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DISTRIBUTION MODELLING OF SOCOTRA CORMORANT USING MAXENT

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United Arab Emirates University

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College of Science

Department of Biology

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Cover: A Socotra Cormorant foraging in coastal area

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Declaration of Original Work

I, Areej Mustafa M. Jaradat, the undersigned, a graduate student at the United Arab Emirates University (UAEU), and the author of this thesis entitled "*Distribution Modeling of Socotra Cormorant Using Maxent*", hereby, solemnly declare that this thesis is my own original research work that has been done and prepared by me under the supervision of Professor Sabir Bin Muzaffar from the College of Science at UAEU. This work has not previously formed the basis for the award of any academic degree, diploma or a similar title at this or any other university. Any materials borrowed from other sources (whether published or unpublished) and relied upon or included in my thesis have been properly cited and acknowledged in accordance with appropriate academic conventions. I further declare that there is no potential conflict of interest with respect to the research, data collection, authorship, presentation and/or publication of this thesis.

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Abstract

This thesis is concerned with species distribution modeling of the Socotra Cormorant (*Phalacrocorax nigrogularis*), a regionally endemic seabird to the Arabian Gulf, the Arabian Sea, and the Gulf of Aden. Socotra Cormorants are important for the marine ecosystem as they apply top-down control and maintain the balance between trophic levels. They also contribute to the cycling of nutrients significantly. The bird is categorized as vulnerable by the IUCN. Large portions of their suitable habitat are disturbed or degraded due to oil exploration and coastal development. The seabird is poorly studied in every ecological aspect. The main objective of this thesis is to predict the potential current and future marine distribution of the species and estimate the effect of climate change on its distribution. The thesis also aims to analyze the important environmental variables for the species distribution. Occurrence data were collected over several years (2013-2015, 2019-2020) using satellite transmitters attached to the birds. Data were obtained from 28 birds in total covering 3 different colonies in the Arabian Gulf. Data were fed to Maxent software along with a chosen set of environmental variables. Results showed that there is a total of 64,100 km^2 of potential current highly suitable areas for the species. These areas existed mainly in the Arabian Gulf and the Red Sea. However, projecting the model on 2050 indicated a sharp decline with nearly 73% loss in suitable areas according to the climate change scenario used. Most contractions occurred in the Arabian Gulf and the Red Sea. However, the Red Sea was still holding considerable areas of moderate suitability. Mixed layer thickness and sea floor depth are the most important variables to the distribution of the seabird. This study showed that there are large highly suitable areas not colonized yet in the Red Sea. It also indicated that if GHGs continue to rise, Socotra Cormorants will be at great risk. It also highlighted

the importance of mixed layer thickness and shallow depth for the species foraging grounds.

Keywords: Socotra Cormorant, Arabian Gulf, Arabian Sea, Red Sea, Habitat Suitability, Habitat Loss, Distribution Modeling, Maxent

Title and Abstract (in Arabic)

نمذجة التوزيع المكاني لطائر الغاق السوقطري باستخدام برنامج ماكسنت

الملخص

الهدف من هذه الأطروحة هو نمذجة التوزيع المكاني لطائر الغاق السوقطري (*Phalacrocorax nigrogularis*)، وهو طائر بحري متوطن إقليميا في الخليج العربي وبحر العرب وخليج عدن. طائر الغاق السوقطري مهم للنظام البيئي البحري حيث انه يطبق تحكما من أعلى السلسلة الغذائية إلى أسفلها ويحافظ على التوازن بين المستويات الغذائية. كما أنه يساهم في تدوير العناصر الغذائية بشكل كبير. تم تصنيف الطائر في فئة ضعيف غير محصّن من قبل الاتحاد الدولي لحفظ الطبيعة. تتعرض أجزاء كبيرة من موطنه للاضطرابات أو التدهور بسبب التنقيب عن النفط وتطوير السواحل. تمت دراسة الطائر بشكل ضئيل في كل جانب من الجوانب البيئية. الهدف الرئيسي من هذه الأطروحة هو التنبؤ بالتوزيع البحري الحالي والمستقبلي المحتمل لهذا الطائر وتقدير تأثير تغير المناخ على توزيعه. تهدف الأطروحة أيضًا إلى تحليل العوامل البيئية المهمة لتوزع الطائر. تم جمع بيانات التواجد على مدى عدة سنوات (2013-2015، 2019-2020) باستخدام أجهزة إرسال للأقمار الصناعية متصلة بالطيور. تم الحصول على البيانات المكانية مما مجموعه 28 طائرًا وتغطي 3 مستعمرات مختلفة في الخليج العربي. تم ادخال البيانات في برنامج ماكسنت (Maxent) جنبًا إلى جنب مع مجموعة مختارة من العوامل البيئية. أظهرت النتائج أن هناك ما مجموعه 64100 كيلومتر مربع من المناطق الحالية المحتملة المناسبة للغاية للطائر. توجد هذه المناطق بشكل رئيس في الخليج العربي والبحر الأحمر. وبالرغم من ذلك، فإن إسقاط النموذج على عام 2050 يشير إلى انخفاض حاد مع خسارة ما يقرب من 73٪ من المناطق المناسبة وفقًا لسيناريو تغير المناخ المستخدم. حدثت معظم التراجعات في الخليج العربي والبحر الأحمر. بالرغم من ذلك، لا يزال البحر الأحمر يحتفظ بمساحات كبيرة ذات ملاءمة معتدلة. سمك الطبقة المختلطة وعمق قاع البحر من أهم العوامل لتوزيع هذا الطائر البحري. أظهرت هذه الدراسة أن هناك مناطق كبيرة مناسبة للغاية لم يتم استعمارها بعد في البحر الأحمر. كما أشارت إلى أنه إذا استمرت الغازات الدفيئة في الارتفاع، فإن طائر الغاق السوقطري سيكون في خطر محدق. كما أنها تسلط الضوء على أهمية عاملي سمك الطبقة المختلطة والعمق الضحل لمواقع التغذية للطائر.

مفاهيم البحث الرئيسية: الغاق السوقطري، اللوه، الخليج العربي، بحر العرب، البحر الأحمر، ملاءمة الموائل، خسارة الموائل، نمذجة التوزيع الجغرافي، ماكسنت.

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Dedication

To the creators of my essence, Zahriya and Mustafa.

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List of Abbreviations

AUC	Area Under the Curve
CBD	Convention on Biological Diversity
CMIP6	Coupled Model Intercomparison Project 6
CMS	Convention on Migratory Species
Depth	Sea Floor Depth
EC	European Commission
EU	European Union
FAO	Food and Agriculture Organization
GHGs	Greenhouse Gases
HadGEM3	Hadley Centre Global Environment Model version 3
HighResMIP	High Resolution Model Intercomparison Project
Maxent	Maximum Entropy Modeling
MESS	Multivariate Environmental Similarity Surfaces Analysis
MLD	Mixed Layer Thickness
MoD	Most Dissimilar Variable Analysis
NetCDF	Network Common Data Form
OR	Omission Rate
PTTs	Platform Terminal Transmitters
RM	Regularization Multiplier
ROC	Receiver Operating Characteristics
SDM	Species Distribution Modeling
SSH	Sea Surface Height
SSPs	Shared Socioeconomic Pathways
SSS	Sea Surface Salinity
SST	Sea Surface Temperature
TSS	True Skill Statistics
UAE	The United Arab Emirates
VIF	Variance Inflation Factor analyses
WCRP	World Climate Research Programme
WHO	World Health Organization

Chapter 1

Chapter 1: Introduction

1.1 Overview

Species distribution modeling (SDM) is an increasingly used tool that helps countries in the designations of marine reserves. It is also used to alert the concerned official bodies with the possible future risks of climate change. This field is important for seabirds like the Socotra Cormorant (*Phalacrocorax nigrogularis)* where little is known on this species. Socotra Cormorant is native to the Arabian Gulf, the Arabian Sea and Gulf of Aden (BirdLife International, 2022; Muzaffar, 2020). Its total population number was low in the 1980s and was classified near threatened but improved slightly in early 2000s and has been vulnerable since then (BirdLife International, 2019). This study is trying to fill the gap in the knowledge of this endemic species by using SDM algorithms to produce predictions of the possible current and future distribution. Predictive models provide beneficial information not only on the complete possible range, but also on the important environmental variables that control the distribution.

1.2 Statement of the Problem

The impacts of climate change on seabirds are becoming more concerning, although it is not viewed as urgent as other threats (Cursach et al., 2019). The biggest concern of this issue might be that increasing temperature can affect large regions and containing its impact is challenging, especially for endemic species (Cursach et al., 2019; Quillfeldt & Masello, 2013) like Socotra Cormorants. Many studies reported reductions or shifts in the distribution range and changes in habitat suitability for seabirds (Krüger et al., 2018; Piatt, Sydeman & Browman, 2007). Shifts in seabird phenology were also reported due to impacts associated with climate warming (e.g., extreme weather events and marine heatwaves) (Glencross, Lavers & Woehler, 2021).This is alarming for

Socotra Cormorant due to its limited range and declining population (BirdLife International, 2019; Muzaffar, 2020). Since the species is poorly studied, more studies are required to help understand the possible species distribution, the marine hotspots they depend on, and future consequences of climate warming on both aspects.

1.3 Research Objectives

This research aims to (I) predict the possible current geographic distribution of Socotra Cormorants using environmental variables and Maxent (maximum entropy modelling); (II) to project the model to 2050 using SSP5-8.5 as a climate change scenario; (III) to analyze the important environmental variables for the species distribution.

1.4 Relevant Literature

1.4.1 Seabirds and Marine Ecosystems

Marine ecosystems consist of various biological networks that maintain energy flow in two directions. The upward direction starts with primary producers at the base of the food web and ends with top predators like seabirds and humans. The downward direction brings nutrients back to the cycle and is led by decomposers and detrital processes. Terrestrial and marine birds are known to provide various ecological services including the top-down pressure control (Doney et al., 2012; Grant, Bond & Lavers, 2022; Piatt et al., 2007). Seabirds in specific regulate their ecosystems by aiding in carcass disposal, physical engineering of habitat and seed dispersal. They also transfer beneficial nutrients and possibly pollutants back to nesting sites on land (Grant et al., 2022). The loss or decline in the populations of these keystone species may lead to destructive impacts on habitats (Bauer & Hoye, 2014; Grant et al., 2022). To sustain these marine services, several countries initiated ecosystem-based management where ecosystem indicators are used to develop sustainability plans and policies (Kruse et al., 2006). Several studies reported the frequent use of seabirds as indicators to the status, health and change in their marine ecosystem (Parsons et al., 2008), even labelled them as cost-effective indicators (Piatt et al., 2007).

