Impact of climate change on the status and distribution of Malabar Parakeet (*Psittacula columboides*), an endemic bird species of Western Ghats.

by

KEERTHANA M. J.

(2016-20-027)

THESIS

Submitted in partial fulfilment of the

requirements for the degree of

B.Sc. – M.Sc. (Integrated) Climate Change Adaptation

Faculty of Agriculture

Kerala Agricultural University

COLLEGE OF CLIMATE CHANGE AND ENVIRONMENTAL SCIENCE

VELLANIKKARA, THRISSUR – 680 656

KERALA, INDIA

2021

DECLARATION

I, Keerthana M. J, (2016-20-027) hereby declare that this thesis entitled "**Impact of climate change on the status and distribution of Malabar Parakeet (*Psittacula columboides*), an endemic bird species of Western Ghats"** is a bonafied record of research work done by me during the course of research and the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar titles, of any other University or Society.

Vellanikkara　　　　　　　　　　　　　　　　　　　Keerthana, M. J.

Date:　　　　　　　　　　　　　　　　　　　　　　(2016-20-027)

CERTIFICATE

Certified that this thesis entitled **"Impact of climate change on the status and distribution of Malabar Parakeet (*Psittacula columboides*), an endemic bird species of Western Ghats"** is a record of research work done independently by Ms. Keerthana M. J., under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, fellowship or associateship to her.

Vellanikkara

Date:

Dr. P. O. Nameer

Dean

College of Climate Change and environment Science,

Kerala Agricultural University

Vellanikkara, Thrissur

CERTIFICATE

We, the undersigned members of the advisory committee of Ms. Keerthana, M. J., a candidate for the degree of B. Sc. – M. Sc. (Integrated) Climate Change Adaptation, agree that the thesis entitled **"Impact of climate change on the status and distribution of Malabar Parakeet (*Psittacula columboides*), an endemic bird species of Western Ghats"** may be submitted by Ms. Keerthana, M. J., (2016-20-027) in partial fulfilment of the requirements for the degree.

Dr. P. O. Nameer
(Chairman, Advisory Committee)
Dean
College of Climate Change and
Environment Science
Kerala Agricultural University
Vellanikkara, Thrissur - 680656

Dr. B. Ajithkumar
Assistant Professor and Head
Department of Agricultural Meteorology
College of Agriculture
Kerala Agricultural University
Vellanikkara, Thrissur - 680656

Dr. M. Shaji
Assistant Professor
Department of Wildlife Science
College of Forestry
Kerala Agricultural University
Vellanikkara, Thrissur - 680656

Dr. M. Krishnadas
Assistant Professor (Agrl. Economics)
Department of Supportive and Allied Courses
College of Forestry
Kerala Agricultural University
Vellanikkara, Thrissur - 680656

(EXTERNAL EXAMINER)

ACKNOWLEDGEMENT

I gave my glory, honour and praises to my **LIVING GOD** who is my supreme guide and beloved, friend for his favour, guidance, strength and health he provided for me to successfully complete this research work.

First and foremost, I extend my deepest sense of gratitude and obligation to the chairman of my advisory committee, **Dr. P. O. Nameer**, Dean, College of Climate Change and Environmental Science, Kerala Agricultural University, Vellanikkara for his valuable assistance and ever motivational spirit all through my course period. It was absolute privilege and great opportunity to be working under his able guidance.

I express my sincere thanks to **Dr. B. Ajithkumar**, Assistant Professor and Head, Department of Agricultural Meteorology, College of Agriculture, Kerala Agricultural University, Vellanikkara, Thrissur, **Dr. M. Shaji**, Assistant Professor, Departmet of Wildlife Science, College of Forestry, Kerala Agricultural University, Vellanikkara, Thrissur and **Dr. M. Krishnadas**, Assistant Professor (Agrl. Economics), Department of Supportive and Allied Courses, College of Forestry, Kerala Agricultural University, Vellanikkara, Thrissur, who were the able members of my advisory committee for their timely cooperation and valuable support extended during the period of my M.Sc. project work.

I profess my heartfelt gratefulness and sincere regard to **Mr. Sreekumar E R**, Ph.D. scholar, College of Forestry, Kerala Agricultural University, Vellanikkara, for the incomparable support he extended to ensure the completion of my M.Sc. project in time. His indefatigable effort and patient attitude were a deep sense of relief to me at peak points of my project for which I am boundlessly thankful to him.

I would also like to extend my thanks to **Dr. Ashish Jha**, Faculty at College of Climate Change and Environmental Science, for helping me with his valuable suggestions and encouragement that improved the results.

I especially thank the e-Bird community for giving the data regarding the avian species on time, which boosted up my work. Without them I couldn’t finish this work on time.

I respectfully extend my huge, warm thanks to everyone at **College of Climate Change and Environmental Science**, teaching and non – teaching staves who at some point of my project period had played crucial roles.

My heartfelt thanks to my batchmates, **Campeones – 2016** for their support given to me during the whole college days.

I would also like to thank my beloved seniors, especially **Mr. Sanjo V. Jose, Mrs. Athulya D Nair** for the critical roles they played in helping me progress with my project.

I am indebted to my **parents, younger brother, grandparents and extended family** for all the moral encouragement and support they have showered on me through. No endeavor in my life would be complete without their blessings alongside the blessings of almighty, for which I am incredibly thankful.

Keerthana, M. J.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SYMBOLS AND ABBREVIATIONS

$\lvert r \rvert$	Pearson correlation matrix
R^2	Coefficient of Determination
AKN	Avian Knowledge Network
alt	Altitude
AR5	Assessment Report 5
AUC	Area Under Curve
BCC CSM 1.1	Beijing Climate Centre Climate System Model 1.1
bio 1	Annual mean temperature
bio 10	Mean temperature of warmest quarter
bio 11	Mean temperature of the coldest quarter
bio 12	Annual precipitation
bio 13	Precipitation of wettest month
bio 14	Precipitation of driest month
bio 15	Precipitation seasonality
bio 16	Precipitation of wettest quarter
bio 17	Precipitation of driest quarter

bio 18	Precipitation of warmest quarter
bio 19	Precipitation of coldest quarter
bio 2	Mean diurnal range
bio 3	Isothermality
bio 4	Temperature seasonality
bio 5	Maximum temperature of the warmest month
bio 6	Minimum temperature of the coldest month
bio 7	Temperature annual range
bio 8	Mean temperature of wettest quarter
bio 9	Mean temperature of driest quarter
BRT	Boosted Regression Trees
CHELSA	Climatologies at high resolution for the earth's land surface regions
DK - GARP	Desktop Genetic Algorithm for Rule – set Prediction
EEA	European Environment Agency

EVI	Enhanced Vegetation Index
GAM	Generalized Additive Models
GARP	Genetic Algorithm for rule – set Prediction
GCMs	General Circulation Model
GCMs	Global Circulation Models
GDM	Generalized Dissimilarity Models
GIS	Geographic Information System
GLM	Generalized Linear Model
HadGEM2 – ES	Hadley Centre Global Environmental Model 2 – Earth System
IPCC	Intergovernmental Panel on Climate Change
MARS	Multivariate Adaptive Regression Splines
MARS-COMM	Multivariate Adaptive Regression Splines-Community data
MaxEnt	Maximum Entropy Modelling
MIROC5	Model for Interdisciplinary Research on Climate Version 5
MM5	Mesoscale Model version 5
OM-GARP	Open-Modeller Genetic Algorithm for Rule-set Prediction

RAMS	Regional Atmospheric Modelling System
RCPs	Representative Concentration Pathways
ROC	Receiver Operating Characteristic Curve
SD	Standard Deviation

CHAPTER 1

INTRODUCTION

Climate change is strengthening its grip on our planet as each day goes by. The direct consequence of climate change varies among different regions, with expected increase in temperature to region – specific changes in precipitation patterns. The effects that the climate change produces are different for different biomes and their respective organisms(Scheffers et al., 2016). Some regions of the world will experience its impacts at the earliest and some regions will experience much slower but at higher severity(Barnett et al., 2005). There are two major causes of climate change. One is natural which is a slow process and takes millions of years to occur and the other one is the outcome of human induced emissions of greenhouse gases and results in large – scale shifts in weather patterns(Oswald & Arnold, 2012). These greenhouse gases can cause a considerable increase in earth's global average temperature and can trigger a chain reaction which in turn aggravate other problems like loss of biodiversity and ecosystem services, water scarcity, floods and droughts, desertification and land degradation and intensified biogeochemical cycle(L. El Zein, 2015). Mitigation and adaptation are the only mechanism through which human kind and other organisms can combat the deleterious effects of climate change.

Intergovernmental Panel on Climate Change (IPCC) points out that anthropogenic activities had caused the global temperature to increase by 0.8°C to 1°C. Even though this seems to be a small number, this puts various organisms under different levels of threats. Some organisms will be able to withstand the threats while others perish. The organisms that stand the threats are the ones who can adapt to the fast changes occurring to their habitat and environment. But the extinction of one organism can have an overall impact on an entire ecosystem and survival of the dependent species as organisms are connected by food webs and other biological interactions. Predicting the impact of climate change on organism is a complex process and it should cover the aspects of ecology, physiology and evolution(Rosenzweig et al., 2008).

But the fact that climate change interact with others stressors of biodiversity like human activities will worsen the problem of biodiversity loss. Apart from that, climate change can induce novel stressors like more frequent forest fires, additional prevalence of pathogens, pest diseases etc. While it is important for all ecosystems of the biosphere to adapt to the changes of climate system, ecosystems confined only to specific geographical areas are at higher chances of facing extinction than those found extensively. Hence constant monitoring of our biodiversity and increased studies on climate change impacts has to be emphasized to prevent further degradation of our ecosystem before things go out of our hands.

Most of organisms have a threshold up to which they can tolerate the stresses. If the tolerance level reaches, the organisms will opt for other mechanisms like migration to sustain their life functions. The common feedback found in most locomotive organisms to survive the negative impacts of climate change is to shift their ranges. But the problem with this range shifting is that it will cause interspecific competitive interaction among the inhabitants and immigrants for food, space and other essentials for survival. This overlapping ranges bought about as a result of climate can decrease the range and survival capacity of species already found in the region.

Like many organisms who shift their ranges, birds are also one among them. Birds are considered to be the bioindicators of climate change as they are sensitive organisms and are easy to monitor. Moreover, there is long term datasets available that can be used to explore how climate change have affected birds in the past and develop predictions as to how it might affect birds in the future. As global temperature rises, birds will tract their thermal niches towards higher latitudes and higher elevations where the environment is favorable for their growth and reproduction. The dilemma of climate change will have more impacts on species confined to certain area or region which are otherwise known as endemic species as these species are adapted to a particular niche and their highly specific requirement for climatic and edaphic factors.

The Western Ghats are one of the ancient mountain ranges in India that has spectacular assemblage of biodiversity. It is home for many plants and animals showing high degree of endemism. Studies have demonstrated the changes in climate in western ghats during recent years, which led to the species distributional range, especially causing migration changes in avian species.

The Malabar Parakeet *Psittacula columboides* is one of the 25 endemic species of western ghats. Their presence is noted from north Maharashtra to south Kerala, chiefly between 500 and 1500 m. Although being a common endemic species, it is poorly studied.

A useful tool in ecology and conservation biology is species distribution modelling (SDM). These are predictive models that assist in understanding the changes in distribution of species with respect to environment. These models have been utilized in various studies including studies related to climate change. MaxEnt or maximum entropy modelling is one of them which have been widely employed in climate change related studies in the recent years. The advantage of SDM is that they use presence data for modelling and do not require absence data. Presence only modeling methods requires only a set of known occurrence points together with some predictor variables. These models are used to predict changes in distribution that would happen in the future by incorporating the climate model data.

In this project we are trying to model the variations in distributional changes that happens to Malabar parakeet using appropriate modelling techniques. The hypothesis we intend to put in our study is that, the distributional changes of Malabar parakeet is due to the changes happening in the climate of western ghats. Even though, there are observational evidences of range shifts by these species, this study will assist to furnish a scientific explanation for the same.

The primary objective of the study is to evaluate the probable distribution of Malabar parakeet, an endemic bird of western ghats in response to changes in response to the future climate projections and figure out the possible reasons of the distributional patterns if any. Utilizing the current climate data, ecological niche model can be produced for Malabar parakeet. This can be laid down as a foundation to project the regional shifts in distributional pattern of Malabar parakeet in changing future climatic conditions under different scenarios using modelling techniques.

This methodology can be incorporated in studies involving species that are changing their distribution as a result of various stressors. These studies have better advantage over statistical data analysis which provide quantitative changes which may not be ecologically significant. Modelling techniques provide an overall insight of physical changes happening in our environment, a way in which we can monitor the species' distributional changes. This model also provides future distributional changes of other significant species also. This study can reflect the impact of climate change on geographic distribution of Malabar parakeet.

CHAPTER 2

REVIEW OF LITERATURE

2.1 MALABAR PARAKEET

The Malabar parakeet is one of the Western Ghats' 25 endemic bird species, with sightings documented from northern Maharashtra to southern Kerala. These species are understudied despite being a well-known endemic (Gaston and Zacharias, 1996). Their presence has been documented between 500 and 1500 metres in the Western Ghats (Ali and Ripley, 1987). These species have been observed mating in December, and they prefer to reproduce during the dry season when the north-east monsoon is present. Nest in a hole in a tree 6–30 metres above ground (high trees preferred), with ironwood (Mesua ferrea) and Grewia tiliifolia being especially popular. The last two weeks of December and the first two weeks of January had the most egg laying. The female lays approximately four to five eggs at a time, with the offspring hatching after 23 days. The species' primary sources of nutrition are grain, seeds and fruits especially of figs (*Ficus*), also buds, petals and nectar, notably *Erythrina* and *Grevillea* plants. They are also crop pest on *Sorghum*, other cereals, vetches *Dolichos* and orchard fruit.

