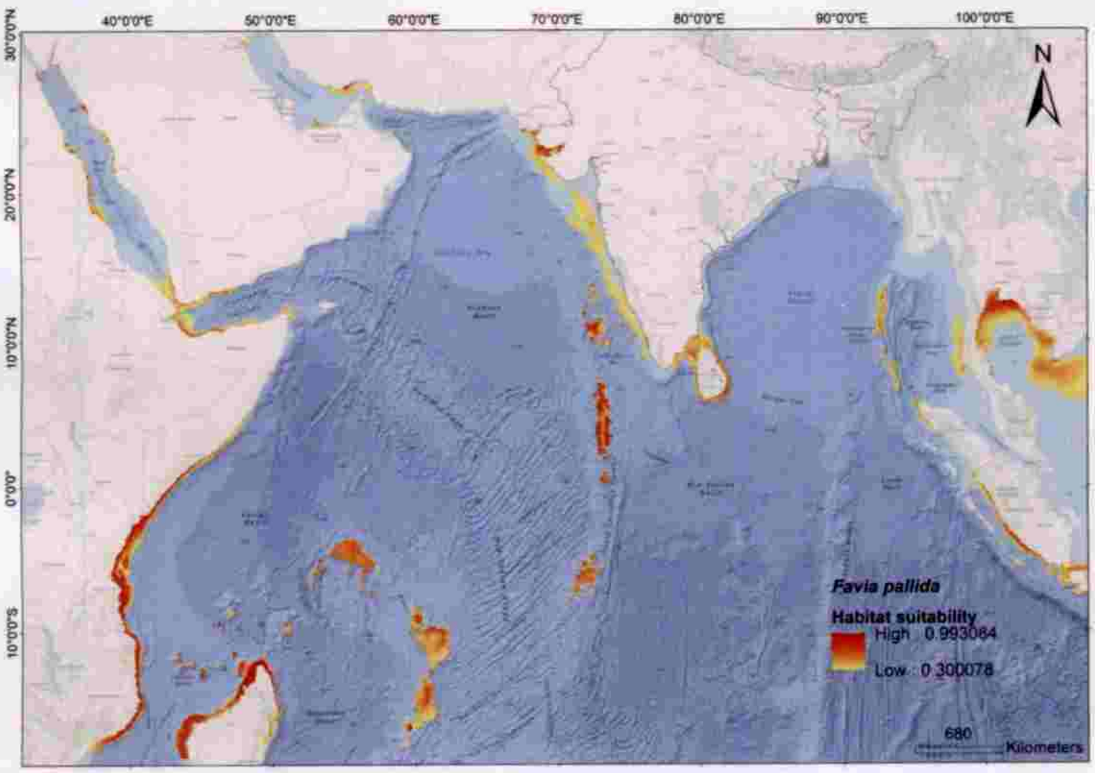


Fig. 26 The predicted distribution of *F. pallida* along the Northern Indian Ocean.

Fig. 26 shows that the predicted distribution of *F. pallida* in the Northern Indian ocean with suitability ranging from 0.30 to 0.99, low to high indicated by a legend of yellow to red.

The *F. pallida* shows higher environmental suitability (80-99%) along the Lakshadweep islands, Maldives, Chagos, Gulf of Kutch, Northern region of Gulf of Thailand, Southwestern boundary of Northern Indian Ocean, North-western coast of Madagascar as well as in the islands and seamounts (which lies in between), the Western coast of Sumatra. A medium to high suitability (50-80%) was predicted in Andaman and Nicobar Islands, Gulf of Mannar and Srilanka coast, Mergui archipelago, boundaries of Red Sea, Persian Gulf, the entire stretch of Seychelles-Mauritius Plateau and along the South-western coast of India.

4.2.2 Future distribution of *F. pallida* under different Climate Scenarios

Models prepared using the optimized variables under three different Representative Concentration Pathways (RCP) such as RCP4.5, RCP6 and RCP8.5 gave the prediction for future distribution of the *F. pallida* in the Northern Indian Ocean for the years 2040-2050 and 2090-2100.

4.2.2.1 Future distribution of *F. pallida* under RCP 4.5 for years 2040-50 and 2090-2100

4.2.2.1.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.924 (SD = 0.011) and 0.911 (SD = 0.026) respectively (Fig. 27).

4.2.2.1.2 Contribution of predictor variables

Among the variables, bathymetry showed the highest contribution of 84.1% and 86.1% for the years 2040-50 and 2090-2100 respectively under RCP 4.5, followed by the current (8.6 & 7.1%) (Table 6). The Maximum Temperature has the least contribution in this particular model developed for *F. pallida*. For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 89.9% & 93.1% and similar to the contribution, maximum temperature also shows the least permutation importance (4.1% & 0.9%) in this scenario.

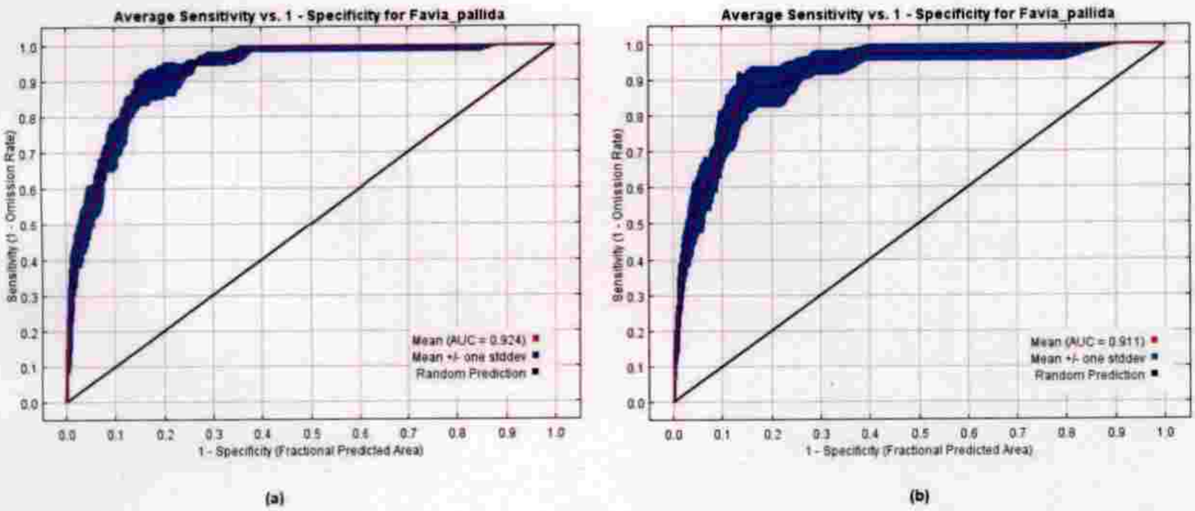


Fig. 27 ROC curve of variable optimization for the *F. pallida* under RCP 4.5 for the years 2040-50 (a) and 2090-2100 (b)

Table 6 Percentage contribution and permutation importance of all environmental variables to the model for *F. pallida* under RCP 4.5 for the decades of 2040-2050 and 2090-2100.

Variable	*Percent contribution RCP4.5 (2040-2050)*	*Permutation importance RCP 4.5 (2040-2050)*	*Percent contribution RCP4.5 (2090-2100)*	*Permutation importance RCP 4.5 (2090-2100)*
Bathymetry	84.1	89.9	86.1	93.1
Current	8.6	1.6	7.1	0.6
Mean temperature	3	3.5	3.1	2.9
Salinity	2.3	0.8	2.3	2.4
Max temperature	2	4.1	1.4	0.9

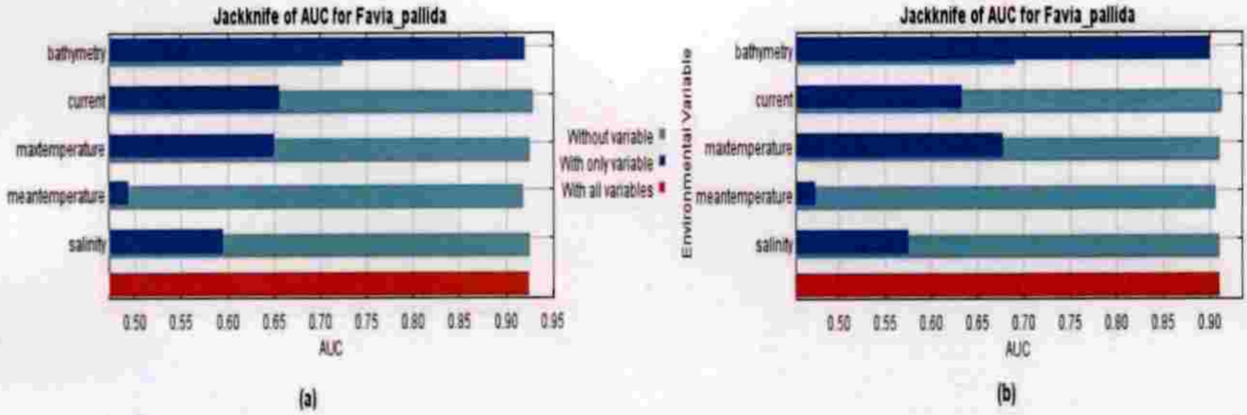


Fig. 28 Jackknife analysis of AUC for the *F. pallida* using variables according to RCP 4.5 for years 2040-2050 (a) and 2090-2100 (b)

4.2.2.1.3 <u>Response curves of variables used in both models</u>

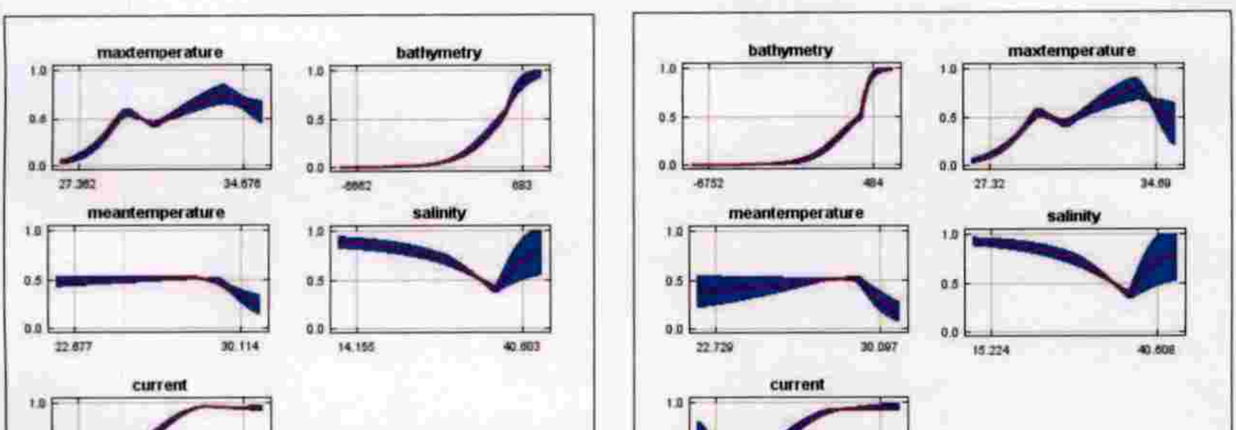
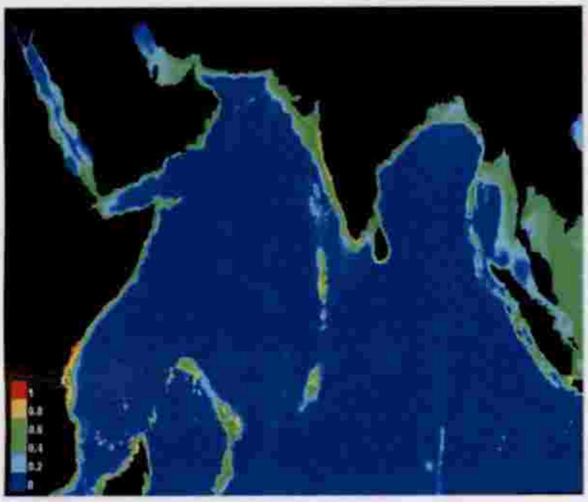


Fig. 29 The Response curve of each variable for 2040-50(a) and 2090-2100(b).

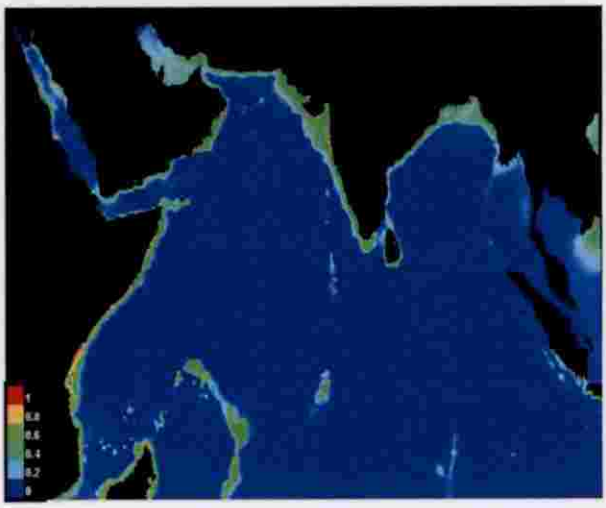
The Jackknife of AUC for *F. pallida* shows environmental variable with the highest gain when used in isolation is bathymetry followed by maximum temperature for the period of 2090-2100 whereas the current and max temperature shows maximum contribution in 2040-50 under RCP 4.5 (Fig. 28). The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas mean temperature shows a lesser gain, lower than 0.50. The values shown are averages over 10 replicate runs.

The response curves for the *F. pallida* model under the RCP 4.5 for the years 2040-50 (Fig. 29a) and 2090-2100 (Fig. 29b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates. For both periods of projection, each variable follows a similar pattern of response to the particular model.

4.2.2.1.4 The predicted habitat suitability of *F. pallida* under RCP 4.5



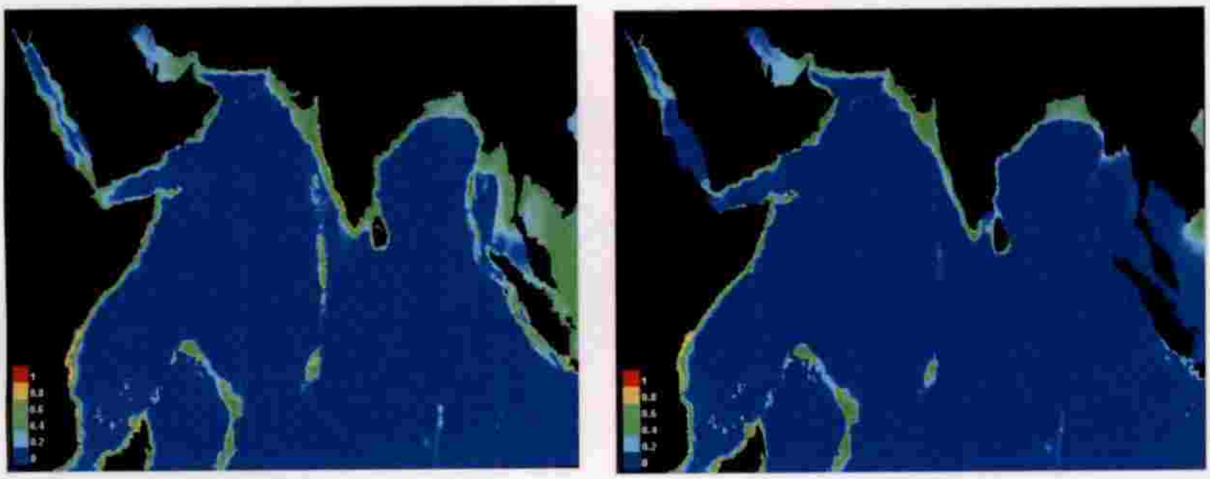
(a)



(b)

Fig. 30 Map showing the predicted habitat suitability of *F. pallida* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 4.5.

On comparing the predicted distribution of *F. pallida* under RCP 4.5 (Fig. 30) for the present situation and for 2040-2050, the range of this species get diminished for 2040-50, in some parts of the Bay of Bengal, *i.e.* in the Gulf of Mannar region; in the Andaman sea; the Red Sea and in the Maldives and Lakshadweep archipelago. The high degree of presence is retained for both cases in the eastern coast of Africa followed by a lesser degree of presence in the entire western coast of India and the SMR.



(a) (b)

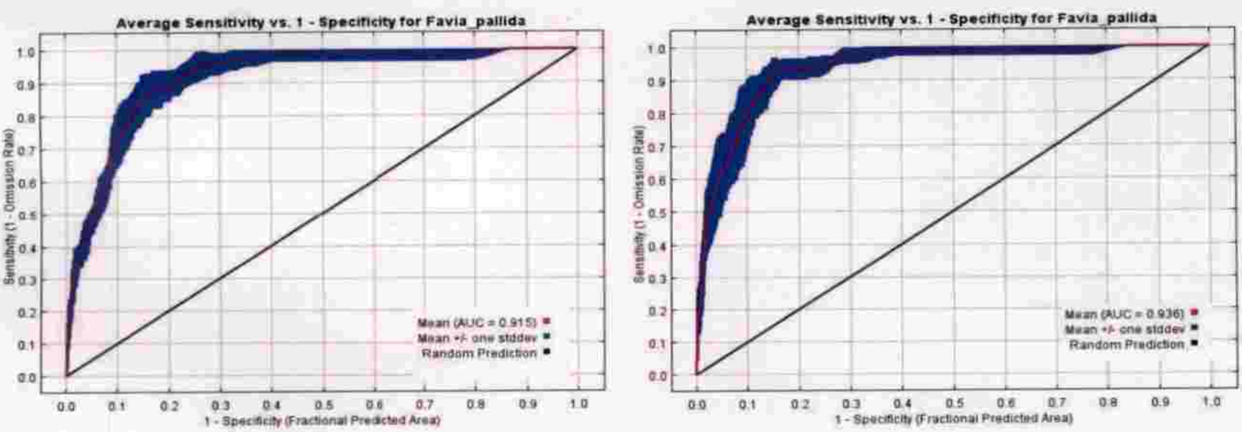
Fig. 31 Map showing the predicted habitat suitability of *F. pallida* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 4.5.

No remarkable reduction in the range of this species is predicted for the decade 2090-2100 under RCP 4.5 (Fig. 31) when compared with its range predicted for 2040-50. However, a slight degree of increase in its presence can be noted for the coast of western India and Bangladesh.

4.2.2.2 Future distribution of *F. pallida* under RCP 6.0 for years 2040-50 and 2090-2100

4.2.2.2.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.924 (SD= 0.011) and 0.911 (SD= 0.026). respectively (Fig. 32(a) and Fig. 32 (b)).



(a) (b)

Fig. 32 ROC curve of variable optimization model of the *F. pallida* under RCP 6.0 for the years 2040-50 (a) and 2090-2100 (b).

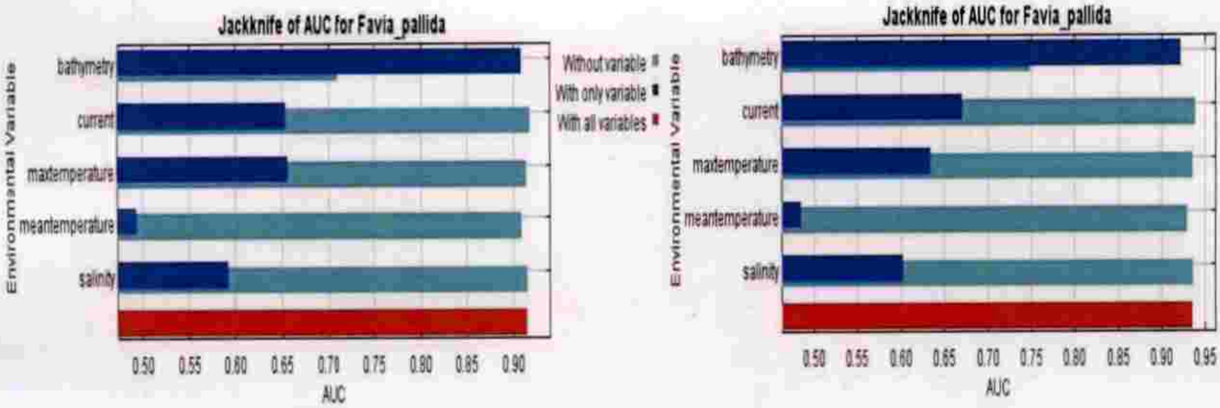
4.2.2.2.2 Contribution of predictor variables

Among the variables, bathymetry showed a significantly higher contribution of 83.8 % and 84.5 % for the years 2040-50 and 2090-2100 respectively under RCP 6.0, followed by the current (8.8 & 9.4%) (Table 7). The Salinity has the least contribution in this particular model developed for *F. pallida.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 93.6 % & 90.6 % and the Salinity itself shows minimum permutation importance in this scenario.

Table 7 Percentage contribution and permutation importance of all environmental variables to the model for *F. pallida* under RCP 6.0 for the decades of 2040-2050 and 2090-2100.

Variable	***Percent contribution (RCP 6.0 2040-2050)***	***Permutation importance (RCP 6.0 2040-2050)***	***Percent contribution (RCP 6.0 2090-2100)***	***Permutation importance (RCP 6.0 2090-2100)***
Bathymetry	83.8	93.6	84.5	90.6
Current	8.8	0.9	9.4	2.3
Mean temperature	3.2	2.4	3.8	4.1
Max temperature	2.4	1.8	1.8	2.5
Salinity	1.9	1.1	0.5	0.6

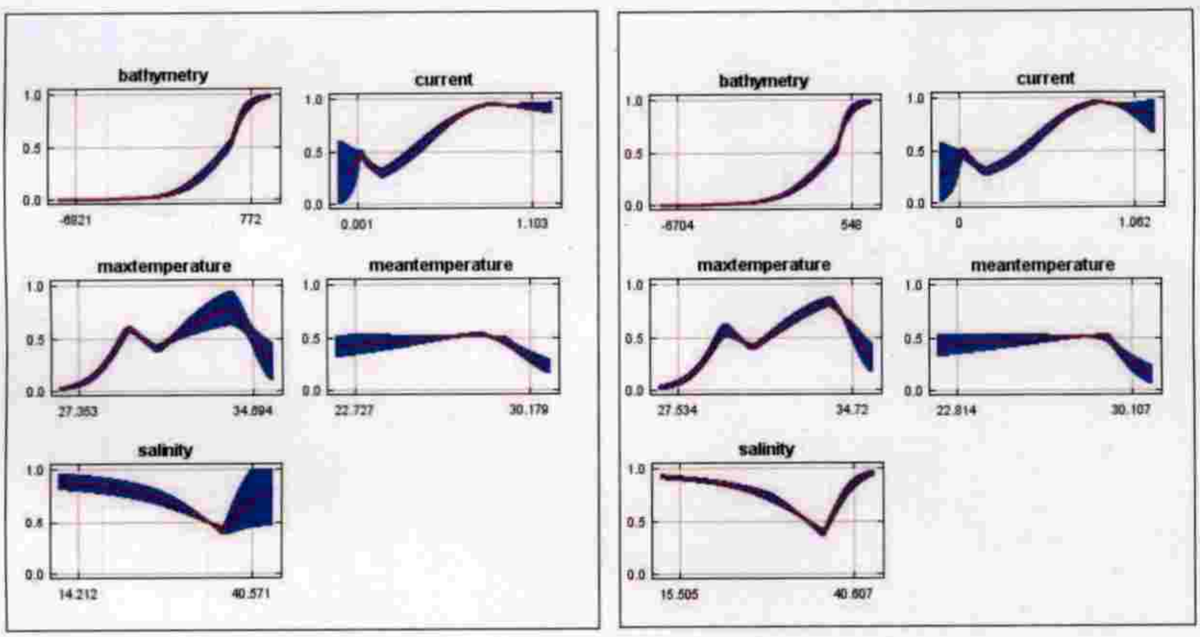
The Jackknife of AUC for *F. pallida* (Fig. 33) shows environmental variable with the highest gain when used in isolation is bathymetry followed by the current for 2040-2050 decade under RCP 6.0. The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, current and maximum temperature which therefore appears to have the most information that isn't present in the other variables. Whereas mean temperature shows a lesser gain, lower than 0.50.



(a) (b)

Fig. 33 Jackknife analysis of AUC for the *F. pallida* using variables according to RCP 6.0 for years 2040-2050 (a) and 2090-2100 (b)

4.2.2.2.3 Response curves of variables used in both models

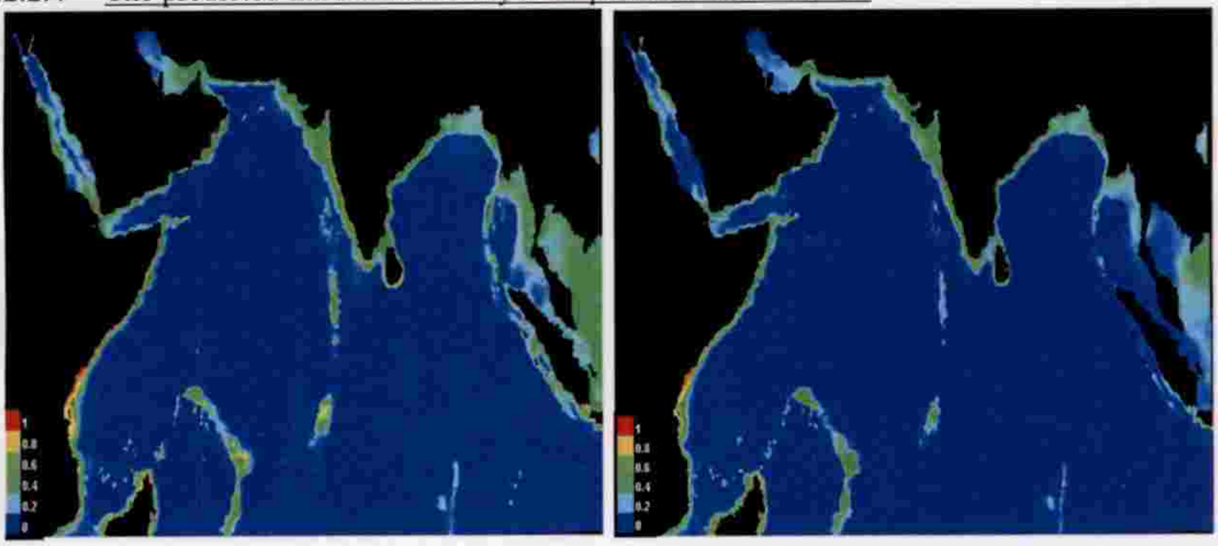


(a) (b)

Fig. 34 The Response curve of each variable for 2040-50(a) and 2090-2100(b).

The response curves for the *F. pallida* model under the RCP 6.0 for the years 2040-50 (Fig. 34a) and 2090-2100 (Fig. 34b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

4.2.2.2.4 The predicted habitat suitability of *F. pallida* under RCP6.0

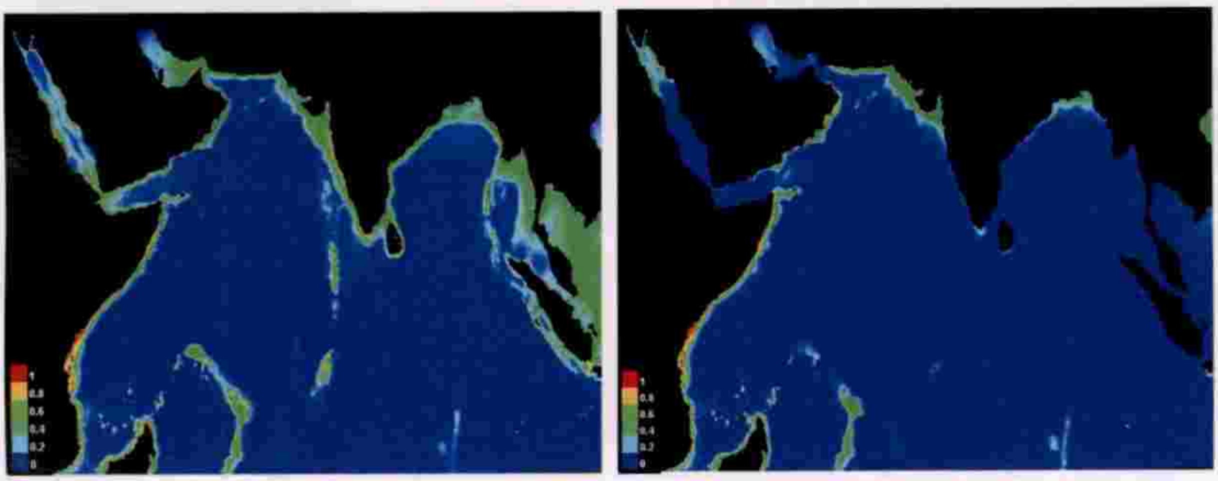


(a) (b)

Fig. 35 Map showing the predicted habitat suitability of *F. pallida* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 6.0.

The distribution forecast of *F. pallida* under RCP 6.0 for the two time periods is similar to that under RCP 4.5.

Compared to the species' range for 2040-50 the population constricted in most regions for 2090-2100 such as, along the entire coast of India, it's two island groups and the Maldives from where it is completely disappeared. Its range over the Red Sea and the Persian Gulf is also shown to be reduced except in the northern parts. The northern regions of SMR also show reduced presence while even more percentage of presence can be seen on the entire east African coast.



(a) (b)

Fig. 36 Map showing the predicted habitat suitability of *F. pallida* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 6.0.

4.2.2.3 Future distribution of *F. pallida* under RCP 8.5 for years 2040-50 and 2090-2100

4.2.2.3.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.932 (SD= 0.025). and 0.940 (SD= 0.011) respectively (Fig. 37).