Comparing with other marine organisms, most of which live under water, seabirds are quite visible. Most seabird species forage as flocks in marine hotspots and gather in certain locations, like islands, to reproduce. This annual assembly allows population census and monitoring of various parameters (Piatt et al., 2007; Sydeman, Brodeur, Grimes, Bychkov & McKinnell, 2006). Monitored parameters can reflect a temporal change in an ecosystem. The annual reproductive performance in seabirds can detect monthly changes (from egg-laying phase to chick rearing). Comparably, deferred reproduction affects the demographics and dynamics in birds' population. These are used to indicate decadal variabilities (Lee, Nur & Sydeman, 2007; Piatt et al., 2007). For instance, the delayed breeding season and lower breeding success for the short-tailed shearwater (*Ardenna tenuirostris*) indicated a North Pacific marine heatwave (Glencross et al., 2021)

Seabirds as indicators can be categorized under two types. First, they act as bio-monitors or qualitative indicators (e.g., pollutants and contamination). Or they serve as quantitative indicators of certain components or elements in aquatic ecosystems (e.g., fish stocks) (Piatt et al., 2007). A study done in the North Sea concluded that the reproductive failure of black-legged kittiwake (*Rissa tridactyla*) was due to an environmental change in the North Sea ecosystem and a collapse in sand eel (*Ammodytes* spp.) population. Another analysis on seabirds' data from the Gulf of Alaska reported an early shift in the physical regime of the gulf (Francis, Hare, Hollowed & Wooster, 1998). Additionally, research on

Peruvian guano-producing birds (cormorants, pelicans, and boobies) that failed to reproduce between the 1950s and 1960s indicated a collapse in the anchoveta (*Engraulis ringens*) stock (Piatt et al., 2007). Another paper reported a similar result were Atlantic puffins (*Fratercula arctica*) suffered from breeding failure due to a collapse in herring (*Clupea harengus*) fish stock near Norway (Piatt et al., 2007).

1.4.2 Climate Change Impact

The concerns toward climate change consequences on seabirds are increasing as it came third after incidental death and introduced species (Croxall et al., 2012; Dias et al., 2019). More than 20% of all seabirds are affected by climate change impacts. Most of these species (89%) are also facing other threats of similar magnitude including invasive exotic species, incidental capture, overfishing, pollution, and hunting (Dias et al., 2019). These threats may appear more dangerously imminent than climate change (Croxall et al., 2012; Cursach et al., 2019; Quillfeldt & Masello, 2013). Yet, this phenomenon can affect complete regions compared to the local impact of some of these threats. It also adds more to the collective pressure on seabirds, mostly the endemic ones (Cursach et al., 2019; Quillfeldt & Masello, 2013) like Socotra Cormorant. These threats also have recognized, and proven solutions compared to climate change where mitigation have limited scope for main impacts like sea level rise and extreme rainfalls (destruction of colonies), increased severe weather events, alteration of oceanographic processes (reduce marine productivity near colonies), and increased infections and severity of avian diseases (Dias et al., 2019).

Moreover, climate warming could reduce the distribution range and change habitat suitability of multiple groups of terrestrial and marine organisms (Cursach et al., 2019; Krüger et al., 2018). For seabirds, the impacts of climate change are mainly due to extreme temperatures and alteration and shifting of habitat, with nearly 40 species exposed for each impact. Storms and flooding are also affecting >20 seabird species (Dias et al., 2019). In fact, a warming period in the southern California Bight favored subtropical seabird species as their numbers increased at the expense of the subarctic ones. Another warming phase in the Gulf of Alaska caused a growth in flatfish and gadoids numbers, whereas several pandalid shrimp and forage fish species disappeared (Piatt et al., 2007). The rising temperature changes the productivity of phytoplankton, thus alters the fecundity and abundance of herbivorous zooplankton like the euphausiids and small copepods. Inevitably, the impact reaches pelagic fish, squid, and carnivorous zooplankton (Crawford, Sabarros, Fairweather, Underhill & Wolfaardt, 2008; Cursach et al., 2019). Seabirds largely feed on these prey species (small pelagic fish, squid, or sizeable zooplankton) (Cursach et al., 2019; Quillfeldt & Masello, 2013) and this is another climate-associated impact on seabirds. Previous studies on demographic dynamics of small populations of pelagic fish in upwelling ecosystems indicated that a collapse in such populations is often succeeded by sharp decline in predator seabirds' populations (Crawford et al., 2008; Cursach et al., 2019). Various seabirds live within the productive upwelling range including Socotra Cormorants (Jennings, 2010; Nelson, 2005).

1.4.3 Remote Sensing

During the last 60 year, seabirds' populations decreased by nearly 70% worldwide (Croxall et al., 2012; Dias et al., 2019; Paleczny, Hammill, Karpouzi & Pauly, 2015). Obtaining the adequate knowledge of their movement patterns and spatial distribution is increasingly important to conserve the marine grounds they depend on. Seabirds are highly mobile, and their use of areas varies between breeding, molting, or stopover purposes (Oppel et al., 2012; Tremblay et al., 2009). In the breeding season, seabirds become central foragers and target surrounding marine hotspots. In contrast, usage areas outside the breeding season are more distant as many species migrate and use foraging spots along migratory routes, or roam broad areas (Oppel et al., 2012). Stopover areas are important for migratory seabirds, hence identifying and protecting it is a step of prime concern (Oppel, Dickson & Powell, 2009; Oppel et al., 2012).

Shipboard surveys of seabirds present a fragmented spatio-temporal distribution where absences may be pseudo-absences due to the time of surveying. These false absences cause uncertainties and lower the predictive performance of density and spatial distribution models (Oppel et al., 2012). The development of remote sensing devices brought the ability to obtain high resolution data on a large scale. These data act as predictor variables when used in distribution modeling (Oppel et al., 2012; Tremblay et al., 2009).

1.4.4 Distribution Modelling

Studying the potential responses and future condition of biodiversity due to climate change has become a busy field in ecology (Cursach et al., 2019; Pecl et al., 2017). Consequently, future distribution modeling is considered a valuable tool for scientists and governments to predict the possible impacts of the warming climate (Cursach et al., 2019; Pereira et al., 2010). Distribution modeling also allows the prediction of the approximate full distribution range of species when used properly (Merow, Smith & Silander, 2013). In comparison with marine environment, terrestrial species are far more studied and numerous comparative modeling studies were conducted. Expectedly, marine environment is highly dynamic and species like seabirds are challenging to study given its mobility and breeding cycle (Oppel et al., 2012; Robinson et al., 2011).

Various modelling methods were applied to predict the potential distribution and density of seabirds at sea (e.g., Nur et al., 2011; Oppel et al., 2012; Tremblay et al., 2009). Some of these models use presence/absence localities while others depend on presence only data (PO data). Since seabirds' presence in certain areas varies temporally, it makes it difficult to obtain true absences and this is the case for most species where only PO data is available. As a result, it is often preferred to use PO modeling whilst considering its limitations (Merow et al., 2013).

1.4.5 Future Scenarios

To predict future impacts of climate change, models must be fed with projected variables. The Coupled Model Intercomparison Project phase 6 (CMIP6) is an experimental framework that focus on studying computer-based models of Earth's climate. In these models, several parts (e.g., oceans, land, atmosphere, ice) are coupled with each other and allowed to interact in computer simulations. The project leads many experiments that vary in the target study time and the resolution of the produced variables (Koomey, Schmidt, Hummel & Weyant, 2019).

CMIP6 uses shared socioeconomic pathways (SSPs) which are scenarios of projected socioeconomic changes and its associated climate policies. Each scenario produces certain amount of greenhouse gas emissions and deals with adaption and mitigation to climate change differently (Riahi et al., 2017). SSP1 represent a future where mitigation and adaptation challenges are low. The opposite is true for SSP3 where both are high. Similarly, SSP4 and SSP5 oppose each other as SSP4 describes low mitigation challenges coupled with high adaptation challenges. Finally, SSP2 is designed as an intermediate scenario where challenges to mitigation and adaptation are moderate (Meinshausen et al., 2020; Riahi et al., 2017). Population is also central in SSP2 with a peak at 9.4 billion around 2070. In

SSP1 and SSP5, population is the lowest with 7 billion by 2100. The highest population is in SSP3, reaching a population of 12.6 billion in 2100 (Riahi et al., 2017).

1.4.6 Socotra Cormorants

The Socotra Cormorant is a flighted bird of an average size and is historically endemic to the majority of the marine region of the Arabian Peninsula (BirdLife International, 2022; Cook, Gubiani, Ryan & Muzaffar, 2017; Muzaffar, 2020). The recent total population is estimated to be 750,000 individual (Muzaffar, 2020), with the majority of it breeding and residing within the Arabian Gulf and a smaller subpopulation within the southern Omani waters and Gulf of Aden off Yemen (BirdLife International, 2022; Muzaffar, 2020). At present, there are up to 16 islands supporting the breeding population within the Arabian Gulf, namely, one in both Bahrain and Qatar, three in the Saudi territory of the Gulf of Salwa and up to 11 in the UAE. Nonetheless, non-breeding birds are still roaming the entire gulf (Muzaffar, 2020). Within the southern subpopulation, 5 islands are reported to host breeding pairs, one island off Oman and 4 islands in the Gulf of Aden (BirdLife International, 2022). A remaining two isles (Kal Farun and Sabuniya) in the Socotra archipelago were previously used for breeding (Porter & Suleiman, 2014) but the current state is unknown. The bird was seen frequently on the coast and islands off the center and south of Eritrea, with more than 1,500 birds in summer to 500-4,000 birds in winter (Semere et al., 2008). Breeding was suspected off the Danakil coast (southern coast of Eritrea to the western coast of Djibouti), but no nesting islands confirmed (BirdLife International, 2022; Semere et al., 2008).

The Gulf of Salwa, located south of Gulf of Bahrain, is characterized with high productivity levels. Socotra Cormorants have been historically known to nest in high concentrations in that area, mainly on the

Hawar archipelago (Jennings, 2010; King, 1999; Muzaffar, 2020). Up to recent time, the Gulf of Salwa was supporting the largest percentage of the species population (Jennings, 2010). Recently, the UAE was estimated to hold 82,800 breeding pairs (Khan et al., 2018; Muzaffar, 2020) out of the total breeding population of 110,000 (BirdLife International, 2022). In the UAE, Abu Dhabi colonies experienced fluctuations over the last decade. Some islands suffered from persistent decline due to human disturbance like Umm Qasr. Whereas many colonies on islands of restricted public access grew in numbers considerably like Bu Tinah, Rufayk and Gagha, that altogether host more than 30,000 breeding pairs each year (Khan et al., 2018; Muzaffar, 2020), making it comparable to the Gulf of Salwa (Muzaffar, 2020). Siniya Island colony in the north of the UAE (in Umm Al Quwain emirate) also have restricted access and has nearly doubled in numbers with 15,500 pairs in the 1990s (Jennings, 2010) to 26,000-41,000 pairs during the breeding seasons count between 2011 and 2016 (Muzaffar, Whelan, Clarke, Gubiani & Benjamin, 2017a). Accordingly, Siniya colony is considered the largest colony within the UAE as it holds about half of the UAE breeding population (Muzaffar et al., 2017a).