2.2 CLIMATE CHANGE AND SPECIES INTERACTIONS AND DISTRIBUTION

Earth's biota is having a significant impact due to anthropogenic climate change. Recent and abrupt changes in abundance and terrestrial distribution are perhaps the most visible indicators of climate change's consequences (Poloczanska *et al*., 2013; Chen *et al*., 2011). Changes of such nature will have cascading effects. Some species with importance conservation concerns will be exposed to extirpation (Cahill *et al*., 2013). There are also chances that, species that can become menace to both ecological integrity and human health spreading to other places where there were absent earlier (Altizer *et al*., 2013). The reaction of species to climate change might be direct or indirect. Physiological acclimation and phenotypic plasticity (Vedder *et al*., 2013; Anderson *et al*., 2012), evolutionary changes in species – environment relationships (Rubidge *et al*., 2011), and interaction among different limiting resources can complicate the direct responses to climate change (Keenan *et al*., 2011). The indirect impacts of climate change occur through interspecific interactions which includes interaction with competitors, consumers, mutualists and facilitators. Evidences from research in terrestrial, freshwater and marine ecosystems suggests that such interspecific interactions can potentially counteract and even erase climate change's direct consequences. Range shifts in species are found to be a common ecological response to climate change. Many taxa in the Northern Hemisphere have a persistent trend of range expansion and altitudinal excursions northward or westward, according to data. (Parmesan et al., 1999; Thomas et al., 2001; Walther et al., 2002; Walther, 2010). Another feedback produced as a result of rising global temperature is the advancement of phenology earlier in spring (Root et al., 2003; Edwards and Richardson, 2004; Parmesan, 2006). In aquatic systems, warming also causes an overall decrease in body size. (Daufresne et al., 2009; Moran et al., 2010). The notion that variables other than climate such as, limited dispersal, long generation times and adaptations influence the large variability in the magnitude and direction of range shift in species. As far as birds are concerned, factors affecting bird dispersion included summer weather, food availability, and habitat distribution and quality. Trends in uniform agricultural land related with crop loss, margin and hedge foraging habitat, and nest sites all had an impact on bird population. Variables in climate such as number of cold days, the length of winter frost and snow periods, summer droughts and spring temperature all had an impact on bird population trends, resulting in varying population trends over time.

2.3 CLIMATE CHANGE AND ENDEMIC SPECIES

Climate change poses threat to all forms of life on Earth. But endangered species with a small range may be particularly susceptible (Thomas et al., 2004). Any changes in climatic variables could have a negative impact on species with limited acceptable habitats, such as range – restricted species. The adaptation potential of the species would determine its survival under the effect of climate change. Species may shift to suitable habitat to meet their climatic niche if the climate change exceeds their adaptive ability, or they may suffer extinction (Singh et al.,2020). Several biomes with the greatest number of endemic species are particularly vulnerable to global warming, and under some climate change scenarios, they will face the greatest decrease in area or even disappear entirely (Enquist, 2002). In comparison with non – endemic taxa, endemic taxa have emerged at various stages along the evolutionary timeline. There are many evidences suggesting that many endemic taxa are under selection pressure due to climate change (Chen, 2016). For example, six of the endemic birds found in the humid mountain forests known as the Yungas are globally endangered (Stattersfield et al., 1998). The percentage of endemic birds is found to be largest at the higher elevations (Ibisch and Merida, 2003). A rise in temperature has the potential to cause tropical species in mountains to shift their distribution upslope (Buermann et al., 2011; La Sorte and Jetz, 2010). They may reduce their range size in quest of colder regions, resulting in population losses (Shoo et al., 2005; Harris et al., 2014). Due to range reductions, most species with narrow range sizes may be extremely vulnerable to climate change. The internationally imperiled may be one of the most vulnerable species to climate change. C. henricae for example is an endemic bird in Andes having small range size that could be drastically reduced in the future, even under full dispersal scenarios (Avalos and Hernandez, 2015). Birds with limited ranges (endemics) and minimal mobility, such as ground birds, are said to be particularly vulnerable to climatic changes and disturbances in mountainous areas (Sekercioglu et al., 2012). Evidences from studies of Hoffmann et al (2020) have discovered a pattern of reduced area and altitudinal displacement for endemic mountain top birds in eastern Brazil for climate change scenarios studied, which is comparable to that expected for bird species in higher mountain ranges in temperate and tropical countries, such as Andes. Studies under various climate change scenarios by Vieira de Souza et al. (2011) predicted a 45 percent loss in the average area of 44 endemic Atlantic Forest bird species. Even if the reasons that causes the loss of natural habitats are managed in the future, climate change is anticipated to result in a decline of 72 to 94 percent in the existing area appropriate for the occurrence of at least one endemic species.

2.4 CLIMATE CHANGE IMPACT ON BIRDS

2.4.1 Birds - the bio indicators of climate change

The most significant impact of recent climatic change is changing air temperatures at the ocean and land surface (Trenberth et al., 2007), which is principal drivers of biotic interactions (Parmesan and Yohe, 2003; Walther et al., 2005; Hansen et al., 2006; Portner and Farrell, 2008). Changes in phenology, demography, distribution and individual behaviour can all be observed across species (Walther et al., 2002; Parmesan, 2006). Anthropogenic activities, according to Willis and Bhagwat (2009), were modifying ecological systems globally, changing the global temperature, and decreasing and fragmenting habitats. Birds were well known indicators of climate change having advantages of best-known class of organisms in climate research (Wormworth and Sekercioglu, 2011). Because birds are popular and have a recognisable and iconic position around the world, they have the potential to be considered key bio-indicators that are easily understood by the public and policymakers (Crick, 2004).

Birdwatchers from all over the world contribute to a large database making the study of birds much more effortless.

2.4.2 Bird physiology and climate change

The weather has an impact on bird metabolism both directly and indirectly, which has modified bird behavior during their evolution. Important behaviors like feeding and nesting are diminished when birds avoid regions with unfavorable conditions (Walsberg, 1993). According to Crick (2004), the success of breeding is dependent on the synthesis of numerous hormones, which might change according on the weather. Variations in temperature and humidity have an indirect impact on bird activity and behaviour. Climate change had already had a measurable continent-wide impact, according to Gregory et al. (2009), with both negative and positive consequences at the level of large species assemblages. Nonetheless, there have been studies that suggest the physiological reactions of birds to climate changes play a major effect (McKechnie, 2008; McNab, 2009).

2.4.3 Responses of birds towards climate change

The species' responses to climate change were generally three-fold: movement (if the species are mobile, it will seek for suitable niches in the environment.), adaptation (if the species has high physiological tolerances and can adapt to changing environments), and extirpation (when neither movement nor adaptation work) (Holt, 1990; Melillo et al., 1995). Aside from climatic variables, changes in land use and habitat, biotic interactions, and evolutionary adaptability all had a role in species dispersion (Huntley et al., 2006; La Sorte and Thompson, 2007; Beale et al., 2008). According to Thomas (2010), climate is one of the key factors of range boundaries. Climate change has an indirect impact on endothermic birds because of its effects on vegetation in their groups rather than direct effects on physiology (Aragon et al., 2010a). Chen et al. (2011) claimed that climate change was responsible for the majority of the shifts in distribution, and he provided evidence of several species shifting their ranges towards the pole and upwards.

2.4.4 Distributional range of birds and climate change

According to the previous studies, the shift in distributional range in many places appeared to reflect changing temperatures, and the relationship between temperature and precipitation also had a key effect in range distributions (Hawkins et al., 2003). A temporal distributional analysis might be conducted to determine how much change has occurred in these interactions over the course of the century (Hawkins et al., 2003). A study that took a different approach by looking at the community index rather than species range borders found that while the northward shift in breeding bird assemblage in France was significant, it was not a quick response to the country's climatic warming (Devictor et al., 2008). Climate change has previously been related to changes in bird distribution (Gregory et al., 2009; Niven et al., 2009; Chen et al., 2011). Predicted changes in range extent and variations in population trend were shown to have a substantial relationship, with those bird species whose ranges were expanding showing an increase in population size and vice versa (Gregory et al., 2009). The breeding bird's distribution throughout the Western Italian Alps showed a non-significant upward movement (Popy et al., 2010). Although not much significant distributional change was observed across the entire bird community, scientists predicted using models based on current distribution and climatic variables that the distribution of a single bird species would be substantially rearranged as a result of predicted climate warming (Virkkala et al., 2010). Range loss was reported in some species at higher latitudes and altitudes due to a lack of habitat, according to Reif et al. (2010). Tropical bird species have become increasingly recognised as being among the most susceptible to climate change (La Sorte and Jetz, 2010; Harris et al., 2011; Sodhi et al., 2011; Wormworth and Sekercioglu, 2011). Bradbury et al. (2011) discovered that *Sylvia undata* extended its range uphill and northward in the UK between 1974 and 2006. The distributional range extension of the Dartford Warbler (Sylvia undata) in the UK during the 1960s has been attributed to the lack of harsh winters, according to Gibbons and Wotton (1996). The effects of climatic change on species distribution were significant because they influenced bird demographic rates (Pautasso, 2012).

2.4.5 Range distribution studies and its significance

For a better understanding of the ecological and evolutionary causes of varied spatial patterns of biodiversity, a broad study of species ecological and geographic distribution was required (Rosenzweg, 1995; Ricklefs, 2004; Graham et al., 2006). Such studies are also vital for conservation forecasts and planning (Ferrier, 2002b; Funk and Richardson, 2002; Rushton et al., 2004). Climate change indicators were still in the early stages of development, and scientists and policymakers were eager to learn more about the biological effects of climate change and how to apply adaptive and mitigation strategies (Mace and Baillie, 2007; GA, 2007).

2.5 MODELLING OF SPECIES DISTRIBUTION

2.5.1 Species distribution modelling and its importance

The spatial configuration and characteristics of habitats that allowed for species continuity in landscapes (Araujo and Williams, 2000; Ferrier et al., 2002b; Scotts and Drielsma; 2003), species distribution in the past (Hugall et al., 2002; Peterson et al., 2004), predictions of species distribution in future climatic conditions (Bakkenes et al., 2002; Skov and Svenning, 2004; Araujo et al., 2004; Thomas et al., 2004; Thuiller et al., 2005), and association between environmental parameters and species richness were investigated using species distribution models (Mac Nally and Fleishman, 2004). Root (1988a, 1988b) and Root and Schneider (1993) discovered a high statistical link between the distribution and abundance of 148 wintering land birds and six environmental variables, most notably climatic variables. Gates et al. (1994) used multivariate regression equations to model the distribution of species in the United Kingdom, with reference to land use and climatic variables, and the results revealed that the climate had a strong relationship with bird distribution, and that redistributions were occurring in response to predicted climate warming. They defined the spatial distribution using climate envelops, and such predictions were to be validated against the actual distribution pattern for changes in distribution data. Additional aspects like as biotic interactions, geographic boundaries, and history were not taken into account, implying that species would only be found in favourable settings on rare occasions (Anderson et al., 2002; Svenning and Skov, 2004; Araujo and Pearson, 2005).

The environmental data was based on the known distributional information of species, parameters were identified, allowing for the identification of geographical locations with similar environmental conditions and the modelling of species dispersion (Pearson and Dawson, 2003). Bio-geographical analysis techniques have been used to investigate the distribution of species abiotic niches in connection to environmental variables at the observed locations (Guisan and Thuiller, 2005). The only method to test the hypotheses or scenarios foretelling the future was to watch the real world develop, and to get around this problem, we could use prior environmental changes to see if species and ecosystems responded in the same way that the models anticipated d (Araujo et al., 2005). Species distribution models attempt to predict the distribution of species based on the presence or abundance of species in relation to environmental factors. These models were frequently utilised to investigate various ecological, evolutionary, and conservation reasons (Elith et al., 2006).

Conservationists used distribution models to estimate the most favourable locations for a species and to forecast the likelihood of occurrence in places where systematic surveys had not been conducted (Elith, 2002). The use of predictive modelling was utilised to investigate changing distributions. If the range of a species was correctly mapped, environmental variables such as climate could be linked to its presence or absence (Crick, 2004). These models could also forecast future species distributions in the face of a variety of climate change scenarios (Jeschke and Strayer, 2008; Sinclair et al., 2010), introduced species' potential spread in freshly colonised areas (Jimenez-Valverde et al., 2011; Jeschke and Strayer, 2008) and could be put to good use while putting together a reserve plan (Thorn et al., 2009). The analysis of these shifts in bird distribution was critical for managing protected area networks and ensuring the conservation of endangered bird species (Aragón et al., 2010b; Araújo et al., 2011). Current protected areas will become obsolete as a result of the alterations in distribution, necessitating the management of the entire landscape for biodiversity protection (Pautasso et al., 2011).