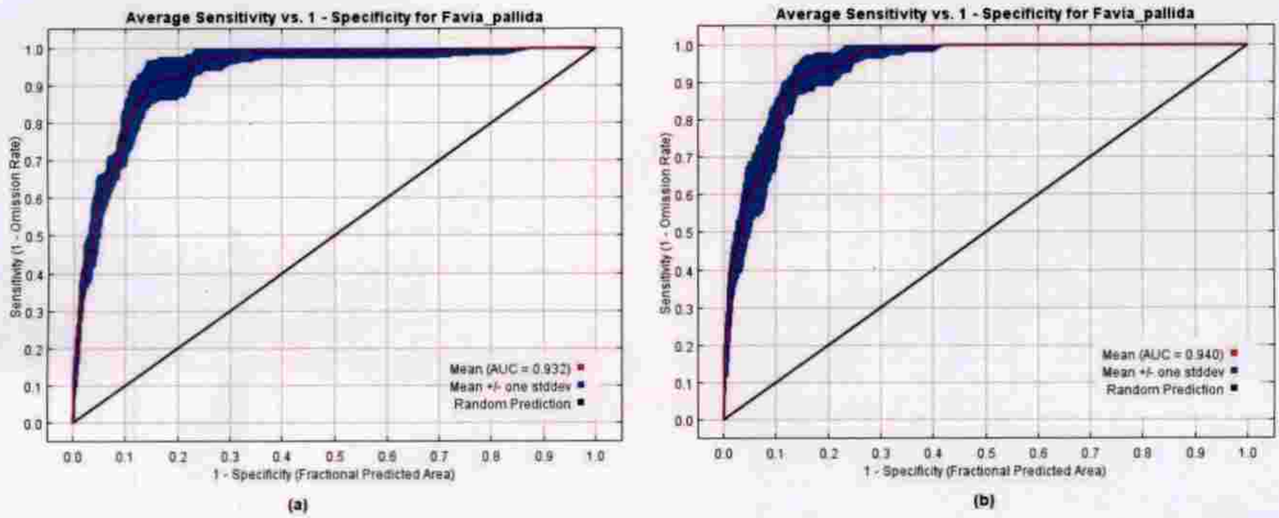


Fig. 37 AUC curve of variable optimization model of the *F. pallida* under RCP 8.5 for the years 2040-50 (a) and 2090-2100 (b)

4.2.2.3.2 Contribution of predictor variables

Table 8 Percentage contribution and permutation importance of all environmental variables to the model for *F. pallida* under RCP 8.5 for the decades of 2040-2050 and 2090-2100.

Variable	*Percent contribution RCP8.5 (2040-2050)*	*Permutation importance RCP8.5 (2040-2050)*	*Percent contribution RCP8.5 (2090-2100)*	*Permutation importance RCP8.5 (2090-2100)*
Bathymetry	86.3	87.6	85.2	92.9
Current	6.7	1.2	8.1	1.1
Mean temperature	3.7	5.5	3.2	3.5

Max temperature	2.1	4.9	1.8	1.4
Salinity	1.3	0.8	1.8	1.1

Among these variables, bathymetry showed a significantly higher contribution of 86.3 % and 85.2% for the years 2040-50 and 2090-2100 respectively under RCP 8.5, followed by current (6.7 & 8.1%) (Table 8). The salinity has the least contribution in this particular model developed for *F. pallida.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 87.6% & 92.9% and the salinity shows the least importance to this scenario.

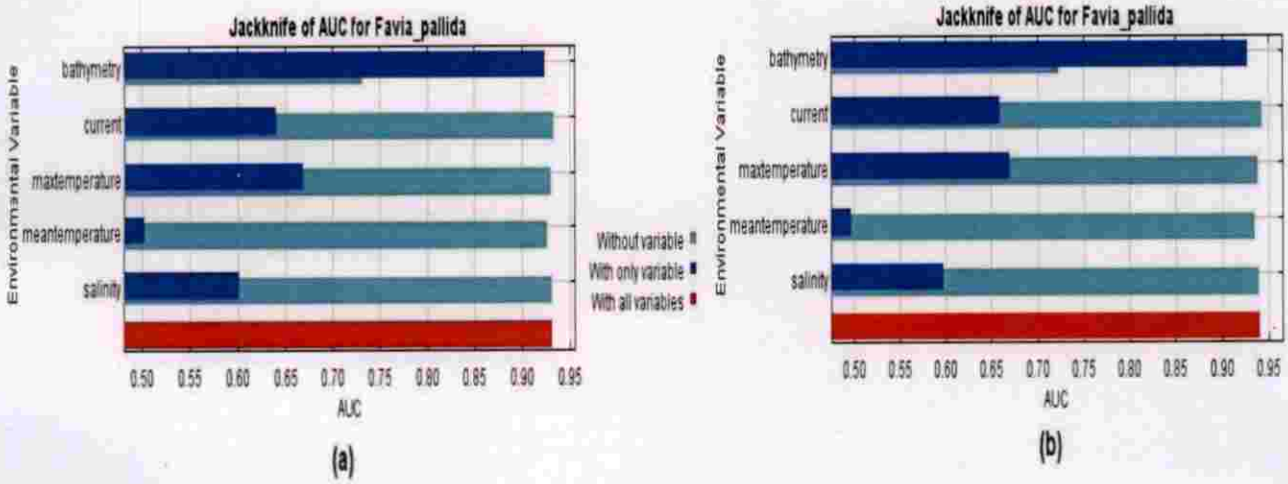


Fig. 38 Jackknife analysis of AUC for the *F. pallida* using variables according to RCP 8.5 for years 2040-2050 (a) and 2090-2100 (b)

The Jackknife of AUC for *F. pallida* (Fig. 38) shows environmental variable with the highest gain when used in isolation is bathymetry followed by maximum temperature for both periods under the RCP 8.5. The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas the mean temperature shows a lesser gain, about 0.50.

4.2.2.3.3 <u>Response curves of variables used in both models</u>

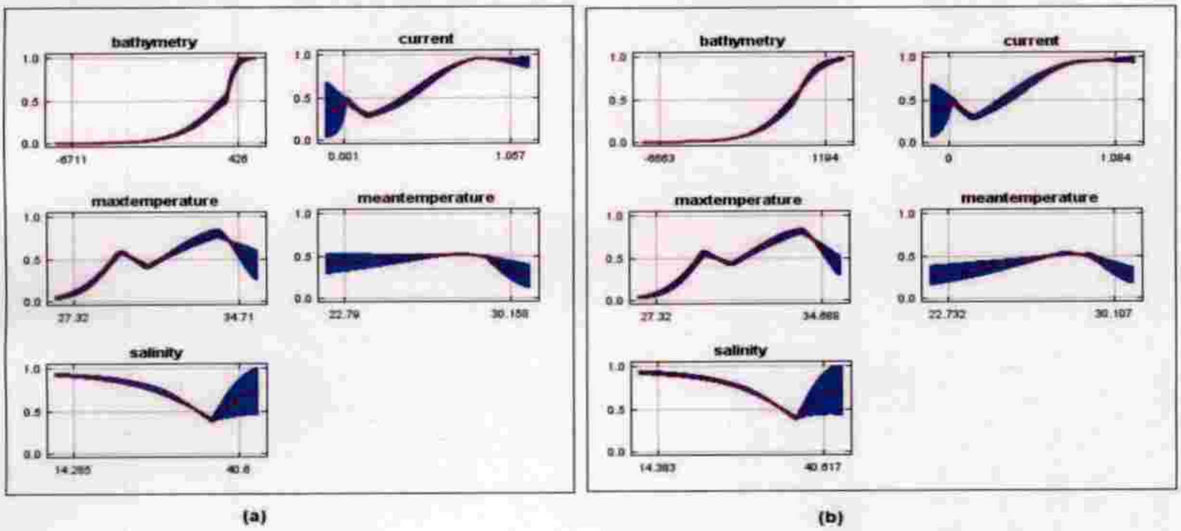


Fig. 39 The Response curve of each variable for 2040-50(a) and 2090-2100(b).

The response curves for the *F. pallida* model under the RCP 8.5 for the years 2040-50 (Fig. 39a) and 2090-2100 (Fig. 39b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

4.2.2.3.4 <u>The predicted habitat suitability of *F. pallida* under RCP 8.5</u>

Under RCP 8.5, *F. pallida* are projected to have an extreme degree of presence in almost all regions where it is predicted in the present situation (

Fig. 40). The exception is seen in the two island groups of India and in the southern Red Sea. The presence is estimated with an extreme degree in the northern Persian Gulf; the coast of Oman, Gujarat, Bangladesh, entire East Africa and Madagascar, and the SMR. Northern parts of the Red Sea are also projected with its good presence.

The presence of *F. pallida* predicted for 2090-2100 under RCP 8.5 (Fig. 41) is strikingly different from that of 2040-50. Here its entire range has dwindled especially on the coasts and islands of India without a single point of presence. A smaller degree of presence is projected for the continental coast and islands in the western part of the north-western Indian ocean.

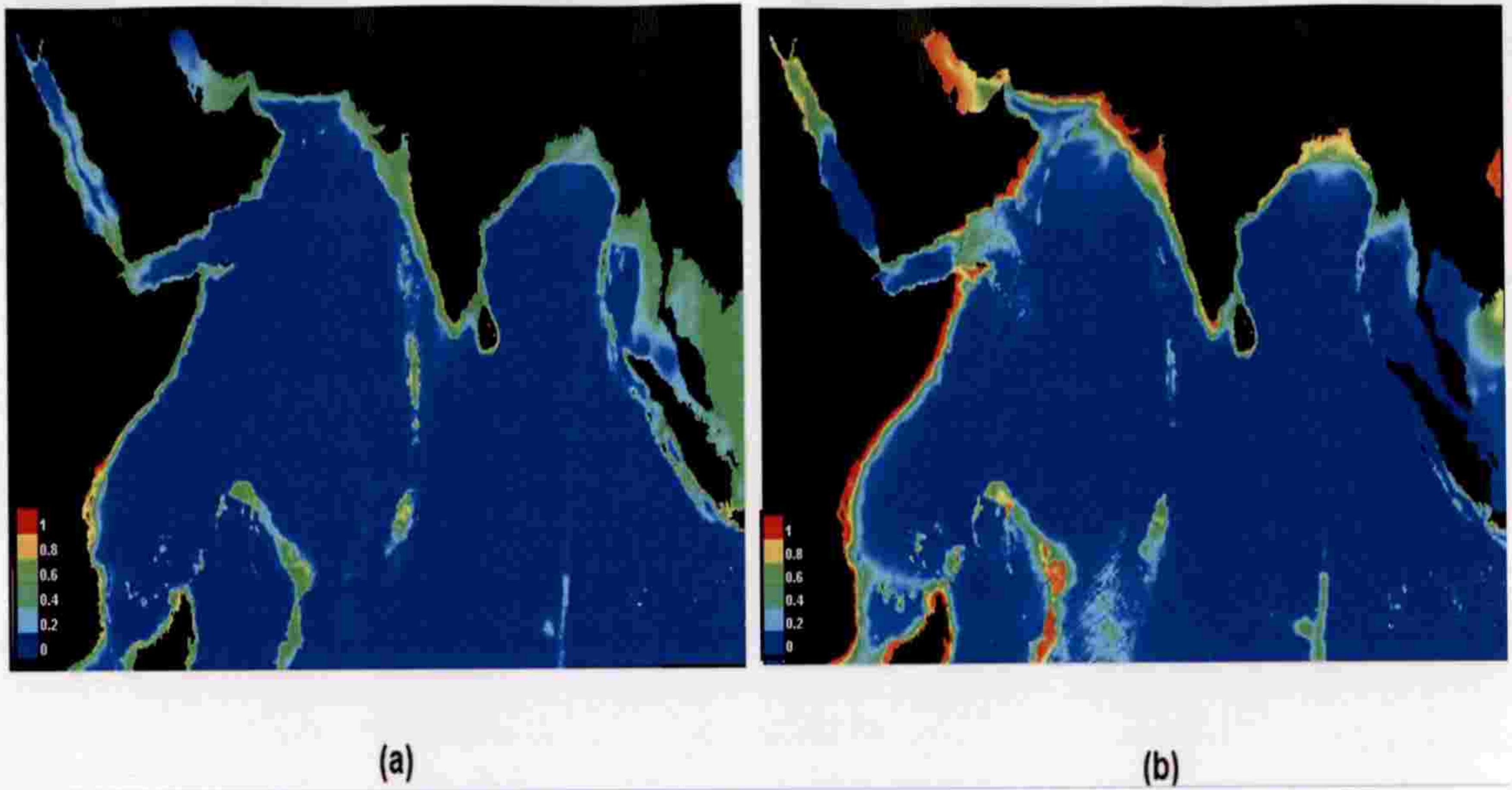
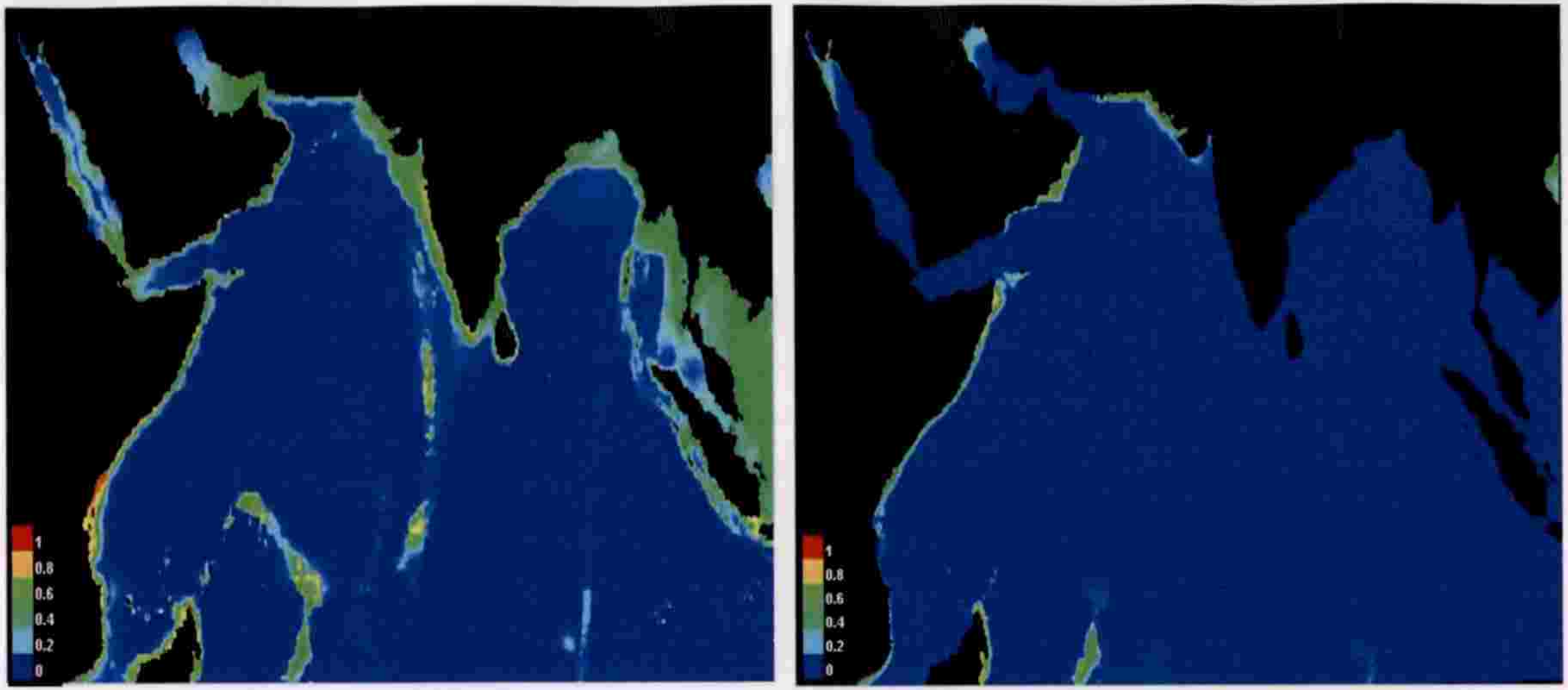


Fig. 40 Map showing the predicted habitat suitability of *F. pallida* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 8.5.



(a) (b)

Fig. 41 Map showing the predicted habitat suitability of *F. pallida* in the Northern Indian Ocean in present condition (a) and for 2090-2100(b) under RCP 8.5.

4.3 *P. daedalea*

4.3.1 Prediction of the current distribution

4.3.1.1 The Model Performance and variable contributions

The model performance assessed by using the average test AUC value for 10 replicates was 0.936 (SD= 0.019). The sensitivity *vs.* 1-specificity graph shows the area under the Receiver Operating Characteristic (ROC) curve or AUC. The test omission rate and AUC curve (Fig. 42 & Fig. 43) was found fit in this model. The Fig. 43 shows that the mean omission line on the test data was passing through the predicted omission line. In the Fig. 42, the AUC line was passing through the left top of the random prediction.

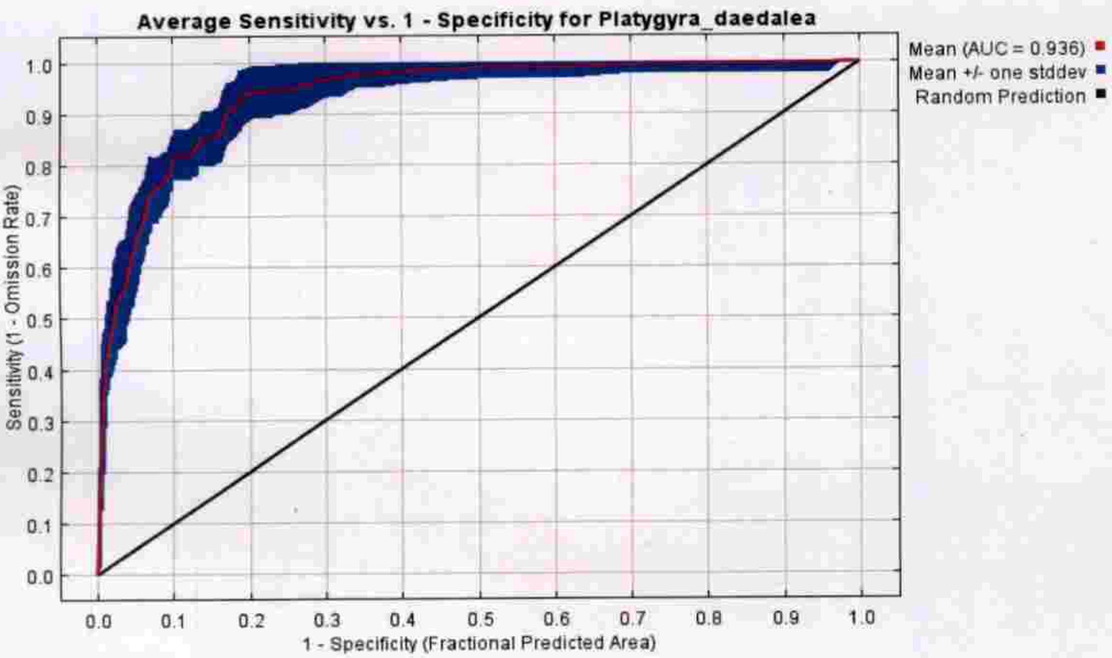


Fig. 42 AUC curve of variable optimization model of the Platygyra deadalea

77

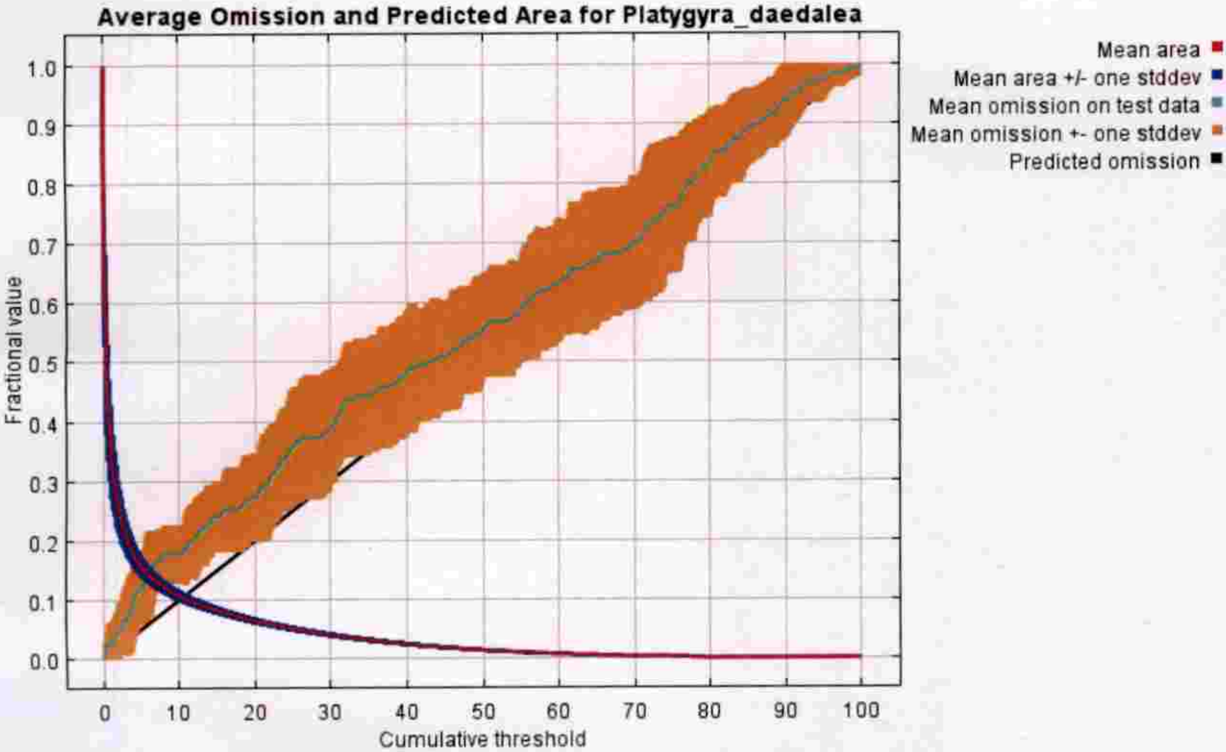


Fig. 43 the Test omission rate and predicted area as a function of the cumulative threshold, averaged over the replicate runs for *Platygyra deadalea*

4.3.1.2 Contribution of predictor variables

Table 9 Percentage contribution and permutation importance of all environmental variables to the model for *P. daedalea*

Variable	*Percent contribution*	*Permutation importance*
Bathymetry	64.5	82.9
Calcite	8.6	1.4
Current	7.1	1.3
pH	5	1.9
Nitrate	4.3	1.9
Kd	2.3	1
Mean temperature	2	1.4
PAR	1.7	1.3
Chlorophyll	1.5	2.1
Phosphate	1.4	1.7
Salinity	0.6	1.2
Max temperature	0.6	0.9
DO	0.4	1.1

The relative contribution of each predictor variable is given by the MaxEnt output and it is shown in Table 9. Among all the variables, bathymetry showed a significantly higher contribution of 64.5 %, followed by calcite (8.6%) and current (7.1%). The dissolved oxygen is the variable with the least contribution in this model developed for *P. daedalea.* For the Permutation importance, for each environmental variable one by one, the values of that variable in training presence as well as in background data were randomly permuted. The variable having high permutation importance (82.9) were bathymetry and the chlorophyll by 2.1 %.

The Jackknife of AUC for *P. daedalea* (Fig. 44) shows environmental variable with the highest gain when used in isolation is bathymetry, which therefore appears to have the most useful information by itself. The values shown are averages over replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas, nitrate shows a lesser gain, lower than 0.50.

The response curves for the *P. daedalea* model (Fig. 45) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates. These plots demonstrate the dependence of predicted suitability on the selected variables as well as on the dependencies induced by correlations between each variable and other variables.

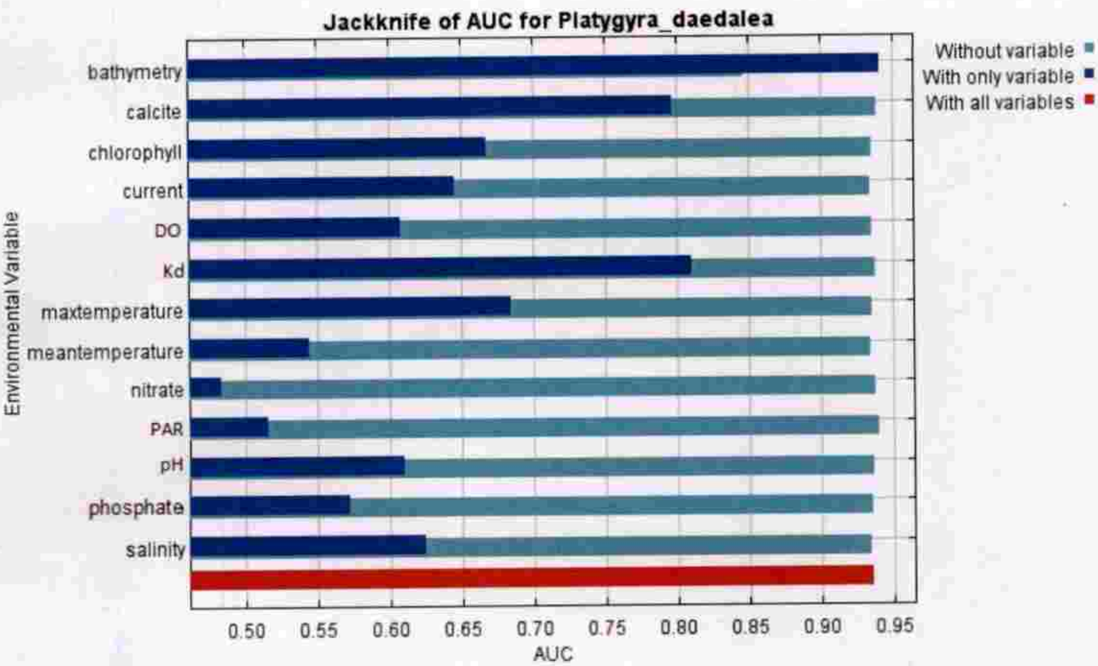


Fig. 44 Jackknife analysis of AUC for the P. daedalea using all the variables

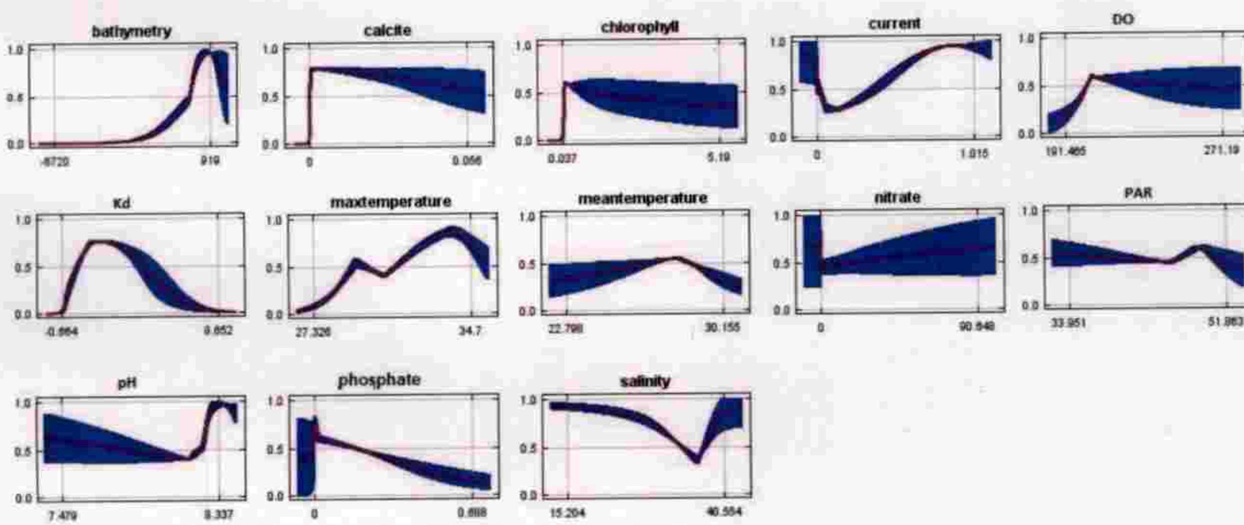


Fig. 45 The response curves for the *P. daedalea* model

4.3.1.3 Prediction of the present distribution of the *P. daedalea*

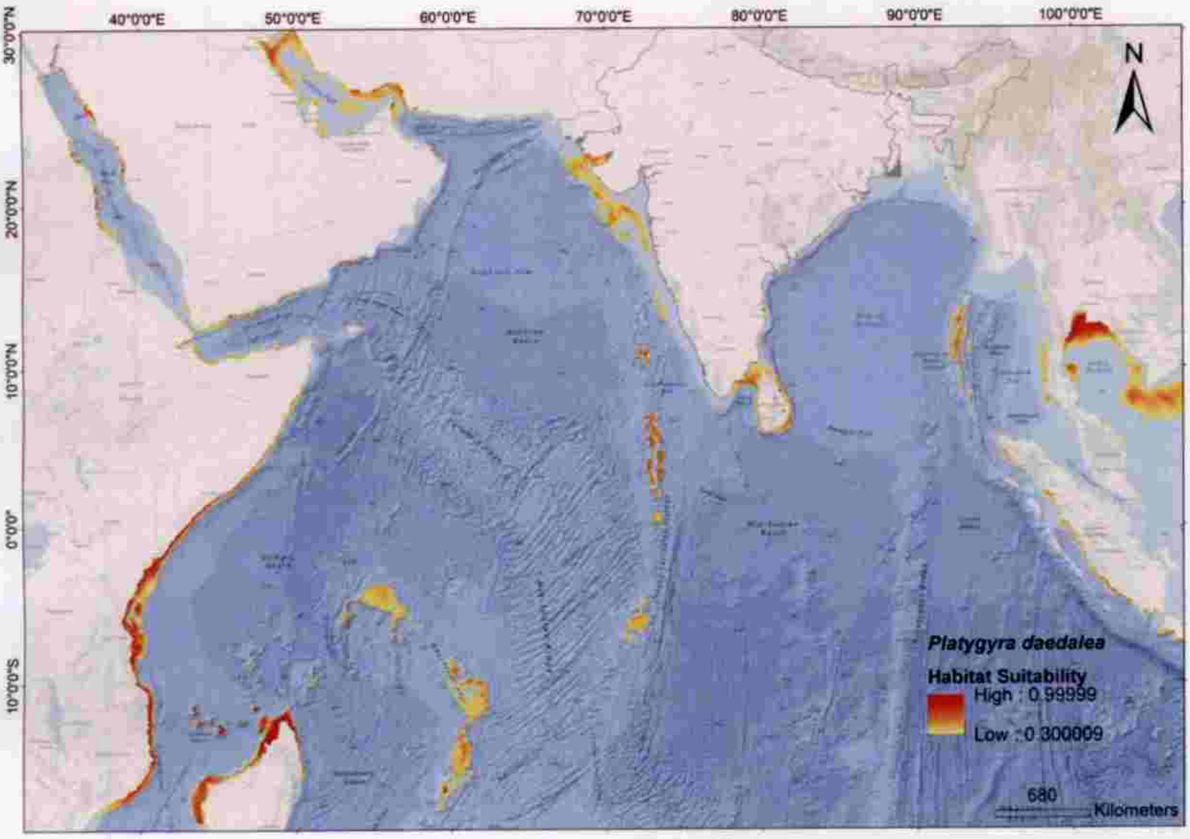


Fig. 46 The predicted distribution of *P. daedalea* along the Northern Indian Ocean.