Overall, Socotra Cormorant is poorly studied in every ecological aspect including their foraging ecology. Several studies reported that they forage in groups (Cook et al., 2017; Jennings, 2010; Muzaffar et al., 2020), with flock size estimated around 33,000 at any time, excluding nonbreeding birds (Cook et al., 2017). Notably, A recent study suggested that foraging flocks over 100,000 individuals could be observed in some parts of the Arabian Gulf (Muzaffar, 2020, Table1). This gregarious behavior is thought to be helping in prey detection and transmission of information (Cook et al., 2017) in a communal rather than cooperative way (Nelson, 2005). Socotra Cormorant diet consist of small to medium sized fish (Muzaffar, 2020). They might be opportunistic as their diet appear to vary from one area to another (Muzaffar et al., 2015). One study from Siniya Island reported their forage fish to be anchovies *Encrasicholina* spp., Blue-Stripe Sardine *Herklotsichthys quadrimaculatus*, Pink Ear Emperor *Lethrinus lentjan*, Sailfin Flying Fish *Parexocoetus mento*, Bigeye Scad *Selar crumenophthalmus*, Pickhandle Barracuda *Sphyraena jello*, and Congaturi Halfbeak *Hyporhamphus limbatus* (Muzaffar et al., 2015). Another study from Hawar archipelago, between Bahrain and Qatar, reported a diet of White Sardines *Sardinella albela*, Yellowtail Scad *Atule mate*, Bigeye Scad *Selar crumenopthalmus*, Spotted Halfbeak *Hemiramphus far* and Silverside *Atherinomorous lacunosus* (Jennings, 2010). There has been an escalating debate on the competition between Socotra Cormorants and fishermen on fishery resources, however, the claim was refuted as low overlap was found (Muzaffar et al., 2015). Annual fish consumption from Siniya Island population alone was estimated between 11000 to 18000 tons (Muzaffar et al., 2015). A succeeding study calculated the average daily fish intake as 47 tons (Cook et al., 2017). With such amounts, it is expected that Socotra cormorants control fish density, improve fisheries, fish diversity and dynamics of their marine ecosystem (Muzaffar et al., 2015). The bird also contributes greatly to marine nutrient cycling and vegetation on nesting islands by its nutrient-rich guano (Aspinall, 1995; Ksiksi, Muzaffar, Gubiani & Alshihi, 2015).

Socotra Cormorants were believed to follow some movement patterns in the Arabian Gulf and the Arabian Sea; however, it was unclear to determine if its dispersal or a seasonal movement (Aspinall, 1996; Johnsgard, 1993). Jennings (2010) suggested a dispersive movement, however, Muzaffar et al. (2017b) showed that one colony (i.e., Siniya Island) exhibited a short directional migration based on data collected using outfitted colony members with satellite transmitters over 2 consecutive years. Movement patterns also indicated an overlap between breeding cormorant distribution and primary productivity, but that was not applicable to the distribution of non-breeders (Muzaffar, 2017b). Comparing with oceanographic variables and fish movements might explain the hanging questions on the distribution of the species, but there were no published studies on pelagic forage fish in the Arabian Gulf. Notably, the species might vagrantly disperse to the west African coast of the Red Sea and west India (Del Hoyo, Elliott & Sargatal, 1992). The breeding season appear to be synced internally within each colony (Del Hoyo et al.,1992) as a response to local conditions of prey availability (Johnsgard, 1993). Colonies off Saudi Arabia in the Arabian Gulf were reported breeding in April, May, and September to November (Bundy, Conner & Harrison, 1989). The Siniya Island colony breeds from August to December, sometimes up to March in events of disruption or delayed breeding (Muzaffar, 2017b). Observations from Al Hallaniyat Islands (previously Kuria Maria islands) off Oman reported breeding events between June to October (Gallagher & Woodcock, 1980). In the Socotra archipelago, the breeding season seems to be from August to February based on several observations from isles in the archipelago (Porter & Suleiman, 2014).

Socotra Cormorant is categorized as vulnerable, and its overall population trend is declining (BirdLife International, 2019; Muzaffar, 2020). The bird lives within a limited range and many of their roosting and breeding islands are disturbed or degraded due to oil exploration and commercial and residential development (BirdLife International, 2022; Jennings, 2010; Khan, et al., 2018; Muzaffar, 2020). Indeed, Socotra Cormorants used to nest on islands all over the Arabian Gulf including Kuwait and Iran which no longer support a breeding population (Jennings, 2010; Muzaffar, 2020). Overall, the Arabian Gulf is considered among the highest anthropogenically impacted areas (Halpern et al., 2008). Two recent studies on the Indian anchovy (*Stolephorus indicus*) and the Indian oil sardines (*Sardinella longiceps*) in the Arabian gulf (the UAE side) found heavy metals including lead, cadmium, and mercury. Zinc, Copper, Cadmium and Chromium were found in concentrations that exceeded the maximum permissible limit listed in several international organizations (EC, FAO and WHO) (Alizada, Malik & Muzaffar, 2020; Malik, Alizada & Muzaffar, 2020). Mercury, lead, and cadmium are highly toxic even in low concentrations. Likewise, the accumulation of essential metals like zinc and copper to toxic levels can harm aquatic ecosystems (Hao et al., 2019).

The Arabian Gulf also represents one of the most extreme marine environments (Diaz Lopez et al., 2021). Consequently, marine organisms were reported to be living near their environmental tolerance boundary (Riegl & Purkis, 2012). Compared with the Gulf of Oman that have over 1200 fish species, the Arabian Gulf has about 700 fish species, though it is still able to host around 20 seabird species (Muzaffar, 2020). Optimistically, Socotra Cormorants are legally protected in most range states (Muzaffar, 2020). The bird is also included in the Convention on Migratory Species under Appendix II since 1994 (CMS, 2022). Appendix II lists migratory species that live in unfavorable conservation status and need international agreements to provide protection on the long term. Currently, from all range states of Socotra Cormorant, only Kuwait, Qatar and Oman are not parties in the convention (CMS, 2022).

Chapter 2

Chapter 2: Materials and Methodology

2.1 Study Area

The study covered the marine area between 9° and 31° north of the equator and 32° to 61° east of the prime meridian, representing mainly the Arabian Gulf, the Arabian Sea, the Gulf of Aden, and the Red Sea (Figure 1). The marine environment in both the Arabian Gulf and the Red Sea are unique as they experience very high levels of surface temperature and salinity. The Arabian Gulf might sometimes exceed the Red Sea levels (Edwards, 1987; Halpern et al., 2008). It is also the shallowest sea in the study area, with an average depth of 36 m and a maximum depth around 90 m near the entrance to the Strait of Hormuz (Al-Yamani & Naqvi, 2019).

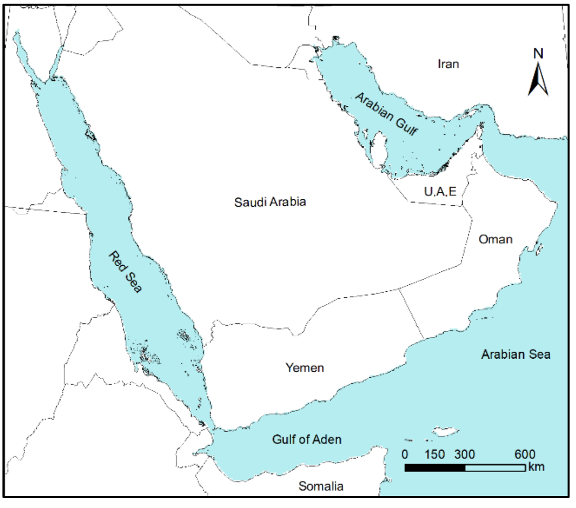


Figure 1: Study area

2.2 Focal Species

The Socotra Cormorant is a seabird species listed as vulnerable by the IUCN (BirdLife International, 2019). The bird lives in a restricted range extending from the Arabian Gulf, the Arabian Sea into the Gulf of Aden (BirdLife International, 2022; Muzaffar, 2020). Most of the population roost and breed within the Arabian Gulf formulating the northern subpopulation. The smaller southern subpopulation resides on islands off Oman and in the Gulf of Aden (BirdLife International, 2022; Muzaffar, 2020). The latest total population estimate was 750,000 birds (Muzaffar, 2020). However, due to range limitations and the continuous human disturbance the bird experience on many of their usage islands (BirdLife International, 2022; Khan, et al., 2018) the population is declining (BirdLife International, 2019). Generally, the movement pattern of Socotra Cormorant is not clear as one study suggested a dispersive movement (Jennings, 2010), with the species visiting the west coast of India and the west of the Red Sea (Del Hoyo et al., 1992). Yet, another study reported a short directional migration by one colony in the UAE (Muzaffar et al., 2017b).

2.3 Materials

2.3.1 Choosing Predictor Variables

The following variables were chosen to perform the distribution modeling: mean sea surface temperature, SST (C); mean sea surface salinity, SSS (ppt); mean sea surface height, SSH (m); mean mixed layer thickness, MLD (m); and sea floor depth, depth (m). These predictors are either known or presumed to be linked to the abundance and distribution of seabirds (Gilmour et al., 2018; Louzao et al., 2006; Tremblay et al., 2009; Oppel et al., 2012; Wakefield, Phillips & Matthiopoulos, 2009). The Socotra Cormorant itself is explicitly marine and lives within the productive upwelling range (Nelson, 2005). Its movement, breeding and foraging patterns also signify the shallow coastal waters for both the bird and forage fish (Muzaffar, 2020).

2.3.2 Source of Current Predictor Variables

All current variables (SSS, SST, SSH, MLD, depth) were obtained at 0.083° (~ 9.2 km) resolution as monthly averages (E.U. Copernicus Marine Service Information, 2022a). Variables covered the period from 2011 to May 2020, except the depth variable as its considered invariant throughout the study period. For the period of June to December 2020, the dynamic variables were obtained also as monthly averaged data at the same resolution (E.U. Copernicus Marine Service Information, 2022b).

2.3.3 Source of Future Predictor Variables

The same dynamic oceanographic variables were extracted as monthly data at 10 km resolution for the period of 2041 to 2050. The future scenario used was SSP5-8.5 from the HadGEM3-GC31-HH model (Roberts, 2019). For this scenario, the radiative forcing in 2050 is projected to reach nearly 4 W/m^2 and 5.9 W/m^2 for CO2 and all GHGs respectively. By 2100, radiative forcing would stabilize at 9.7 W/m^2 for all GHGs and between 8 to 8.5 W/m^2 for CO2 (Meinshausen et al., 2020).