2.5.2. Process of species distribution modelling

2.5.2.1 Steps in species distribution modelling

Several procedures were taken to predict the distribution of species: (1) current data on species in the form of occurrence points (Peterson et al., 1998; Peterson and Stockwell, 2001); (2) models of ecological niches are created and tested using distributional data (Guisan and Zimmerman, 2000; Kobler and Adamic, 2000); (3) the shift in distribution is projected onto the landscape of interest using general circulation models of climate change; (4) ecological niche models of specific species are projected onto changed landscapes to model distributional alterations. Environmental space models can predict the appropriate ecological niche by analysing species responses to abiotic environmental elements (Soberon and Peterson, 2005) and using this information to infer the probability of species presence in any given area or track the precise environmental conditions that fit the species (Elith et al., 2011).

2.5.2.2 Methods of testing accuracy

There were numerous approaches for modelling species distribution that differed in the steps of the modelling process; choosing the most appropriate predictor variables, create functions for each variable, contributions of variables are weighted, the connections between predictors and species, as well as the prediction of occurrence patterns across geographic boundaries (Guisan and Zimmerman, 2000; Burgman et al., 2005; Wintle and Bardos, 2006). Individual algorithms make up the numerous rules in the models, and it was based on them that the landscapes within and outside the biological niche were recognised (Peterson, 2001a). Hierarchical portioning could be used to evaluate alternative models and investigate the weight of evidence for various components contained in the model (Mac Nally, 2002). Concerns about the accuracy of future species distribution predictions under various climatic circumstances were addressed by putting climatic envelope models to the test (Akcakaya et al., 2006; Pearson et al., 2006; Araujo and 13 Rahbek, 2006; Zimmer, 2007). The degree of environmental dimensions that defined the species distributional limitations determined the accuracy of model descriptions about the range of conditions suited for a species (Pearson et al., 2007). Because of autocorrelation among the variables, models were developed mostly on correlations between variables and distribution patterns, which could not identify the causal relationship (Bahn and McGill, 2007; Currie, 2007; Beale et al., 2008), however, because all of the models used the same data source, this strategy was constrained. Large geographical areas were evaluated to prevent misinterpretation of species dispersion responses, and thus the connection of environmental variables with climatic variables was reduced (Maclean et al., 2008). It was used to resolve ambiguities produced by correlated predictors, but it was unable to detect false correlations among the environmental components that were used to determine spatial distribution (Ashcroft et al., 2011). Generalized linear mixed models were used to increase the accuracy of species distribution range forecasts (Swanson et al., 2013).

2.5.3 Advancements in species distribution modelling

Climate has a major impact on species distribution on land, and niche modelling was developed on this concept. Even while the prediction power of models has improved, understanding the principles that underpin them has been difficult (Shipley, 1999). Although there were fewer studies comparing the modelling of future distribution shifts to previous distribution shifts, the climate envelope approach was widely employed to tackle this issue (Berry et al., 2002; Thomas et al., 2004; Harrison et al., 2006). The use of ecological niche modelling for predicting species distribution from environmental data was complimented (Pearson and Dawson, 2003). Advances in research and technology led to the development of complicated mathematical general circulation models (GCMs), which influenced global climate and forecasted future climate by combining multiple greenhouse gas emission scenarios (Raper and Giorgi, 2005). The lack of data on species-specific physiological characteristics and processes, as well as the link between climatic and non-climatic factors, remained an issue (Kearney, 2006). The models were used to estimate the current distribution of bird species based on current climate data, and they may also be used to predict future distributions based on projected future climatic parameters (Huntley et al., 2006). Predictive models based on the relationship between climate and vertebrate distribution, with a focus on birds, have been constructed (Jetz et al., 2007).

2.5.4. Species distribution studies

Environmental variables such as climatic conditions could be used to explain animal species richness and dispersion patterns s (Kerr, 2001; Ricklefs, 2004; Ceballos and Ehrlich, 2006; Mittelbach, 2010). Using climatic data, a number of studies have been successful in predicting species distribution (Pearson et al., 2002; Bakkenes et al., 2002; Burns et al., 2003; Thuiller et al., 2005; Calef et al., 2005; Rehfeldt et al., 2006; Hamann and Wang, 2006; McKenney et al., 2007; Peterson et al., 2008; Stankowski and Parker, 2010; Joyner et al., 2010; Beever et al., 2010). Since both used the same climate-space, it was anticipated in studies of future distribution predictions that changes in species ranges occurring under warmer conditions would be mirrored by changes in the colder extremities (Berry et al., 2002; Thomas et al., 2004; Harrison et al., 2006). There have been studies that suggest that species will become extinct in the next century (Peterson et al., 2002; Bakkenes et al., 2002; Thomas et al., 2004; Thuiller et al., 2005; Malcom et al., 2006), as well as the re-distribution of species' ranges (Iverson and Prasad, 1998; Pearson et al., 2002; Burns et al., 2003; Calef et al., 2005; Rehfeldt et al., 2006; Hamann and wang, 2006; McKenney et al., 2007; Peterson et al., 2008). As a result of the detrimental effects of climate change on biodiversity, a number of analytical tools have been developed to correlate quantifiable environmental variables with known species locations (Heikkinen et al., 2006; Elith et al., 2006; Guisan et al., 2007; Loiselle et al., 2008; Graham et al., 2008; Feeley and Silman, 2010; Beever et al., 2010). Range shifts or range extension could cause changes in distribution, and the impact of temperature dependence has been investigated (Maclean et al., 2008). Environmental variables had been used to predict species richness at various levels (Coops et al., 2009; Hinsley et al., 2009; Hansen et al., 2011; BarMassada et al., 2012; Fitterer et al., 2012). Temperature factors were shown to be substantially connected with forest bird richness, while precipitation variables were found to be strongly correlated with open woodland bird richness (Goetz et al., 2014).

2.6. DATA USED FOR MODELLING

2.6.1. Type of data and model performance

The presence only models failed to get a general test of model accuracy when using withheld data for predicting species distribution due to biases in the geographic and environmental space (Bojorquez et al., 1995, Hijmans et al., 2000; Soberon et al., 2000; Kadmon et al., 2004). It was possible to assess the model's performance by introducing false data and comparing the accuracy of projected responses, or by modelling both presence and absence data and comparing fitted functions (Austin et al., 1995). When independent data was not utilised to develop the model, which was referred to as "test" data, and just "training" data was used to build the model, it had a higher prediction success rate (Fielding and Bell, 1997). For model performance testing, a variety of test statistics or discrimination indexes were used (Fielding and Bell, 1997; Pearce and Ferrier, 2000). By splitting the data set, k-fold partitioning, or bootstrapping, the predictive performance of the models was more concentrated in the evaluation step, and some known occurrences were withheld (just presence data) from the model construction (Fielding and Bell, 1997; Hastie et al., 2001; Araujo et al., 2005).

The accuracy of the forecast was evaluated based on the correctness of the withheld data (Boyce et al., 2002; Hirzel and Guisan, 2002b). The generally used indices, such as Kappa and the area under the receiver operating characteristic curve (AUC), were not suited for evaluating poorly sampled regions (Boyce et al., 2002; Phillips et al., 2006). Because the model was statistically equivalent to a random prediction, predicting a higher proportion of test localities (low omission rate) while not predicting a big proportion of study area would produce relevant predictions. When data portioning was done for testing, the Chi-square test or upper-tailed binomial probability was utilised to examine the statistical significance of the model (Anderson et al., 2002). The anticipated model's performance was based on the available absence data (Loiselle et al., 2003). A 2-2 confusion matrix could be used to describe the frequency of correctly and wrongly predicting absences and presences, and tests were limited to presence-only models that did not require absence data (Anderson et al., 2003).

It was advised that absence data (which may occur owing to non-inclusion of data in the model) not be included since false-positive predictions would be judged as failures when possible appropriate habitat was predicted (Anderson et al., 2003; Pearson and Dawson, 2003; Sobero´n and Peterson, 2005). The most frequent and straightforward method was to use a random or regionally stratified partition (Peterson and Shaw, 2003), however the data was too tiny to partition into test and training data sets, and negative data was troublesome (Anderson and Martinez-Meyer, 2004). When some investigations were conducted with small samples, predictive performance was reduced (Stockwell and Peterson, 2002; Reese et al., 2005). Given the widespread usage of distribution models and the progress of data availability and modelling methodologies, large synthetic studies of high prediction capacity and accuracy of species distribution modelling methods for presence only data were urgently needed (Elith et al., 2006). The validation of the model was improved by using an independent, well-structured presence-absence dataset (Elith et al., 2006).

Many methods capable of capturing complicated answers have been developed as a result of advancements in machine learning and statistical disciplines, even when the data was quite noisy. Despite the fact that the study seemed promising, it did not acquire any attention in distribution modelling (Phillips et al., 2006, Leathwick et al., 2006). Resampling designs had biases in the spatial and environmental space as well (Elith et al., 2006). When there were few observed locale records available, the jackknife approach might be employed to measure predicting abilities. The Jackknife ('leave-one-out') approach performed well in evaluating models with a modest number of occurrences. The model was built using the remaining n-1 localities after excluding each observed locality (n) once. The predictability of the model was measured by building 'n' different models, and the model's ability to predict a single locale from the training data (Pearson et al., 2007). Because absence data was infrequently accessible and difficult to detect in surveys, the modelling methodologies and validation relied only on presence data (Pearson et al., 2007). Algar et al., (2009) found that temporal prediction was quite accurate, but that spatial autocorrelation may be used to eliminate biases using regression models.

2.6.2. Presence and absence records

The development of distribution modelling research had previously concentrated on the production of models based on presence/absence or abundance data, with systematic sampling methods utilised in the study areas (Austin and Cunningham, 1981; Hirzel and Guisan, 2002b; Cawsey et al., 2002). Previously, presence-only data were analysed using envelope calculations or distance-based measures designed particularly for that purpose (Silverman, 1986; Busby, 1991; Walker and Cocks, 1991; Carpenter et al., 1993). Breeding environments were expected to be saturated in most presence/absence models (Capen et al., 1986). As several methods in the species distribution modelling indicated, only presence data were evaluated (Nix, 1986; Carpenter et al., 1993).

When utilising presence/absence models, there was a risk of two sorts of errors: false positives and false negatives (Fielding and Bell, 1997). Adaptation to model presence-only data from presence-absence approaches (which employed a binomial response for modelling) employing background environment samples (data created by selecting random locations over the research area) or 'non-use' or 'pseudo absence' area were used later on (Stockwell and Peters, 1999; Boyce et al., 2002; Ferrier et al., 2002b; Zaniewski et al., 2002; Keating and Cherry, 2004; Pearce and Boyce, 2006). Due to low sampling or missing species occurrences during surveys, absence data were rarely available, so some techniques used background data for the entire research area (Hirzel et al., 2002b) or used pseudoabsences instead of true absence data (Ferrier et al., 2002a; Engler et al., 2004).

Species occurrence data was widely available and easier to obtain, as it was available as high-resolution environment data layers developed using satellite imagery (Turner et al., 2003) and through very sophisticated climate data (Thornton et al., 1997; Hijmans et al., 2005). Even if there was a chance for a species to be spotted at a site, it was difficult to corroborate the absence data because there was no wildlife-habitat correlation (MacKenzie et al., 2004; Gu and Swihart, 2004).

Modeling ecological niches was done using a variety of methodologies, the majority of which included both presence and absence records (Bourg et al., 2005). Predictions from each approach differed significantly, emphasising the importance of method selection and cross-validation of results from diverse methods (Thuiller et al., 2004; Pearson et al., 2006). The majority of the species occurrence data had been acquired without any defined sampling methods, and a large amount of these data came from presence-only records from museum or herbarium collections that were electronically available (Graham et al., 2004; Huettmann 2005; Soberon and Peterson, 2005). There were currently ways that employed the presence information of other community members to supplement the data regarding the modelled species, and this strategy was promising for rare species because the wider community information assisted in revealing the modelled relationships (Elith et al., 2006). The problem with this type of presence data was that the goal and methods used to collect it were rarely known, and we couldn't extrapolate the absence data with accuracy (Elith et al., 2006). Over the last decade, new approaches have emerged that rely just on presence data, eliminating the need for absence locations (Baldwin, 2009).

2.7. ASSESMENT OF CLIMATE CHANGE

Regional models were more useful for determining local climate change than global models that relied on global forcings (Pitman et al., 2000). These models could depict changes in land use and how they affect cloud production mechanisms. However, not all regions had access to the results of these models. Dynamic vegetation models, forest gap models, biome envelope models, and species envelope models all used GCM and regional climate models to shed light on different elements of future climate change biogeography (Cramer et al., 2000).

Global climate models, regional climate models, dynamic and equilibrium vegetation models, species bioclimatic envelope models, and site-specific sensitivity analysis were utilised to estimate the impact of climate change on biodiversity (Sulzman et al.,1995). Equilibrium simulations using a step increase in CO2 revealed rising temperatures in both hemispheres, but transient simulations revealed both ups and downs in the temperature distribution (Sulzman et al., 1995). Regional models could be used in conjunction with the more detailed Global Circulation Models (GCMs) to produce more resolution. The two major regional models that were commonly utilised were MM5 (Mesoscale Model version 5) and RAMS (Regional Atmospheric Modelling System) (Sulzman et al., 1995). Because the climate dynamics of the southern and northern hemispheres differed, models designed with a major focus on one hemisphere would not produce excellent findings in the other (Grassl, 2000).