Fig. 46 shows the predicted distribution of *P. daedalea* in the Northern Indian ocean with suitability ranging from 0.30 to 0.99, low to high indicated by a legend of yellow to red. The *P. daedalea shows* higher environmental suitability (80-99%) along the Maldives, Southwestern boundary of Northern Indian Ocean, North-western boundary of Madagascar Island as well as in the islands and seamounts (which lies in between), and the northern region of the Gulf of Thailand. A medium to high suitability (50-80%) was predicted in Lakshadweep Islands, Gulf of Kutch, Andaman and Nicobar Islands, boundaries of Red Sea, along the Seychelles-Mauritius Plateau and along the Gulf of Mannar and the coasts of Srilanka.

4.3.2 The Future distribution of *P. daedalea* under different Climate Scenarios.

Models prepared using the optimized variables under three different Representative Concentration Pathways (RCP) such as RCP4.5, RCP6, and RCP8.5 gave the prediction for future distribution of the *P. deadalea in* the Northern Indian Ocean for the years 2040-2050 and 2090-2100.

4.3.2.1 Future distribution of *Platygyra deadalea* under RCP 4.5 for years 2040-50 and 2090-2100

4.3.2.1.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.959 (SD= 0.011) and 0.955 (SD= 0.011). respectively (Fig. 47).

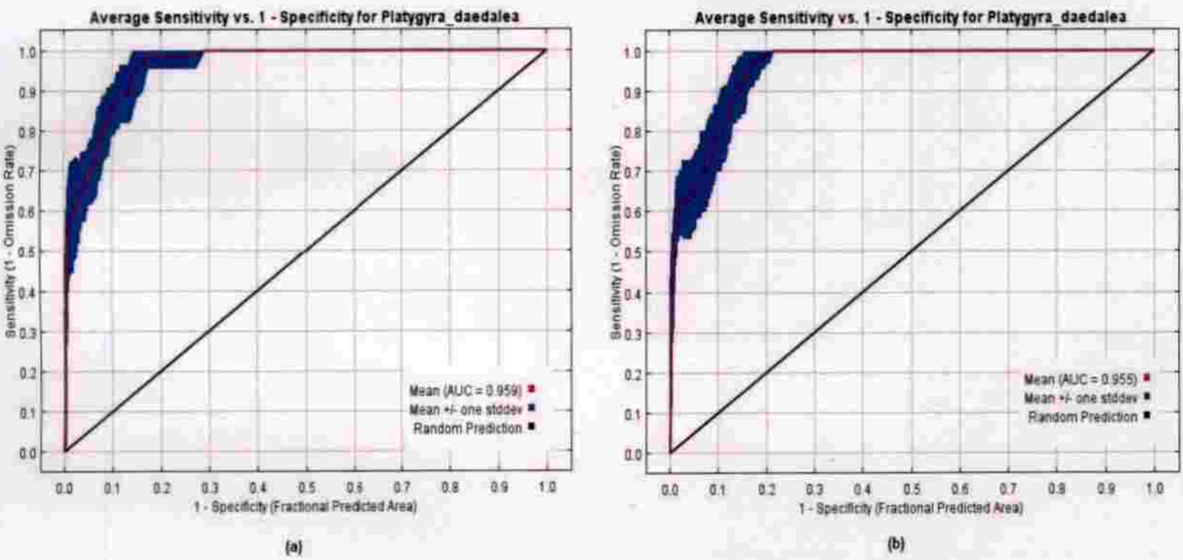


Fig. 47 AUC curve of variable optimization model of the *P. daedalea* under RCP 8.5 for the years 2040-50 (a) and 2090-2100 (b)

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4.3.2.1.2 Contribution of predictor variables

Table 10 Percentage contribution and permutation importance of all environmental variables to the model for *P. daedalea* under RCP 4.5 for the decades of 2040-2050 and 2090-2100.

Variable	*Percent contribution RCP4.5 (2040-2050)*	*Permutation importance RCP4.5 (2040-2050)*	*Percent contribution RCP4.5 (2090-2100)*	*Permutation importance RCP4.5 (2090-2100)*
Bathymetry	78.5	81.6	76.7	85.1
Mean temperature	11.8	6.8	13.9	7.2
Salinity	4.5	1.8	3.7	0.6
Max-temperature	3.1	9	2.9	5.4
Current	2	0.8	2.8	1.8

Among these variables, bathymetry showed a significantly higher contribution of 78.5 % and 76.7% for the years 2040-50 and 2090-2100 respectively under RCP 4.5, followed by Mean Temperature (11.8 & 13.9%) (Table 10). The ocean current has the least contribution in this model developed for *P. daedalea.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 81.6% & 85.1% in this scenario.

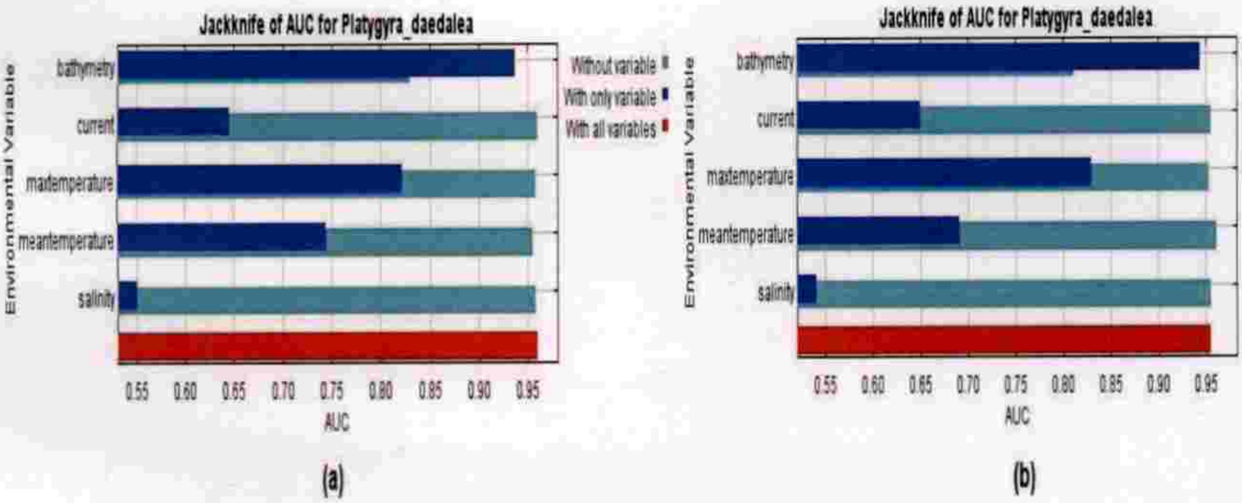


Fig. 48 Jackknife analysis of AUC for the *P. daedalea* using variables according to RCP 4.5 for years 2040-2050 (a) and 2090-2100 (b)

The Jackknife of AUC for *Platygyra deadalea* (Fig. 48) shows environmental variable with the highest gain when used in isolation is bathymetry followed by maximum temperature for both periods under the RCP 4.5. The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas salinity shows a lesser gain, lower than 0.55.

4.3.2.1.3 Response curves of variables used in both models

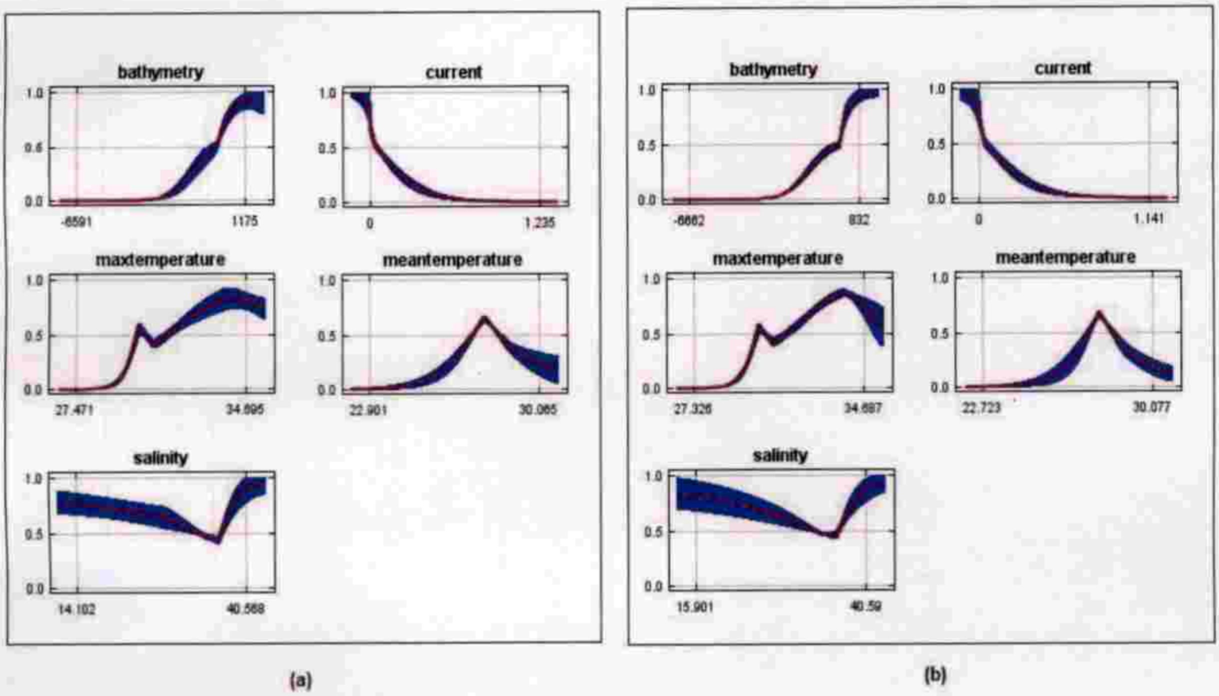
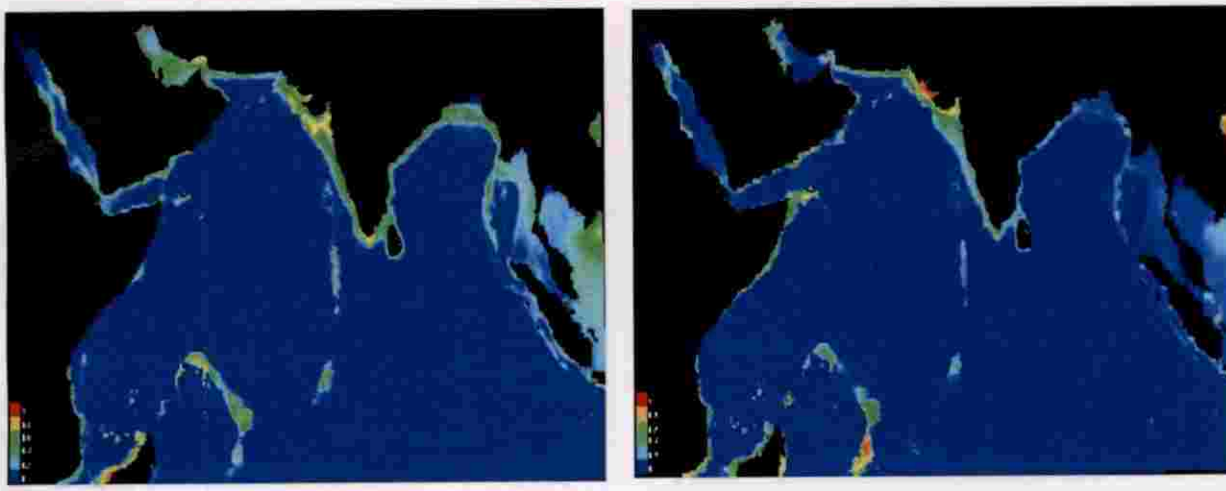


Fig. 49 The Response curve of each variable for 2040-50(a) and 2090-2100(b).

The response curves for the *P. daedalea* model under the RCP 4.5 for the years 2040-50 (Fig. 49a) and 2090-2100 (Fig. 49b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

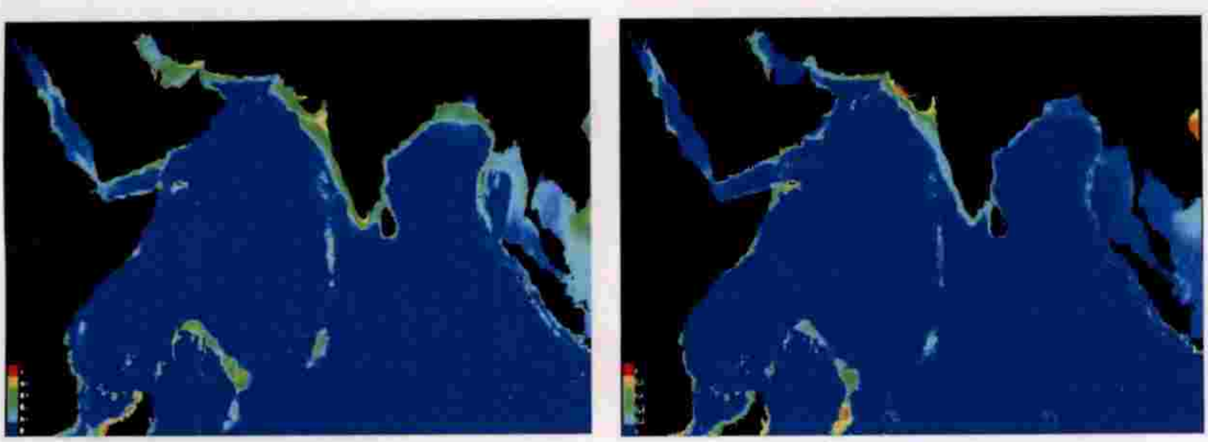
4.3.2.1.4 The predicted habitat suitability of *P. daedalea* under RCP 4.5



(a) (b)

Fig. 50 Map showing the predicted habitat suitability of *P. daedalea* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 4.5.

The predicted distribution of *P. daedalea* under RCP 4.5 for the current and 2040-50 period shows significant population reduction around the coasts of the Bay of Bengal and Andaman sea (Fig. 50). On the west coast of India, its presence gradually decreased towards the south for the 2040-50 decade as is the case in Lakshadweep and Maldive group of islands. Another major population constriction in the decade is in the Persian Gulf.



(a) (b)

Fig. 51 Map showing the predicted habitat suitability of *P. daedalea* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 4.5.

No major difference in the range of *P. daedalea* is forecasted for the 2090-2100 decade when compared to its range in the 2040-2050 period.

4.3.2.2 Future distribution of *Platygyra deadalea* under RCP 6.0 for years 2040-50 and 2090-2100

4.3.2.2.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.960 (SD= 0.018). and 0.960 (SD= 0.019). respectively (Fig 52).

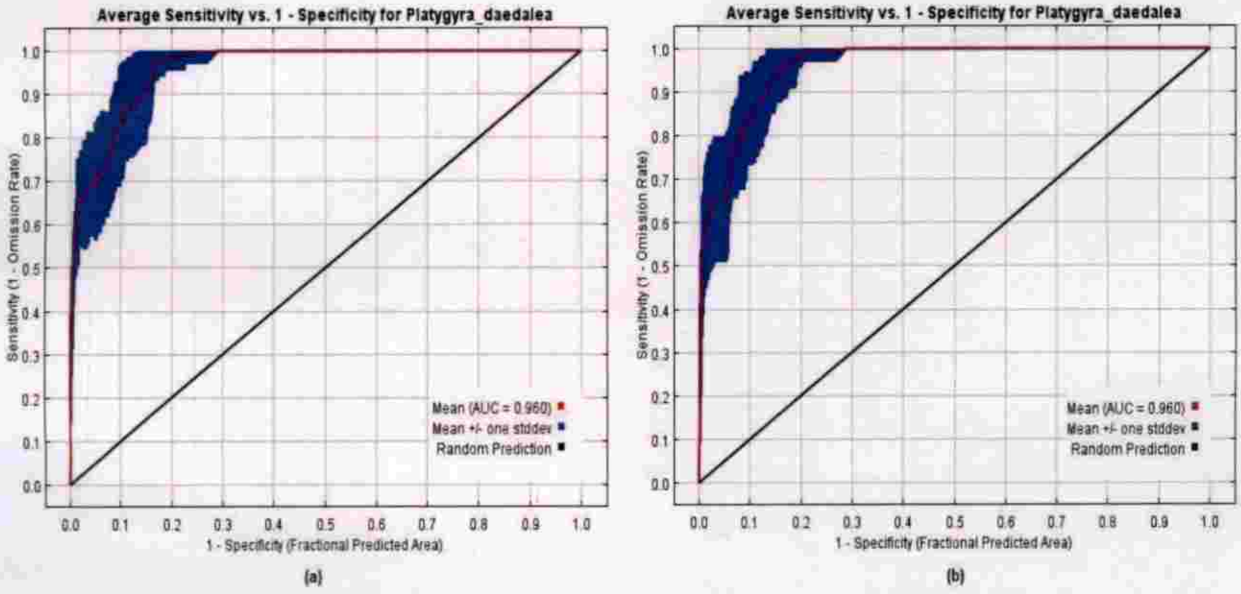


Fig. 52 ROC curve of variable optimization model of the *P. daedalea* under RCP 6.0 for the years 2040-50 (a) and 2090-2100 (b)

4.3.2.2.2 Contribution of predictor variables

Table 11 Percentage contribution and permutation importance of all environmental variables to the model for *P. daedalea* under RCP 6.0 for the decades of 2040-2050 and 2090-2100.

Variable	*Percent contribution (RCP 6.0-2040-50)*	*Permutation importance (RCP 6.0- 2040-50)*	*Percent contribution (RCP 6.0 2090-2100)*	*Permutation importance (RCP 6.0 2090-2100)*
Bathymetry	77.3	90.9	76.2	88.4
Mean temperature	14.1	4.2	13.7	4.3
Max temperature	3.6	3.5	4.9	1.7
Salinity	3.5	0.7	3.2	3.7
Current	1.5	0.7	2	1.9

Among these variables, bathymetry showed a significantly higher contribution of 77.3 % and 76.2% for the years 2040-50 and 2090-2100 respectively under RCP 6.0, followed by Mean Temperature (14.1& 13.7%) (Table 11). The ocean current has the least contribution in this particular model developed for *P. daedalea.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 90.9% & 88.4 % and the current show the least importance for the year 2040-50 whereas Max temperature has the least importance (1.7%) during 2090-2100 for this scenario.

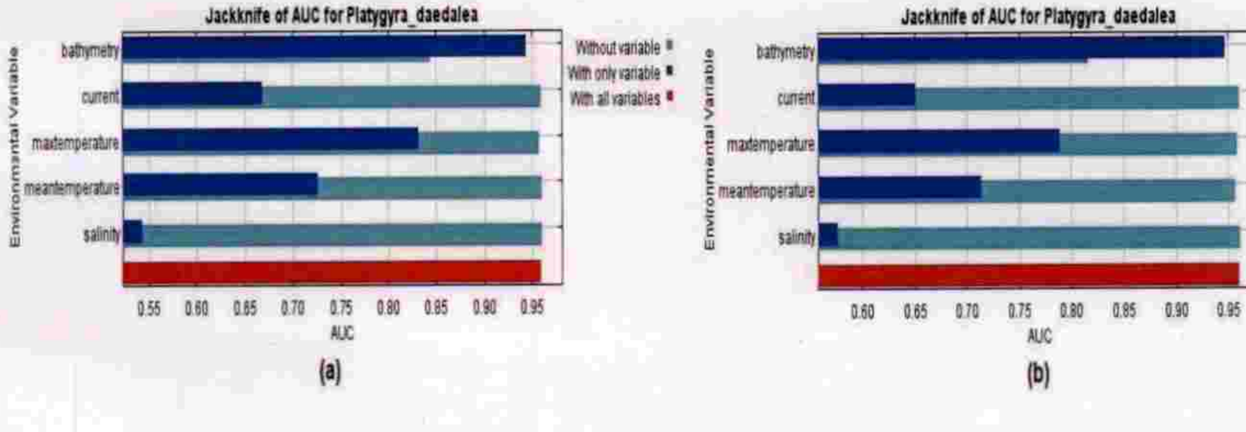


Fig. 53 Jackknife analysis of AUC for the *P. daedalea* using variables according to RCP 6.0 for years 2040-2050 (a) and 2090-2100 (b)

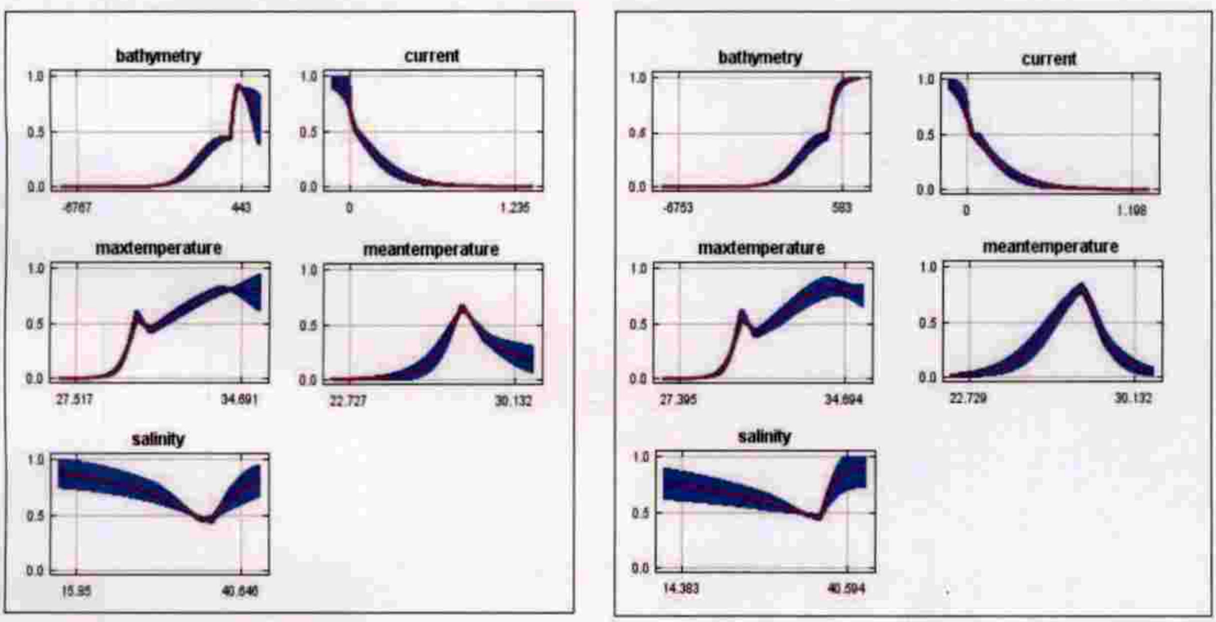
The Jackknife of AUC for *P. daedalea* (Fig. 53) shows environmental variable with the highest gain when used in isolation is bathymetry followed by max temperature for both periods under the RCP 6.0. The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas salinity shows a lesser gain, lower than 0.55.

4.3.2.2.3 Response curves of variables used in both models

The response curves for the *P. daedalea* model under the RCP 4.5 for the years 2040-50 (Fig. 54a) and 2090-2100 (Fig. 54b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

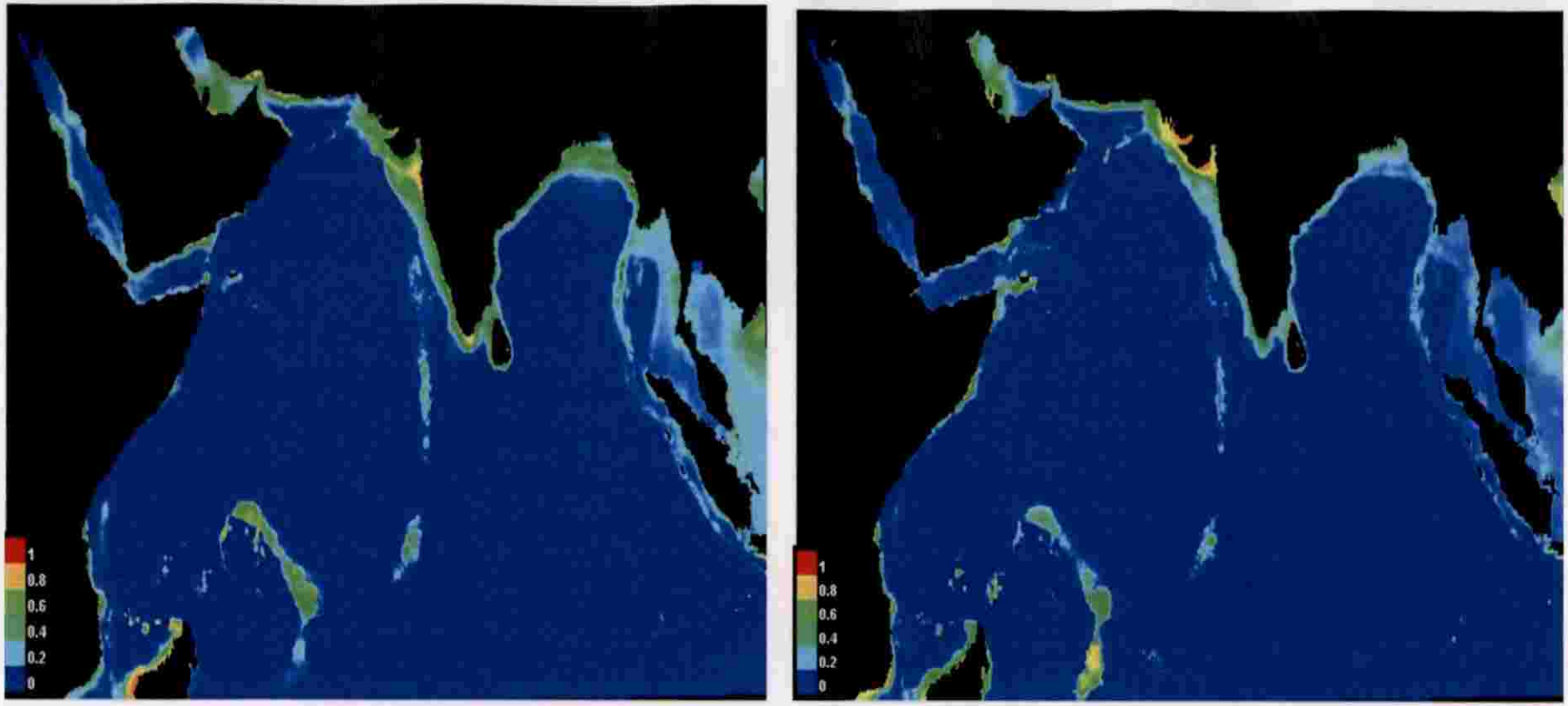
4.3.2.2.4 The predicted habitat suitability of *P. daedalea* under RCP 6.0

Here also the projected range and extremity of the population is similar to that shown under RCP 4.5 for the same period. For 2040-50, under RCP 6.0, the predicted distribution of *P. daedalea* is somewhat similar to the range given under RCP 4.5 for the same period.



(a) (b)

Fig. 54 The Response curve of each variable for 2040-50(a) and 2090-2100(b).



(a) (b)

Fig. 55 Map showing the predicted habitat suitability of *P. deadalea* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 6.0.

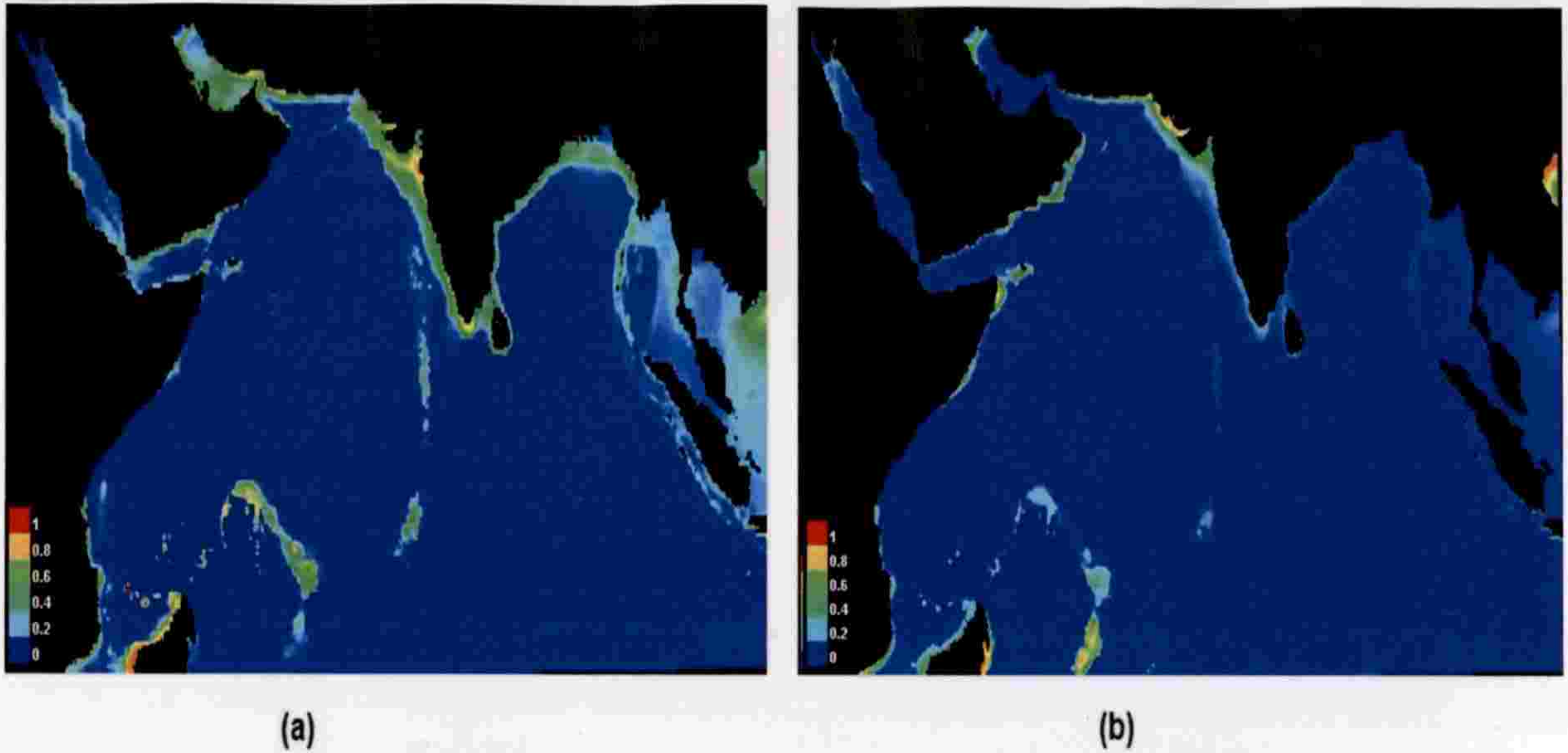


Fig. 56 Map showing the predicted habitat suitability of *P. daedalea* in the Northern Indian Ocean in present condition (a) and for 2090-2100(b) under RCP 6.0.