The data is provided by the World Climate Research Programme (WCRP) website under the Coupled High Resolution Model Intercomparison Project Phase 6 (CMIP6 HighResMIP). The CMIP6 is an internationally coordinated project that provides simulation data aimed at answering fundamental science concerns and is used by the Intergovernmental Panel on Climate Change (IPCC-AR6) (Roberts, 2019). The SSPs or “Shared Socioeconomic Pathways” examine how the world would evolve using five different narratives. Each narrative looks at different levels of socioeconomic factors (e.g., population, education, economic growth, technological development, and urbanization). These narratives are:

- SSP1 highlights a global sustainability trend where challenges to mitigation and adaptation are low. The narrative suggests a global gradual shift toward more sustainable development and an economic growth concerned with human well-being. Consumption pattern is lower in energy and resources demands and uses less material. Inequality also declines globally.
- SSP2 is a middle narrative where challenges to adaptation and mitigation are moderate. Population moderately grows then stabilizes after 2050. The social, technological, and economic patterns almost remain the same as historical trends. Income growth is uneven; as a result, inequality generally remains. The consumption of resources and energy decreases and a slow sustainable trend takes place globally and nationally. However, ecological systems will still suffer from degradation.
- SSP3 expects a regional rivalry where high challenges to adaptation and mitigation exist. A nationalism trend appears, and regional conflicts make policies shift toward securing energy and food on regional and national levels. This lowers the allotments to development, technology, and education. Population growth is high in developing nations and the opposite is true in developed countries. Inequality worsen or remain at same levels. Consumption of material is high. Ultimately, severe environmental degradation occurs in some regions
- SSP4 is a narrative of major disparities and challenges to mitigation are low but high to adaptation. The world experience uneven economic and political power leading to inequalities even within countries. The resulted gap creates two ‘worlds’, one has higher income, education, and technological development while the other is completely the opposite where societies are mainly labor intensive. Consequently, conflict arise and social structure collapse. Environmental policies in moderate and high developed countries focus on national challenges.

- SSP5 suggests a rapid development correlated with fossil fuel exploitation. This produces high mitigation challenges, however, challenges to adaptation are low. Societies interest and trust toward competitive but collaborative markets increase. They also largely invest in human capital in terms of education, health, and social capital as a way to achieve sustainable development. Markets worldwide become more integrated over time. The fast economic growth is largely dependent on fossil fuels and the consumption of resources and energy is high. World population peaks then drops during the century. Environmental issues like air pollution are successfully managed on local scales and positive views toward the ability of societies to handle its social and environmental systems increase (Meinshausen et al., 2020; Riahi et al., 2017).

2.3.4 Instruments

The instruments used in the field survey were:

- Portable transmitter terminals (Kiwisat Platform Terminal Transmitters (PTTs), Model K3H 174A, Sirtrack).
- Harnesses of Teflon ribbons (14 mm), to attach transmitter devices on the backs of the seabirds.

2.3.5 Software

The software used for data preparation, processing, and interpretation were:

- ArcGIS Desktop 10.8.1
- MS-OFFICE 2022
- R-studio version 4.1.1.
- Maxent v 3.4.3 (Maximum entropy modeling)

2.4 Methods

2.4.1 Occurrence Data Collection

Occurrence data were collected over three periods by Dr. Muzaffar. The first period was from November 2013 to December 2013 then May to June 2014. The gap in data was due to a technical error in the ARGOS satellite system that prevented signal recording. In this phase, 8 PTT devices were attached to individuals from the Siniya Island colony using a harness of Teflon ribbons in a back-pack style. The second period took place on the same island from November 2014 to August 2015 and 10 PTT devices were attached. The third period lasted from December 2019 to December 2020. Devices in this phase were attached to birds from 2 different colonies in southern Arabian Gulf, namely 4 transmitters for Bu Tinah colony, and 6 devices for Hawar archipelago colony. Birds were chosen randomly, and their condition was checked prior to device attachment. The recommended payload of a transmitter is less than 3% of the bird's body mass (Phillips, Xavier & Croxall, 2003). One transmitter weights 36.5 g and the average body mass of an adult Socotra Cormorant is 1.5 ± 0.1 kg (Cook et al., 2017). Therefore, the transmitter load is 2.4 ± 0.2%, and is within the recommended range.

2.4.2 Preparation of Bird Location Data

Occurrence data collected using satellite transmitter devices tend to be repetitive and spatially clustered as birds roost for certain period of time during the day. Clustering of data can increase model overfitting and bias (Boria, Olson, Goodman & Anderson, 2014; Veloz, 2009). As a result, data were rarefied using the spatially rarefy occurrence data tool in SDM toolbox in ArcGIS at a resolution of 10 km, matching the environmental predictors. Moran's Index was calculated to check spatial autocorrelation in the species distribution. The index ranges from +1 (perfect correlation) to -1 (perfect dispersion) and values near zero indicate randomness in the spatial pattern (Oppel et al., 2012)

2.4.3 Preparation of Predictor Variables

Variables were obtained in NetCDF format and rasterized using the multidimension tools. Variables were then masked to the desired spatial extent using spatial analyst tools. Future predictor variables come in a grid format that needs interpolation. Hence, the kriging method was used (e.g., Cursach et al., 2019). Kriging method has a good sensitivity and is known to produce accurate re-gridded surfaces (Lima-Ribeiro, et al., 2015; Varela, Lima-Ribeiro & Terribile, 2015). Furthermore, current variables were re-grided from 9.2 to 10 km to match the resolution of the future variables. Monthly data for each variable were then averaged using cell statistics in the spatial analyst tools to produce one layer of that variable.

2.4.4 Autocorrelation Test of Predictor Variables

Multicollinearity was assessed between the environmental variables using Variance Inflation Factor analyses (VIF) in R (version 4.1.1) using VIF >10 as a threshold (Duque-Lazo, Van Gils, Groen & Navarro-Cerrillo, 2016).

2.4.5 Bias File Creation

A bias file was created using the gaussian kernel density of sampling localities tool in SDM toolbox in ArcGIS. The purpose of the bias file is to allow the model to control the density and place of where background points are selected. By this method, the model avoids sampling background points that are significantly outside the known range of the species. These points might be less informative and affect model prediction. Gaussian kernel density also accounts for sampling bias by providing Maxent with a background file that have the same level of bias in presence localities (Barbet-Massin, Jiguet, Albert & Thuiller, 2012; Brown, Bennett & French, 2017).

2.4.6 Modeling Algorithm

Maxent 3.4.3 (Phillips, Dudík & Schapire, 2022) was used for the modeling analyses. Maximum Entropy Modeling (Maxent) is one of the commonly used techniques in niche and species distribution modeling because it requires PO data only (Bradie & Leung, 2017; Cursach et al., 2019; Merow et al., 2013; Phillips & Dudik, 2008). Since 2006, more than 1000 papers used it for simple and sophisticated cases. Maxent have a user-friendly interface and offers a bundle of settings the user can manipulate to better compare outcomes (Merow et al., 2013). It also performed better when compared to most other PO modeling programs (Elith et al., 2011; Merow et al., 2013; Phillips & Dudik, 2008; Wisz et al., 2008). To predict spatial distributions, Maxent takes a list of presence locations for a single or multiple species as input, and a set of environmental predictor variables (e.g., temperature, precipitation) of a defined area by the user (Merow et al., 2013). Maxent method is considered robust as it employs machine learning and statistical modeling to predict occurrence probability, build model and project it into another period of time (Phillips, Anderson & Schapire, 2006).

2.4.7 Model Calibration

It is recommended to make modeling decisions based on biological considerations that is driven by species-specific conditions and research goals (Merow et al., 2013). Indeed, one of Maxent most argued points is the common use of its default settings and visualizing it as a ‘blackbox’ tool (Hernandez, Graham, Master & Albert, 2006; Phillips & Dudik, 2008). From this scoop, the study used the spatial jackknifing tool in SDM toolbox in ArcGIS (i.e., Brown et al., 2017). The tool tests Maxent model performance on multiple levels to produce the most possible calibrated powerful model. First, it creates groups of spatially segregated and independent occurrences based on natural spatial clustering . It then calibrates the model with one group and evaluate it using the remaining groups. Second, it tests the model over a range of regularization multipliers (RMs) and feature class types (linear, quadratic, product, threshold, and hinge) to enhance the model performance. Lastly, the best model is automatically chosen based on a defined order of priorities by the user. In this study, the order was: the model with lowest omission rate (OR) of test localities, then highest area under the curve (AUC) and finally the least complex model (e.g., simplest feature class types) (Brown et al., 2017; Radosavljevic & Anderson, 2014). In fact, the RM parameter of Maxent algorithm aids the model to achieve the maximum entropy or the most uniform distribution over study area while accounting for recognized constrains in distribution modeling. It also plays a crucial role in reducing model overfitting (Hernandez et al., 2006; Phillips & Dudik, 2008).

The final model was run using an RM of 2 with linear and quadratic features. It was replicated for 15 runs by the subsampling method where 25% of occurrence data were allocated for model testing. The purpose of replication is to average prediction probabilities and avoid any skewness in the model outcome. To further prevent the model from under or overpredicting spatial relationships, iterations were set at 5000 considering the recommended convergence threshold of 10^{-5}. Finally, Maxent projected the current model distribution relationships onto 2050 year using the provided future variables of SSP5-8.5 scenario.

2.4.8 Model Significance Evaluation

We evaluated the accuracy of the final predictive model using threshold independent Receiver Operating Characteristics (ROC) Area Under Curve (AUC) method conducted by Maxent software itself. AUC value ranges from 0 to 1, with value closer to 1 indicating a better model performance. AUC<0.5 means a model performance no better than random (Merckx, Steyaert, Vanreusel, Vincx & Vanaverbeke, 2011).

We also evaluated model significance using threshold dependent tests, namely true skill statistics (TSS) and Cohen's kappa, using the maximum training sensitivity and specificity threshold (West, Kumar, Brown, Stohlgren & Bromberg, 2016). Cohen's kappa (k) works by estimating the expected accuracy that occurred by chance. When $k < 0.4$, model accuracy is considered low, while $0.4 < k < 0.75$ indicate a good accuracy, and $k > 0.75$ represent an excellent model accuracy (Landis & Koch, 1977). Kappa statistic was criticized for being dependent on prevalence in data. As a result, TSS was calculated to support kappa result since it retains all kappa advantages, less affected by prevalence and accounts for omission and commission errors (Allouche, Tsoar & Kadmon, 2006; Lantz & Nebenzahl, 1996). TSS ranges from −1 to +1, where TSS<0 reflecting a random model and the closer the value to +1 is excellent for a model performance (West et al., 2016). Both statistics were calculated using Microsoft Excel and R (ROCR, vcd and boot packages).

2.4.9 Sensitivity and Contribution Analysis

Maxent performs jackknife analysis to assess the relative importance of each environmental predictor. It estimates the training gain for each predictor if used in isolation by the model and if omitted while keeping all the variables in the model. The analysis mainly shows variable importance for the model. Contribution percentage of all variables is estimated as well by Maxent. Response curves for predictor variables are also produced by Maxent. These curves show how habitat suitability changes with changing environmental variable levels, while withholding all other variables at the average value.