GCMs, which modelled the global climate and provided projections at various resolutions, with differences in projected climate change values for each grid cell, were regarded as the entry points for climate change conservation assessments because only these models provide estimates of future climate change due to greenhouse gas emissions (Hannah et al., 2002). Results from transient (not equilibrium) simulations of CO2 growth and models that were completely connected with ocean and atmosphere to the regions of interest improved the evaluations (Hannah et al., 2002).

2.8. SPECIES DISTRIBUTION MODELLING – TYPES AND TECHNIQUES

2.8.1 Modelling in relation to landscape and vegetation

Forest ‘gap' models were utilised to mimic species-specific succession dynamics in an area less than 1 ha, however the landscape-level changes were not represented well (Shugart, 1990). Using the limiting environmental parameters, global biome models forecast the future distribution of present vegetation. Because the vegetation in these models was in equilibrium with the climate, they couldn't predict species transition patterns. However, while dynamics are included in the dynamic global vegetation model, they cannot be exploited to produce species-specific findings (Woodward and Beerling, 1997). Models cannot forecast species composition at a landscape scale in a competitive and dynamic environment. Dynamic vegetation lacked species-specific characteristics, envelope models lacked dynamic and competitive aspects, and gap models lacked spatial resolution (Woodward and Beerling, 1997). Land use projection models depicted the pattern of habitat fragmentation and predicted the future based on forecasts of characteristics such as population and consumption levels (Sala et al., 2000).

The potential range shift of a species caused by bioclimatic models was lowered by the predicted land use model. For example, if a species' probable climate envelope shifts into an agricultural area or into an urban settlement, the species may face extinction. Even though it lacked the geographic specificity of models, integrative and sensitivity analysis based on site ecology and individual species features might be utilised as a vital adjunct to modelling goals (Hannah et al., 2002).

The species-specific interaction needs to be studied in conservation planning strategies, and species bioclimatic envelope models were the greatest instrument available for this. They were based on the same premise as biome envelope models, in which the existing distribution of species was used to ‘train' a future model that included expected climatic conditions (Hannah et al., 2002). Envelopes were made with the help of Geographic Information System (GIS) software, genetic algorithms, and generic additive modelling (Peterson et al., 2001a; Berry et al., 2002; Midgley et al., 2002). These models, on the other hand, were unable to account for dynamic transitions, interspecific competition, herbivory, dispersal, or other aspects. The results of the bioclimatic envelope models could be employed in real-world conservation by linking with land-use projection models (Hannah et al., 2002).

2.8.2. Generalized Dissimilarity Models (GDM)

Generalized Dissimilarity Models (GDM) were used to describe spatial turnover in community composition between a pair of sites as a function of environmental changes between these locations. Within the altered environmental space produced by GDM, the kernel regression algorithm was utilised to estimate the probability of occurrence of species distributions of a particular species (Lowe, 1995). The user was able to model non-linear reactions of the environment using elements of matrix regression and generalised linear modelling, which represented ecologically relevant correlations between dissimilarity and ecological distance (Ferrier, 2002, Ferrier et al. 2002c).

2.8.3. GLM and GAM models

Generalised Linear Models (GLM) utilised non-parametric and non-linear functions, whereas Generalised Additive Models (GAM) used parametric and combinations of linear, quadratic, or cubic terms. Because of its higher flexibility, GAMS can model more complex ecological response forms than GLM (Yee and Mitchell, 1991). Because ecological interactions were accurately modelled and they have strong statistical foundations, GLM and GAM were widely utilised in species distribution modelling (Austin, 2002).

2.8.4. Multivariate Adaptive Regression Splines (MARS)

An alternative regression-based method called Multivariate Adaptive Regression Splines (MARS) was utilised to fit non-linear responses. Instead of smooth functions, it used piecewise linear fits. It was simple to use in GIS applications for making prediction maps, and it was faster to implement than GAMs. It also had the ability to analyse community data (MARS-COMM), which aided in relating variation in species occurrence to environmental predictors in a single analysis, and then estimating the individual model coefficients for each species simultaneously (Leathwick et al., 2005).

2.8.5. Genetic Algorithm for Rule – set Prediction (GARP)

BIOCLIM (Nix, 1986), logistic multiple regression (Austin et al., 1990), and Genetic Algorithm for Rule-set Prediction (GARP) have all been used to approximate species fundamental ecological niches. GARP was defined by a set of heterogeneous rules that defined the polyhedrons in ecological niche spaces that were believed to be habitable by a certain species. The model's quality was determined by splitting the occurrence points into "training data" and "test data" for training and testing purposes (Fielding and Bell, 1997). GARP had two versions: DK-GARP, which was widely used for modelling data from natural history collections, and OM-GARP, a new open modeller implementation, both of which used a genetic algorithm to select a set of rules for regression and range specification adaptations, resulting in the best species distribution prediction (Stockwell and Peters, 1999). GARP is a machine-learning approach that also used envelope (variables are restricted to lower and higher bounds), atomic (values are assigned to each variable), and logistic regression rules to link the occurrence records to the environment variables. Because the model operates with presence-absence data, the algorithm used pseudo-absence locales (Stockwell and Peters, 1999). GARP was based on artificial intelligence and combined the capabilities of both BIOCLIM and logistic multiple regression (Stockwell and Noble, 1992; Stockwell and Peters, 1999). The GARP model has been extensively tested and found to have a strong prediction capacity for species geographic distributions (Peterson and Cohoon, 1999; Peterson and Stockwell, 2001b; Peterson et al., 2001a).

2.8.6. Maximum Entropy Modelling (MaxEnt)

For estimating the species distribution, MaxEnt uses the maximum entropy distribution, which was subjected to the constraint that the predicted value of each environment variable (interactions) in the estimated distribution matched its empirical average (Phillips et al., 2006). It approximated the most uniform distribution using background locations and data-derived constraints (Philips et al., 2004; Philips et al., 2006). If presence only species data were used in this model, the complexity of the fitted functions may be chosen. Maximum entropy modelling (MaxEnt) was found to perform better or equally well as other modelling strategies (Elith et al., 2006; Hernandez et al., 2006; Philips et al., 2006). MaxEnt had a higher success rate than other algorithms, and it was able to detect differences even with small sample sets (Pearson et al., 2007). When sample sizes were artificially reduced, the model performance suffered. MaxEnt models projected a greater range of appropriate circumstances, and the MaxEnt projection had the potential to anticipate excluded areas as well (Pearson et al., 2007).

MaxEnt had investigated the distributional patterns of geckos (Uroplatus spp.) in order to forecast the distribution of species (Pearson et al., 2007), for the assessment of denning habitat of American black bear (Ursus americanus) (Baldwin and Bender, 2008), to appraise the excellence of protection of Bush dog (Speothos venaticus) (DeMatteo and Loiselle, 2008), for modelling the seasonal distribution changes of Little bustard (Tetrax tetrax) (Suárez-Seoane et al., 2008), for predicting and mapping of Sage grouse's (Centrocercus urophasianus) nesting habitat,and to estimate the threats to Asian slow lorises (Nycticebus spp.) were analysed, and species distribution was examined to determine conservation priorities (Thorn et al., 2009). MaxEnt can precisely create the model even if there are less location points, which is a useful feature because there are often insufficient dependable locations available for mapping the distribution of species (Baldwin, 2009).

2.8.7. Boosted Regression Trees (BRT)

Regression Boosting Trees were created in a stage-by-stage fashion, with tiny changes to the model made at each step to improve data fitness (Friedman et al., 2000). To construct a combination or "ensemble" of trees, BRT employed a combination of two algorithms: regression-tree algorithm, also known as the boosting method. Regression trees were used to aid in the selection of important variables and also to model interactions. The observations that were poorly fitted in the previous model were accounted for by altering the weights on the weighted versions of the data set (Elith et al., 2006). Cross-validation in BRT was used to expand the models progressively during the predicted accuracy testing on withheld portions of the data, avoiding overfitting of data (Elith et al., 2006).

CHAPTER 3

MATERIALS AND METHOS

3.1. STUDY SPECIES

The Malabar parakeet, the subject of our research is a beautiful bird and can only be found in the jungles of India's Western Ghats. Vigors first described this species as the Blue – winged Paroquet Palaornis columboides (1835). Baker later identified it as *Psittacula columboides* in 1927. Due to its range restriction in Western Ghats, it was renamed to Malabar parakeet by Inskipp et al (1996), Grimmett et al. (1999), Kazmierczak and Van Perlo (2000) and Rasmussen and Anderton (2005). The long yellow-tipped tail of the blue-winged parakeet is bluish grey. The male's black collar has a bluish-green lower edge, and his upper mandible is red with a white tip, whereas the female's bill is entirely black, with only the black collar. The male's black collar has a bluish-green lower edge, and his upper mandible is red with a white tip, whereas the female's bill is entirely black, with only the black collar. In both males and females, the black neck ring is perfect. The female resembles the plum-headed parakeet's female, but the plum-headed parakeet's female can be distinguished by her broad yellow collar. They are identified by their peculiar keek – keek sound. Usually, they are seen in flocks flying through the woodlands. According to IUCN red list, this species is categorized into least concerned with a stable population.

3.2. STUDY AREA

The term "Western Ghats" refers to a nearly unbroken hill chain (with the exception of the Palakkad Gap) that runs roughly north-south for about 1500 kilometers parallel to the Arabian sea coast, from the river Tapi (about 210 16' N) to just short of Kanyakumari (about 8019' N) at the tip of the Indian peninsula. It includes sections of the states of Gujarat, Maharashtra, Goa, Karnataka, Kerala, and Tamil Nadu (Shameer et al. 2019), and is divided by the Palghat Gap in northern Kerala, which is 30 kilometres wide (Srinivasulu et al., 2014). The mountain range contains a diverse range of ecosystems and is known for its biodiversity and endemism (Molur et al., 2011; Myers et al., 2000). Mahabaleshwar, Coimbatore—Palani Hills, the Nilgiris, the Anamalai, Silent Valley, and Agasthyamalai are all part of the WG bioregion, which supports a varied range of biological types. The Nilgiri and Agasthyamalai Biosphere Reserves are designated Biosphere Reserves in the south, with the Nilgiri Biosphere Reserve being a UNESCO World Heritage Site. The mountain range rises over 2500 msl in the Nilgiri and Anamalai areas, divided by the Palghat gap, which is 22 km wide. The flora at these mountain ranges' high altitudes, particularly in southern WG, is peculiar, with shola grassland complexes (Ramachandra and Suja 2006). The sholas are a kind of prehistoric highland semi-evergreen plant that is thought to be a living fossil (Jose 2012). With 4000 plant species, 218 fish species, 126 amphibian species, 508 bird species, and mammals of 137 species endemic to them, the shifting altitudinal gradient produces a variety of habitat that accounts for the richness (Das et al. 2006).

3.3. OCCURRENCE POINTS OF MALABAR PARAKEET

The compilation of place of occurrence or existence of the species is one of the main components of the Species Distribution Model (SDM) (Trisurat et al., 2011). The presence data for Malabar parakeets was collected from the e-Bird reference data (www.eBird.org), a free Internet-based checklist tool. The data is copyrighted with the National Audubon Society and the Cornell Lab of Ornithology, and it is released in accordance with the Avian Knowledge Network (AKN). The information comes from the Breeding Bird Survey, which began in 1966 and continues to this day. It has advanced geo-referencing capabilities and a large user base. It was used to get georeferenced data on the Malabar parakeet from 1964 to 2020. Using Excel's capabilities, duplicate records were eliminated, and a matching shape file was created in ArcMap 10.8. The occurrence points of Malabar parakeet are shown in figure 1.

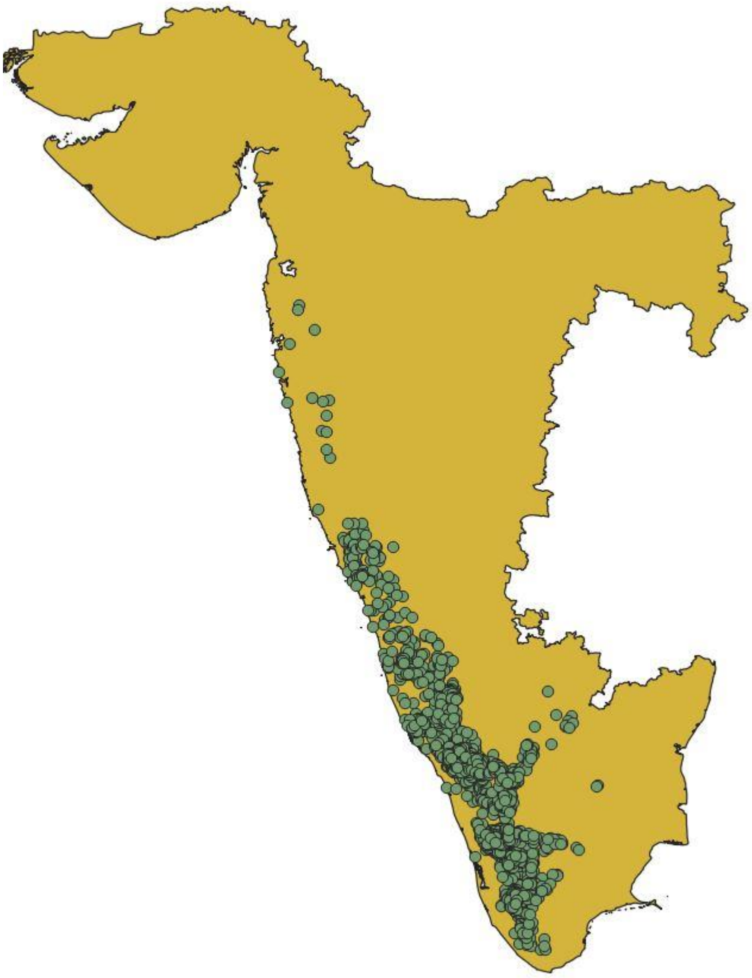


Figure 1. occurrence points for Malabar parakeet in southern India (source: eBird, 2020)

3.4. ENVIRONMENTAL VARIABLES

Because of their inherent needs and life cycles, changes in environmental variables such as flora and atmosphere make tiny animal species delicate (Rowe and Terry 2014). As a result, selecting influential predictor variables based on species ecological significance will improve niche modelling precision. We utilised 19 bioclimatic variables retrieved from the CHELSA database (https://chelsa-climate.org/) based on the available information on the species ecological needs. These variables were created by combining monthly rainfall and temperature data to produce 19 more relevant variables. Annual patterns, seasonality, and severe or limiting environmental conditions are all represented by these variables. They are designated with many names, such as:

3.4.1 bio1 (Annual Mean Temperature): The yearly mean temperature was calculated using the 12-month average temperature. This approximated an ecosystem's total energy inputs.