4.3.2.3 Future distribution of *P. daedalea* under RCP 8.5 for years 2040-50 and 2090-2100

4.3.2.3.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.953 (SD= 0.015) and 0.942 (SD= 0.018) respectively (Fig. 57 (a) and Fig. 57 (b)).

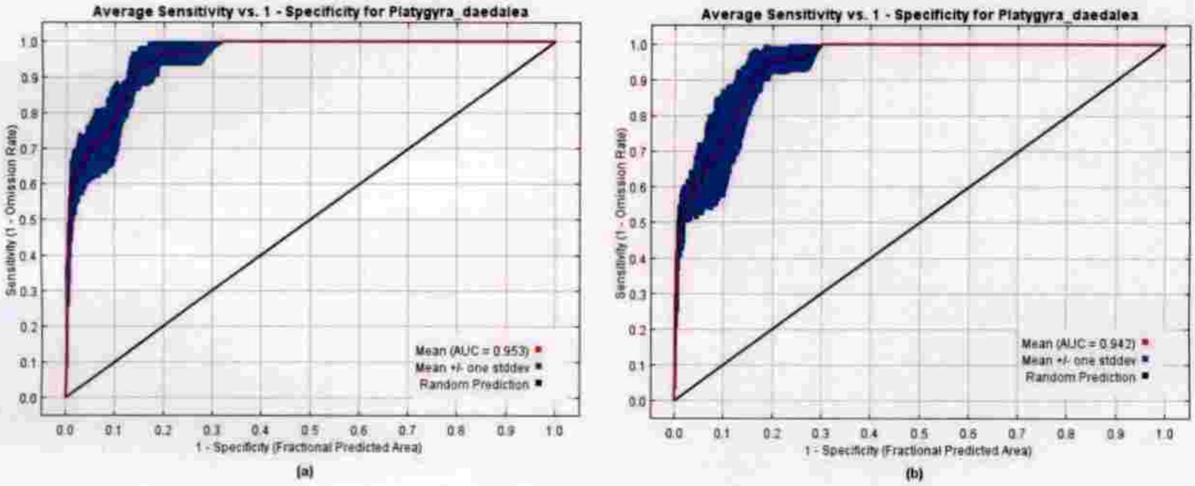


Fig. 57 AUC curve of variable optimization model of the *P. daedalea* under RCP 8.5 for the years 2040-50 (a) and 2090-2100 (b)

4.3.2.3.2 Contribution of predictor variables

Table 12 Percentage contribution and permutation importance of all environmental variables to the model for *P. daedalea* under RCP 8.5 for the decades of 2040-2050 and 2090-2100.

Variable	*Percent contribution RCP8.5 (2040-2050)*	*Permutation importance RCP8.5 (2040-2050)*	*Percent contribution RCP8.5 (2090-2100)*	*Permutation importance RCP8.5 (2090-2100)*
Bathymetry	78.9	85.6	75.7	88.6
Mean temperature	11.9	6.7	12.7	7.3
Salinity	4.1	2.1	5.1	1.4
Max temperature	2.6	4.1	3.9	1.8
Current	2.4	1.5	2.6	0.9

Among these variables, bathymetry showed a significantly higher contribution of 78.9 % and 75.7 % for the years 2040-50 and 2090-2100 respectively under RCP 8.5, followed by mean temperature (11.9 & 12.7%) (Table 12). The current has the least contribution in this particular model developed. For the Permutation importance, The variable having high permutation importance for both periods were bathymetry with 85.6% & 88.6% and the current has the minimum importance in this scenario.

The Jackknife of AUC for *P. daedalea* (Fig. 58) shows environmental variable with the highest gain when used in isolation is bathymetry followed by maximum temperature for both periods under the RCP 8.5. The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas the salinity shows a lesser gain, about 0.55.

4.3.2.3.3 Response curves of variables used in both models

The response curves for the *P. daedalea* model under the RCP 8.5 for the years 2040-50 (Fig. 59a) and 2090-2100 (Fig. 59b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

4.3.2.3.4 The predicted habitat suitability of *P. daedalea* under RCP 8.5

As clear from the map (Fig. 60), almost complete disappearance of the species is predicted in the entire study region for the decade 2040-50 though population size of very lesser degree is shown to have remained in the islands of Maldives, Chagos, and Andaman.

Here the range of distribution is shown to reappeare in some regions in 2090-2100 from where it is predicted to be absent for the 2040-50 period. A major population can be seen on northern Persian Gulf, Oman, Gujarat, and the SMR (Fig. 61).

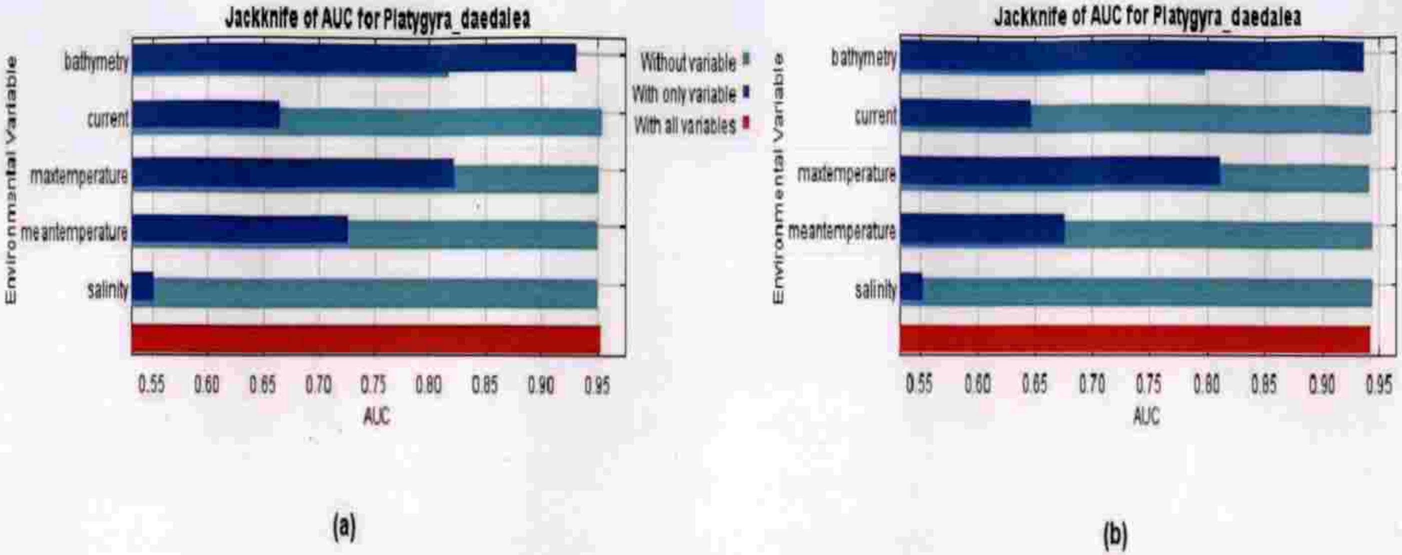


Fig. 58 Jackknife analysis of AUC for the *P. daedalea* using variables accrding to RCP 8.5 for years 2040-2050 (a) and 2090-2100 (b)

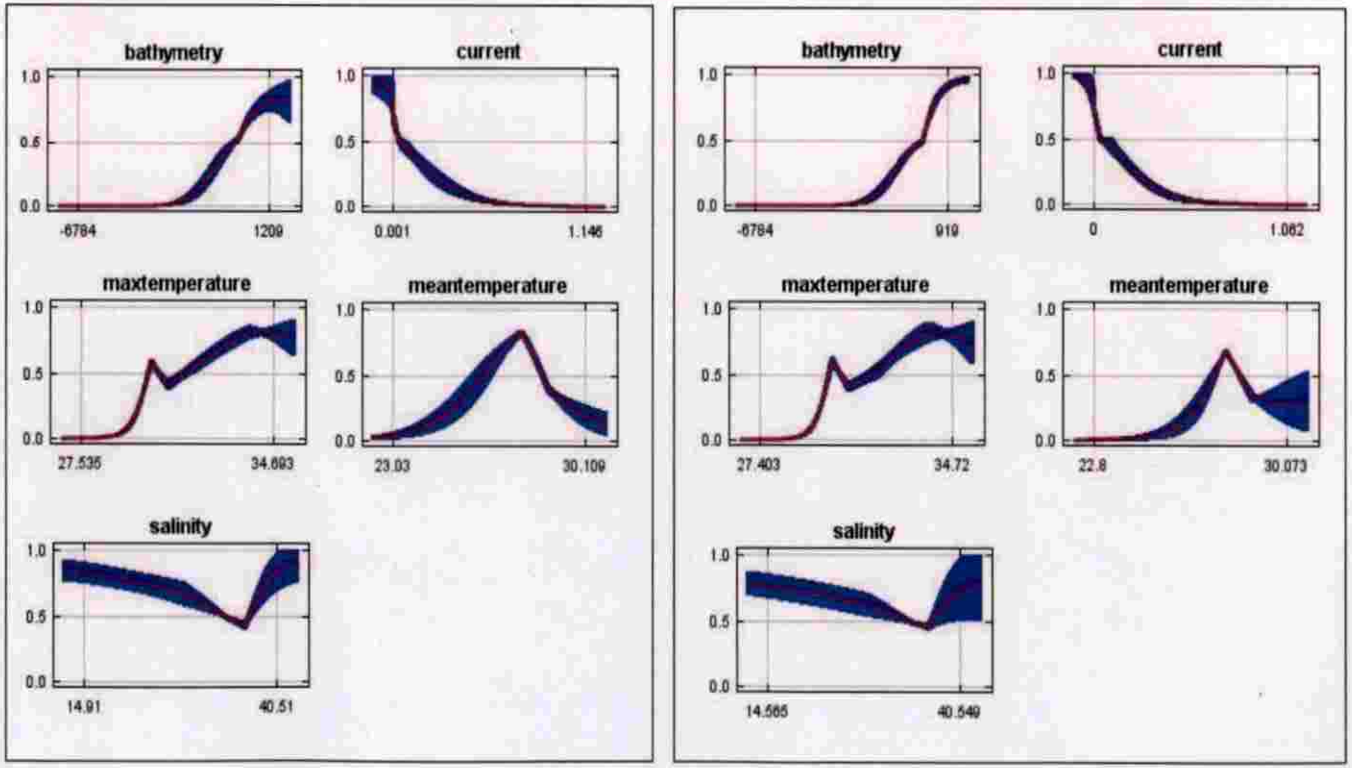
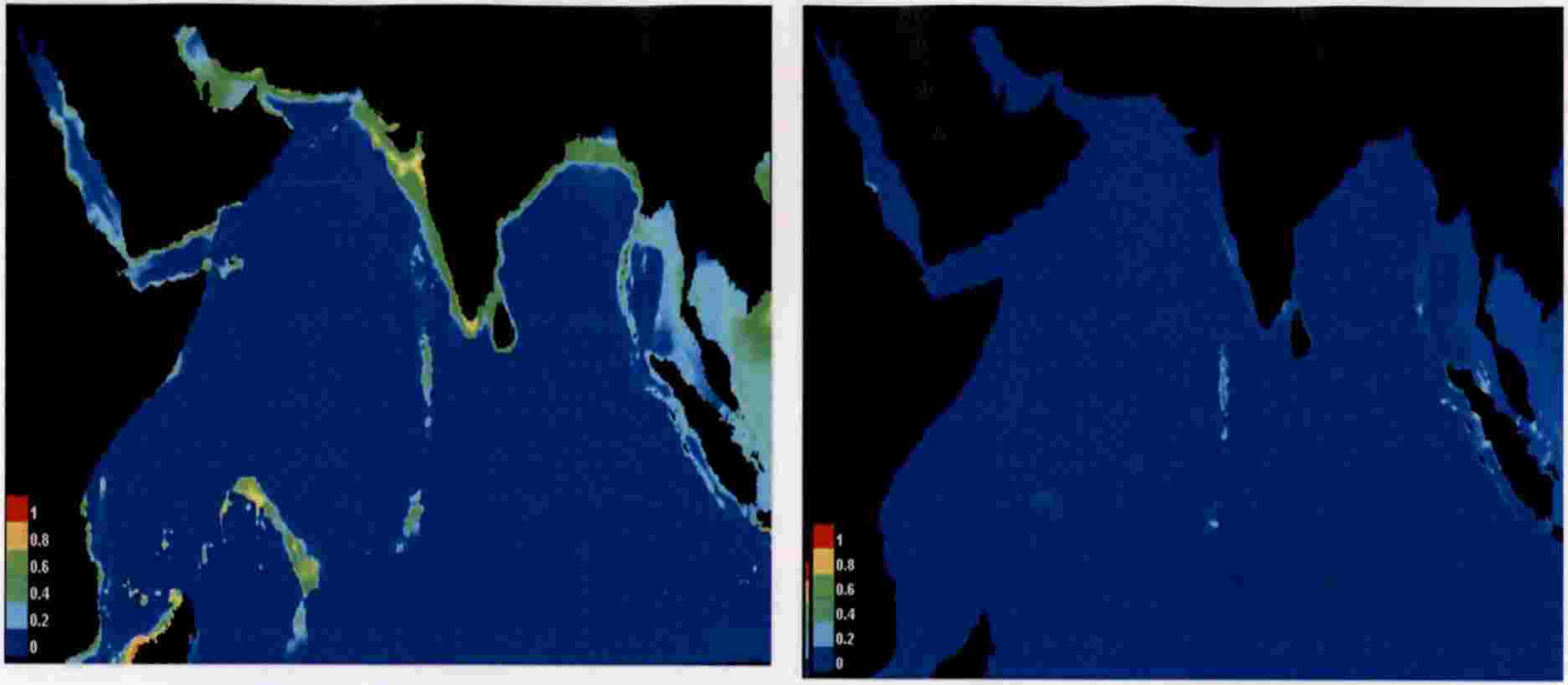
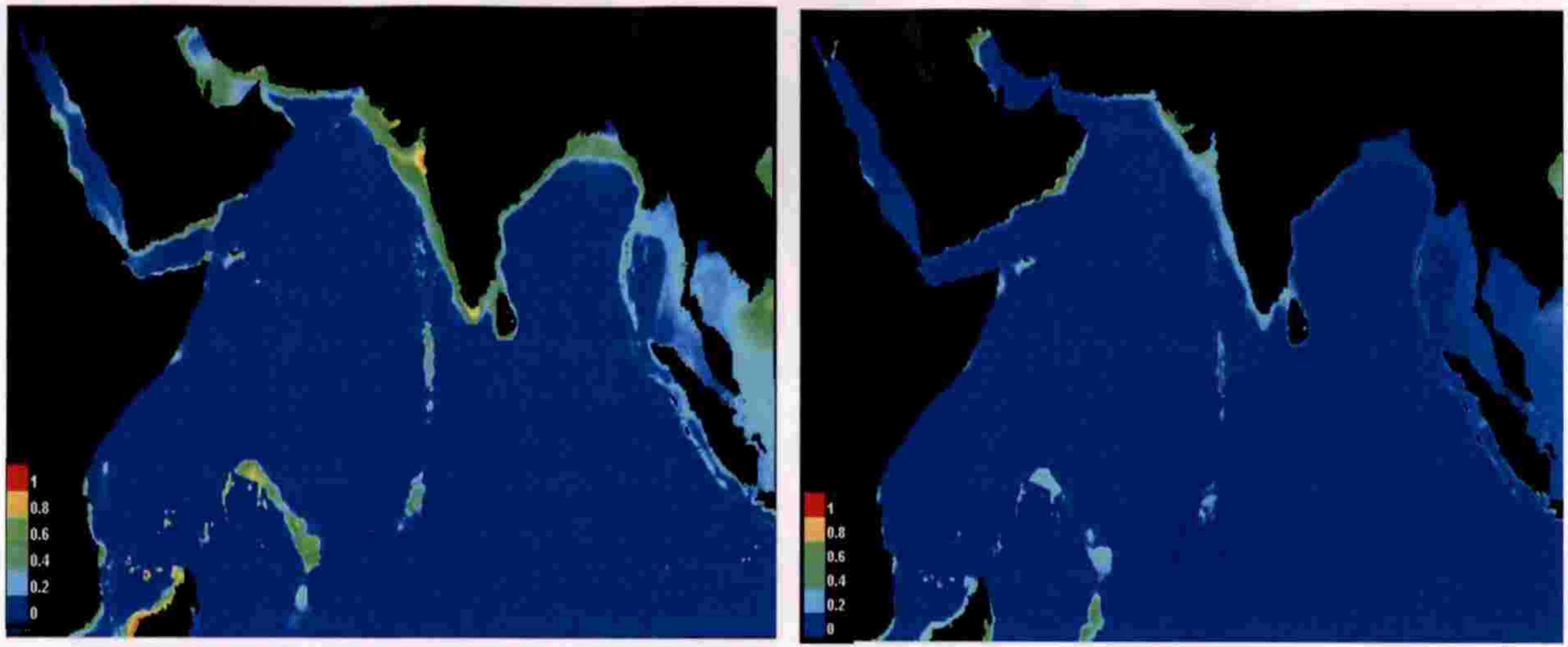


Fig. 59 The Response curve of each variable for 2040-50(a) and 2090-2100(b).



(a) (b)

Fig. 60 Map showing the predicted habitat suitability of *P. daedalea* in the Northern Indian Ocean in present condition (a) and for 2040-50(b) under RCP 8.5



(a) (b)

Fig. 61 Map showing the predicted habitat suitability of *P. daedalea* in the Northern Indian Ocean in present condition (a) and for 2090-100 (b) under RCP 8.5

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4.4 *P. damicornis*

4.4.1 Prediction of the current distribution

4.4.1.1 The Model Performance and variable contributions

The model performance assessed by using the average test AUC value for 10 replicates was 0.880 (SD= 0.056). The sensitivity *vs.* 1-specificity graph shows the area under the Receiver Operating Characteristics (ROC) curve or AUC. The test omission rate and AUC curve (Fig. 62 & Fig. 63) was found fit in this model. The Fig. 63 shows that the mean omission line on the test data was passing through the predicted omission line. In the Fig. 62, the AUC line was passing through the left top of the random prediction.

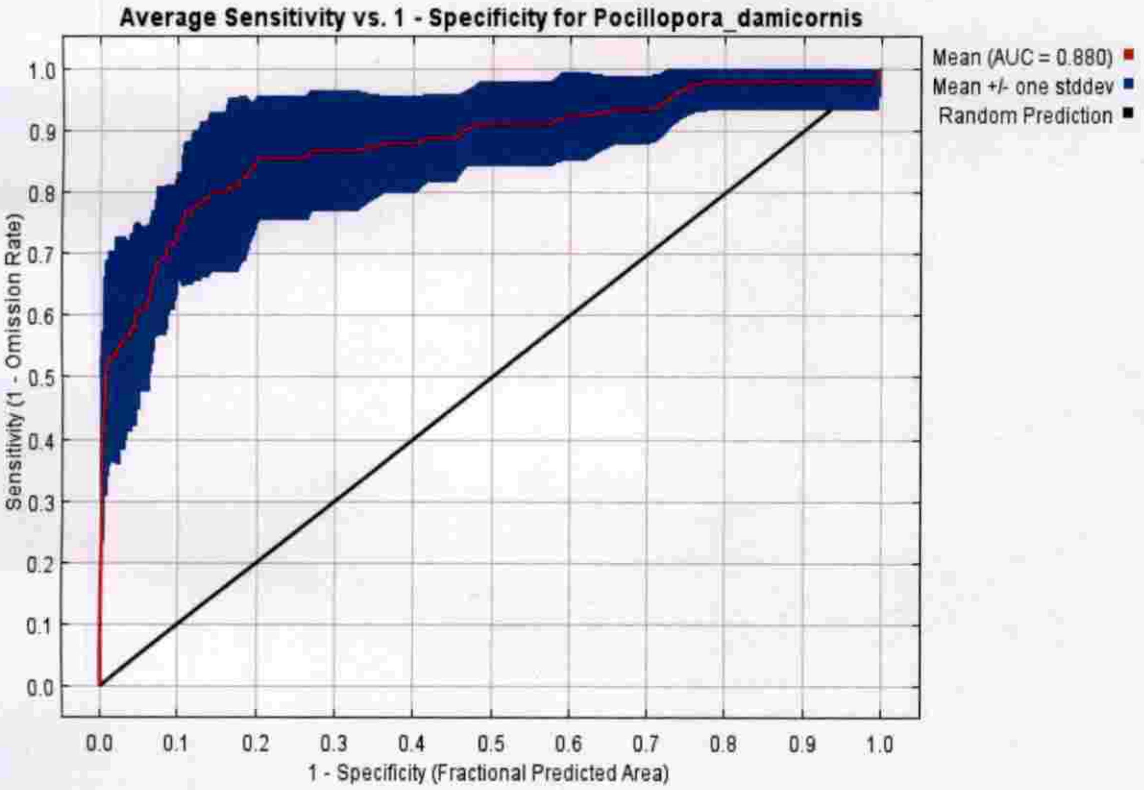


Fig. 62 ROC curve of variable optimization model of the *P. damicornis*

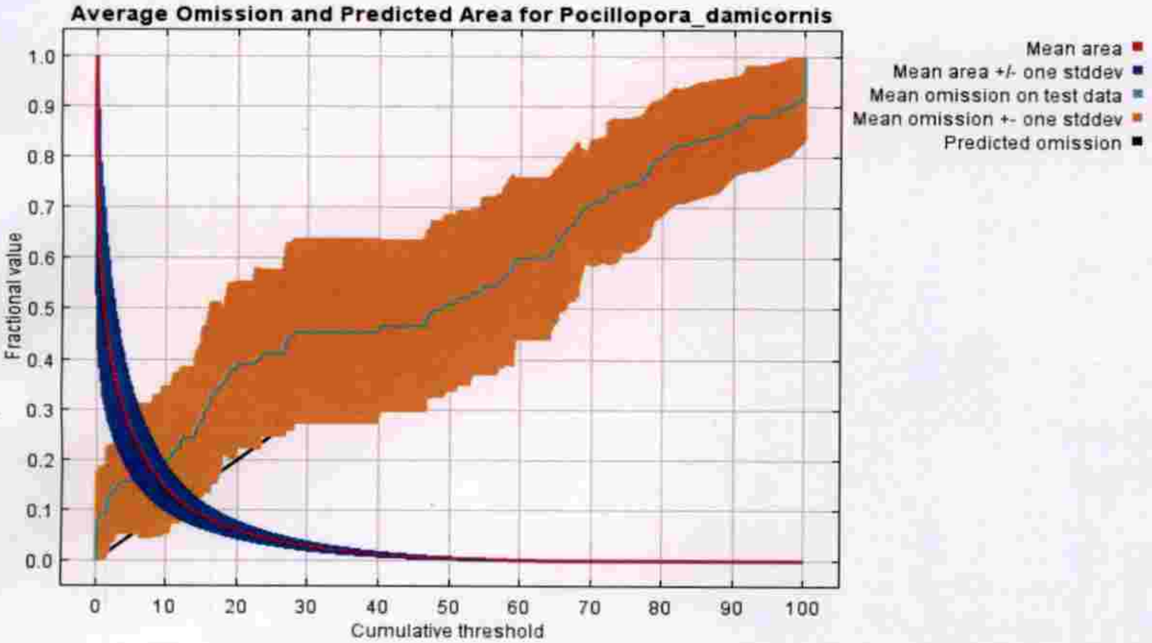


Fig. 63 Test omission rate and predicted area as a function of the cumulative threshold, averaged over the replicate runs for *P. damicornis*

4.4.1.2 Contribution of predictor variables

Table 13 Percent contribution and permutation importance of all environmental variables to the model for *P. damicornis*

Variable	*Percent contribution*	*Permutation importance*
Bathymetry	41.5	64.8
Chlorophyll	13.6	3
Nitrate	12	7
Calcite	10.6	2
Mean temperature	9.9	11.1
Phosphate	5.1	3.4
Current	4.1	1.9
Max Temperature	1.3	0.3
pH	0.8	2.8
Kd	0.7	0.7
DO	0.3	3.1
salinity	0	0
PAR	0	0

The relative contribution of each predictor variable is given by the MaxEnt output and it is shown in Table 13. Among all the variables, bathymetry showed a comparatively higher contribution of 41.5 %, followed by chlorophyll (13.6%) and nitrate (12%). The salinity, as well as par, shows no contribution in this particular model developed for *P. damicornis*. For the Permutation importance, for each environmental variable one by one, the values of that variable in training presence as well as in background data were randomly permuted. The variable having high permutation importance (64.8) were bathymetry and the mean temperature by 11.1 percent.

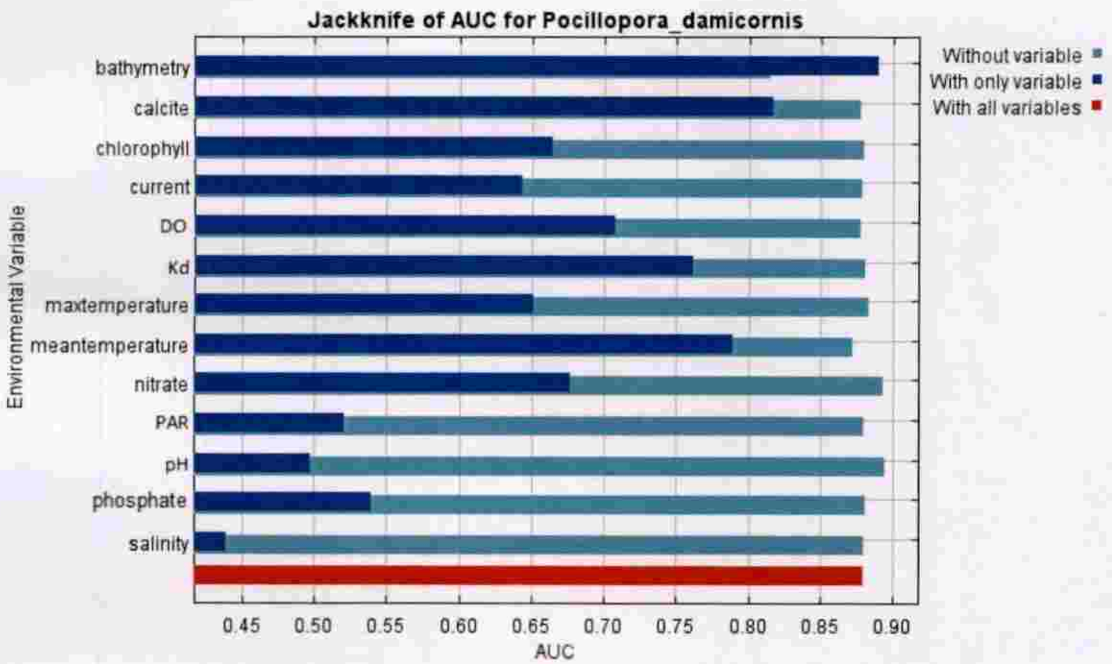


Fig. 64 Jackknife analysis of AUC for the *P. damicornis* using all the variables

The Jackknife of AUC for *P. damicornis* (Fig. 64) shows environmental variable with the highest gain when used in isolation is bathymetry, which therefore appears to have the most useful information by itself. The values shown are averages over replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Also, salinity shows a lesser gain, lower than 0.45.

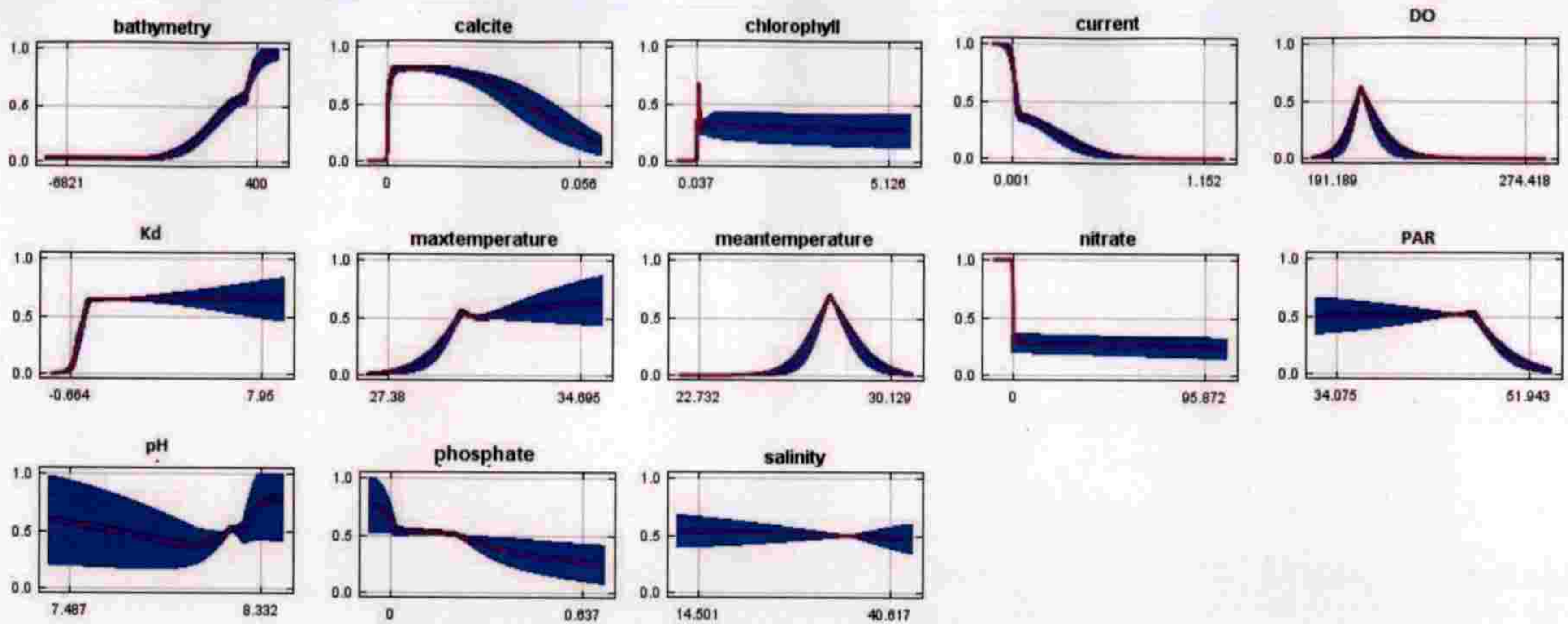


Fig. 65 The response curves for the *P. damicornis* model

The response curves for the *P. damicornis* (Fig. 65) model showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates. These plots demonstrate the dependence of predicted suitability on the selected variables as well as on the dependencies induced by correlations between each variable and other variables.