2.4.10 Assessing Environmental Novelty

Analysis of extent of extrapolation using multivariate environmental similarity surfaces (MESS) analysis measures the similarity of a given point or to a reference point or location. In other words, it measures closeness between current and future variable values (Elith, Kearney & Phillips, 2010; Rodder et al., 2013). MESS score ranges from positive to negative, with positive values indicating that the future variables level at that location is similar to the current training range. Positive values of 100 score suggest that the point is not novel at all. On the contrary, negative values indicate that a future point is outside the current training range and there is extrapolation in that location in the future (Rodder et al., 2013). The most dissimilar variable (MoD) analysis is based on the MESS, as it shows which variable is affecting the MESS value the most at any given point.

MESS and MoD analyses were made using Maxent bat file, following the method reported by Elith et al. (2010). Results were processed and visualized in ArcGIS.

2.4.11 Limiting Factors

The limiting factor is the most variable that influence the model prediction at each location. The statistical analyses run through one variable each turn and change its value at that point to the mean value of that variable across species presence data. The resulted model value is recorded. The variable that increases model value the most, that is the occurrence probability, is considered a limiting factor (Elith et al., 2010). This step is interesting and could be powerful when combined with ecological knowledge (Elith et al., 2010).

The analysis was made for both current and future predictions using Maxent bat file. The method followed is available in Elith et al. (2010). Results were processed and visualized in ArcGIS.

2.4.12 Visualizing of Maps and Related Spatial Analyses

The final distribution map for both current and future were rasterized then visualized in ArcGIS using the reclassify tool. Area calculations were made for current and future predicted distributions using the fields toolset in data management toolbox in ArcGIS. The process was speeded up after developing a python code script that run several steps automatically. Python code can be run using the python window integrated within ArcGIS. To examine how occurrence probability changed in the future, cell statistics tool was used to subtract the current layer from the future layer. The change was visualized in a map and area calculations were made accordingly.

Chapter 3

Chapter 3: Results

3.1 Overview of the Main Findings

Model performance power was found to be highly accurate. Mixed layer thickness and sea floor depth were the most important environmental variables for understanding Socotra Cormorant distribution. The potential current distribution model predicted large areas of high suitability in southern Red Sea region. However, the future model indicated a severe decline in suitability in almost all regions, based on SSP5-8.5 scenario for 2050.

3.2 Results

3.2.1 Occurrence Data

Filtering of occurrence data resulted in58 presence points that were used for the distribution modeling (Figure 2), based on a 10 km spatial grid.

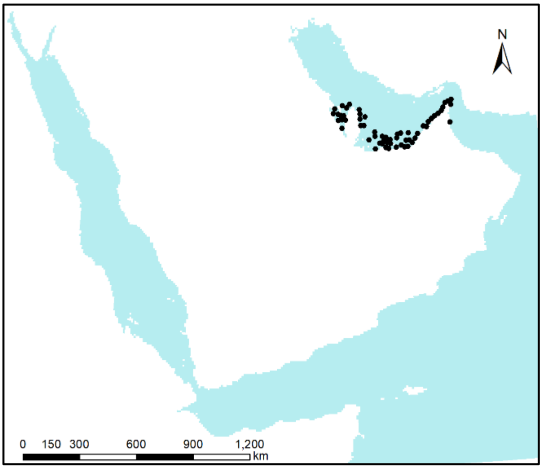


Figure 2: Occurrence points used for modelling of *Phalacrocorax nigrogularis*

The spatial autocorrelation performed using Moran's *I* is around zero indicating a random distribution of presence points. Negative value indicates a tendency towards dispersion while positive value indicates tendency towards clustering. Moran's *I* value is slightly negative (-0.0023) but its negligible since its close to zero (Figure 3).

The *P*-value is a probability that measures if the observed spatial pattern a result of random processes. In this case, the *P*-value is 0.72 which is greater than 0.05 (Figure 3) and this shows that the observed spatial pattern was very possibly created by random. The z-score of -0.36 also shows that the pattern does not appear to be significantly different than random, in other word, the species localities are randomly distributed.

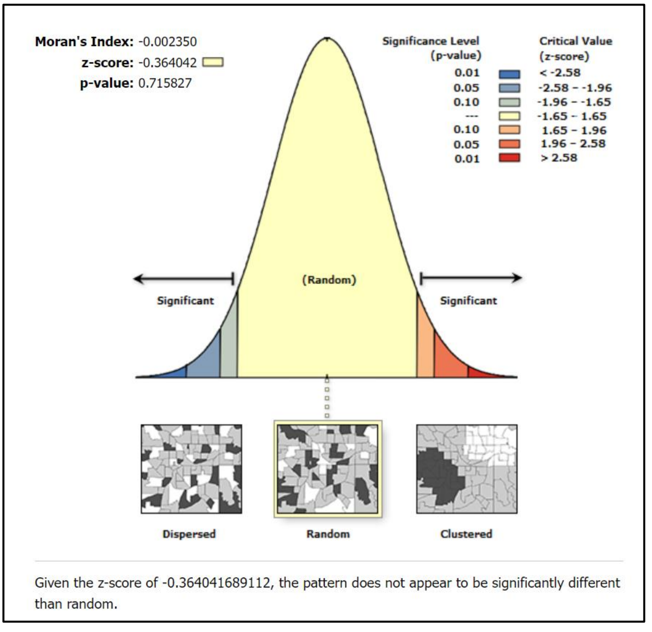


Figure 3: Spatial Autocorrelation report for *Phalacrocorax nigrogularis*

3.2.2 Autocorrelation Test of Predictor Variables

VIF analysis showed no correlation between the predictor variables considering a VIF >10 as a critical threshold (Duque-Lazo, 2016). Thus, no variables were excluded.

3.2.3 Model Evaluation

The model calculated the omission rate for test data (Figure 4) where it indicates the proportion of test presence points incorrectly predicted. A good omission rate is the one with a good match or relatively close to the predicted omission as the definition of the cumulative threshold states. The fractional value for predicted area at any point indicate that up to this value the occurrence probability is incorrectly predicted.

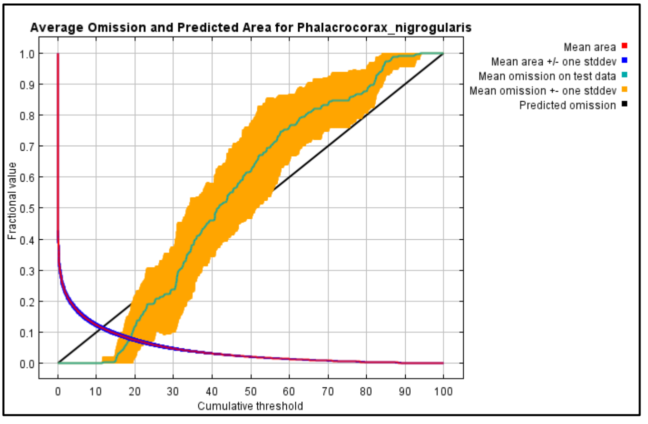


Figure 4: Average omission rate for test data of *Phalacrocorax nigrogularis* (The shading in blue and orange represent variation)

The averaged Area Under the ROC curve (AUC) for test data (Figure 5) shows sensitivity and specificity. Sensitivity measures the proportion of presence data correctly predicted by the model. The specificity is defined using predicted area, rather than true commission (Phillips et al., 2006).

The AUC is an indicator to the performance and validity of the model. As stated earlier, AUC $\leq$ 0.5 indicates that a model is not better than random, and the higher the AUC value the better the model in discriminating suitable versus unsuitable areas for the species (Phillips et al., 2006). Our model showed a credible level of accuracy with AUCtest at 0.965 and

AUCtrain at 0.966 and standard deviation of 0.006, meaning the model has 96.5% performance (Table 1).

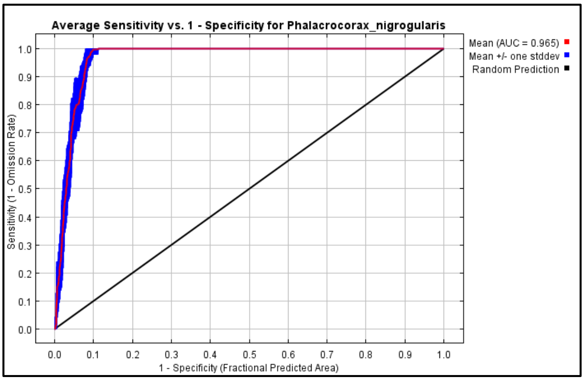


Figure 5: The receiver operating characteristic (ROC) curve for the data averaged over the replicate run

Cohen's Kappa analysis also indicated a good model accuracy as Kmax= 0.438 and it falls within the good range (0.4 < k < 0.75) (Landis & Koch, 1977) (Table 1). TSS result also supported the earlier results as the averaged value is TSS= 0.874, and this indicates a high performance (West et al., 2016).

Table 1: Mean AUC, TSS and Kappa analyses values of the distribution model for *Phalacrocorax nigrogularis*

AUCtest	AUCtrain	TSS	Kappa max
0.965	0.966	0.874	0.448

3.2.4 Sensitivity Analysis

Examining Table 2, mixed layer thickness (MLD) and sea floor depth (Depth) were the top contributors, with 43.3% and 41.1% respectively. The contribution of other variables was much lower, however, that shouldn’t underestimate their role in helping the model to better understand environmental relationships.

Table 2: Percent contribution for each variable in the distribution model for *Phalacrocorax nigrogularis*

Variable	Contribution to the model (%)
MLD	42.3
Depth	41.1
SST	9.6
SSH	6.4
SSS	0.6

The jackknife test conducted by Maxent highlights the important environmental variables for the potential distribution of Socotra Cormorant (Figure 6). The red bar in the plot indicates the overall performance of the model. The blue bar reflects model’s performance when only the corresponding variable is used while the light blue bar shows the performance of the model after omitting the underlying variable. The environmental variable with highest gain when used in isolation is mixed layer thickness (MLD), which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is also MLD, which therefore appears to have the most information that isn't present in the other variables. Sea floor depth is the second most important variable with a clear drop in average gain when it is not used in the model.

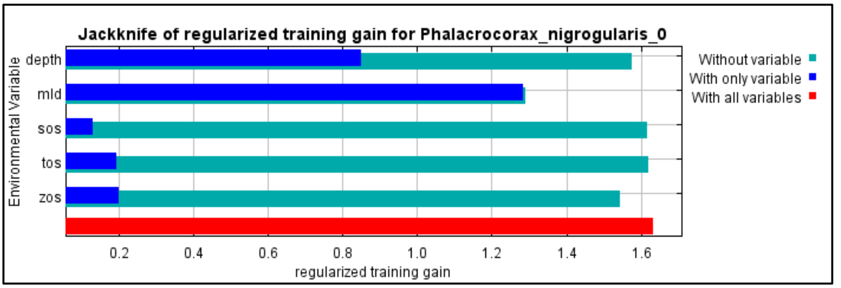


Figure 6: Jackknife evaluation of the relative importance of each variable

Depth: sea floor depth, MLD: mixed layer thickness, SOS: SSS (sea surface salinity, TOS: SST (sea surface temperature), ZOS: SSH (sea surface height)

3.2.5 Predicted Potential Suitability

Examining the predicted current distribution (Figure 7a), Socotra Cormorants have large moderate and high suitability areas across the study area. The total predicted suitable area is 331,600 km^2, with 64,100 km^2 predicted as highly suitable areas (>0.6) (Table 3). From that, the Arabian Gulf alone had 24,000 km^2 which equals 37.4% of the total (Table 5, Appendix). The model also predicted suitable areas off Oman extending from Masirah Island in the north, with highly suitable areas, to Al Hallaniyat archipelago where suitability was mostly low (<0.4). Interestingly, the model predicted considerable highly suitable areas in southern Red Sea, with 31,300 km^2 or 48.8% from the total (Table 5, Appendix).