3.4.2 bio2 (Mean Diurnal Range): The diurnal range (the difference between the maximum and minimum temperature) for each month was averaged over the course of a year. This gave data on the importance of temperature fluctuations for various species.

3.4.3. bio3 (Isothermality): Isothermality was employed to measure the day-night temperature oscillations in relation to the yearly oscillations (bio2/bio7) x100). This might indicate the impact of bigger or smaller temperature fluctuations in a month compared to the previous year.

3.4.4. bio4 (Temperature Seasonality): It's the difference between the SD (variation) of monthly temperature averages and the temperature variation (SDx100) throughout a year (or averaged years). The bigger the SD, the greater the temperature fluctuation.

3.4.5. bio5 (Maximum Temperature of Warmest Month): It was effective in determining the effects of warm temperature anomalies on species distribution since it monitors the maximum monthly temperature over a year.

3.4.6. bio6 (Minimum Temperature of Coldest Month): Measures the lowest temperature during a period of time, which is important for analysing the effects of cold temperatures**.**

3.4.7. bio7 (Temperature Annual Range): Quantifies temperature change over time (bio5-bio6), which aids in the study of species distribution and the effects of severe temperatures on it.

3.4.8. bio8 (Mean Temperature of Wettest Quarter): This makes it possible to investigate the effect of approximating mean temperatures occurring throughout the wettest season on species distribution.

3.4.9. bio9 (Mean Temperature of Driest Quarter): The driest quarter's mean temperature was monitored to see how it affected species distribution.

3**.4.10. bio10 (Mean Temperature of Warmest Quarter):** The mean temperature across the hottest quarter is quantified, which aids in the study of species distribution.

3.4.11. bio11 (Mean Temperature of Coldest Quarter): The coldest quarter's mean temperature was monitored to see how it affected species distribution.

3.4.12. bio12 (Annual Precipitation): It is the sum of all monthly precipitation and assesses total water inputs, and it proved beneficial in evaluating the significance of water availability in influencing species distribution.

3.4.13. bio13 (Precipitation of Wettest Month): The wettest month's precipitation was observed, and the species distribution was studied when an extreme precipitation event occurred.

3.4.14. bio14 (Precipitation of Driest Month): To examine the severe circumstances and their consequences on species distribution, total precipitation received during the driest month was recorded.

3.4.15. bio15 (Precipitation Seasonality): The variation in monthly precipitation throughout the course of the year was calculated. It is the ratio of SD of monthly total precipitation to the mean monthly total precipitation.

3.4.16. bio16 (Precipitation of Wettest Quarter): The wettest quarter's precipitation was observed, and the species distribution was studied when an extreme precipitation condition occurred.

3.4.17. bio17 (Precipitation of Driest Quarter): To examine the severe circumstances and their consequences on species distribution, total precipitation received during the driest quarter was recorded.

3.4.18. bio18 (Precipitation of Warmest Quarter): The hottest quarter's precipitation was observed, and the species distribution was studied when an extreme precipitation condition occurred.

3.4.19. (Precipitation of Coldest Quarter): The impacts of the coldest quarter's mean precipitation on species distribution were measured.

Table: 1. Variables and their sources

Variables	Code/unit	Source
Annual mean temperature	Bio 1 (℃)	CHELSA (Climatologies at high resolution for the earth's land surface regions)
Mean diurnal range (max. Tem. – min. Temp)	Bio 2 (℃)	
Isothermality (bio 2/bio 7)× 100	Bio 3	
Temperature seasonality (SD × 100)	Bio 4 (℃)	

Maximum temperature of the warmest month	Bio 5 (°C)	
Minimum temperature of the coldest month	Bio 6 (°C)	
Temperature annual range (bio 5 – bio 6)	Bio 7 (°C)	
Mean temperature of the wettest quarter	Bio 8 (°C)	
Mean temperature of the driest quarter	Bio 9 (°C)	
Mean temperature of the warmest quarter	Bio 10 (°C)	
Mean temperature of the coldest quarter	Bio 11 (°C)	
Annual precipitation	Bio 12 (mm)	
Precipitation of wettest month	Bio 13 (mm)	
Precipitation of driest month	Bio 14 (mm)	
Precipitation seasonality (Coefficient of variation)	Bio 15	
Precipitation of wettest quarter	Bio 16 (mm)	
Precipitation of driest quarter	Bio 17 (mm)	
Precipitation of warmest quarter	Bio 18 (mm)	
Precipitation of coldest quarter	Bio 19 (mm)	
Altitude	Alt (m)	United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre
Slope	SL (%)	
Aspect	As (degrees)	
Evi average	EVI_avg	
Evi peak monsoon	EVI_mon	

Evi peak dry season	EVI_dry	United States Geological Survey (USGS) Landsat imagery dataset

For both current and future conditions, 30 arc seconds (0.86 km^2 at the equator) data were employed. We were using the WGS84 datum in the latitude/longitude coordinate reference system. Monthly precipitation, minimum, mean, and maximum temperatures were used to determine the bioclimatic variables. Interpolating average monthly data from weather stations was used to create the data layers. This information has its own set of benefits and drawbacks. Climate is defined by the World Meteorological Organization (WMO) as the measurement of the mean and variability of significant amounts of specific variables (such as temperature, precipitation, or wind) across time, which can range from months to hundreds or millions of years. 30 years is the standard time for considering climate.

Many applications in environmental and ecological sciences require high-resolution information on climate conditions. We utilised downscaled model output temperature and precipitation estimates from the ERA-Interim climatic reanalysis to a high resolution of 30 arc sec from the CHELSA (Climatologies at high resolution for the earth's land surface regions) data. The temperature algorithm is based on atmospheric temperature statistical downscaling. With a bias correction, the precipitation method integrates orographic predictors such as wind fields, valley exposition, and boundary layer height. The result is a monthly climatology of temperature and precipitation for the years 1979–2013. Many studies compare the CHELSA algorithm's output with other gridded products and station data from the Global Historical Climate Network. In species distribution modelling, we compare the performance of the new climatologies and show that CHELSA data may improve the accuracy of species range forecasts. Many studies also demonstrate that CHELSA climatological data is as accurate as other temperature products, but that its precipitation pattern forecasts are superior. The information is designed for high-resolution applications in ecology, agriculture, and meteorology. The CHELSA methods might be used to downscale climate model predictions of past and future climate, despite the fact that the core dataset is generated from a reanalysis. Some of the key limitations of CHELSA data includes: (1) The data does not adequately reflect low-level temperature inversions, (2) There is no coverage across seas and (3) information about the uncertainty is not supplied.

Table 2. Different RCPs and its characteristics

Scenario	Model used	Radiative forcing	CO_2 equivalent (ppm)	Global warming until 2100 (Mean and Likely range)
RCP 2.6	IMAGE	At this time, the radiative forcing reaches its highest point before 2100, 3W/m^2 and then declines	490	1.0 (0.3 – 1.7)°C
RCP 4.5	MiniCAM	This is one among the intermediate stabilization pathway, where the radiative forcing stabilized at around 4.5 W/m^2 after 2100	650	1.8 (1.1 – 2.6)°C
RCP 6.0	AIM	Stabilization without overshoot pathway to ~ 6 W/m2 at stabilization after 2100	850	2.2 (1.4 – 3.1)°C
RCP 8.5	MESSAGE	One high-energy route, in which radiative forcing exceeds 8.5 W m-2 by 2100 and continues to grow for some time	1370	3.7 (2.6 – 4.8)°C

Apart from the bioclimatic layers, using ArcGIS version 10.8, we created a topographic layer including elevation, slope, and aspect using digital elevation model data. (http://www.ngdc.noaa.gov/mgg/topo/globe .html). The DEM (GTOPO30) downloaded from the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre. Topographic variables like slope, aspect and altitude are calculated from the downloaded DEM file using Quantum GIS (QGIS) version 3.16. Besides these variables, we also downloaded EVI (Enhanced Vegetation Index) United States Geological Survey (USGS) Landsat imagery dataset for 10 years (2011 – 2020). Enhanced Vegetation Index layers represent the greenness of a region and help to understand the vegetation cover. By using that 10-year average EVI by considering all months (2011 – 2020) (evi_avg), 10-year average EVI in peak monsoon (June – August) (evi_mon) and 10 year average EVI in peak summer (March – May) (evi_dry), were calculated and used in SDM process. Since these data were downloaded on monthly basis they were obtained in different tiles. Hence, Arcgis 10.8 was used to stich those tiles for dry season (March to May), wet season (June to August) and yearly average. The spatial resolution of all predictor variables was fixed at 30 arc seconds. (Table 1)

3.5. DATA THINNING

eBird provided a total of 27,798 Malabar parakeet presence locations, as on (provide the date of download) . The first step to data reduction was to filtered the data based on the following: (1) protocol type – travelling and stationary, (2) duration minutes <300, (3) effort distance km <5, (4) number of observers - ≤ 10. All these operations were done using Microsoft excel software. After the data is filtered, it was subjected to removing the duplicates which is also employed with the help of excel. After completing these actions, the raw data were narrowed down to 4273 occurrence points which were saved in the extension '.csv'. For better prediction, most SDM require spatially independent occurrence data. Environmental biases in SDMs are frequently introduced by spatially autocorrelated occurrence sites (Hijmans, 2012). Model performance metrics are exaggerated as model becomes "over – fit" towards environmental biases, limiting the model's capacity to predict spatially independent data (Veloz, 2009; Hijmans, 2012; Boria et al., 2014). To better calibration and model building, it is necessary to eliminate spatially auto correlated points from spatial clusters of locales. The occurrence data for the species was spatially thinned using spThin package (Aiello-Lammens et al., 2015) in R studio, with 1 km buffer, to remove duplicate records within a 1 km circular radius of each other.

3.6. SELECTION OF BIOCLIMATIC VARIBLES

Variable optimization is a critical step in the model development process. Not all of the characteristics in the list will be equally important to our species of interest. Some factors may have a minor impact on the outcome, and it is usually recommended to remove such variables in order to improve the interpretability of the final model (epistemic sparcity) or assure better predictability (predictive sparcity) from our model (De Bin et al., 2015). To reduce the autocorrelation, highly correlated variables should be removed before evaluating the contributions of each individual environmental variable. Incorporating the correlated variables not only affects the quality of MaxEnt model prediction, but it also restricts the contribution of additional correlated variables in the output. Using a highly correlated variable in the model prevents all other correlated variables from being included, which could be quite important for our species of interest. (Brown, 2014). If there is a correlation, the response curves derived from the presence might be inaccurate. The outputs of the model generated by incorporating strongly correlated variables into the model can be deceptive.

When there are a lot of variables that are highly correlated, it is best to avoid them using percentage contribution. If the test and training data were spatially auto correlated, the test omission line was significantly lower than the predicted omission line, indicating that the model was not well fitted. Because geographically auto – correlated data would inflate the accuracy measurements for presence only models (Veloz, 2009), spatially correlated variables have to be eliminated beforehand to the modelling procedure.

The correlation matrix (Pearson) and coefficients of determination (R^2) were used to analyse the bioclimatic variables (bio1-bio19) for the present conditions (1979–2013). The correlation values $|r| > 0.7$ and $R^2 > 0.7$ were used to classify the variables. The variables with the highest percentage contribution were chosen, and permutation important findings based on the MaxEnt model output were utilised to make future predictions. The percentage contribution chart depicted each environment variable's proportional contribution to the MaxEnt model. The increase in regularised gain was added to the contribution of the associated variable in each iteration of the training process, or removed from it if the change in the absolute value of lambda was negative. They were dependent on the MaxEnt code's path to the solution, and the contribution numbers varied when it followed a different approach to reach the same result. When there were a lot of strongly linked (correlated) variables, it was important to evaluate the results carefully. The permutation importance id determined by MaxEnt model, rather than the path it took to reach the value. The significance was determined by arbitrarily permuting the values of that variable among the presence and background (training points) and determining the reduction in training AUC. The greater the drop, the more dependent the model was on that variable. The Jack-knife test of variable relevance showed that the environment variable with the highest gain when utilised alone (containing the most relevant information) and the environment variable with the lowest gain when omitted (having the most data that isn't available in the other variables). After removing the correlated variables, the selected variables were used for further modelling.