4.4.1.3 Prediction of the present distribution of the *P. damicornis*

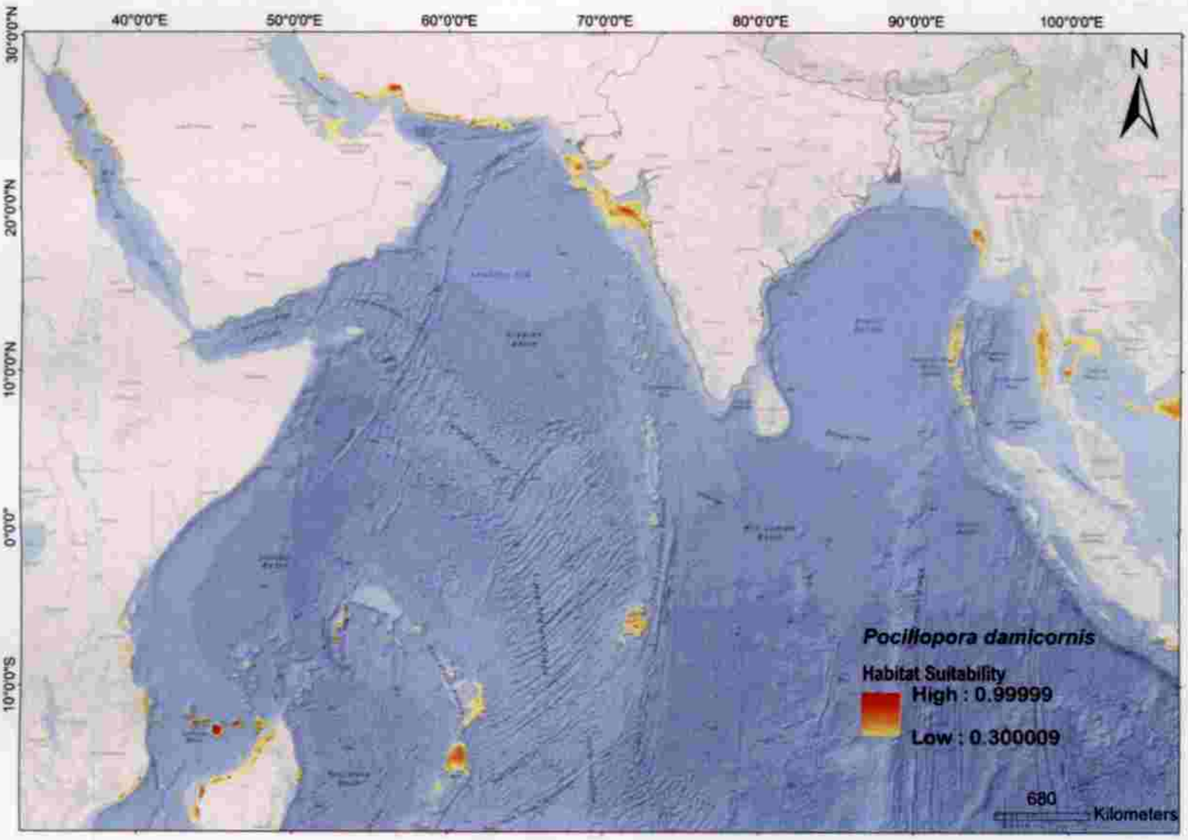


Fig. 66 The predicted distribution of *P. damicornis* along the Northern Indian Ocean.

Fig. 66 shows that the predicted distribution of *P. damicornis* in the Northern Indian ocean with suitability ranging from 0.30 to 0.99, low to high indicated by a legend of yellow to red. The *P. damicornis* is a species which shows lower environmental suitability in the northern Indian ocean compared with other selected coral species. The map shows environmental suitability ranging from 50 to 99% along the islands in the Mozambique

Channel, Chagos, Gulf of Kutch, Gulf of Aden, Andaman & Nicobar Islands, Mergui Archipelago, Southwestern boundary of Northern Indian Ocean, North-western boundary of Madagascar Islands, northern waters of the Gulf of Thailand, boundaries of Red Sea, and Mauritius.

4.4.2 The Future distribution of *P. damicornis* under different Climate Scenarios.

Models prepared using the optimized variables under three different Representative Concentration Pathways (RCP) such as RCP 4.5, RCP 6.0 and RCP 8.5 gave the prediction for future distribution of the *P. damicornis* in the Northern Indian Ocean for the years 2040-2050 and 2090-2100.

4.4.2.1 Future distribution of *P. damicornis* under RCP 4.5 for years 2040-50 and 2090-2100

4.4.2.1.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.932, (SD= 0.042) and 0.947 (SD= 0.036) respectively (Fig. 67).

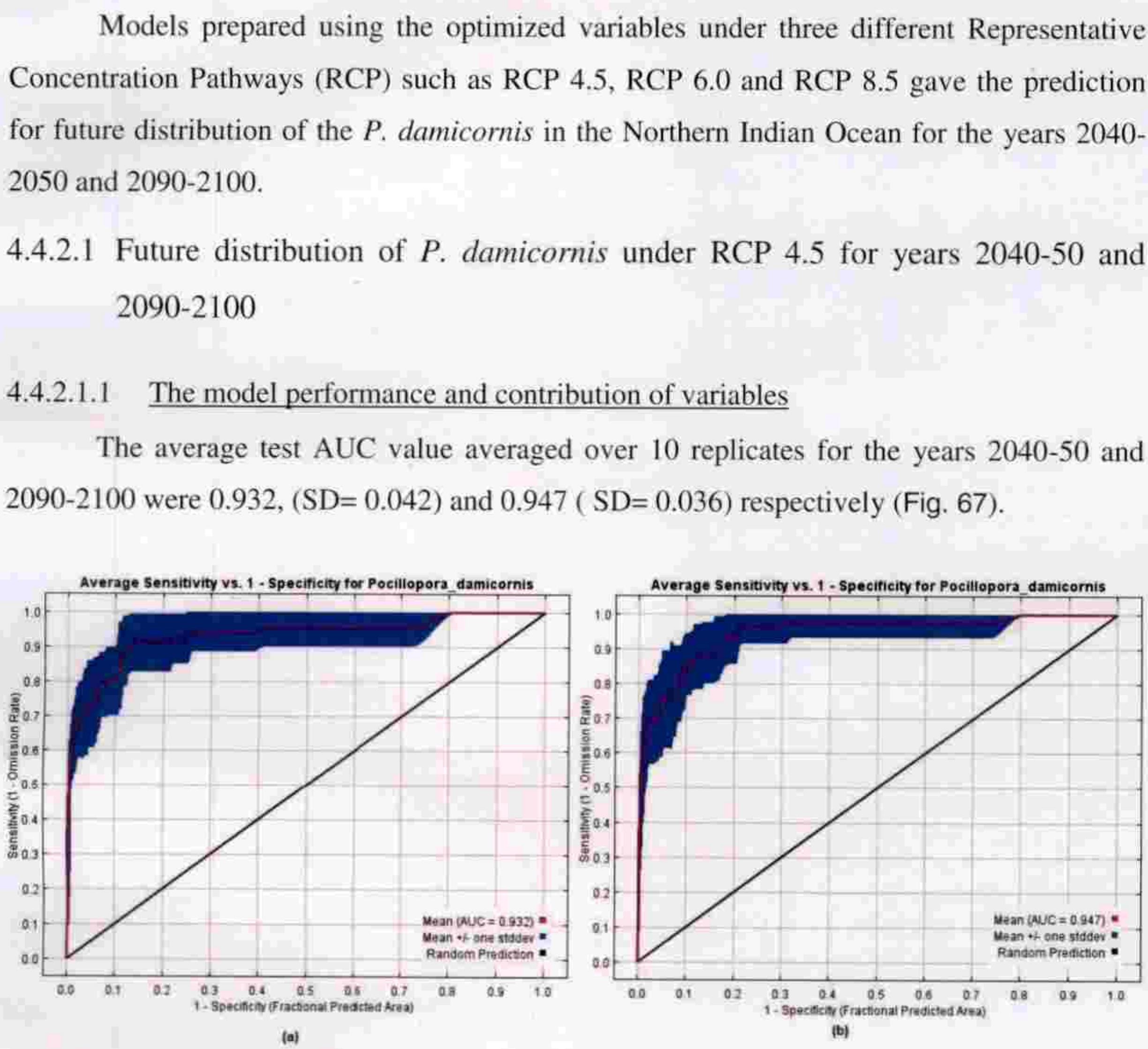


Fig. 67 ROC curve of variable optimization model of the *P. damicornis* under RCP 4.5 for the years 2040-50 (a) and 2090-2100 (b)

4.4.2.1.2 Contribution of predictor variables

Table 14 Percent contribution and permutation importance of all environmental variables to the model for *P. damicornis* under RCP 4.5 for the decades of 2040-2050 and 2090-2100.

Variable	*Percent contribution RCP4.5 (2040-2050)*	*Permutation importance RCP 4.5 (2040-2050)*	*Percent contribution RCP4.5 (2090-2100)*	*Permutation importance RCP 4.5 (2090-2100)*
Bathymetry	65.9	60.2	65.5	69.6
Mean temperature	19.9	18.1	21.4	14.7
Current	8.1	13.2	7.1	8.3
Salinity	5.1	7.1	5	3.7
Max temperature	1	1.5	0.9	3.7

Among these variables, bathymetry showed a significant contribution of 65.9 % and 65.5% for the years 2040-50 and 2090-2100 respectively under RCP 4.5, followed by Mean Temperature (19.9 & 21.4%) (Table 14). The Maximum Temperature has the least contribution in this model developed for *P. damicornis*. For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 60.2% & 69.6% and the Maximum temperature shows the least contribution to this scenario.

The Jackknife of AUC for *P. damicornis* (Fig. 68) shows environmental variable with the highest gain when used in isolation is bathymetry followed by mean temperature for both periods under the RCP 4.5. The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas salinity shows a lesser gain, lower than 0.40.

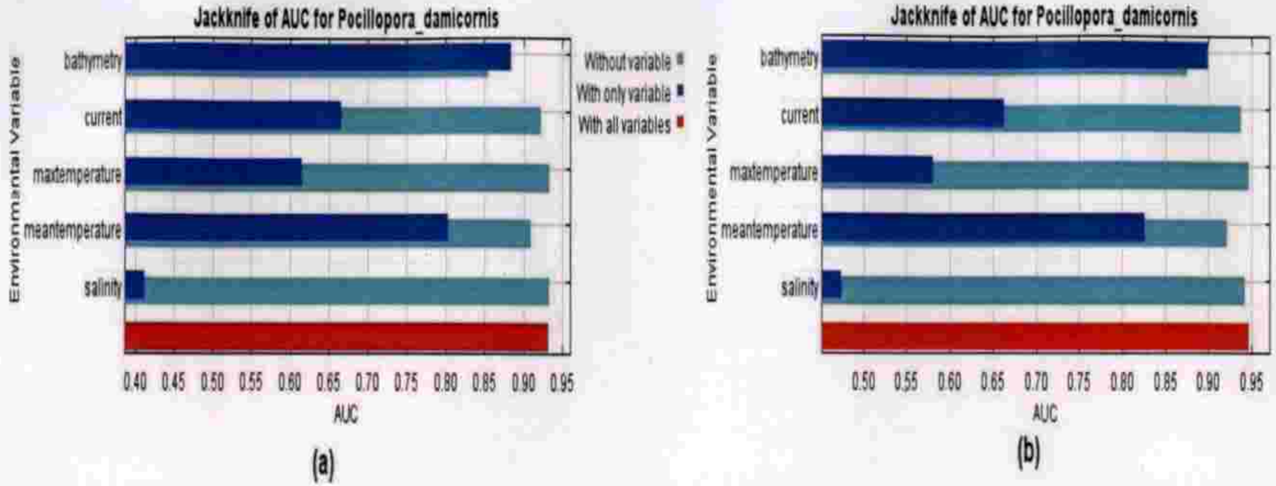


Fig. 68 Jackknife analysis of AUC for the *P. damicornis* using variables according to RCP 4.5 for years 2040-2050 (a) and 2090-2100 (b)

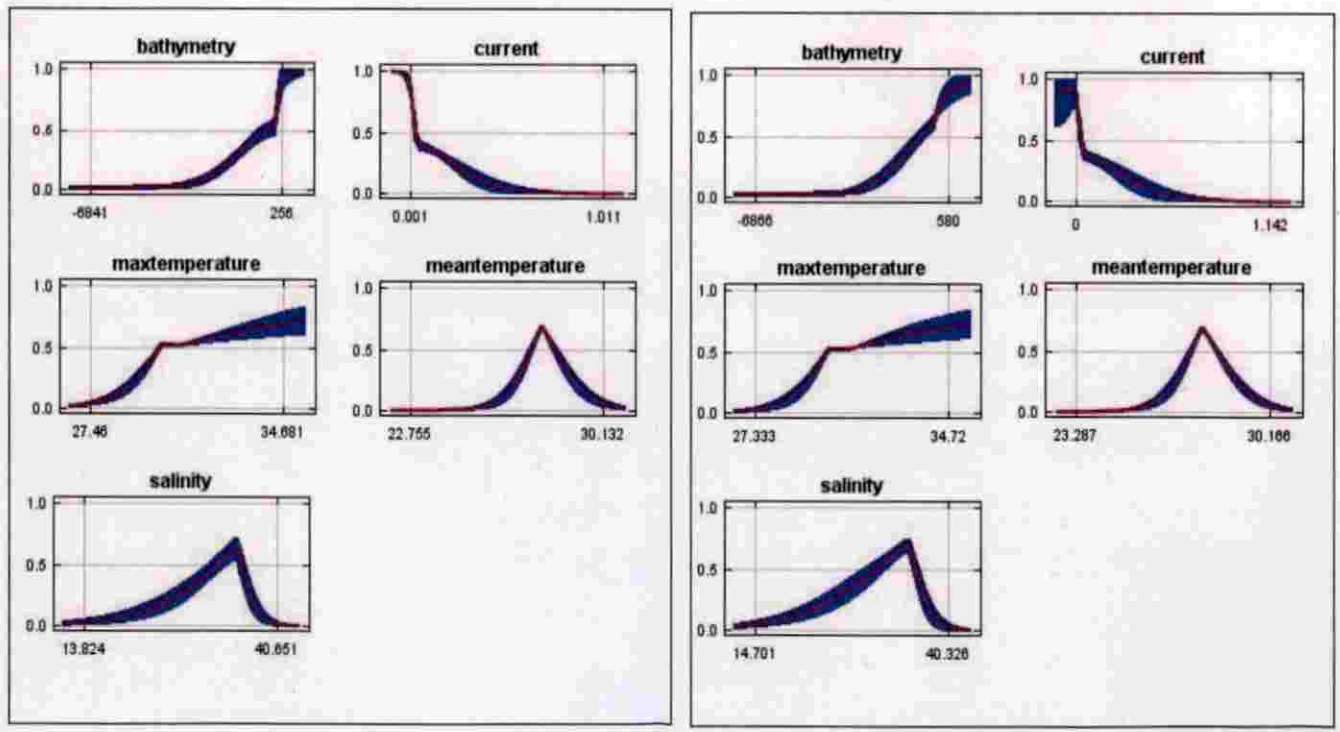
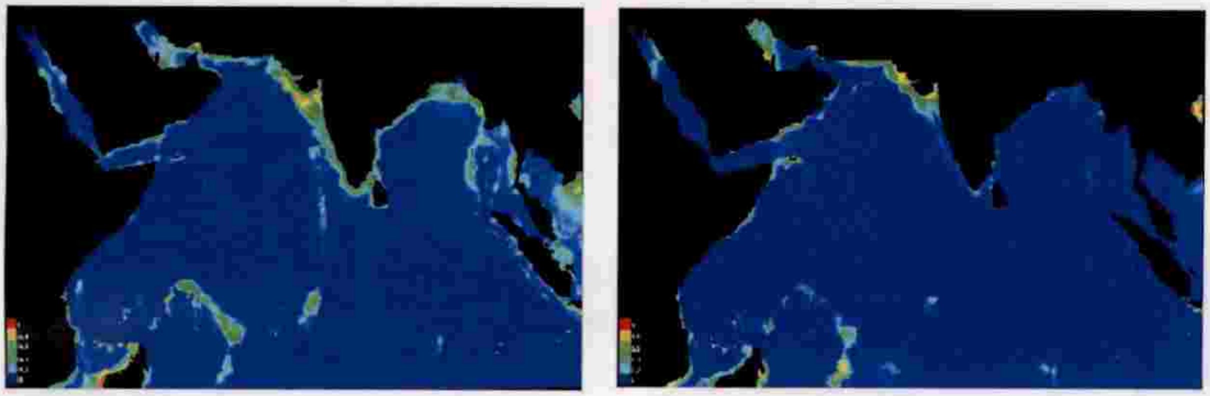


Fig. 69 The Response curve of each variable for 2040-50(a) and 2090-2100(b).

4.4.2.1.3 Response curves of variables used in both models

The response curves for the *P. damicornis* model under the RCP 4.5 for the years 2040-50 (Fig. 69a) and 2090-2100 (Fig. 69b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

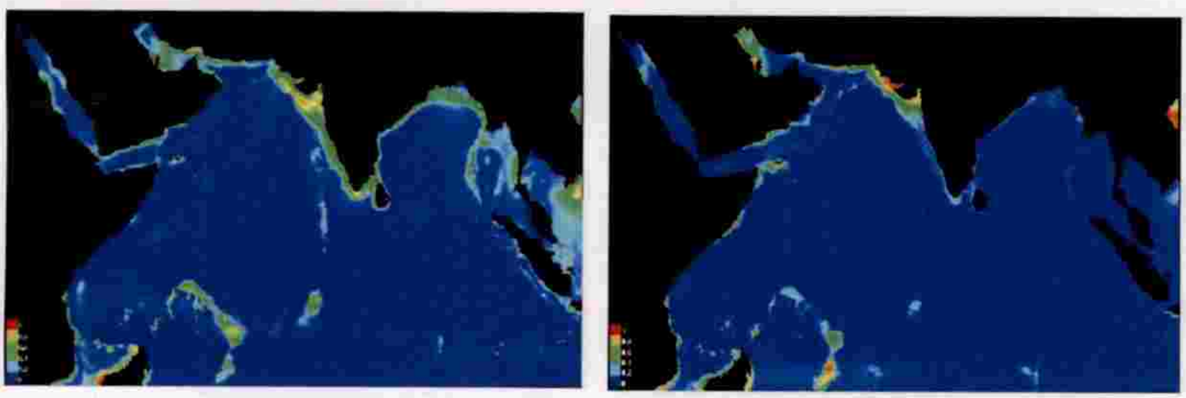
4.4.2.1.4 The predicted habitat suitability of *P. damicornis* under the RCP 4.5 Scenario



(a) (b)

Fig. 70 Map showing the predicted habitat suitability of *P. damicornis* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 4.5

For *P. damicornis* the distribution will get diminished across the Bay of Bengal, the west coast of India and the Chagos, Maldives and Lakshadweep group of islands for the period 2040-50 under RCP 4.5. The population is shifted to new areas across the Red Sea, the Persian Gulf and through the Oman coast with not much difference in the strength of occurrence(Fig. 70).



(a) (b)

Fig. 71 Map showing the predicted habitat suitability of *P. damicornis* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 4.5

No remarkable difference in the distribution of *P. damicornis* is predicted for 2090-2100 under RCP 4.5 in comparison to 2040-50.

4.4.2.2 3.4.2.2 Future distribution of *P. damicornis* under RCP 6.0 for years 2040-50 and 2090-2100

4.4.2.2.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.917(SD= 0.043) and 0.955 (SD= 0.012). respectively (Fig. 72 (a) and Fig. 72(b))

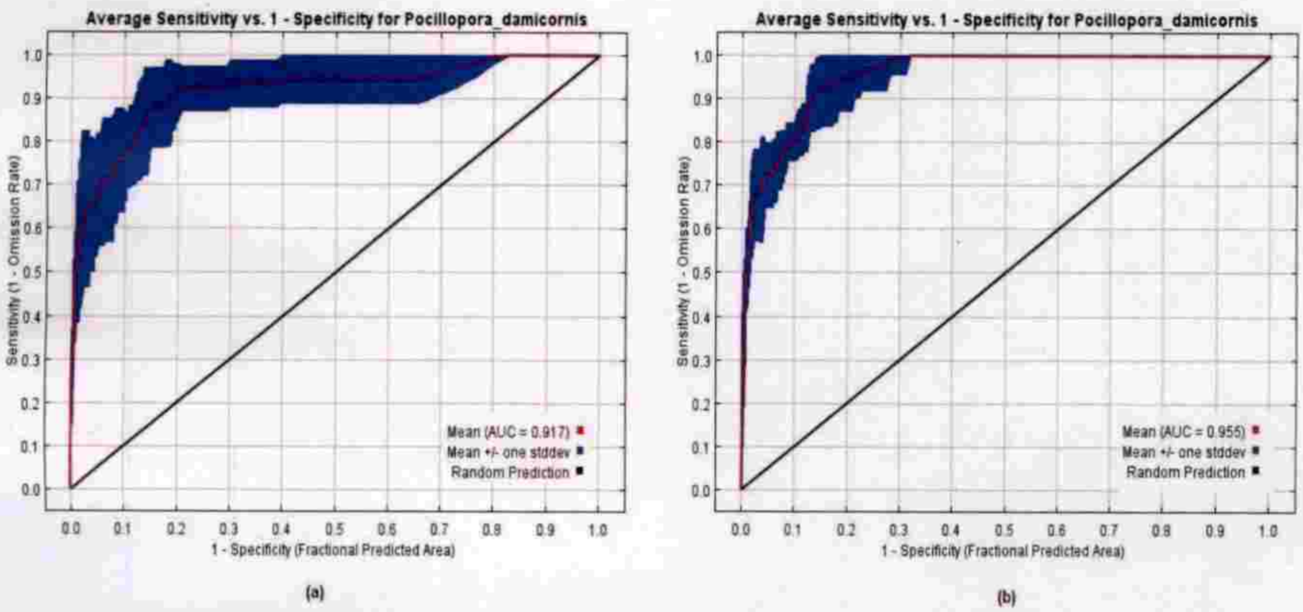


Fig. 72 ROC curve of variable optimization of the *P. damicornis* under RCP 6.0 for the years 2040-50 (a) and 2090-2100 (b)

4.4.2.2.2 Contribution of predictor variables

Table 15 Percentage contribution and permutation importance of all environmental variables to the model for *P. damicornis* under RCP 6.0 for the decades of 2040-2050 and 2090-2100.

Variable	***Percent contribution (RCP 6.0 2040-50)***	***Permutation importance (RCP 6.0 2040-50)***	***Percent contribution (RCP 6.0 2090-2100)***	***Permutation importance (RCP 6.0 2090-2100)***
Bathymetry	61	65.2	62.8	51.9

Mean temperature	23.4	22.9	23.3	20.2
Salinity	7.9	6.6	7.3	18.9
Current	7.2	4.1	5.6	7.5
Max temperature	0.5	1.2	1	1.6

Among these variables, bathymetry showed a significantly higher contribution of 61 % and 62.8 % for the years 2040-50 and 2090-2100 respectively under RCP 6.0, followed by Mean Temperature (23.4 & 23.3%) (Table 15). The Maximum Temperature has the least contribution in this model developed for *P. damicornis.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 65.2 % & 51.9 % and the Maximum temperature shows the least contribution (1.2 & 1.6 %) for this scenario in both periods.

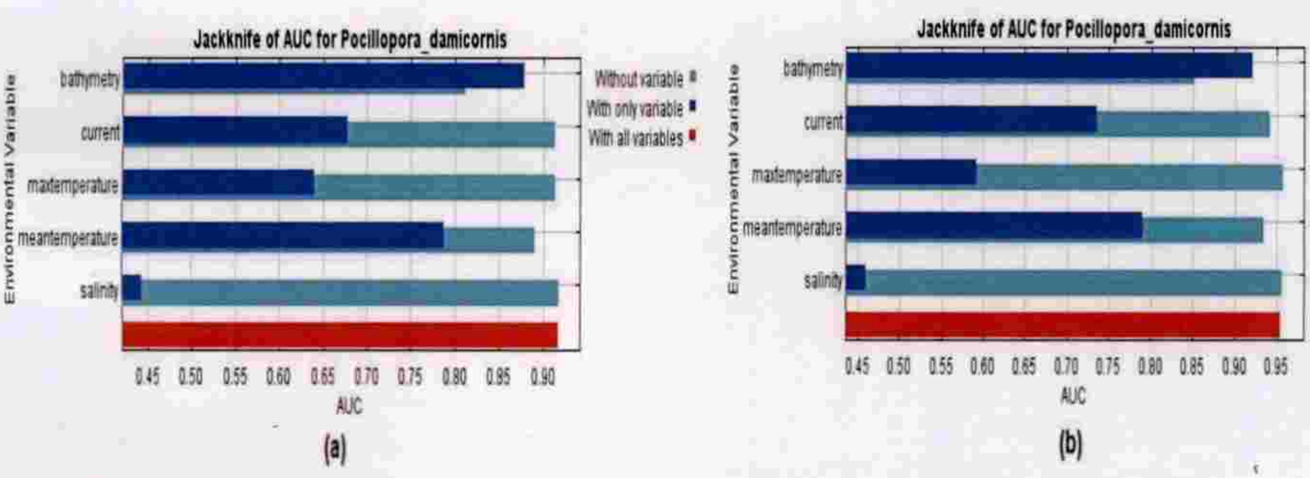
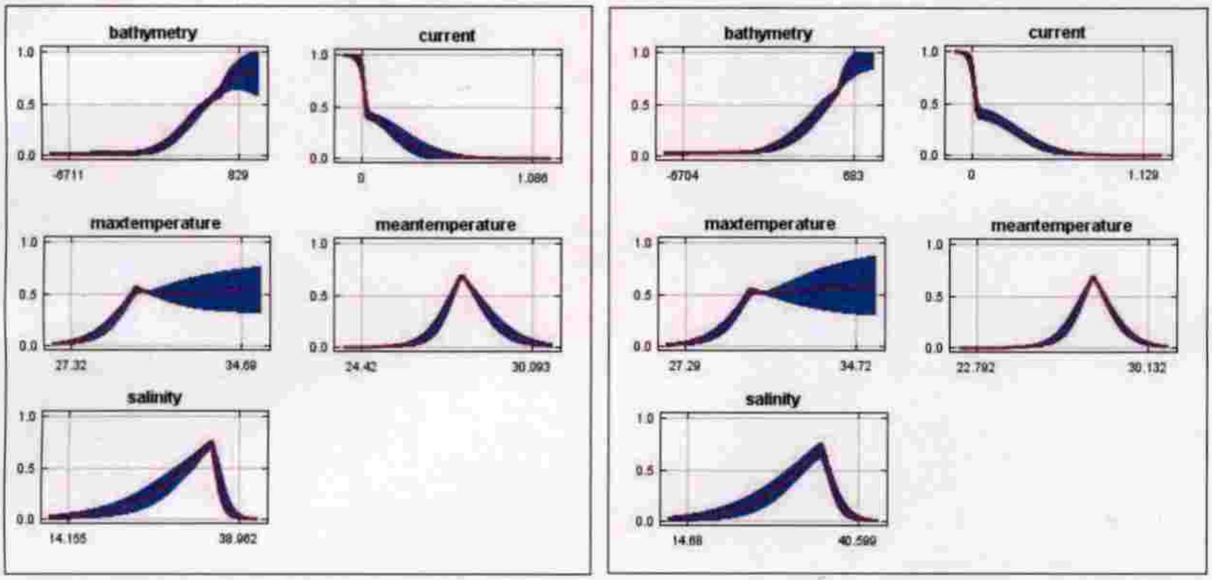


Fig. 73 Jackknife analysis of AUC for the *P. damicornis* using variables according to RCP 6.0 for years 2040-2050 (a) and 2090-2100 (b)

The Jackknife of AUC for *P. damicornis* (Fig. 73) shows environmental variable with the highest gain when used in isolation is bathymetry followed by mean temperature. The values shown are averages over 10 replicate runs. The salinity shows a lesser gain in both periods is about 0.45.

4.4.2.2.3 Response curves of variables used in both models

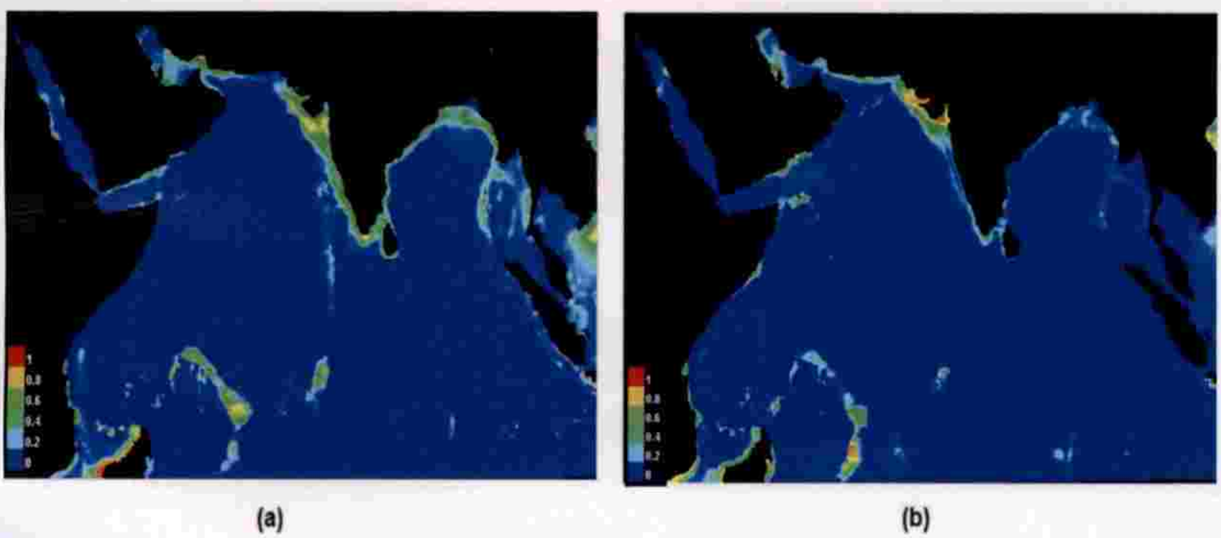


(a) (b)

Fig. 74 The Response curve of each variable for 2040-50 and 2090-2100.