The potential future distribution for Socotra Cormorant was based on SSP5-8.5 scenario for 2050 (Figure 7b). The visual observations suggest that the potential current distribution will decline sharply in the future, under Maxent model assumptions. The total suitable area is 89,900 km^2, which means 72.9% loss of suitable area by 2050 under SSP5-8.5 scenario. More precisely, only 1,700 km^2 of the total area was highly suitable (>0.6) (Table 3). These areas are mostly found near Socotra archipelago (Figure 7b). The Red Sea mostly had moderately suitable areas of 5,200 km^2, and 100 km^2 of highly suitable area. The Arabian Gulf lost all its highly and moderately suitable areas (Table 5, Appendix).

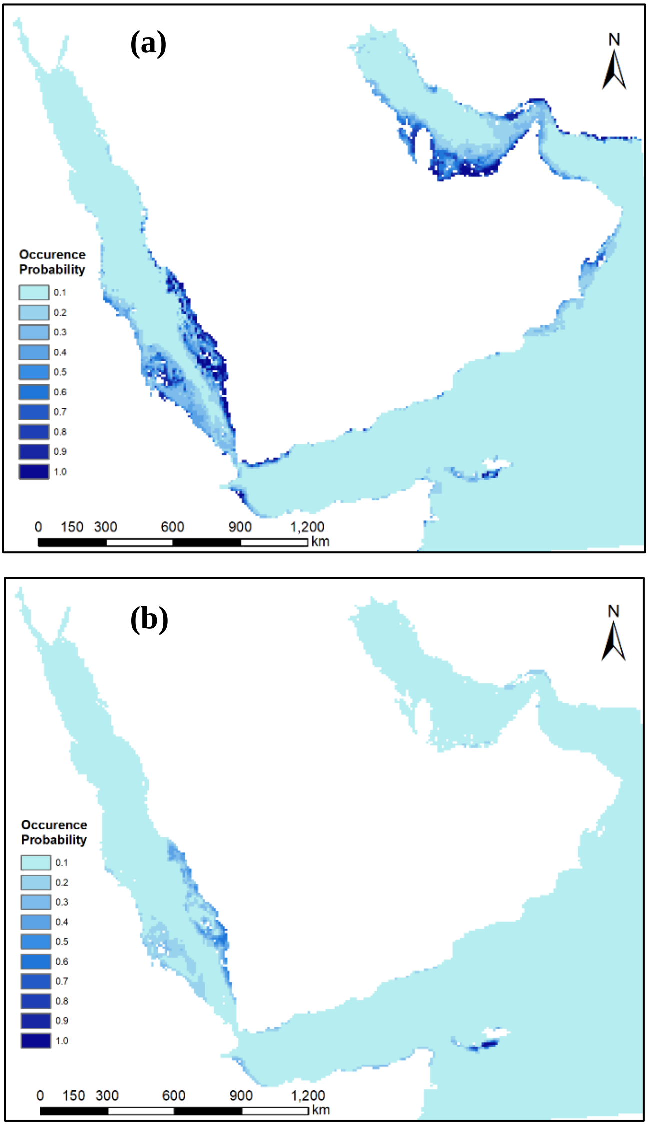


Figure 7: Potential current and future geographic distribution of *Phalacrocorax nigrogularis*

(a) Predicted current distribution (b) Projected future distribution under SSP5-8.5 scenario in 2050

Table 3: Probability of occurrence for *Phalacrocorax nigrogularis* expressed in surface area

Occurrence probability	Current (km²)	Future (SSP5-8.5 scenario) (km²)
0.1 - 0.2	112200	57300
0.2 - 0.3	73400	15500
0.3 - 0.4	39900	9400
0.4 - 0.5	21700	4000
0.5 - 0.6	20300	2000
0.6 - 0.7	15600	400
0.7 - 0.8	13000	500
0.8 - 0.9	14400	100
0.9 - 1.0	21100	700
Total	331600	89900 (72.9% loss)

3.2.6 Spatial Analyses of Suitability Change

Visual comparison of the change in area suitability from present to future showed a decreasing trend in suitable areas for Socotra Cormorants (Figure 8). The total contraction is estimated to be 125,300 km^2 (Table 4), where most of it occurring in the Arabian Gulf and the Red Sea. Specifically, in the Arabian Gulf, the contraction is a complete loss in moderate and high suitable areas, while in the Red Sea it is a decline in suitability degree (Figure 7b). On the other hand, the total expansion is 17,100 km^2 (Table 4) and is mostly present in the Gulf of Aden (Figure 8). Precisely, areas near Socotra Islands increased to high suitability degree, whilst areas along the northern coast of Somalia acquired new but low suitable areas (Figure 7a & b).

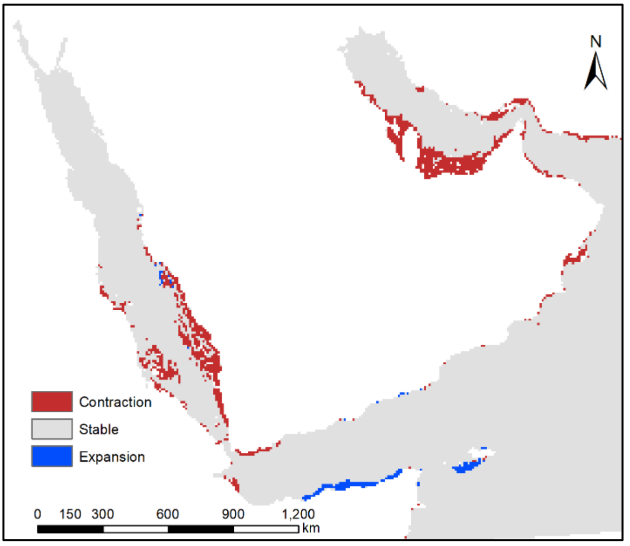


Figure 8: Change in geographic distribution from present to future (2050) for *Phalacrocorax nigrogularis* under SSP5-8.5 scenario

Table 4: Change in area suitability from current to future (2050) under SSP5-8.5 scenario expressed in surface area

	Suitability change (km^2)		
Region	Contraction	No change	Expansion
All	125300	2057500	17100
Arabian Gulf	51600	172300	0
Arabian Sea, Gulf of Aden	20800	1493900	15500
Red Sea	52900	391300	1600

3.2.7 Response Curves

Response curves indicate how each predictor variable affects Maxent prediction. The response curves for Maxent model were created using only the corresponding variable (Figure 9). Each curve reflects the dependence of potential suitability on the selected variable and on dependencies induced by correlations between the selected variable and other variables.

The results showed that the probability of presence declines sharply with the increasing value of depth and MLD variables. For these two variables, high suitability (>0.6) occurs in areas where depth is ≤ 30.3 m and MLD is ≤ 12.5 m. On the contrary, potential suitability increases with increasing SSS and SST values, with highly suitable areas (>0.6) occurring when SSS is ≥ 37.2 ppt and SST is ≥ 28.3°C. For SSH, suitability increases with the corresponding value of the variable up to 0.24 m in heigh then begins to decrease gradually.

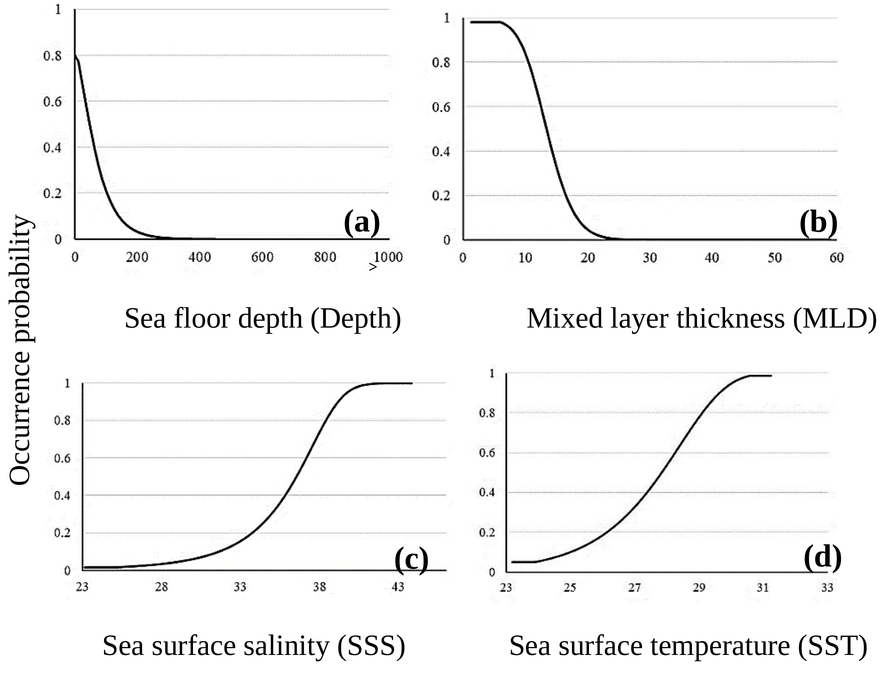


Figure 9: Response curves of the environmental variables showing occurrence probability for *Phalacrocorax nigrogularis*

Depth, MLD and SSH in meters, SSS in ppt and SST in °C

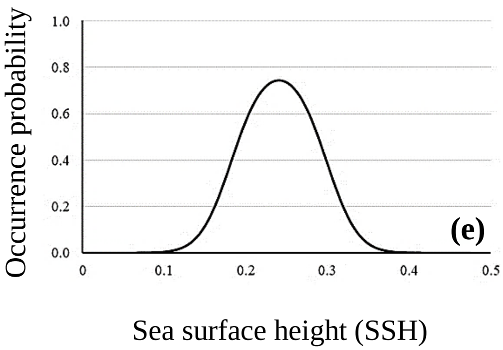
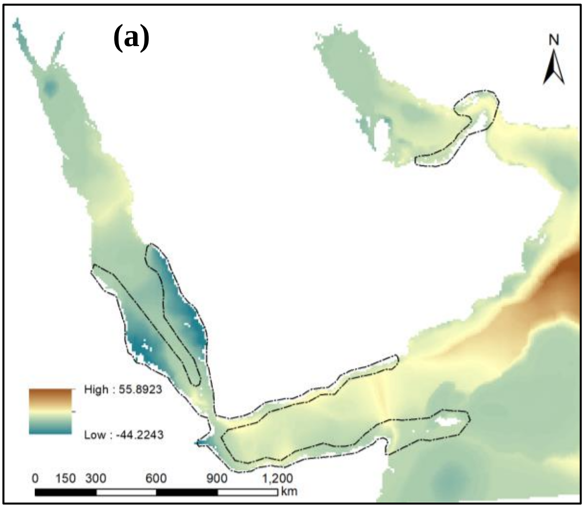


Figure 9: Response curves of the environmental variables showing occurrence probability for *Phalacrocorax nigrogularis* (Continued)

3.2.8 Assessing Environmental Novelty

The MESS (Multivariate Environmental Similarity Surface) analysis below shows the extrapolated region of Socotra Cormorant distribution (Figure 10a). The MESS score ranges from -44.2243 to 55.8923 averaged over 15 replicates. The negative values reflect extrapolated areas, and the higher negative MESS value indicates that locations lie outside the current training range. Whereas positive MESS values indicate points within the training range (Rodder et al., 2013). The most extrapolation region within the predicted distribution of Socotra Cormorant (areas within the black polygon) is found in southern Red Sea (Figure 10a). This extrapolation is more influenced by sea surface temperature (SST) (Figure 10b). The Gulf of Aden area appears to be the least extrapolated region within the predicted future distribution of the species (Figure 10a). The extrapolation is influenced more by sea surface temperature (SST) along Yemen and Somalia coastlines, and sea surface salinity (SSS) with mixed layer thickness (MLD) near the Socotra archipelago (Figure 10b).