3.7. MAXIMUM ENTROPY SPECIES DISTRIBUTION MODELLING (MAXENT)

The Maxent model is a useful tool for simulating the distribution of geographical species based on the most important environmental factors (Phillips et al. (2004, 2006). Maxent is built on a machine-learning reaction that predicts outcomes based on inadequate data. Taking into account the limitations determined from the data, this method calculates the most evenly distributed “maximum entropy” of sample points compared to background locations. The maximum entropy algorithm is deterministic and converges to the probability distribution with the highest maximum entropy (Baldwin, 2009; Berger et al., 1996; Phillips et al., 2006). Depending on whether or not a specific species is present, a given site may be assigned to a “absence” or “presence” group. The environmental characteristics most closely related with a species' presence can be extended to similar biotopes to determine the species' likely geographical range. The model starts with a uniform distribution for each species and undertakes a series of iterations based on the most important environmental variables until no more improvements in prediction can be made. For the set of grid cells containing data on all of the environmental variables, the Maxent distribution is calculated. To see if Maxent predictions (training data) are better than random guesses, we employed 25% of the sample points. The method employs both categorical and continuous environmental data, and all of the variables were treated as continuous variables. To determine the likelihood of the species' occurrence, a logistic output continuous map was chosen, which allows one to discriminate between the suitability of the geographical area under consideration. We added 25 predictor environmental variables, including 19 bioclimatic variables retrieved from the CHELSA database, lateral to the geographical position data of Malabar parakeet occurrence. Maxent uses the area under the curve (AUC) to statistically analyse the model, and it is one of the most commonly used statistics in ecological niche modelling and nest-site selection (Baldwin, 2009; Barry and Elith, 2006; Peterson et al., 2007; Peterson and Nakazawa, 2008; Yost et al., 2008). The species distribution model is created using a set of georeferenced occurrence sites and environmental layers collected from the CHELSA database. MaxEnt can be freely downloaded online (https://biodiversityinformatics.amnh.org/open_source/maxent/). The information must be entered into the software in the correct format. The species data was saved in ‘csv’ format, but the bioclimatic layers should be saved in ‘asc’. Under the settings options, software was configured to acceptable levels based on our requirements for the run (Philips et al., 2004; 2006).

3.8. MODEL OPTIMIZATION

3.8.1 MODEL FEATURES

The optimal combination of model features was identified as the initial stage in optimising the model to meet the requirements of our investigation. In terms of feature selection, the MaxEnt software's default configuration is auto features. The model also allows you to use five additional features alone or in various combinations. The complexity of the models was varied by changing MaxEnt features like linear (L), product (P), quadratic (Q), and hinge (H), and Threshold (T). The models were adjusted to the varying regularisation multiplier (rm) values. The "ENMeval" R package is used to assess models of various complexity and rm values. Among the 48 different models, the one with the lowest AIC (LQHP and rm=3) was chosen for future projections. In order for us to reach to the variables with lowest AIC, we had to run MaxEnt according to the model settings received from ENMeval (the one with deltaAICc = 0) and then exclude variables according to the permutation importance. After a couple of repetition of the previous steps, the model settings turned out to be best for the setting LQHP 3.

3.8.2. REGULATION MULTIPLIER AND REPLICATION RUN TYPE

To prevent the model overfitting, regulation multiplier features are used (Philips, 2008). The model was fine-tuned by experimenting with different amounts of regulation multipliers, a model setting that regulates the model's complexity (Radosavljevic and Anderson, 2014). The model assigns a value of 1 to the regulation multiplier by default, but in order to fine tune the model, we assigned different values to the regulation multiplier. The other numbers assigned were 1.5, 2, 2.5, 3, 4 and 5, however the model fitting was shown to be significantly higher with the default value 1, and generally setting one as the regulatory multiplier value appears to produce the highest test Area Under the Curve (AUC) among numerous experiments (Warren and Seifer, 2011).

Cross validation works only by randomly partitioning the species location data into groups (k) of comparable sizes, leaving one part out, but the model fits into k – 1 parts and accounts for it with predictions. The model performs the method for each part on its own in this run type, and the results are merged to create the final output. The best feature of this run type is that it does not leave any data unvalidated, which is especially important when dealing with data sets with small number of occurrence points. The data is effectively used to accurately report the range and standard error. This run type recognises the uncertainties in prediction and ensures that the measures are incorporated into the model to reduce the uncertainty and produce a believable output. The disadvantage of this run type is that, model fitting only employs a portion of the data, making it difficult to gather test data that is spatially independent of the training data (Hijmans, 2012). When such spatially connected groups are introduced during model evaluation, there is a potential that model performance will be exaggerated and standard error predictions will be underestimated.

Crossvalidate, bootstrap and subsampling are the three replication run types accessible in MaxEnt settings. All three run types were configured to run types were configured to run three distinct models under similar conditions, with the cross validation run type proving to be the most effective.

The model settings were adequately tuned by assessing discriminatory ability to examine overfitting, as well as visual inspections of maps to conclude on the output's credibility (Radosavljevic and Anderson, 2014).

3.9. PREDICTING THE CURRENT DISTRIBUTION OF SPECIES

Following the model optimization for the essential and important features, the other software settings were programmed appropriately to meet our requirements for a run under the settings option. Maximum iterations were set to 5000 and the convergence threshold (0.00001) were left at their normal settings. The method employs both categorical and continuous environmental data, and all of the variables were treated as continuous variables. The random test percentage was set at 25% to ensure that the entire model output was free of bias. Following the assignment of model features to our specifications, the environmental variables in '.asc' format and species occurrence data in '.csv' format were fed into the software as input, the model was run, and the results were produced. The result files from the optimized model run indicated that visual forecasts of model predictions obtained looked to match with quantitative evaluations previously performed, showing the improved mode's reliability. The presence-only distribution model's high inaccuracy could be due to sampling bias, which could lead to erroneous prediction findings (Fourcade et al., 2014; Deb et al., 2017). In order to limit the background points for the species occurrence and determine the favoured site within the research area, a bias layer was utilised in the Maxent model (Deb et al., 2017a; Phillips et al., 2009). 10,000 was chosen as the maximum number of background points. The model's expected area of appropriate habitat was then evaluated in a Geographic Information System (GIS) context for better understanding. The best model feature was the one with lowest AIC obtained after the exclusion of variables in accordance with their permutation importance and jacknife results. The future variables were run with the same model settings.

3.10. PREDICTING THE POTENTIAL DISTRIBUTION OF THE SPECIES

The bioclimatic variables were used to simulate the typical concentration pathways RCP 2.6, 4.5, RCP 6.0, and RCP 8.5 available from four different ESMs namely, Beijing Climate Centre Climate System Model 1.1 (BCC CSM 1.1), Model for Interdisciplinary Research on Climate Version 5 (MIROC5) and Hadley Centre Global Environmental Model 2 – Earth System (HadGEM2 – ES) at 30 arc-second (1 km) spatial resolution for future climatic forecasts. This is in line with the Intergovernmental Panel on Climate Change's (IPCC) fifth assessment report (AR5), which assumes that greenhouse gas concentration trajectories follow a range of radiative forcing. We made projections for the WG region for the period 2050 (average for 2040–2069) for long-term planning and habitat protection, using data from the Consultative Group on International Agricultural Research (CGIAR), Research Program on Climate Change, Agriculture and Food Security (CCAFS) climate data archive (data available from http://www.ccafs-climate.org/data). To estimate the probable distribution of the selected endemic species of Western Ghats in the future, the trained environment layers are projected to another available set of environmental layers including future climate data in MaxEnt model. The projection layer should include training layers that are compatible but have varied circumstances. The names of the layers and map projection should be the same as the trained data. On the basis of current climatic data, a model was trained on environmental factors that are related to future climatic conditions and projected into distinct layer. Future forecasts were made for 2050, assuming static features such as aspect will be the same in future and omitting dynamic non-climatic variables such as EVI (Enhanced Vegetation Index).

3.11. MODEL EVALUATION

The model's performance was assessed using two metrics: the receiver operating characteristic curve (AUC) and true skill statistics (TSS). The metric isn't affected by thresholds. TSS is a threshold-dependent measure of accuracy, while AUC measures the model's ability to differentiate between random and background points. The AUC isn't very informative or trustworthy (Phillips et al. 2006; Austin 2007; Lobo 2008). As a result, TSS ratings are approximated for accuracy as well.

CHAPTER 4

RESULTS

4.1. MODEL VALIDATION

Various ways for measuring the accuracy of model outputs include AUC, specificity and sensitivity. Visual assessment of graphs and maps, whose settings were primarily agreed upon from the result of the ENM evaluate script ran in R studio, is critical for assessing the outputs of the completed model. Since EVI (Enhanced Vegetation Index) expected to change in the future, we had to run the model without EVI and with EVI. The model settings were same for both the models with EVI and without EVI which is LQHP 3, but the only difference is that for future projection EVI was not chosen to be a variable since its future records are not available. The test AUC and TSS values for the model with EVI were 0.887 and 0.833, respectively, indicating that the model is better in predicting the suitable habitat area for Malabar parakeet in WG. With an overall accuracy of 0.8813, the specificity and sensitivity were 0.8619 and 0.9713, respectively. After the cross-correlation tests, the best model incorporated five bioclimatic variables (Precipitation of coldest quarter, Annual precipitation, Mean temperature of warmest quarter, Precipitation of warmest quarter and Precipitation of driest month), one topography layer (Slope), and EVI (Average of 10 years [2011 – 2020]). Precipitation in the coldest quarter (40.3% contribution), annual precipitation (27.5 % contribution), and mean temperature of the warmest quarter (11.2% contribution) were the important factors affecting the spatial distribution of Malabar parakeet among the seven variables considered for modelling. These factors combined to contribute 79.0 percent of the total. Mean temperature of warmest quarter (48.6 percent) and annual precipitation (26.1 percent), on the other hand, had significant permutation relevance. (Table 3)

Table 3: Analysis of variable contribution (with EVI)

Variable	Percent contribution	Permutation importance
bio 19	40.3	6.8
bio 12	27.5	26.1
bio 10	11.2	48.6
bio 18	10	7.9
slope	6.9	3.7

evi _ avg	3.4	4.2
bio 14	0.7	2.6

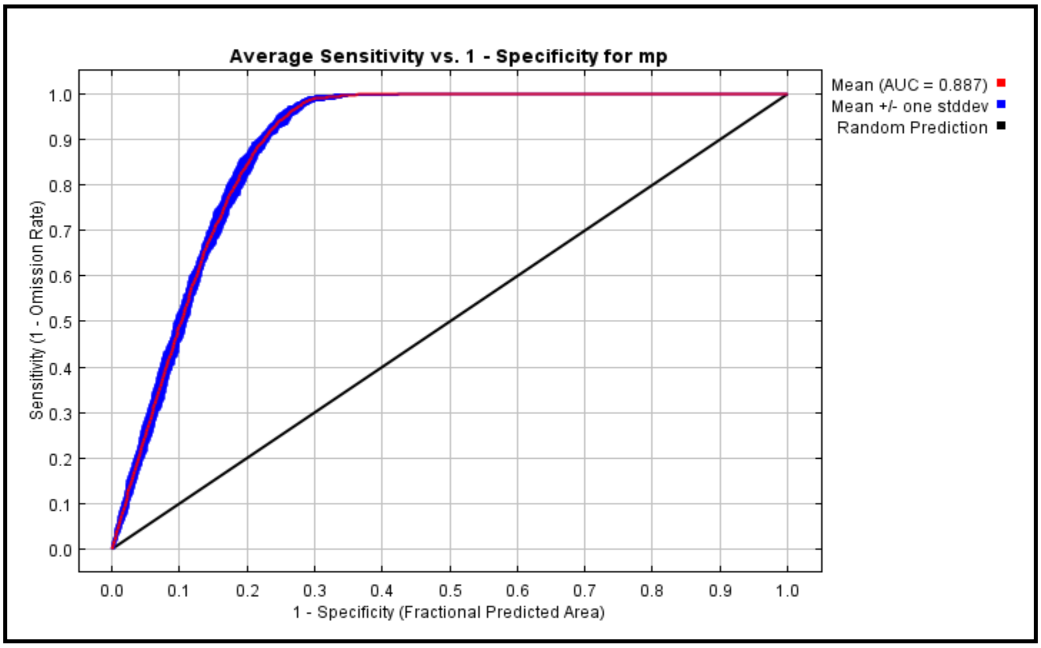


Figure 2: Receiver Operating Characteristic Curve (ROC) curve of the finalized model settings output in MaxEnt (with EVI)

The model's performance in terms of average test AUC value is 0. 887, with a standard deviation of 0.006, according to ROC curve above. AUC values range from 0 to 1, and any AUC number greater than 0.8 indicates that the model's performance is satisfactory. The average sensitivity vs specificity graph in figure 2 provides these values. The AUC curve curves up to the top left of the plot, indicating that the model is competent. (Figure 2)