The response curves for the *P. damicornis* model under the RCP 6.0 for the years 2040-50 (Fig. 74a) and 2090-2100 (Fig. 74b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged over 10 replicates.

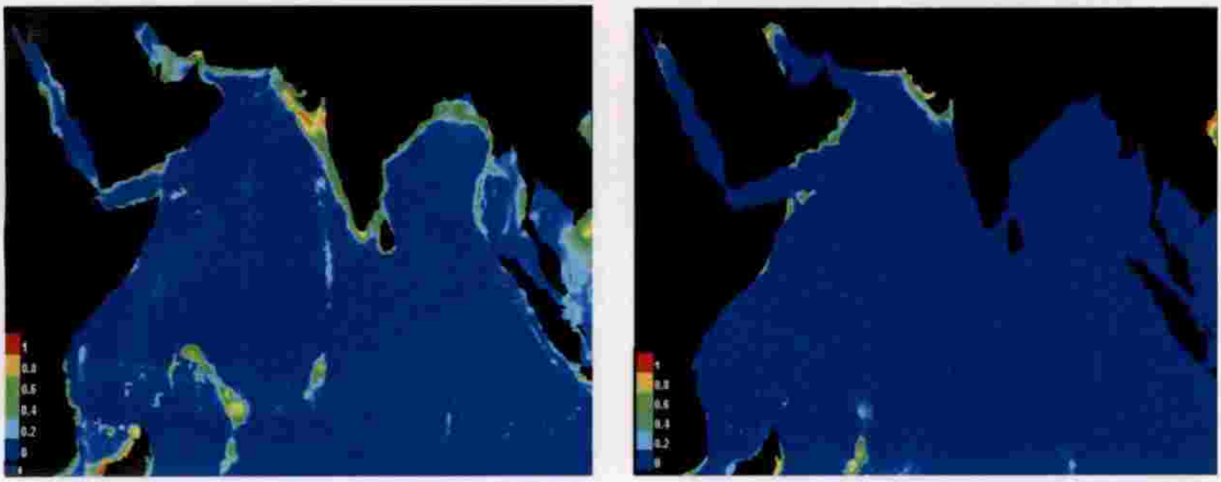
4.4.2.2.4 Predicted habitat suitability of *P. damicornis* under the RCP 6.0



(a) (b)

Fig. 75 Map showing the predicted habitat suitability of *P. damicornis* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 6.0

The extent of distribution of *P. damicornis* under RCP 6.0 for the 2040-50 decade is also similar to distribution projected for the same period under RCP 4.5.



(a) (b)

Fig. 76 Map showing the predicted habitat suitability of *P. damicornis* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 6.0

Here the extent is further decreased and the species is predicted to be vanished from eastern Indian ocean regions of this study and from the west coast of India and the Lakshadweep archipelago. In addition, further decrease is projected in the Red Sea, Persian Gulf, Maldives, Chagos and northern SMR region.

4.4.2.3 3.4.2.3 Future distribution of *P. damicornis* under RCP 8.5 for years 2040-50 and 2090-2100

4.4.2.3.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.956 (SD= 0.044) and 0.924 (SD = 0.043). respectively (Fig. 77(a) and Fig. 77 (b)).

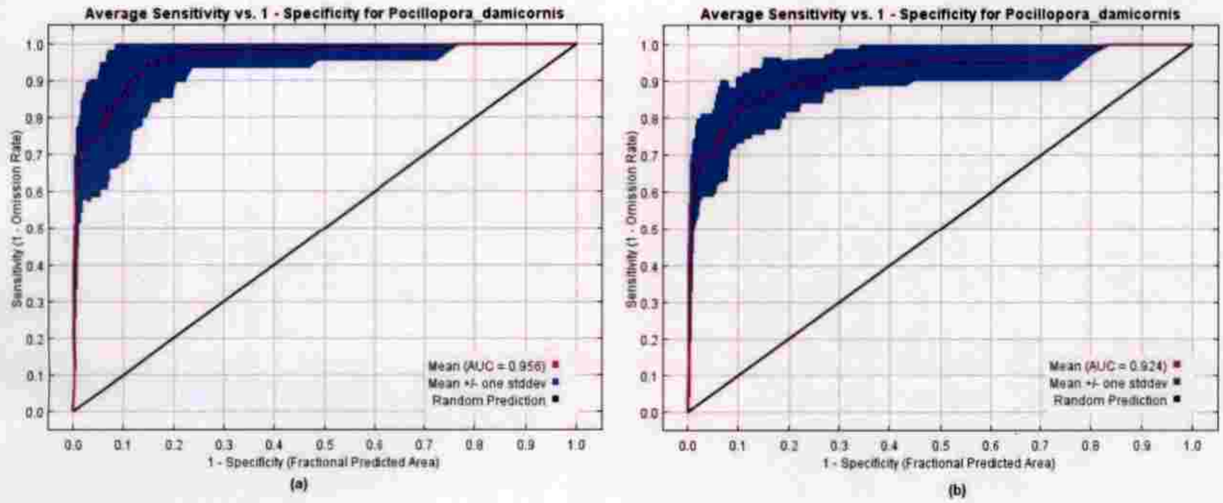


Fig. 77 the AUC curve of variable optimization of the *P. damicornis* under RCP 8.5 for the years 2040-50 (a) and 2090-2100 (b)

4.4.2.3.2 Contribution of predictor variables

Table 16 Percentage contribution and permutation importance of all environmental variables to the model for *P. damicornis* under RCP 8.5 for the period of 2040-2050 and 2090-2100.

Variable	*Percent contribution RCP 8.5 (2040-2050)*	*Permutation importance RCP 8.5 (2040-2050)*	*Percent contribution RCP 8.5 (2090-2100)*	*Permutation importance RCP 8.5 (2090-2100)*
Bathymetry	62.1	74.2	65.2	76.3
Mean Temperature	23.8	14.2	21.6	15.7
Salinity	7.4	4.9	7	3.6
Current	6.2	5.3	5.1	2
Max Temperature	0.6	1.5	1.1	2.4

Among these variables, bathymetry shows highest contribution of 62.1 % and 65.2% followed by Mean Temperature (23.8 & 21.6%) for the years 2040-50 and 2090-2100

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respectively (Table 16). Maximum Temperature has the least contribution in this particular model developed. For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 74.2% & 76.3% and the Maximum temperature shows the least contribution for the year 2040-2050 and 2090-2100 during this scenario.

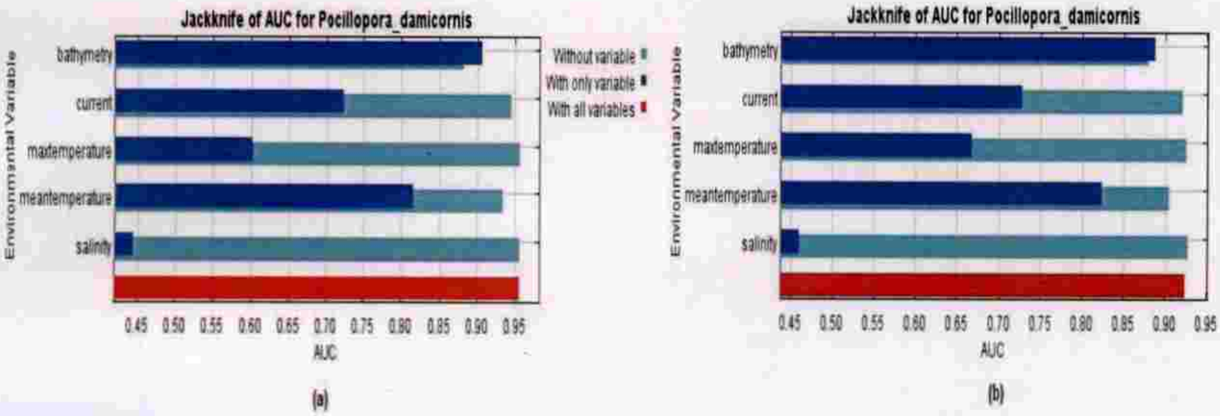
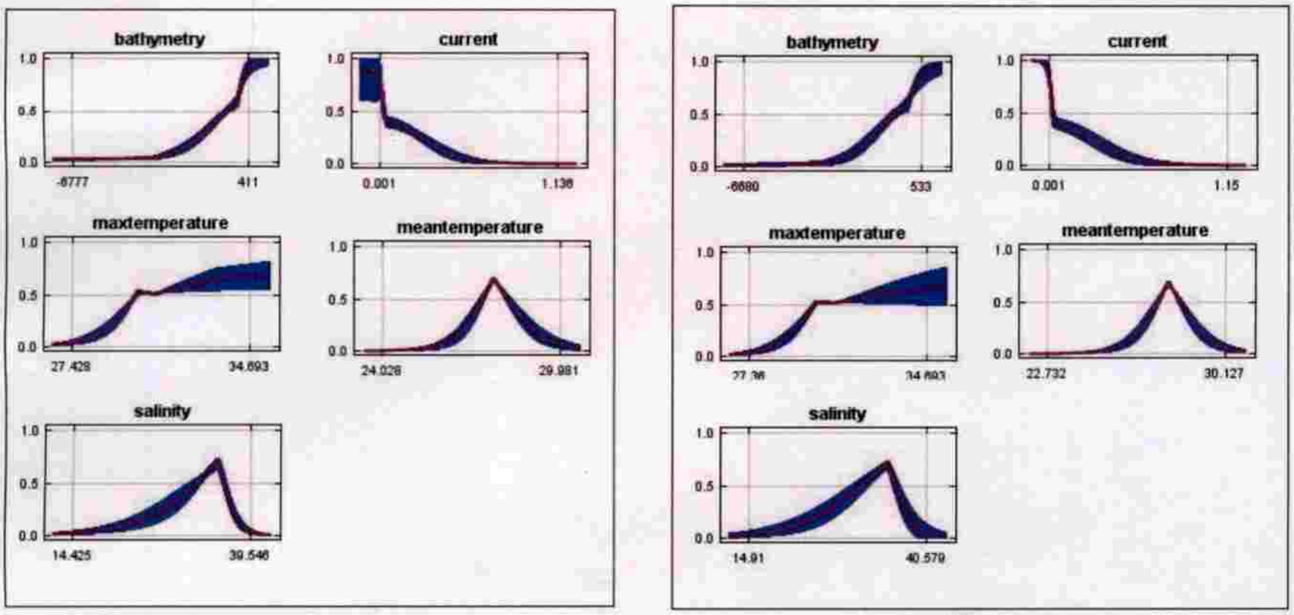


Fig. 78 Jackknife analysis of AUC for the *P. damicornis* using variables according to RCP 8.5 for years 2040-2050 (a) and 2090-2100 (b)

The Jackknife of AUC for *P. damicornis* (Fig. 78) shows environmental variable with the highest gain is bathymetry when used in isolation, followed by mean temperature for both periods under the scenario RCP 8.5. The values shown are averaged over 10 replicates. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas salinity shows a lesser gain in both periods similar to the other scenarios.

4.4.2.3.3 Response curves of variables used in both models

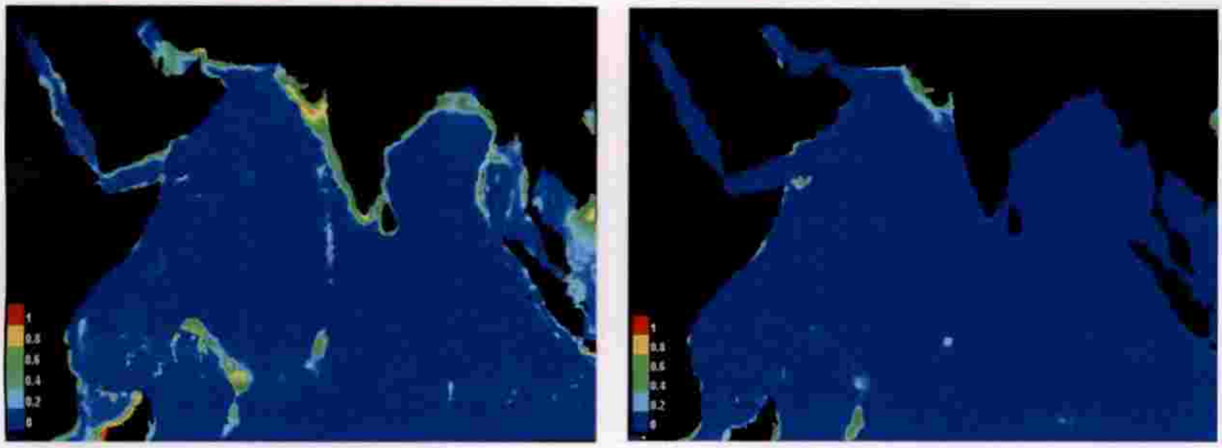


(a) (b)

Fig. 79 The Response curve of each variable for 2040-50 and 2090-2100.

The response curves for this species under the RCP 8.5 for the period of 2040-50 (Fig. 79a) and 2090-2100 (Fig. 79b) showed the response of each variable in determining the distribution of the *P. damicornis* created using only the corresponding variable, averaged for 10 replicates.

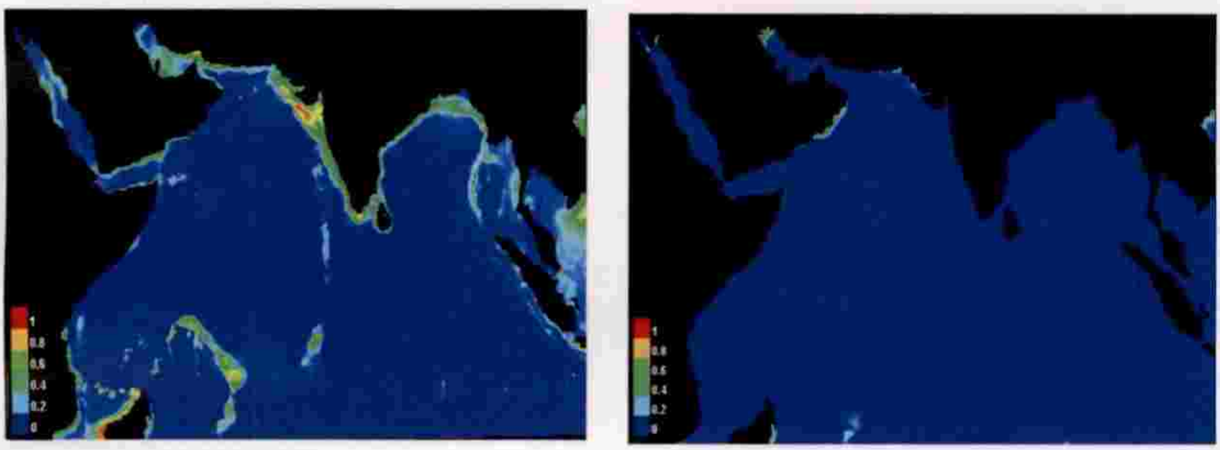
4.4.2.3.4 Predicted habitat suitability of *P. damicornis* under the RCP 8.5



(a) (b)

Fig. 80 Map showing the predicted habitat suitability of *P. damicornis* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 8.5

Here, for the 2040-2050 decade (Fig. 80), the species is completely absent in the Red sea and the two island groups of India. It is retained only in small degree across Gujarat coast, Chagos, eastern Madagascar, islands off Somalia, Oman, North-eastern Arabian Peninsula and south SMR.



(a) (b)

Fig. 81 Map showing the predicted habitat suitability of *P. damicornis* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 8.5

For the decade 2090-2100 the species shows further drop in the percentage distribution when compared to the projection for 2040-50 as it is completely absent in the Chagos, northern SMR and entire eastern Africa (Fig. 81). However, the population remains in the northern Persian Gulf and Oman coast in a moderate degree.

4.5 *P. lutea*

4.5.1 Prediction of the current distribution

4.5.1.1 The Model Performance and variable contributions

The model performance is assessed by using the average test AUC value for 10 replicates was 0.933 (SD = 0.016). The sensitivity *vs*. 1-specificity graph shows the area under the Receiver Operating Characteristic (ROC) curve or AUC. The test omission rate and AUC curve (Fig. 82 & Fig. 83) found to fit into this model. The Fig. 83 shows that the mean omission line on the test data was passing through the predicted omission line. In the Fig. 82, the AUC line was passing through the left top of the random prediction.

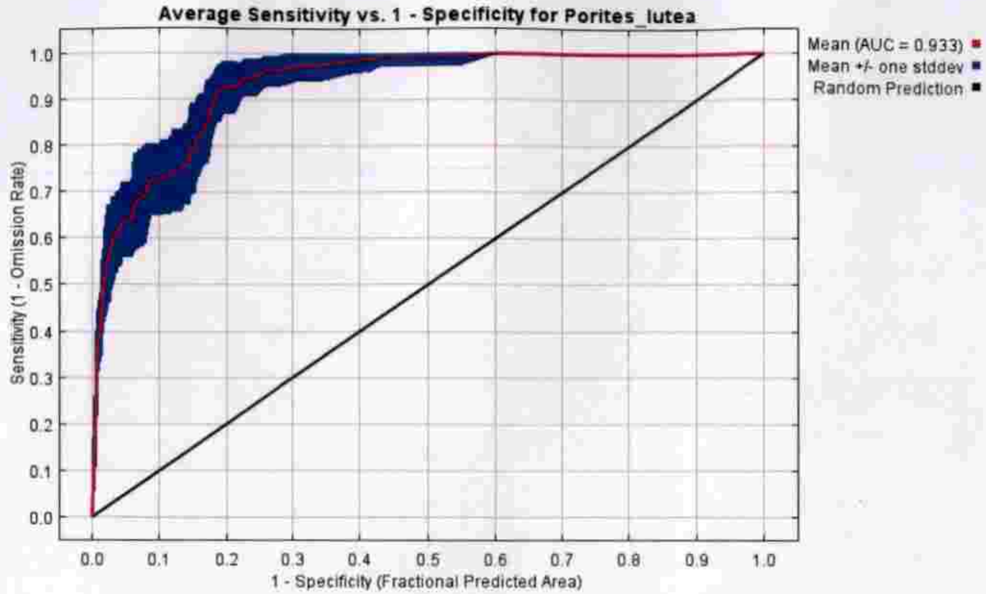
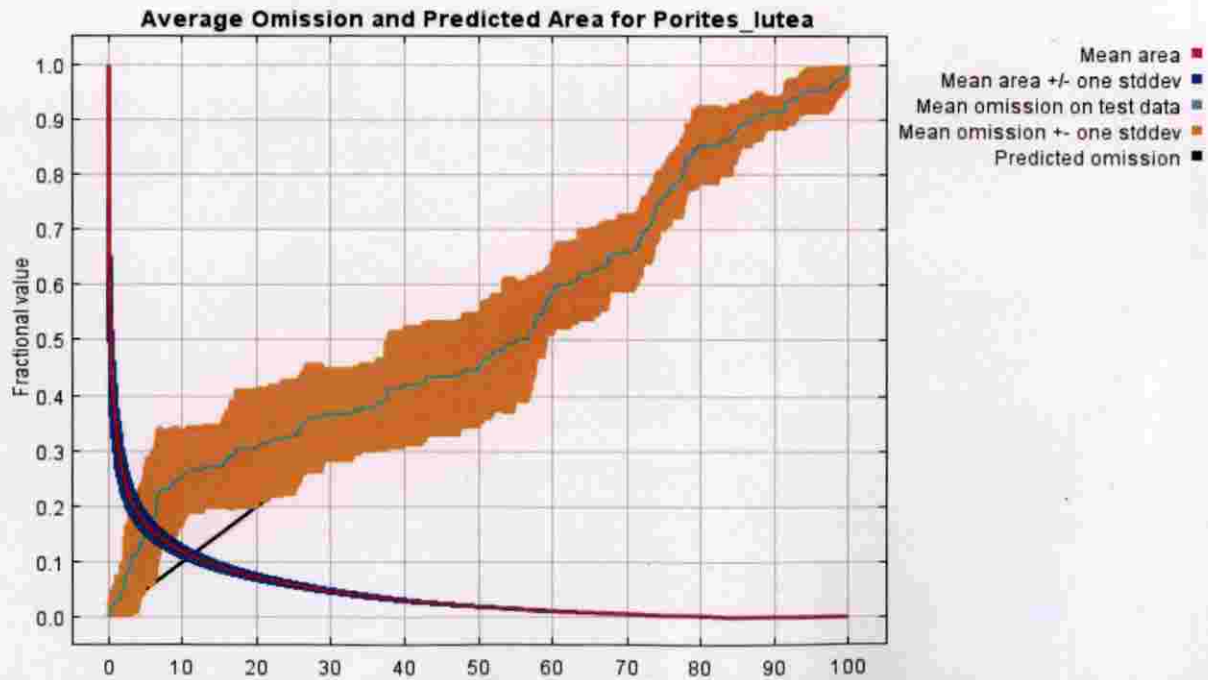


Fig. 82 the ROC curve of variable optimization model of the *P. lutea*

Fig. 83 Test omission rate and predicted area as a function of the cumulative threshold, averaged over the replicate runs for *P. damicornis*



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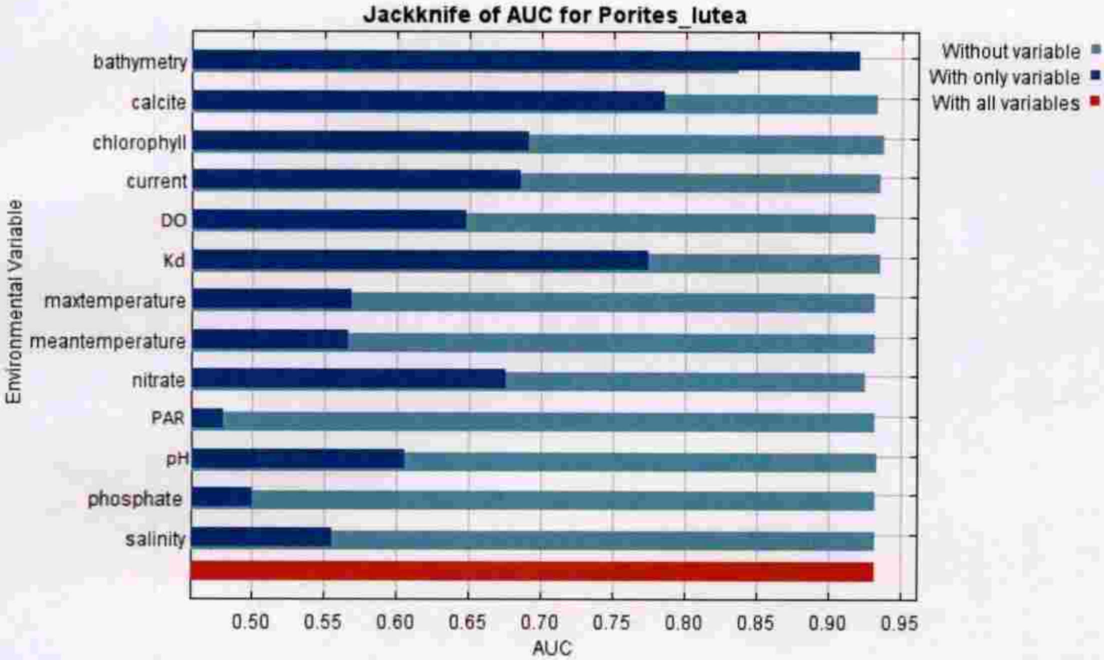

Fig. 84 Jackknife analysis of AUC for the *P. damicornis* using all the variables

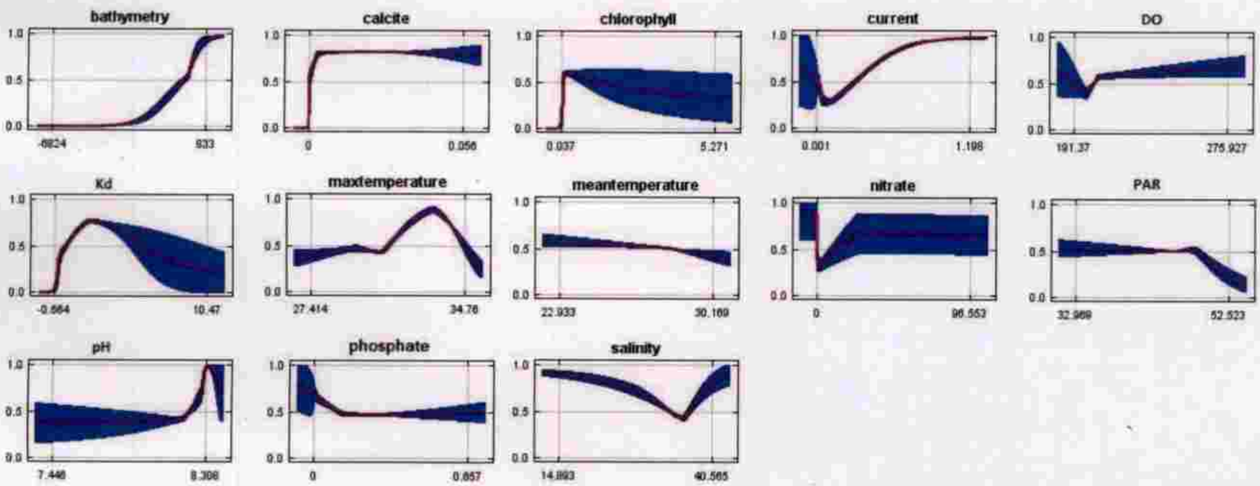

Fig. 85 The response curves for the *P. lutea*

4.5.1.2 Contribution of predictor variables

Table 17 Percent contribution and permutation importance of all environmental variables to the model for *P. lutea*

Variable	*Percent contribution*	*Permutation importance*
Bathymetry	71.4	88.9
Current	8.2	0.9
Nitrate	7.9	2.2
pH	4.4	2.3
Phosphate	2.4	2.9
Calcite	2.2	0.9
Chlorophyll	1.2	0.7
Kd	1.2	0.3
Max Temperature	0.5	0.2
PAR	0.4	0.2
Mean Temperature	0.4	0.2
DO	0	0.2
Salinity	0	0.1

The relative contribution of each predictor variable is given by the MaxEnt output and it is shown in Table 17. Among all the variables, bathymetry showed a comparatively higher contribution of 71.4 %, followed by current (8.2%) and nitrate (7.9 %). The salinity, as well as DO, shows no contribution in this particular model developed for *P. lutea.* For the Permutation importance, for each environmental variable one by one, the values of that variable in training presence as well as in background data were randomly permuted. The variable having high permutation importance (88.9) were bathymetry and the phosphate (2.9%).

The Jackknife of AUC for *P. lutea* (Fig. 84) shows environmental variable with the highest gain when used in isolation is bathymetry, which therefore appears to have the most useful information by itself. The values shown are averages over replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. The PARshows a lesser gain, lower than 0.45.

The response curves for the *P. lutea* showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates (Fig. 85). These plots demonstrate the dependence of predicted suitability on the selected variables as well as on the dependencies induced by correlations between each variable and other variables.

4.5.1.3 Prediction of the present distribution of the *P. lutea*

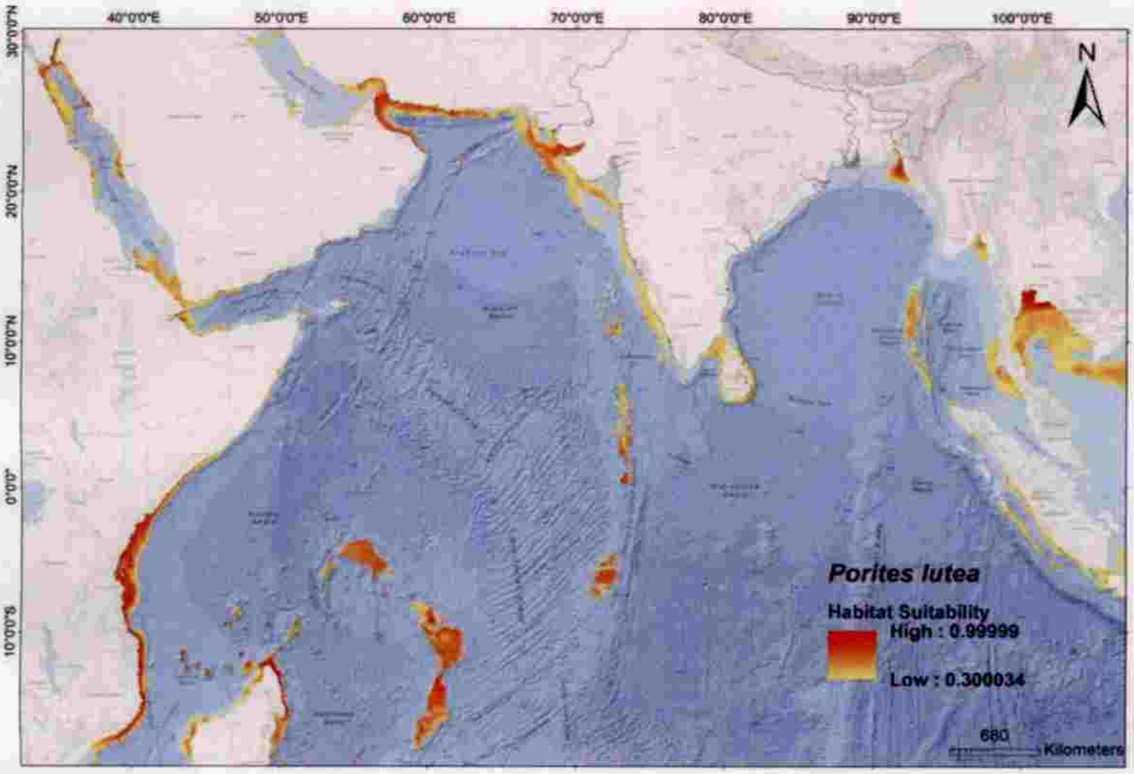

Fig. 86 The predicted distribution of *P. lutea* along the Northern Indian Ocean.