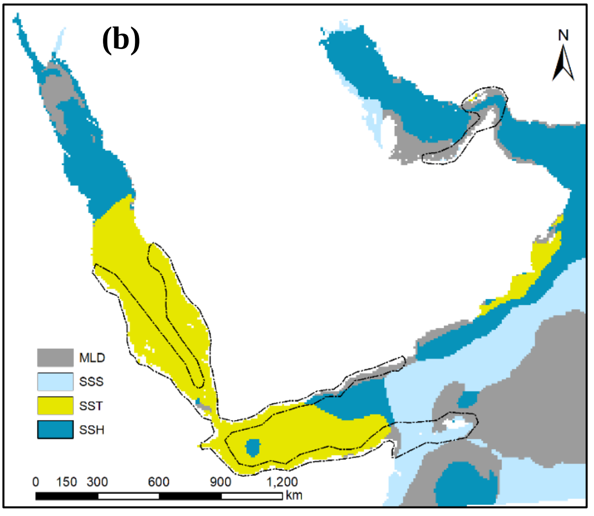


Figure 10: Extrapolation region and clamping of *Phalacrocorax nigrogularis*

The black polygon represents potential future distribution range of *Phalacrocorax nigrogularis* based on Maxent prediction. (a) Extrapolation region under SSP5-8.5 scenario in 2050 using MESS analysis. (b) Clamping map for SSP5-8.5 scenario in 2050 using MoD analysis

3.2.9 Limiting Factors

The limiting factor analyses indicated that mixed layer thickness (MLD) is the dominant limiting factor over the predicted current range (areas within the black polygon) (Figure 11a). Shallow areas in the south of the Arabian Gulf, off the UAE coast, has sea floor depth (Depth) as the limiting factor. While areas around Hawar Islands have sea surface salinity (SSS) as the limiting factor.

The limiting factor analyses for the potential future distribution (Figure 11b) showed that sea surface height (SSH) is the limiting factor in almost all the predicted future range (areas within the black polygon). Areas near the Socotra archipelago shows that mixed layer thickness (MLD) is the limiting factor.

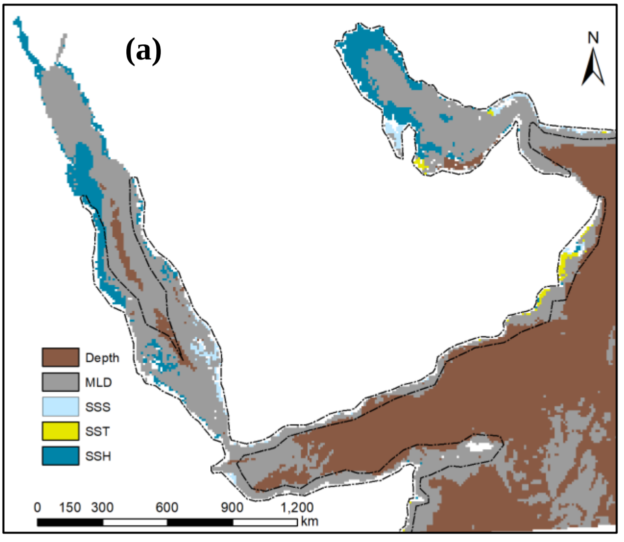


Figure 11: Limiting factors analyses for predicted current and future distribution of *Phalacrocorax nigrogularis*

The black polygon represents potential current distribution range of Maxent prediction. (a) Limiting factors based on the potential current distribution model

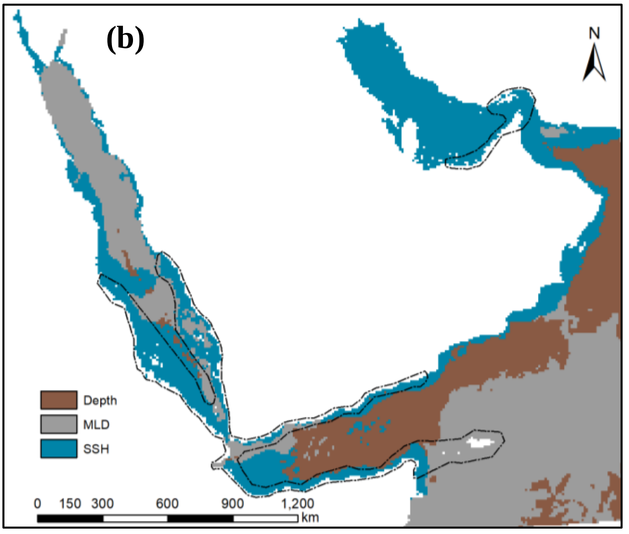


Figure 11: Limiting factors analyses for predicted current and future distribution of *Phalacrocorax nigrogularis* (Continued)

The black polygon represents potential future distribution range of Maxent prediction. (b) Limiting factors based on the projected future distribution under SSP5-8.5 scenario in 2050

Chapter 4

Chapter 4: Discussion

4.1 Predicted Suitability and Predictive Power

The predicted current distribution of Socotra Cormorants shows consistency with the current known distribution (Figure 7a). The predicted large areas of high suitability in the Arabian Gulf strengthen the recent evaluation of Muzaffar (2020) and Khan et al. (2018). Markedly, the model predicted large patches of highly suitable areas in the southern Red Sea region. Those areas even exceeded the prediction in the Arabian Gulf, which currently supports the largest portion of the bird population, by 7,300 km^2 (Table 5, Appendix). Some islands in this region are either historically used or not colonized yet, and the species might be foraging in the surrounding marine grounds (BirdLife International, 2022).

In regard to colonization, there are no studies that extensively investigated Socotra Cormorant movement between colonies and how fast or slow it responds to change in their islands and marine foraging ground status. Khan et al. (2018) reported that Socotra Cormorants were able to relocate to inactive colonies and colonize new areas as seen in the case of Ghagha, Bu Tinah and Digala Islands off western Abu Dhabi coast. However, the proximity between these islands and the surrounding active colonial islands must be considered as it was ≤150 km. These three colonies showed low disturbance levels and two of them (Ghagha and Bu Tinah) have restricted access, and this highlights the importance of conserving suitable areas for possible colonization. Since the study was conducted on decadal bases (1996, 2006, 2016), the temporal movement of colonization/recolonization was not documented precisely. But the general outcome indicated that the species made a gradual shift to these colonies.

Intermixing between the UAE colonies was reported during the post-breeding period at roosting sites where recolonization is suggested to occur (Khan et al., 2018; Muzaffar, 2020). Indeed, the breeding population in Abu Dhabi Islands increased significantly in the last decade. The movement was suspected to be from nearby colonies off eastern Qatar or other UAE colonies (Khan et al., 2018). Our tracking data showed that birds from Siniya and Abu Dhabi colonies have visited eastern Qatar and Hawar Archipelago colony between January and March for few days. And the opposite is also true. However, recolonization movement between these two areas cannot be determined unless long-term tracking takes place. If future data showed that the species can recolonize areas that are ≥300 km away; the colonization of southern Red Sea region may occur from nearby colonies off Yemen. A previous study also reported observations of Socotra Cormorants near the Eritrean coastline and islands with numbers surpassing 1,500 birds in the summer season alone (Semere et al., 2008). Breeding was also suspected to occur on southern Eritrea coast extending to Djibouti (Semere et al., 2008), but no confirmation up to this date (BirdLife International, 2022). The Red Sea is one of the busiest shipping routes globally and anthropogenic disturbance is expected to be high. Taking the Arabian Gulf as an example, it is also among the heavily used lanes and experienced significant pollution levels due to oil industry, however, the species persisted and increased in numbers with the growing protection. This case encourages conservation efforts in the Red Sea.

Our future prediction under SSP5-8.5 scenario showed an extreme declining trend in area suitability with nearly 73% between complete loss and reduced suitability (Figure 7b). This trend is similar to other studies investigating climate change impact on seabirds (e.g., Cursach et al., 2019; Jenouvrier et al., 2014; Krüger et al., 2018). A recent study surveyed 538 animal and plant species globally and predicted that ≥ 30% may become extinct within their regions based on all future scenarios. The study indicated that dispersal alone might not be enough to face temperature change and niche shifts may be highly important to avoid extinction (Román-Palacios & Wiens, 2020). The present study used SSP5-8.5 scenario that expects temperature to increase more than 1.5°C by 2050 (Meinshausen et al., 2020). Despite the major loss in area suitability, southern Red Sea region was still holding 5,300 km^2 of moderate and high suitable areas in future prediction (Table 5, Appendix). Although the model highly extrapolated in this region (Figure 10a), extrapolation doesn't necessarily mean that all environmental conditions will change. The change might be driven by one or two variables and the species may be able to adapt and spread through this region. A niche shift could also facilitate its adaptation to the new environmental conditions, and it may reduce extinction rate in northern subpopulation.

Interestingly, in contrast to all other regions, area suitability near the Socotra Archipelago increased under future prediction (Figure 7b). This can be explained by the MESS analysis (Figure 10a) that showed less extrapolation in this area, meaning that the environmental conditions will likely be the most similar to the current suitable conditions. Therefore, this area appears to be somewhat resistant to climate change impacts under the SSP5-8.5 scenario. Overall, moderate and high suitable areas in the future should grab the conservation attention. The successful enforcement of the Paris Agreement goals of limiting the warming to less than 1.5°C by 2100 can possibly reduce major declining trends regionally and globally (Román-Palacios & Wiens, 2020).