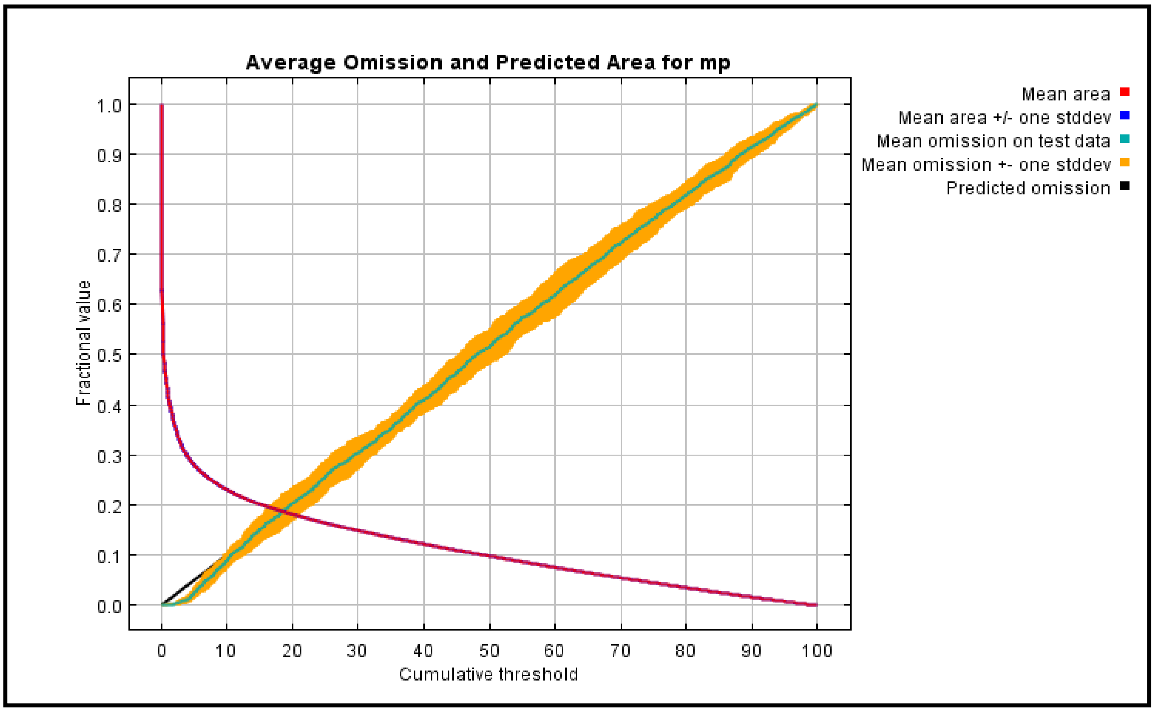


Figure 3: Average omission curve and predicted area for Malabar parakeet, an endemic bird species of Western ghats (With EVI).

A metric that indicates the model's predictive capacity is the average omission and projected area curve for the selected species averaged over the replicate runs. (Figure 3)

As a result, the visual interpretation of the model outputs indicated that the optimized model's settings were fixed based on TSS values had appropriate predictive capacity. The model feature combinations, regulatory multiplier value, and replication run type that were previously fixed using TSS values were finalized and proceeded with after the model settings were tested for their credibility and concluded to be a model with a strong predictive capacity.

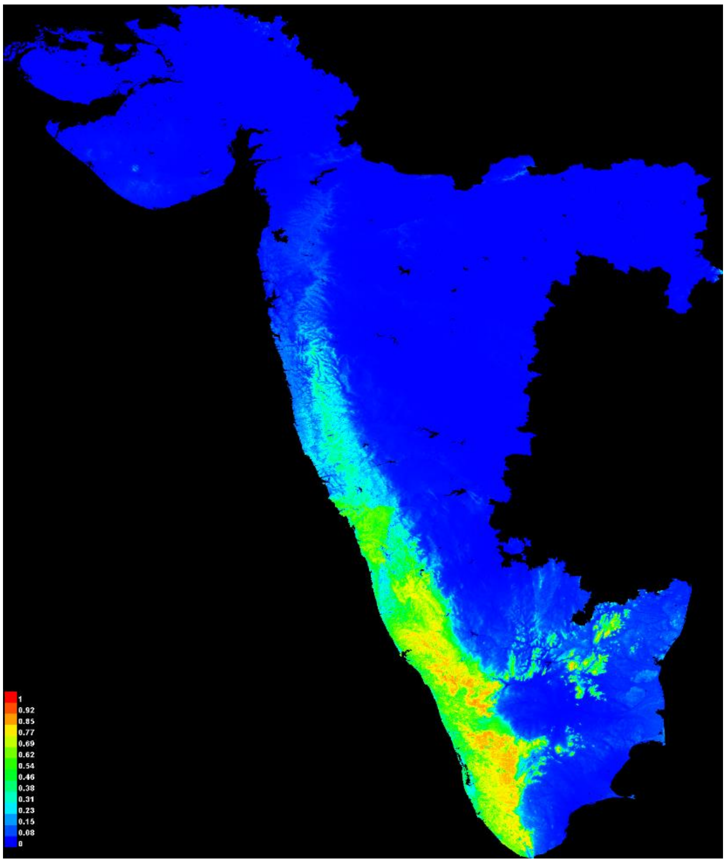


Figure 4: Shows the current distribution of Malabar parakeet by Maxent (With EVI)

This projection goes hand in hand with the actual distribution of Malabar parakeet hence we can say that this projection provided by MaxEnt with the setting LQHP 3 can be used to project the future distribution of Malabar parakeet. (Figure 4)

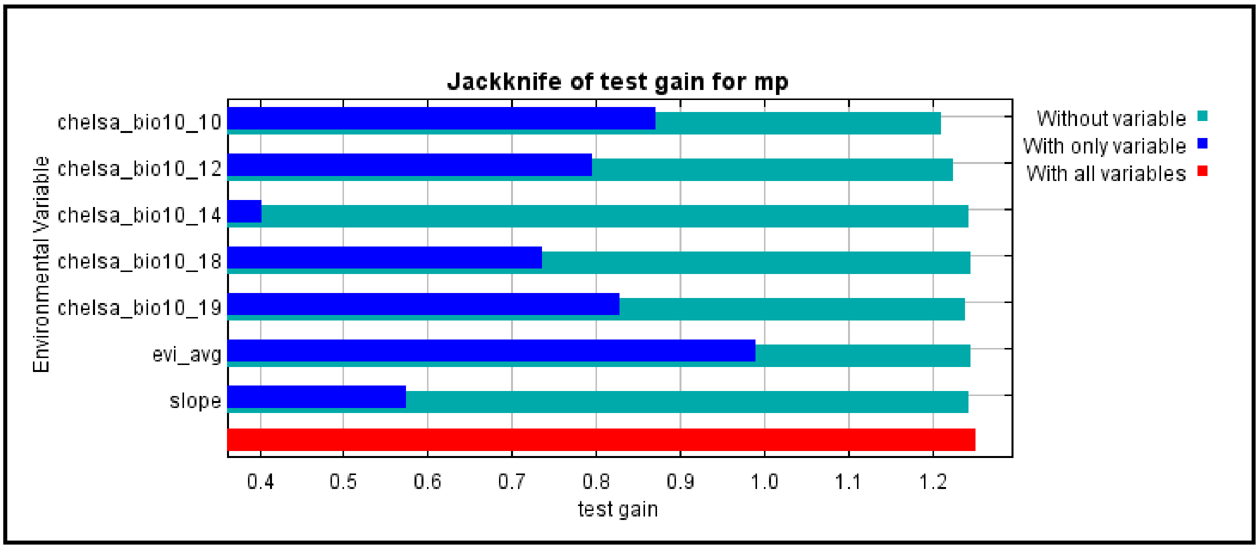


Figure 5: Jackknife test gain for Malabar parakeet for the current distribution (with EVI)

According to the results of the Jackknife test, evi avg contributes the most, followed by mean temperature of warmest quarters, precipitation of coldest quarters, and yearly precipitation. This finding is comparable to MaxEnt's, implying that it is trustworthy. (Figure 5)

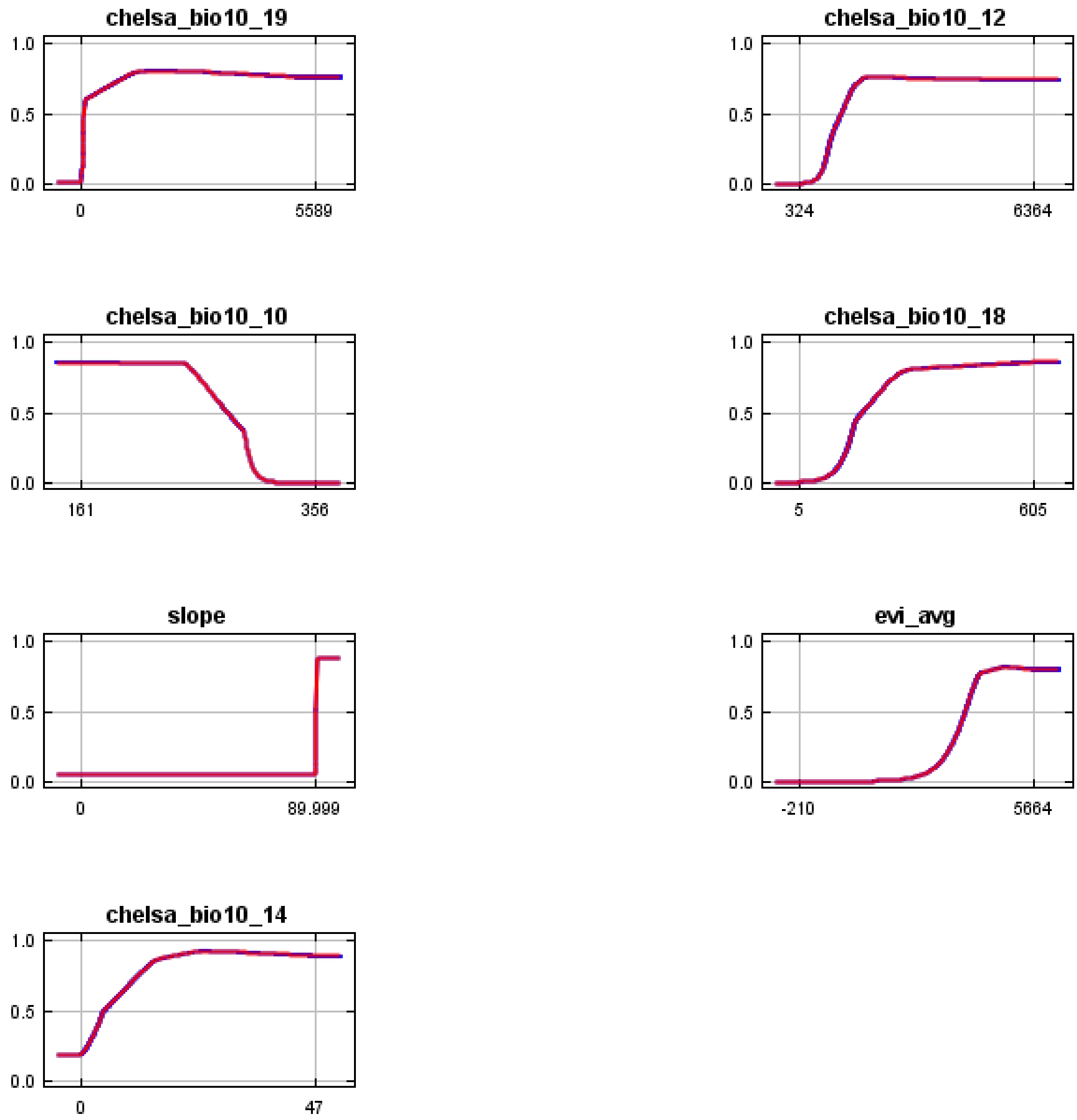


Figure 6: Response curves generated by MaxEnt for variables (With EVI)

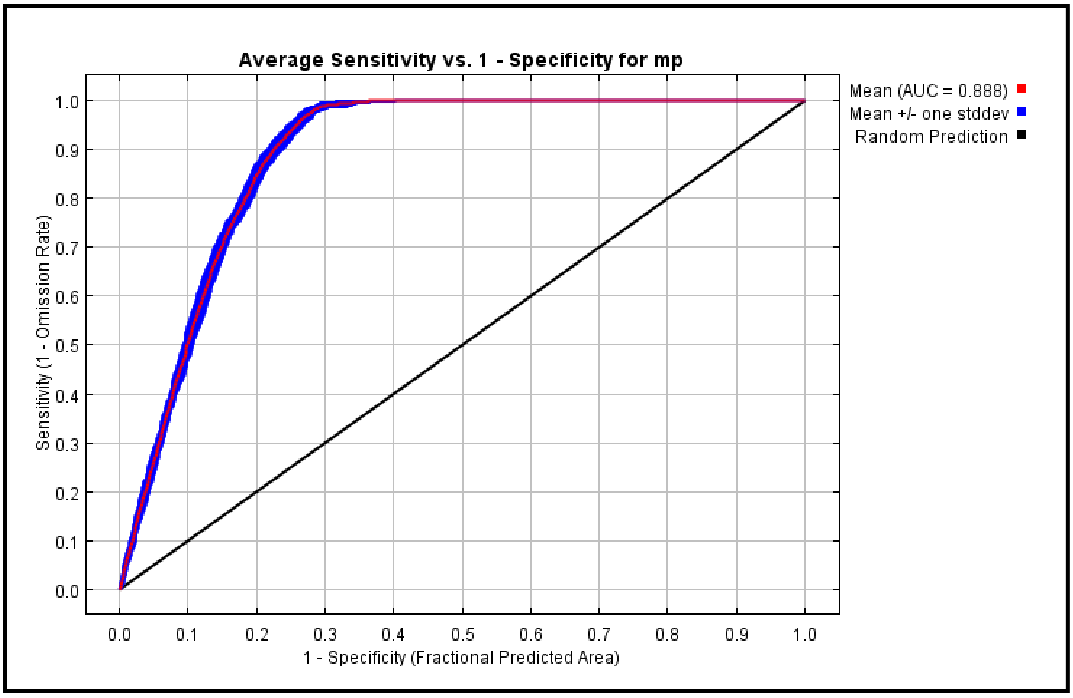


Figure 7: Receiver Operating Characteristic Curve (ROC) curve of the finalized model settings output in MaxEnt (Without EVI)