Fig. 86 shows that the predicted distribution of *P. lutea* in the Northern Indian ocean with suitability ranging from 0.30 to 0.99, low to high indicated by a legend of yellow to red. *P. lutea* is a species which shows lower environmental suitability in the northern Indian ocean compared with other selected coral species. The map shows environmental suitability ranging from 80 to 99% along the islands in the Mozambique Channel, the entire seychelles Mauritius ridge, Lakshadweep, Maldives Chagos, Gulf of Kutch, Gulf of Aden, Southwestern boundary of Northern Indian Ocean, Northwestern boundary of Madagascar Islands, northern waters of the Gulf of Thailand, boundaries of Red Sea. A medium suitability of about 50-80% were observed at Andaman and Nicobar Islands, Mergui Archipelago, Gulf of Mannar, Malacca strait and in the Persian Gulf.

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4.5.2 The Future distribution of *P. lutea* under different Climate Scenarios.

Models prepared using the optimized variables under three different Representative Concentration Pathways (RCP) such as RCP4.5, RCP6.0 and RCP8.5 gave the prediction for future distribution of *P. lutea* in the Northern Indian Ocean for the years 2040-2050 and 2090-2100.

4.5.2.1 Future distribution of *P. lutea* under RCP 4.5 for years 2040-50 and 2090-2100

4.5.2.1.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.950(SD = 0.009) and 0.931 (SD = 0.012) respectively (Fig. 87).

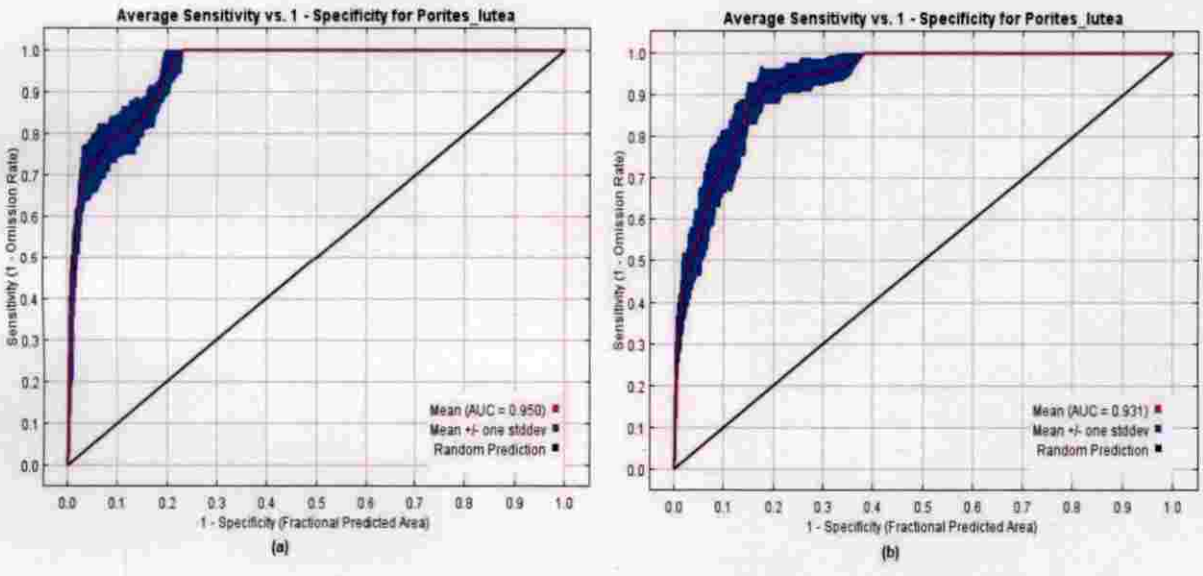


Fig. 87 the ROC curve of variable optimization model of the *P. lutea* under RCP 4.5 for the years 2040-50 (a) and 2090-2100 (b)

4.5.2.1.2 Contribution of predictor variables

Table 18 Percent contribution and permutation importance of all environmental variables to the model for *P. lutea* under RCP 4.5 for the decades of 2040-2050 and 2090-2100.

Variable	***Percent contribution RCP4.5 (2040-2050)***	***Permutation importance RCP 4.5 (2040-2050)***	***Percent contribution RCP4.5 (2090-2100)***	***Permutation importance RCP 4.5 (2090-2100)***
bathymetry	75.5	85.2	84.4	94.6
Mean temperature	15.3	10.7	13.7	3.5
current	3.4	1.8	1.1	0.8
salinity	3.2	2	0.5	1
Max temperature	2.5	0.2	0.3	0.2

Among these variables, bathymetry showed a significant contribution of 75.5 % and 84.4% for the years 2040-50 and 2090-2100 respectively under RCP 4.5, followed by Mean Temperature (15.3 & 13.7%) (Table 18). The Maximum Temperature has the least contribution in this model developed for *P. lutea.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 85.2% & 94.6% and the Maximum temperature shows the least contribution to this scenario.

The Jackknife of AUC for *P. lutea* (Fig. 88) shows environmental variable with the highest gain when used in isolation is bathymetry followed by max temperature for both periods under the RCP 4.5. The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas salinity shows a lesser gain, which is lower than 0.55 in 2040-2050 whereas the mean temperature shows the lowest value for 2090-2100 decade.

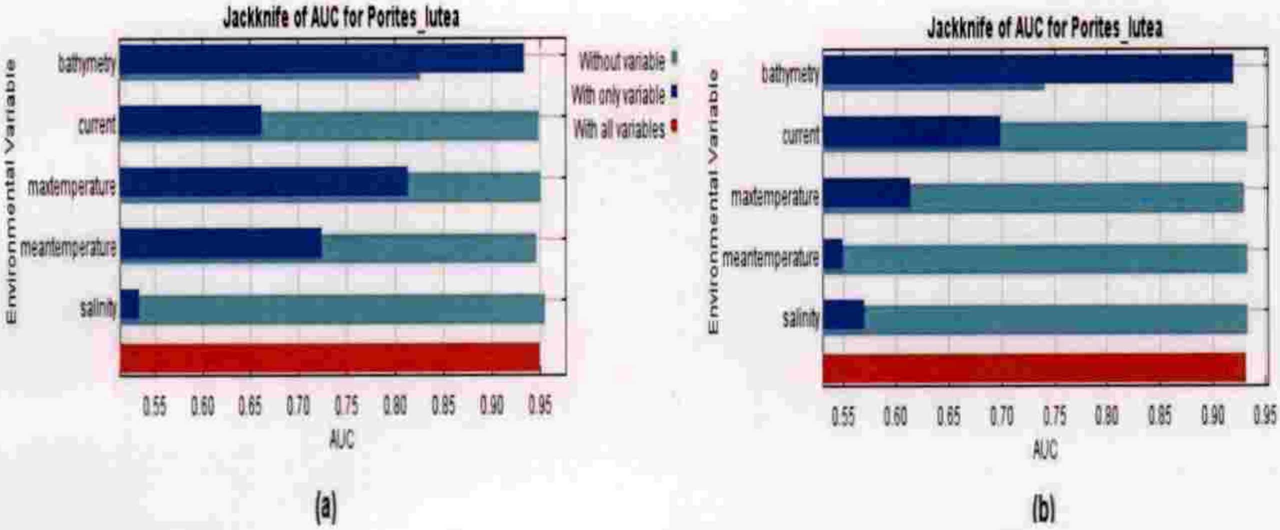


Fig. 88 Jackknife analysis of AUC for the *P. lutea* using variables according to RCP 4.5 for years 2040-2050 (a) and 2090-2100 (b)

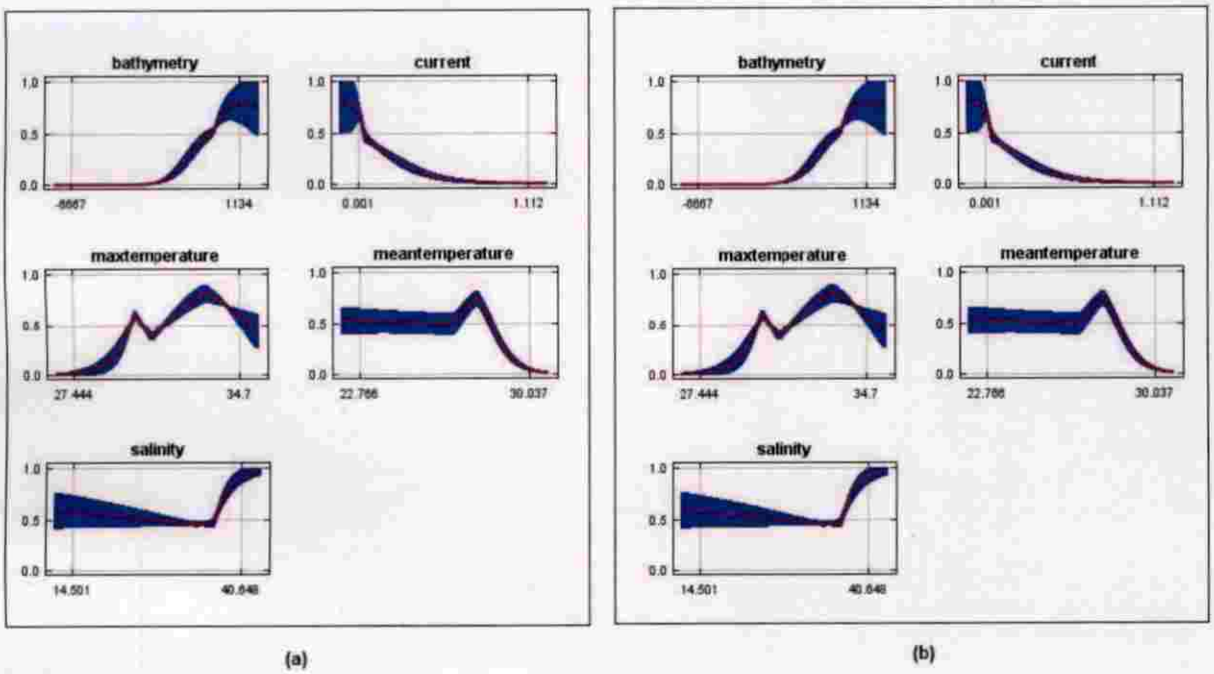
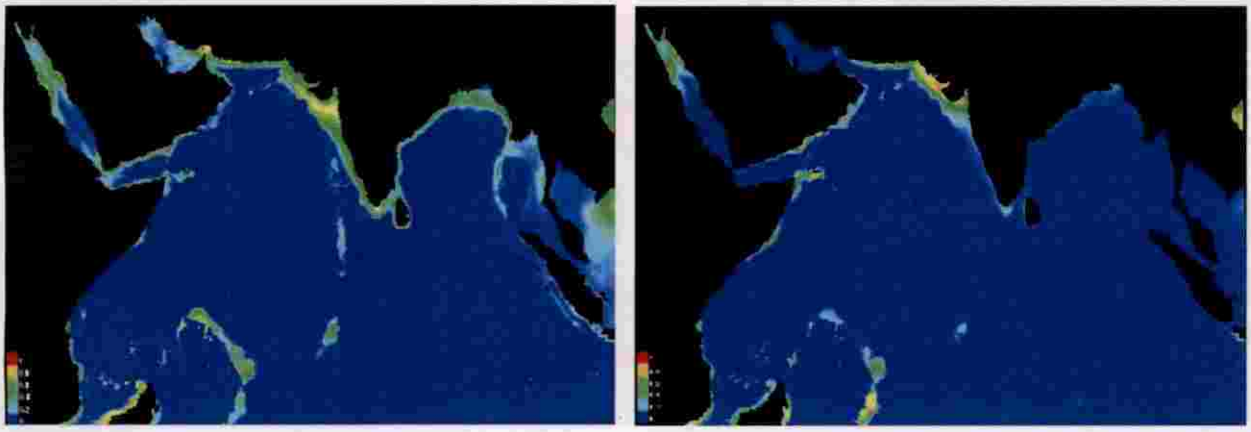


Fig. 89 The Response curve of each variable for 2040-50(a) and 2090-2100(b).

4.5.2.1.3 Response curves of variables used in both models

The response curves for the *P. lutea* model under the RCP 4.5 for the years 2040-50 (Fig. 89a) and 2090-2100 (Fig. 89b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

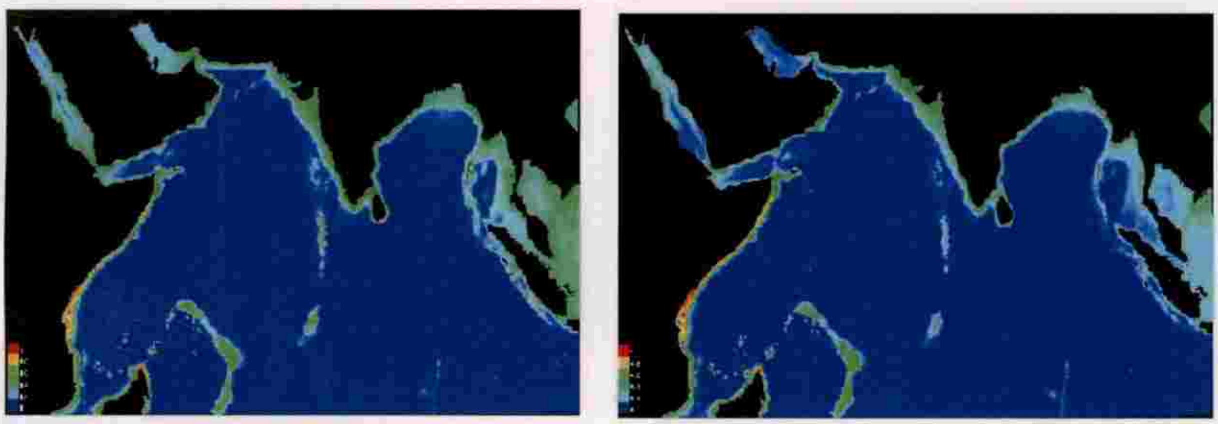
4.5.2.1.4 The predicted suitability of *P. lutea* under the RCP 4.5



(a) (b)

Fig. 90 Map showing the predicted habitat suitability of *P. lutea* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 4.5

The predicted distribution of *P. lutea* under RCP 4.5 for the 2040-50 period shows marked reduction when compared to the current situation. Entire coast of India and Andaman group of islands shows either reduction or complete decline of the species. However, it is predicted with a good degree of presence in the Lakshadweep, Maldives and Chagos islands; the east African coast and the Red Sea than its presence in these areas in the present condition.



(a) (b)

Fig. 91 Map showing the predicted habitat suitability of *P. lutea* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 4.5

For the projection obtained under RCP 4.5 for 2090-2100 the species shows a notable increase in its range as it is then present in the Bay of Bengal regions from where it is absent for 2040-50 decade. In addition, the species shows a strong foothold in the eastern coast of Africa, Red Sea and Oman; around Madagascar and entire SMR.

4.5.2.2 Future distribution of *P. lutea* under RCP 6.0 for years 2040-50 and 2090-2100

4.5.2.2.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.916 (SD = 0.022) and 0.925 (SD = 0.015). respectively (Fig. 92).

4.5.2.2.2 Contribution of predictor variables

Table 19 Percentage contribution and permutation importance of all environmental variables to the model for *P. lutea* under RCP 6.0 for the decades of 2040-2050 and 2090-2100.

Variable	***Percent contribution (RCP 6.0 2040-50)***	***Permutation importance (RCP 6.0 2040-50)***	***Percent contribution (RCP 6.0 2090-2100)***	***Permutation importance (RCP 6.0 2090-2100)***
Bathymetry	85.7	93.1	82.5	94.9
Current	12.2	4.4	15.3	3.3
Mean Temperature	1	1.2	1.3	0.7
Max Temperature	0.8	1.1	0.5	0.6
Salinity	0.3	0.2	0.3	0.6

Among these variables, bathymetry showed a significantly higher contribution of 85.7 % and 82.5% for the years 2040-50 and 2090-2100 respectively under RCP 6.0, followed by the ocean currents (12.2 & 15.3%) (Table 19). The salinity has the least contribution (0.3%) in this model developed for *P. lutea.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 93.1% & 94.9 % and the salinity shows the least contribution (0.2 & 0.6 %) for this scenario in both periods.

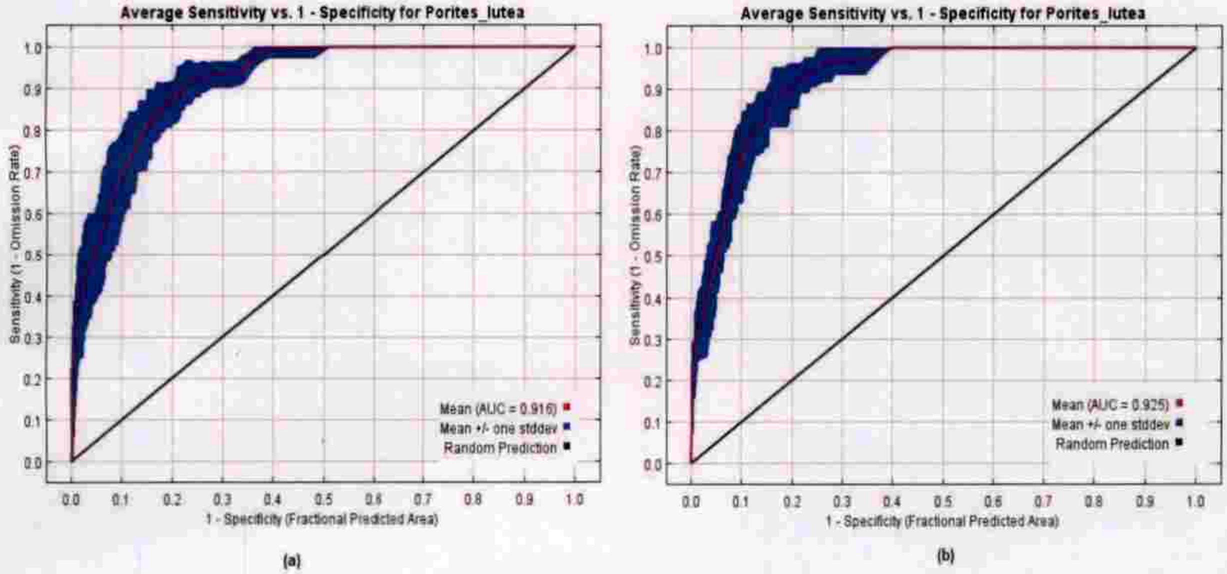


Fig. 92 the ROC curve of variable optimization of the *P. lutea* under RCP 6.0 for the years 2040-50 (a) and 2090-2100 (b)

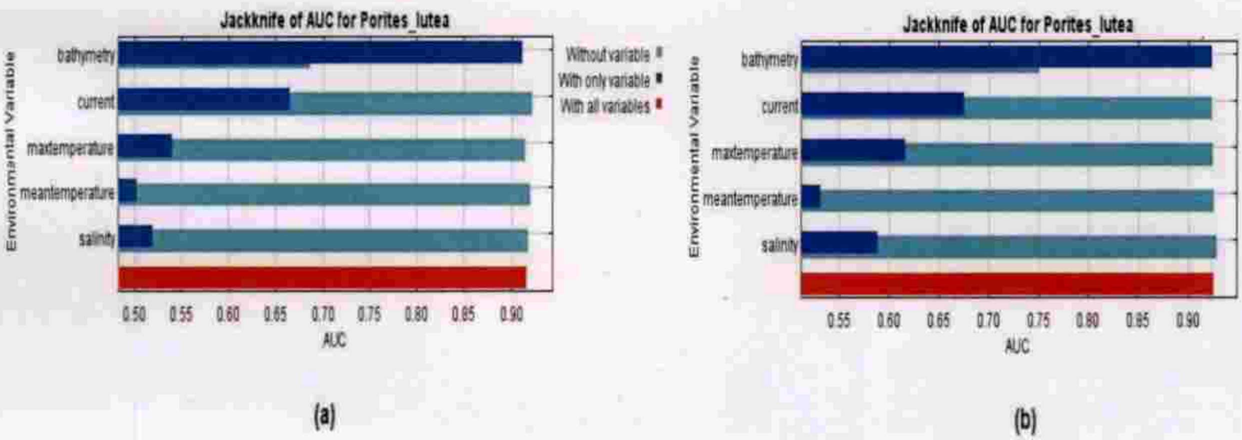


Fig. 93 Jackknife analysis of AUC for the *P. lutea* using variables according to RCP 6.0 for years 2040-2050 (a) and 2090-2100 (b)

The Jackknife of AUC for *P. lutea* (Fig. 93) shows environmental variable with the highest gain when used in isolation is bathymetry followed by the current. The values shown are averages over 10 replicate runs. The mean temperature shows a lesser gain in both periods is about 0.45.

4.5.2.2.3 Response curves of variables used in both models

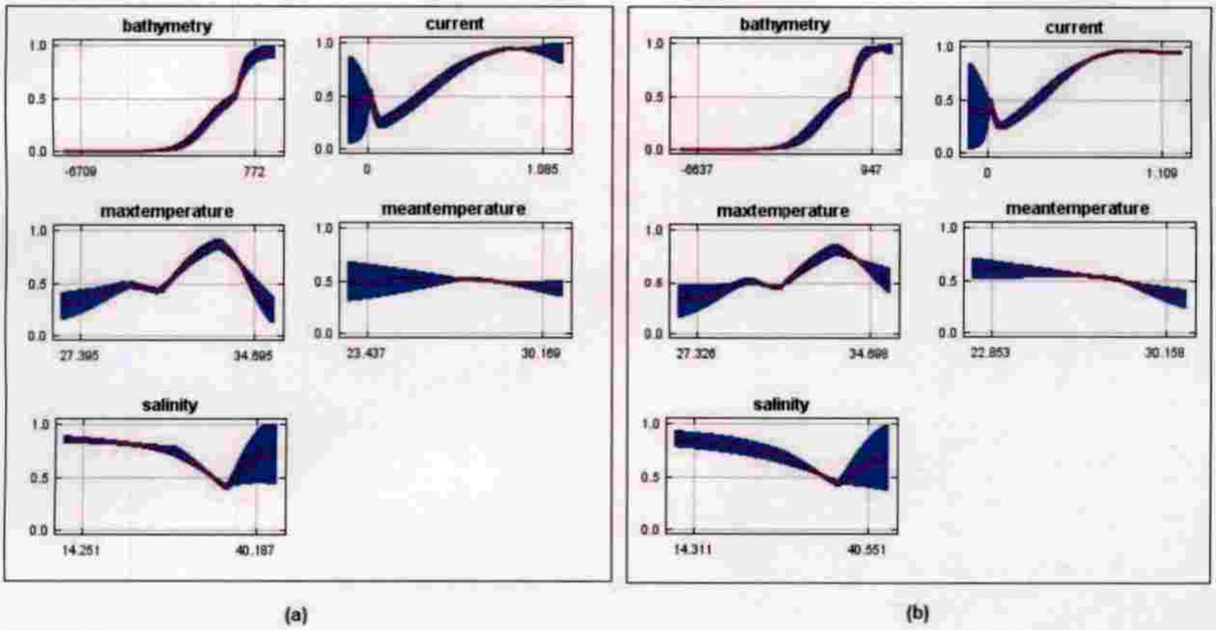


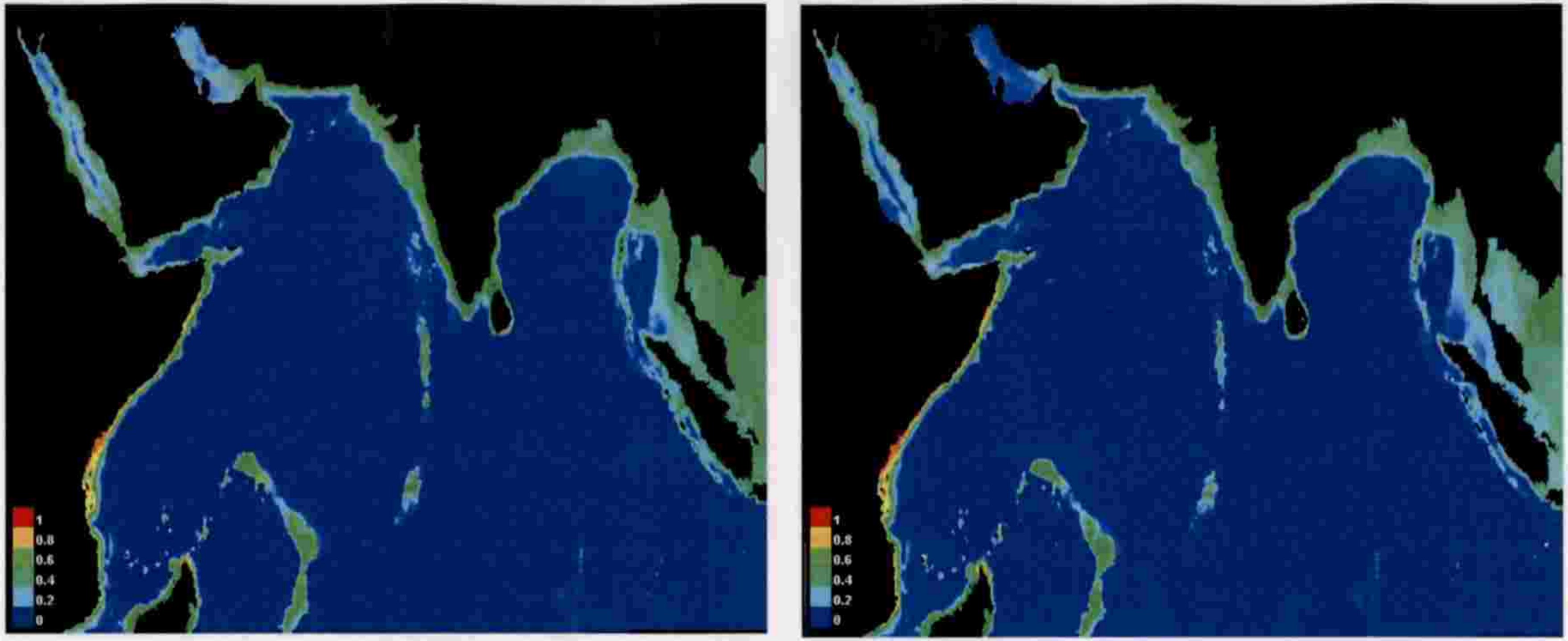
Fig. 94 The Response curve of each variable for 2040-50 and 2090-2100.

The response curves for the *P. lutea* model under the RCP 6.0 for the years 2040-50 (Fig. 94a) and 2090-2100 (Fig. 94b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged over 10 replicates.

4.5.2.2.4 The predicted habitat suitability of *P. lutea* under RCP6.0

Under RCP 6.0, for the period 2040-50 the distribution of *P. lutea* resembles its range predicted under RCP 4.5 for 2090-2100 (Fig. 95)

In this case, the range of occurrence of *P. lutea* is diminished in lesser degree in all regions where it is predicted for the 2040-50 period (Fig. 96). However, it remains the same for the east African coast, Madagascar and SMR.



(a) (b)

Fig. 95 Map showing the predicted habitat suitability of *P. lutea* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 6.0

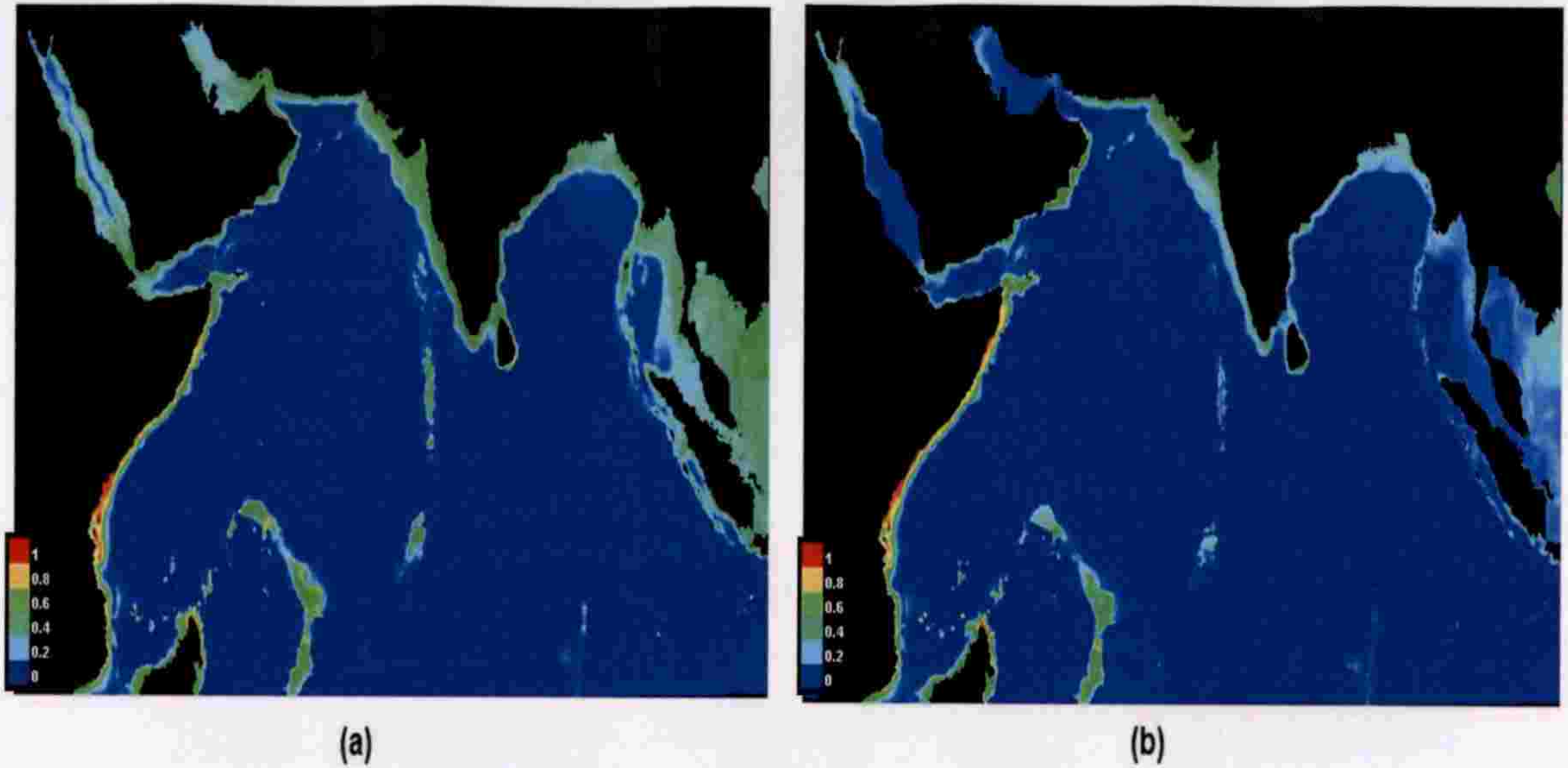


Fig. 96 Map showing the predicted habitat suitability of *P. lutea* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 6.0

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4.5.2.3 Future distribution of *P. lutea* under RCP 8.5 for years 2040-50 and 2090-2100

4.5.2.3.1 The model performance and contribution of variables

The average test AUC value averaged over 10 replicates for the years 2040-50 and 2090-2100 were 0.924 (SD = 0.016) and 0.931 (SD = 0.023). respectively (Fig. 97).