It is evident that the present study samples didn't cover the complete known range of the species (i.e., the southern subpopulation). However, the sensitivity of Maxent algorithm, maximum entropy, to sample sizes was reported to be among the least sensitive algorithms (Wisz et al., 2008). Likewise, its able to predict reasonable and representative total area regardless of sample size (Hernandez et al., 2006). In addition, our samples covered the marine distribution and foraging range of the main colonies in the Arabian Gulf. We assume that since the Arabian Gulf hosts most of the population, hence most useful environmental information exist. Examining Figure 7a, the model was able to predict the current known distribution in the Omani waters and in the Gulf of Aden. We also applied precautionary measurements (bias layer, data filtering, Moran's I test, etc.) and calibrated Maxent parameters (RM, features, etc.) based on recommended practice (e.g., the spatial jackknifing tool) to reduce overfitting and enhance model predictive power. As a result, all evaluation metrics showed a credible level of performance power (Figure 4 & 5, Table 1).

4.2 Influence of Environmental Predictor Variables

Socotra Cormorants like many other birds are exclusively marine and only come to cliffs and offshore islands to breed or roost (Nelson, 2005). In the modeling analysis we used static and dynamic marine variables thar are commonly associated with the distribution and foraging range of seabirds (Gilmour et al., 2018; Louzao et al., 2006; Tremblay et al., 2009; Oppel et al., 2012; Wakefield et al., 2009).

4.2.1 The Shallow Depth

The importance of shallow sea floor lies in its association with upwelling areas of high productivity (Gilmour et al., 2018). This study showed that shallow coastal areas are important for Socotra Cormorants as the contribution percentage of the depth variable came in second (41.1%) (Table 2). Specifically, areas where depth is ≤ 30.3 m were predicted to be highly suitable for the species distribution (Figure 9a). Likewise, examining the predicted current and future distribution maps (Figure 7a & b) the relationship can be clearly seen as suitable areas existed mainly off coastlines and islands such as Masirah Island in Omani waters, Socotra archipelago in the Gulf of Aden, Farasan Island and Dahlak archipelago in the Red Sea and Abu Dhabi western islands. In the limiting factors analyses (Figure 11a), areas off southern UAE coast had depth as the limiting factor. As stated earlier, this area is currently holding large portion from the total bird population (Muzaffar, 2020). Socotra Cormorants of Siniya Island colony were observed foraging mostly at depths of 15 m or lower, and this is where forage fish are commonly encountered in winter (Muzaffar, 2020).

4.2.2 Mixed Layer Thickness

The study also indicated that mixed layer thickness (MLD) has a great contribution to the species distribution. MLD was the top contributor variable to Maxent model with 42.3% (Table 2) and had the highest gain when used in isolation (Figure 6). This is interpreted as it contains the most useful information to the model. It was also the most variable that decreased Maxent model gain when omitted, suggesting that it holds the most information that isn't present in the other variables. Maxent also predicted MLD as the limiting factor in most of the potential current distribution (Figure 11a). The Arabian Gulf, which holds major high suitable areas, is very shallow and most of its parts have no thermal stratification. The combination of these two factors enhances nutrient mixing process, thus productivity (Riegl & Purkis, 2012). This result was also supported in a survey study that found that the whole water column was mixed in most areas in winter. Even in summer, water column was moderately well-mixed in shallow areas (Azizpour, Chegini, Khosravi & Einali, 2014).

MLD was also the limiting factor near Socotra archipelago in the projected 2050 model (Figure 11b). This location is where most highly suitable areas existed in the predicted future distribution (Figure 7b). Thus, MLD ≤ 12.5 m (Figure 9b) will aid the bird to persist under the future climate change scenario.

4.2.3 Sea Surface Height

Sea surface height reflects ocean surface topography and large-scale circulations (Gilmour et al., 2018; Landerer, Jungclaus & Marotzke, 2007). It is used a proxy for eddies, upwelling areas, and current dynamics. These processes bring nutrients to sea surface and affect its distribution on sea water surface, thus contribute to marine productivity (Gilmour et al., 2018). SSH for example is used to as a proxy for the potential location of many commercial fish catches like tuna (Syah, Siregar, Siregar & Agus, 2020). In the Arabian Gulf, many fish species migrate from the northern areas off the UAE coastline toward the south off Abu Dhabi emirate. This migration is correlated with main surface water currents in the area (Hoolihan, 2006; Hoolihan & Luo, 2007; Kampf & Sadrinasab, 2006).

In this study, SSH was the limiting factor off Iraq and Kuwait according to Maxent current model (Figure 11a). It was also the dominant limiting factor in all remaining suitable areas in the future (Figure 11b.) As sea surface level is expected to rise because of climate change, islands and shallow coastlines will be submerged. This explains why the Arabian Gulf was predicted to lose all its moderate and high suitable areas (Figure 7a & b). Socotra Cormorants will face increasing challenges to find suitable breeding and roosting sites. The moderate and high suitable areas in southern Red Sea and Socotra Archipelago may be the last resort for the species to survive if it does not adapt or make a shift in its niche.

4.2.4 Sea Surface Temperature

SST gradient aggregate forage fish and is commonly used to identify foraging grounds for seabirds (Gilmour et al., 2018). Fish movement pattern is not well understood within some important regions holding the Socotra Cormorant population, essentially in the Arabian Gulf (Muzaffar, 2020). One study on Siniya Island colony suspected that forage fish such as sardines and anchovies, move westwards to the cooler waters in the central Arabian Gulf when temperature peaks in summer (Muzaffar et al., 2017b). In addition, large numbers of seabirds including Socotra Cormorants are found between January and June near Umm Qasr and Bu Tinah islands off Abu Dhabi emirate coastline. This distribution is associated with a little cooler SST compared to the coastal areas (Muzaffar, 2020). In the future, SST is expected to increase and extreme environment conditions of high SST and SSS already exist in the Arabian Gulf and the Red Sea (Diaz Lopez et al., 2021; Edwards, 1987; Halpern et al., 2008). As a result, wide range of marine organisms including the Socotra Cormorant are expected to decrease. Overall, studying forage fish migration, especially those that constitute a large portion in Socotra Cormorant diet, will allow a better use of this variable in predicting the distribution.

4.3 Current Conservation Policies

The Federal Law of the UAE forbids any destruction of Socotra Cormorant habitat, hunting of chicks or adults and egg collection (UAE Federal Law # 24, 1999). Even though it is not competently enforced (Muzaffar et al., 2017a; Khan et al., 2018), the law was supported the declaration of all breeding islands of Socotra Cormorants as Important Bird and Biodiversity Areas (IBAs) (BirdLife International 2019). Additionally, several islands have restricted access or not open for the public (e.g., Ghagha, Yasat, Dinah, Bu Tinah, Rufayq) (Khan et al., 2018). Regionally, all range states of Socotra Cormorant, except Kuwait, Qatar and Oman are parties in the Convention on Migratory Species (CMS, 2022). CMS lists Socotra Cormorant in Appendix II. However, species listed in this appendix are not always included in legally binding agreements which happens to be the case for Socotra Cormorant. Despite Oman and Qatar being non-party in the CMS, they had joined the Convention on Biological Diversity. The CBD is a legally binding treaty and requires its members to conserve their marine biodiversity (CBD, 2022).

4.4 Limitations and Unresolved Questions

Species distribution models have some methodological constraints mainly for not integrating representative variables of the ecological interactions such as fishing exploitation and human disturbance (Cursach et al., 2019). As a result, its recommended for future modeling algorithms to develop techniques and procedures that allow researchers to include field data measurements about fishing and anthropogenic disturbance.

It is important to recognize that modeling marine species have significant challenges compared to terrestrial animals and stationary plants as the conditions of marine environment are constantly changing (Oppel et al., 2012). Consequently, data availabilities are affected as there are much less sources with calibrated, high-resolution, and continuous temporal coverage available for marine researchers. Further, SDMs for seabirds face an unresolved question regarding the best spatiotemporal scale to use for modeling. Several approaches were suggested for seabird distribution modeling and there is no preponderance for a certain approach over another. One approach collects occurrences over several years and use averaged environmental data (e.g., Cursach et al., 2019). Another similar approach pools presence data and averages the predictor variables on seasonal basis (e.g., Oppel et al., 2012). There is also the annual approach which as the word suggests model the seabird distribution separately for each year (Tuanmu et al., 2011).

Chapter 5

Chapter 5: Conclusion

Species distribution modeling is a significant tool for scientists and policy makers to forecast the potential future changes in habitat suitably and species ecological niche due to climate change (Pereira et al., 2010). In present, selecting marine protected areas can benefit from the information predicted by the modeling of multiple species distribution (Oppel et al., 2012). Likewise, the statistical tools for distribution modeling have been available for a considerable time now. Despite, the present study is one of only a few climate change evaluations conducted on a seabird in the Arabian Peninsula and maybe the middle east region. It is also the only study of such approach on the Socotra Cormorant, according to our knowledge. We recommend integrating the information provided in this study along with other species distribution data that may interest the public and stakeholders to designate marine reserves that are self-financed from ecotourism.

There is a need for baseline studies on the movement patterns of forage fish in the Arabian Gulf as its highly lacking. Understanding their movement will help scientists better understand the gaps in Socotra Cormorant breeding and nonbreeding distribution (Sabir, 2020). It will also facilitate the conservation of the marine hotspots they depend on. Conservation measures should be conducted regularly on the islands used by the bird. Equally important, framing protective transboundary policies across the known range of Socotra Cormorant.

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List of Publications

Naher, H., Al-Razi, H., Ahmed, T., Hasan, S., **Jaradat, A**., & Muzaffar, S. B. (2021). Estimated Density, Population Size and Distribution of the Endangered Western Hoolock Gibbon (*Hoolock hoolock*) in Forest Remnants in Bangladesh. *Diversity*, *13*(10), 490.

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Appendix

Table 5: Suitability area for *Phalacrocorax nigrogularis* in each region expressed in surface area. In appendix

Regions	Suitability area (km^2)							
	Unsuitable (<0.2)		Least suitable (0.2-0.4)		Moderately suitable (0.4-0.6)		Highly suitable (>0.6)	
	Current	Future	Current	Future	Current	Future	Current	Future
All	1980500	2172700	113300	24900	42000	6000	64100	1700
Arabian Gulf	156200	225600	27300	0	16400	0	24000	0
Gulf of Oman, Arabian Sea, Gulf of Aden	1488100	1524600	25500	4100	7800	800	8800	1600
Red Sea	336200	422500	60500	20800	17800	5200	31300	100

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This thesis is concerned with species distribution modeling of the Socotra Cormorant (*Phalacrocorax nigrogularis*), a regionally endemic seabird to the Arabian Gulf, the Arabian Sea, and the Gulf of Aden. The seabird is poorly studied, and large portions of its habitat are disturbed or degraded. The main objectives of this thesis are to predict the potential current and future marine distribution of the species and estimate the effect of climate change on its distribution. The thesis also aims to analyze the important environmental variables for the species distribution.

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