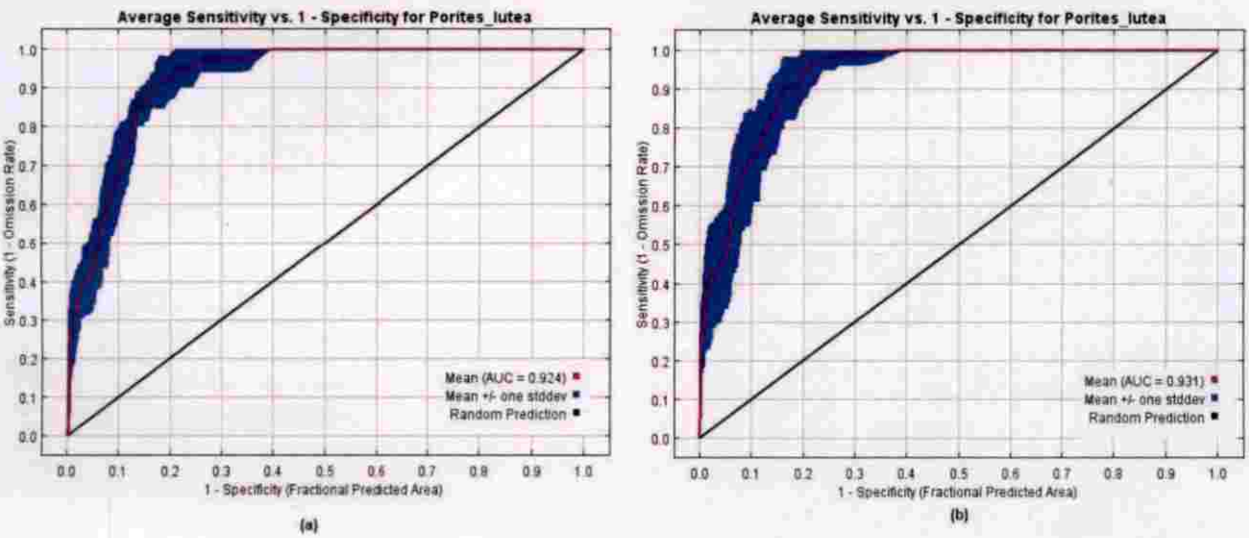

Fig. 97 the AUC curve of variable optimization model of the *P. lutea* under RCP 8.5 for the years 2040-50 (a) and 2090-2100 (b)

4.5.2.3.2 Contribution of predictor variables

Table 20 Percentage contribution and permutation importance of all environmental variables to the model for *P. lutea* under RCP 8.5 for the decades of 2040-2050 and 2090-2100.

Variable	***Percent contribution RCP8.5 (2040-2050)***	***Permutation importance RCP8.5 (2040-2050)***	***Percent contribution RCP8.5 (2090-2100)***	***Permutation importance RCP8.5 (2090-2100)***
Bathymetry	84.5	93.3	85.1	95.8
Current	12.6	4.3	12.2	2.3
Mean Temperature	1.7	1.4	1.4	1
Max Temperature	0.8	0.8	0.7	0.5
Salinity	0.4	0.2	0.6	0.4

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Among these variables, bathymetry showed a significantly higher contribution of 84.5% and 85.1 % for the years 2040-50 and 2090-2100 respectively under RCP 8.5, followed by current (12.6 & 12.2 %) (Table 20). The salinity has the least contribution in this particular model developed for *P. lutea.* For the Permutation importance, the variable having high permutation importance for both periods were bathymetry with 93.3% & 95.8 % and the salinity shows the least importance to this scenario.

The Jackknife of AUC for *P. lutea* (Fig. 98) shows environmental variable with the highest gain when used in isolation is bathymetry followed by ocean currents for both periods under the RCP 8.5. The values shown are averages over 10 replicate runs. The environmental variable that decreases the gain the most when it is omitted is bathymetry, which therefore appears to have the most information that isn't present in the other variables. Whereas mean temperature in the first decade and max temperature in the second decade shows the least gain.

4.5.2.3.3 Response curves of variables used in both models

The response curves for the *P. lutea* model under the RCP 8.5 for the years 2040-50 (Fig. 99a) and 2090-2100 (Fig. 99b) showed the change in predicted probability when the corresponding variable is used in isolation and averaged for 10 replicates.

For 2090-2100 decade, the probability of distribution of *P. lutea* is restricted to Oman, East Africa, northern Red Sea, eastern Madagascar, southern SMR. It is not predicted to be present across the entire Indian coast except Gujarat (Fig. 101).

Under RCP 8.5 the probability of distribution of the species is found to be increased in the whole of the Persian Gulf, eastern Africa and the Andaman sea while slight reduction is noted in the Red sea; Chagos, Maldives and Lakshadweep group of islands (Fig. 100).

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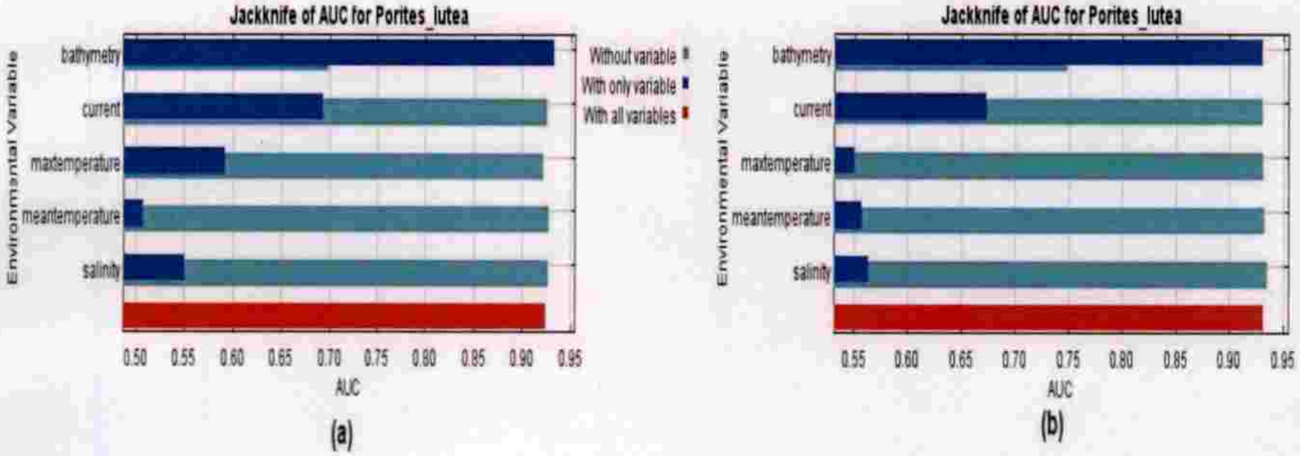


Fig. 98 Jackknife analysis of AUC for the *P. lutea* using variables according to RCP 8.5 for years 2040-2050 (a) and 2090-2100 (b)

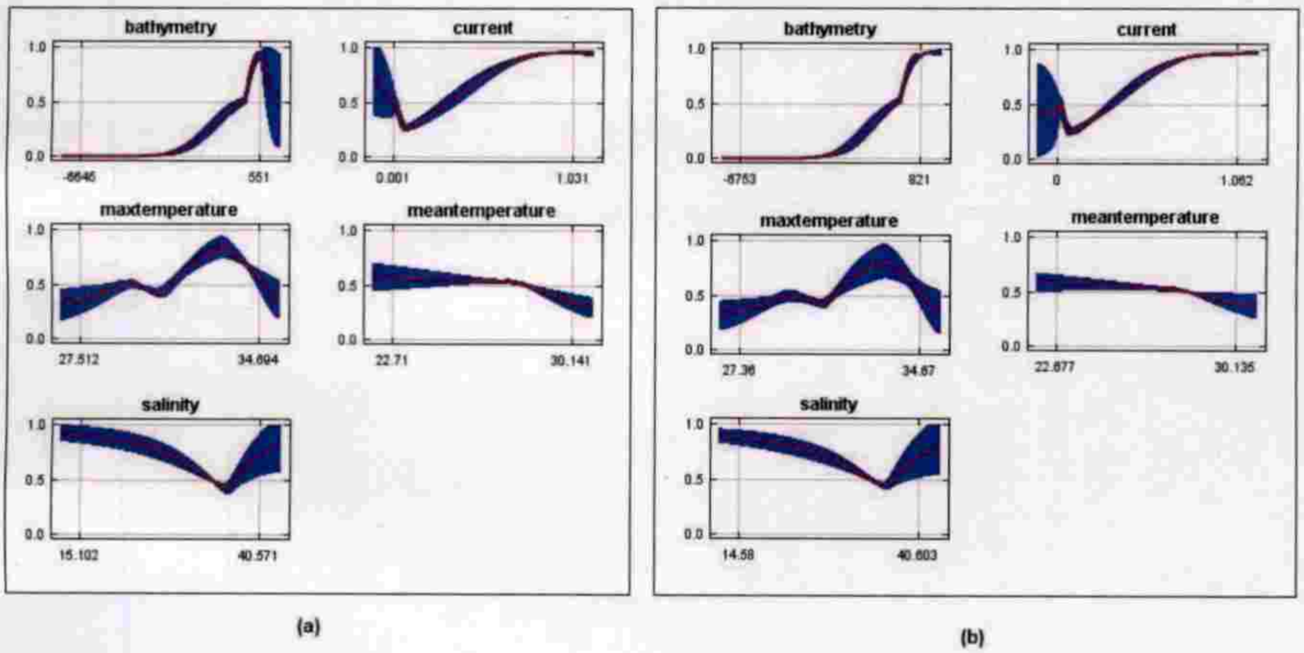
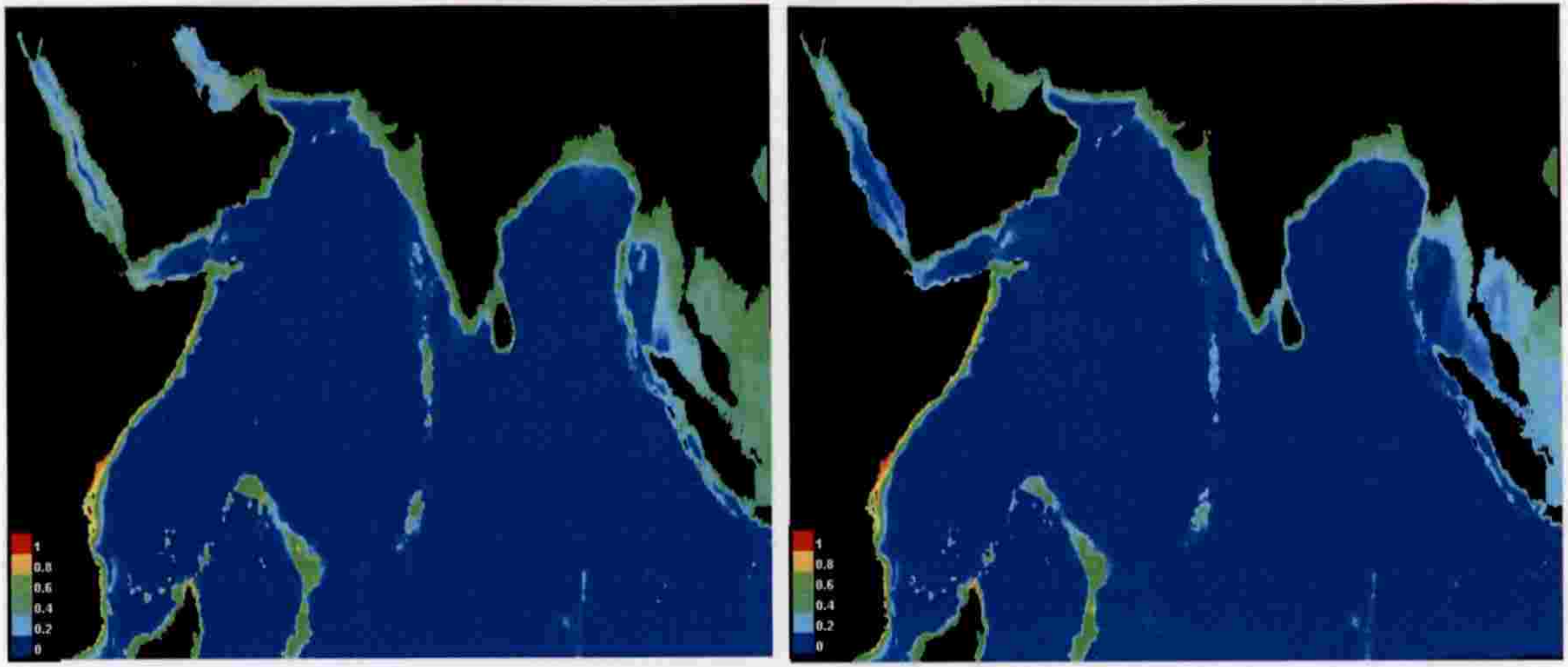


Fig. 99 The Response curve of each variable for 2040-50(a) and 2090-2100(b).

4.5.2.3.4 <u>The predicted habitat suitability of *P. lutea* under RCP 8.5</u>



(a) (b)

Fig. 100 Map showing the predicted habitat suitability of *P. lutea* in the Northern Indian Ocean in present condition (a) and for 2040-50 (b) under RCP 8.5

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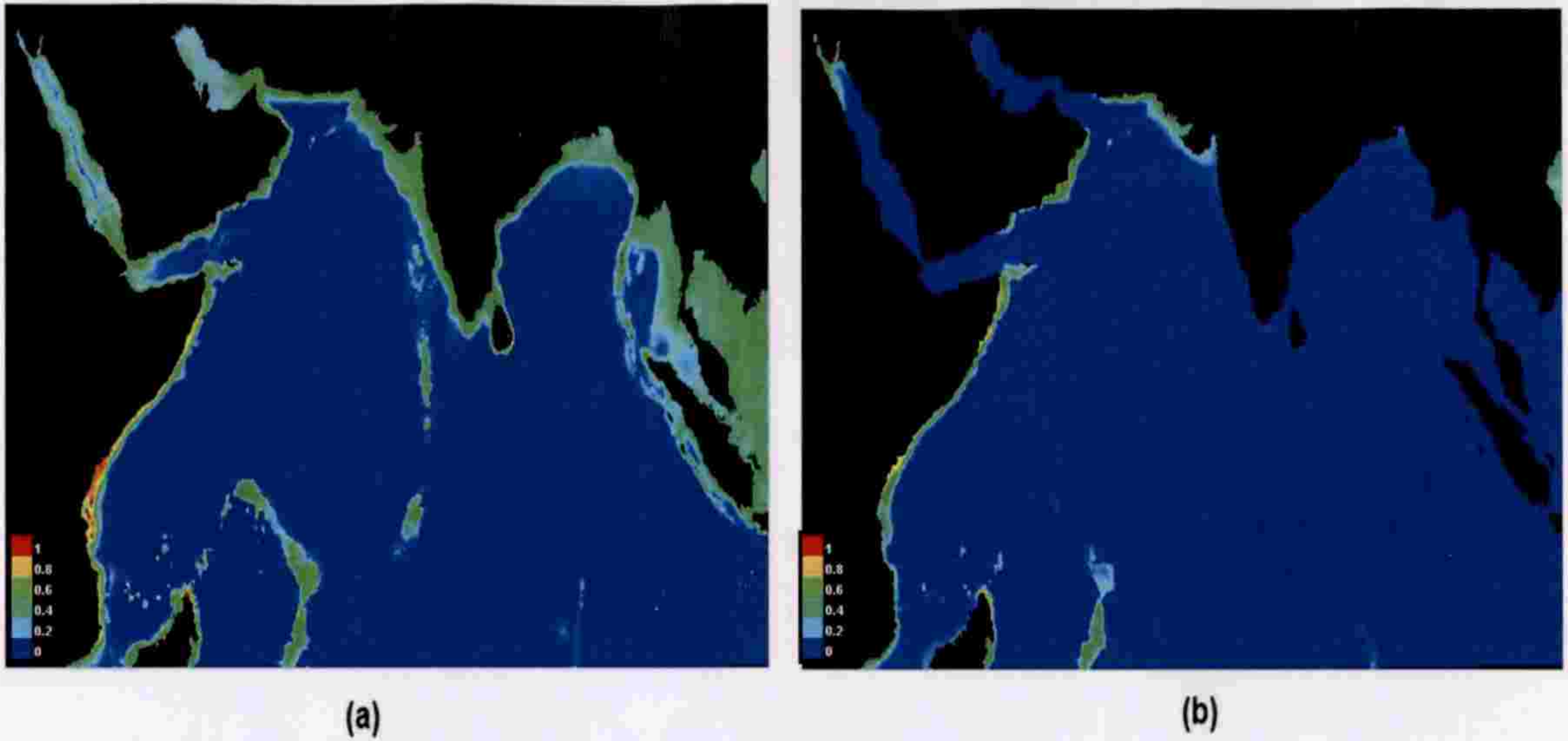

Fig. 101 Map showing the predicted habitat suitability of *P. lutea* in the Northern Indian Ocean in present condition (a) and for 2090-2100 (b) under RCP 8.5

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CHAPTER 5
DISCUSSION

Coral reefs are among the world's most intricate as well as economically important ecosystem that function as a single unit and provides ecosystem services that are vital to human societies and industries. However, coral reefs have continued to deteriorate because of human impacts in the decade since the inaugural International Year of the Reef in 1997. The rapid increase in greenhouse gas emission may be the ultimate insult to this living community by accelerating global warming as well as ocean acidification. This study clearly portrays the current response of hard coral species towards various environmental parameters, predicted the environmentally suitable habitat in the northern Indian ocean and the future changes in coral distribution using three RCP emission scenarios *viz.*, RCP 4.5, RCP 6.0 and RCP 8.5.

The criteria used in the study to assess model performance are Area Under the Curve (AUC), which is independent of thresholds (Fielding and Bell, 1997; Philips et al., 2006). As per the suggestions put forwarded by Lobo *et al.,* (2008) the sensitivity *Vs* 1- specificity were taken into consideration to account the relative significance of commission and omission error, along with AUC. All 35 models used in this study gives excellent performance as the AUC value for all models shown above 0.88. The contribution of each variable in each model for different species were analysed separately using the Jack-knife of AUC as well as the response curves.

The bathymetry remained as the major predictor in all models since the growth of coral reefs is always facilitated, as the corals tend to grow at shallow waters in order to harness the available sunlight. Corals also prefer a hard bottom substrate to which the corals attached. In the case of models that predicted the present distribution of the five species, the nutrients like Calcite, Phosphate, Nitrate, and diffusion attenuation coefficient holds the place of other contributors in the models. Calcite is the major structural compound of a reef ecosystem. Based on the correlation between current coral reef distribution and aragonite saturation state of the surrounding ocean waters, Kleypas et al. (1999a.) observed the importance of calcite for the calcification of coral reefs. The nutrients like phosphate and nitrate should be discussed with caution that it may be misinterpreted of having a directly proportional influence with coral reefs. According to Fig. 5 the influence of nitrate and phosphate is found to be increasing slightly up to a point after which it declines. The first inclination may not be really indicating a positive association but can be due to the greater impact of these nutrients in the shallow waters near the coast which are fed by terrestrial run offs having high concentration of these chemicals. According to some earlier studies, (Marubini & Davies, 1996) nitrate can increase the zooxanthellae symbiont density but reduces the skeletogenesis of corals. Phosphate also has the same effect on corals (Rosset *et al.*, 2017). The diffusion attenuation coefficient (Kd), a measure of turbidity is the next contributor to coral flourishment. Scleractinians always prefer clear waters, which only can pave a smooth path for light through the water column. In the models of future predictions, mean temperature is the major influencing variable after bathymetry. This may be because of the rise in sea surface temperature coupled with increased greenhouse gas emissions in future scenarios.

The future distribution of five species of scleractinian corals in the northern Indian Ocean shows the varying percentage probability of occurrence under various RCPs such as 4.5, 6.0 and 8.5. No particular similarity in the future occurrence for these species can be observed from the results obtained as the species show varying percentage of occurrence in different regions in the study area. Individual reefs respond differently to disturbances based on the community composition, population structure, climatic parameters and level of coral recruitment (Hatcher, 1997). For example, pocilloporids and acroporids are more affected by elevated temperature than that of other massive corals (Marshall & Baird, 2000). The northern Indian Ocean is home to some of the rich coral ecosystems such as the Red Sea, Madagascar, the Lakshadweep-Maldives and Chagos group of islands on the North-western part while the islands of Andaman Sea on the eastern part of Indian Ocean. These ecosystems are under the action of different physicochemical variables having a varying degree of influence.

In the case of *A. muricata*, a higher probability of occurrence is shown for the regions such as north-western India, Madagascar and the Seychelles-Mauritius Ridge for the two different decades (2040-2050 and 2090-2100) under RCP 4.5 and 6. Its occurrence for different periods under these two RCP is more or less similar, with slight variations, in different regions. However, the situation is grim under RCP 8.5 for the decade 2090-2100 in which the species is narrowed to Oman coast and the northern Persian Gulf only with minimal possibility while completely absent in all other regions. A similar plight can be seen for *P. damicornis* under the same RCP for the same period. *P. daedalea*, for the 2040-50 decade under RCP 8.5, have an occurrence, with a very low percentage of presence, only in the Maldives, Chagos and Andaman Islands while showing total absence in remaining study areas.

Another remarkable observation is the predicted presence of all five species along the Indian coasts under all the three RCPs, with a few exceptions. This is especially true for all five species except *A. muricata.* Under RCP 8.5 for the period 2040-50, *F. pallida* shows the highest percentage of occurrence all along the Indian coast. The Andaman and Nicobar along with other islands in that region indicate greater vulnerability in the future existence of the species in various scenarios. The same is true in the case of the Red Sea that is now a major reef ecosystem in the world. The LMC archipelago and the SMR in the north-western study region are also pregnable to the future changes in the variables influencing corals. In the case of *F. pallida*, a change in this situation is observed in which the species is found to be less probable to occur in these regions for the period 2090-2100 under RCP 8.5 and 6.0. However, *P. daedalea* is found to have a good percentage of occurrences under all RCPs in every time period studied. The status of occurrence of *P. lutea* is remarkably high in all regions except for the period 2090-2100 under RCP 8.5 and for 2040-50 under RCP 4.5 in which it showed absence around Indian coast and the Andaman Sea. The Red Sea and the Persian Gulf exhibit a very low percentage of occurrence probability for *A. muricata, P. damicornis* and *P. daedalea* while the other two species managed to maintain a comparatively moderate percentage of distribution.

In the existing scenario of accelerated warming of the global oceanic waters, the current study shows a bleak future of the vulnerable sessile organisms like the hard corals. The current rate of development in the business as usual scenario that is the RCP 8.5 will be a sure nemesis for the coral reefs of Northern Indian Ocean. The decrease in the spatial diversity can in turn reduce the minimum stocking biomass and connectivity. Such cascading effects will make the coral reefs to reach a point of no return. The wider oceanic biodiversity who are depending directly or indirectly on the coral reefs also will definitely take the heat. A need to acknowledge the global warming and there by controlling the carbon emissions is an imminent requirement and the countries across the world should have already taken measures towards this. In addition, it is also important to reduce and manage the secondary stressors that can cause the decline of coral reefs after each bleaching event. Conserving the most resilient coral reefs and keeping the major source reefs of coral larvae alive will help these sensitive ecosystems to thrive against the oddities and continue sustained provisions for human wellbeing.

CHAPTER 6
SUMMARY

Global warming and climate change are terms for the observed century-scale rise in the average temperature of the earth's climate system and its related effects. Climate change prior to the industrial revolution can be explained by natural phenomena. Anthropogenic climate change has a significant impact on the physical and biological systems all over the globe. The multiple components of climate change are anticipated to affect all the levels of biodiversity, from organism to ecoregions. Researches have been done in identifying the factors affecting species distribution and analysing their current and future distribution pattern. Species are affected in a different manner; the species niche is migrated northward from the tropics with the elevation in ocean temperature. The northern Indian Ocean is landlocked and further extension of suitable habitat towards north seems impossible in this region. The shift in habitat suitability is directly associated with the environmental variables like sea surface temperature, sea surface salinity, chlorophyll, pH, ocean currents, PAR, diffusion attenuation coefficient, and nutrients like calcite, phosphate, nitrate etc. The present study is a supporting element for the above statements. The spatial and temporal distribution of selected hard coral species was studied with respect to the changing climate. Certain warm water coral species having greater incidence as well as importance in Indian ocean such as *Acropora muricata, Favia pallida, Platygyra daedalea, Pocillopora damicornis* and *Porites lutea* are selected for the study. For analysing the distribution of different species, environmental niche modelling (ENM) or species distribution modelling (SDM) was done. The best-suited niche model used is the maximum entropy based model i.e., MaxEnt. This predictive niche model provided very good results for modelling the hard-coral species' distribution for present conditions as well as predictions for future scenarios. Using these SDMs it is able to identify the potential places of their occurrences and helpful in executing conservation steps to protect them in the changed habitat. Using the current occurrence data collected from GBIS and OBIS database and the climate data acquired from the GMED and Bio-Oracle database, the modelling for the present condition was done. Then utilising the current distribution analysis, it would project the distribution of the coral species into the future by converging it to the maximum entropy probability distribution. To carry out the modelling process for the future prediction, the same current environmental layers along with the future predictor layers for different RCPs such as RCP 4.5, RCP 6.0 and RCP 8.5 were utilized.

The study revealed the current and projected distribution patterns of the selected hard coral species for the years 2040-2050 and 2090-2100 under different RCP projections. The nature of the relationship between each environmental variable and coral species were analysed using this model technique. The models developed shows that the variables like bathymetry, calcite, diffusion attenuation coefficient, nitrate and phosphate have a great deal with the coral distribution in the northern Indian ocean in present condition. Looking into the future changes, the Mean temperature and current become major contributors after bathymetry. The salinity shows lower variable contribution as its gradient in this tropical region is very narrow but its contribution is evident in the waters of Persian Gulf, the region with extreme fluctuations in salinity (Wilson *et al.*, 2002).

All the reef ecosystems in the study region are found to be at risk because of the changing climate and its effects on environmental factors affecting species. Under different RCPs and time periods the five selected study species show varying degree of distribution and occurrence probability. For the majority of future estimates of occurrences, all these corals are noted in new areas which are now devoid of coral reefs. These include mainly the entire Indian coast and the east African coast. Two species viz., *P. daedalea* and *P. lutea,* reveal a high percentage of future and current occurrence in all the regions except for the lesser percentage of distribution possibility for *P. lutea* in two different time periods. *A. muricata* is found to be the most vulnerable species under all the three RCPs. Different regions exhibit varying degrees of response to species distribution with the changing environmental variables in different time periods. Red Sea, Persian Gulf and Indian coasts are found to be more exposed to the vagaries of climate change regarding coral distribution.

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CLIMATE ENVELOPE MODELLING OF HARD CORALS

by

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THESIS ABSTRACT

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ABSTRACT

The global climate change is pushing marine ecosystems towards extinction. The sensitive ecosystems like coral reefs will be the first few to take the imminent impacts of an increase in temperature. Unlike any other oceans, Northern Indian Ocean (NIO) is thought to be highly vulnerable due to its typical topography with the massive Eurasian Continent in the north. The Indian Ocean is the warmest among all tropical oceans and more vulnerable in the era of climate change. The ecosystems of this landlocked sea will not permit the migration of the organisms to cooler waters as the years' progress. Scleractinians, the Hard Corals, are sessile and are very sensitive to the shifts in biogeochemical variables. The hard corals in the northern Indian Ocean are increasingly susceptible to elevated anthropogenic stressors, including impacts from climate change, overfishing, runoff, and ocean acidification. In order to study the precise impact of such stressors, the knowledge about the existing extent of hard coral distribution is necessary. The wider distribution and their growth in the oceanic remote islands and ridges makes their complete distribution unknown to science. With the emergence of new powerful statistical techniques and GIS tools, the development of predictive habitat distribution models has become easier. In this study, climate envelope modeling is carried out using maximum entropy principle (MaxEnt) to predict the occurrence of five hard coral species *viz., Acropora muricata, Favia pallida, Platygyra daedalea, Pocillopora damicornis* and *Porites lutea* by correlating their point observations of data with gridded environmental variables. The statistical model that expresses the correlation and the species threshold to different independent variables is thus employed to create maps of predicted occurrence by applying the model to maps of the environmental parameters. The future distribution of each species was delineated using the IPCC emission scenarios, RCP 4.5, RCP 6.0, and RCP 8.5 for the period of 2040-50 and 2090-2100. The study unveils possible distribution areas of these hard-coral species' in the northern Indian Ocean and their vulnerability towards elevated greenhouse gas emissions in the future decades. Much of future estimates of occurrences, all these corals are noted in new areas that are now devoid of coral reefs mainly the entire Indian coast and the east African coast. *A. muricata* is found to be most vulnerable species under all the three RCPs. It is also found that the Red Sea, Persian Gulf and Indian coasts are found to be more exposed to the vagaries of climate change regarding coral distribution. The nature of the relationship of coral distribution with the climatic parameters as predicted by this study can also help conservators and marine protected area managers well prepared for expected but sudden environmental changes. Prediction of future shifts in the hard-coral occurrence will provide a guideline to the management actions either to decrease the impact or prevent possible extinction events.