The test AUC and TSS values for the model with EVI were 0.888 and 0.828, respectively, indicating that the model is better in predicting the suitable habitat area for Malabar parakeet in WG. With an overall accuracy of 0.8859, the specificity and sensitivity were 0.8703 and 0.9579 respectively. Precipitation in the coldest quarter (42.6% contribution), annual precipitation (27.6 % contribution), and mean temperature of the warmest quarter (10.8% contribution) were the important factors affecting the spatial distribution of Malabar parakeet among the six variables considered for modelling. These factors combined to contribute 81.0 percent of the total. Mean temperature of warmest quarter (44.1 percent) and annual precipitation (34.8 percent), on the other hand, had significant permutation relevance. The model's performance in terms of average test AUC value is 0. 888, with a standard deviation of 0.005, according to ROC curve above. (Figure 7)

Table 4: Analysis of variable contribution (without EVI)

Variable	Percent contribution	Permutation importance
bio 19	42.6	7.3
bio 12	27.6	34.8
bio 10	10.8	44.1
bio 18	10.4	7.1
slope	7.3	3.2
bio 14	1.3	3.5

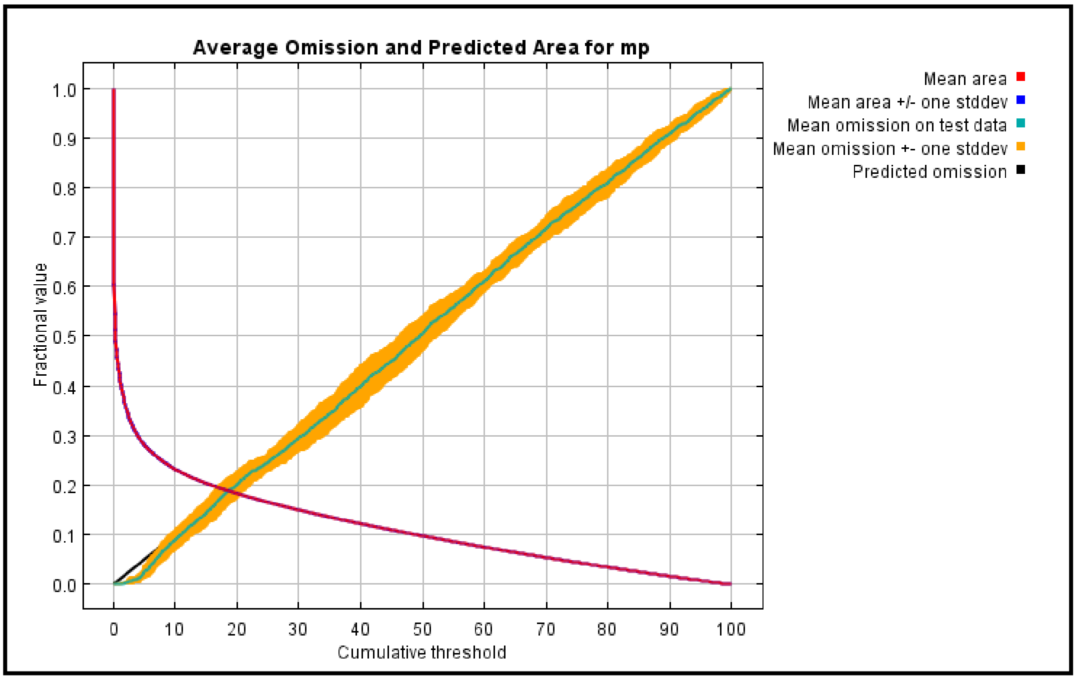


Figure 8: Average omission curve and predicted area for Malabar parakeet, an endemic bird species of Western ghats (Without EVI).

The model feature combinations, regulatory multiplier value, and replication run type that were previously fixed using TSS values were finalized and proceeded with after the model settings were tested for their credibility and concluded to be a model with a strong predictive capacity.

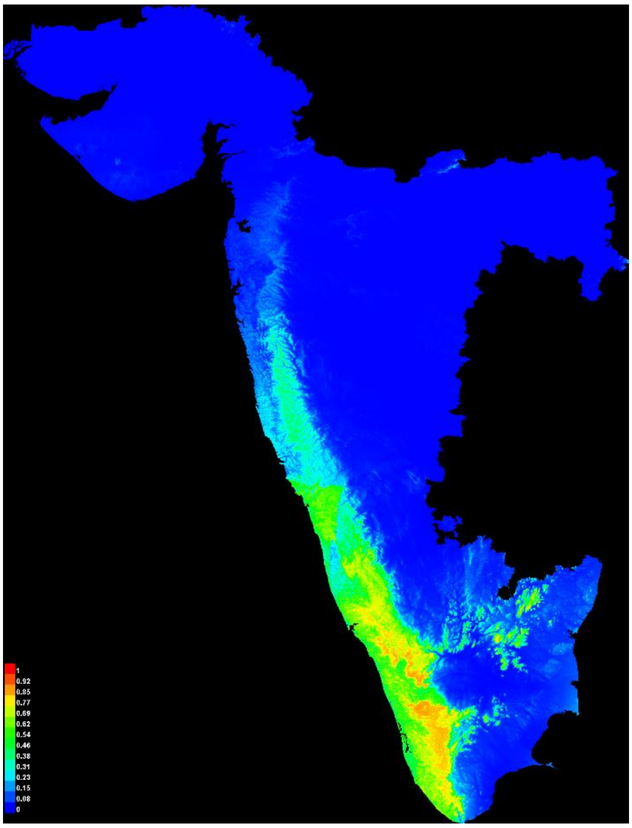


Figure 9: Shows the current distribution of Malabar parakeet by Maxent (Without EVI)

This projection depicts the current Malabar parakeet distribution, which is similar to the previous one but does not include EVI. The model settings for this projection are the same as for the previous one, namely LQHP 3. The current distribution of Malabar parakeets and Maxent's projection go hand in hand. (Figure 9)

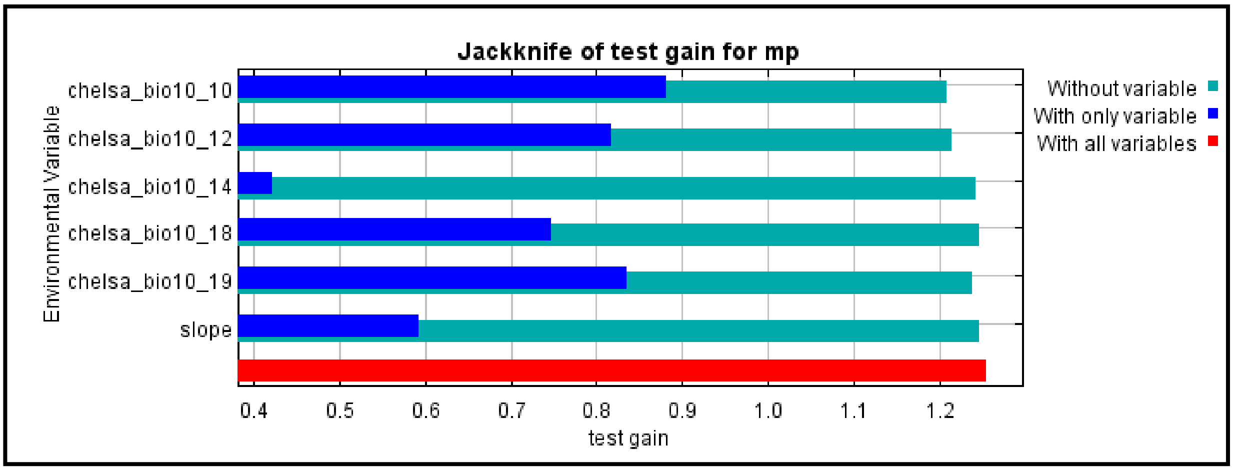


Figure 10: Jackknife test gain for Malabar parakeet for the current distribution (without EVI)

The jackknife test gain without EVI implies that the most contributing variable is mean temperature of the warmest quarters followed by precipitation of coldest quarters and annual precipitation. These results are comparable to those produced by MaxEnt thus making them a reliable finding. (Figure 10)

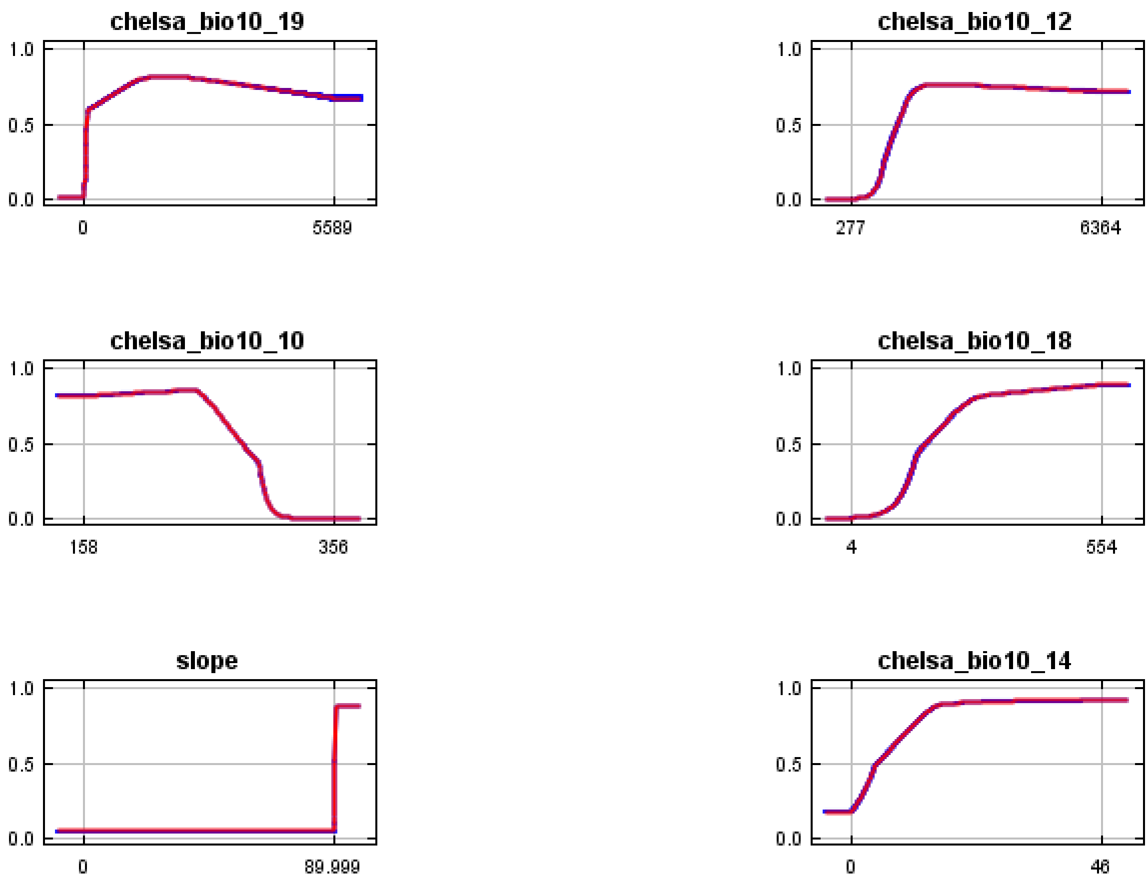


Figure 11: Response curves generated by MaxEnt for variables (Without EVI)

The response curves of each selected bioclimatic variable, as well as other key parameters are shown in figure 11. These mainly depict the species' probability distribution in response to several bioclimatic variables. The response curve of bio 19 suggests that maximum probability can be seen when the precipitation of coldest quarter is between 1000- and 2000 mm. Bio 12 (Annual precipitation) response curve shows a similar peak as bio 19 and suggests that the most ideal value range to give maximum probability is 2000 mm. For bio 10 (mean temperature of the warmest quarters) the highest probability is seen between 24℃ and 26℃ and then their distribution declines on further increment in temperature. The response curve of bio 18 clearly depicts that as precipitation of warmest quarters increases their probability also increases and peaks at between 600 and 700 mm. The response curve of slope works in agreement with the percentage contribution table as they are not likely to exert any influence on the probable distribution of species. Bio 14 (precipitation of driest month) response curve have a wider range of values to which the maximum probability distribution corresponds. (Figure 11)

Table 5: Comparison of MaxEnt predictions with and without EVI

Model	Variable	Percent contribution	Permutation importance	AUC	SD	TSS	Maximum test sensitivity plus specificity cloglog threshold
Current with EVI	bio 19	40.3	6.8	0.887	0.006	0.833	0.2127
	bio 12	27.5	26.1				
	bio 10	11.2	48.6				
	bio 18	10	7.9				
	slope	6.9	3.7				
	evi_avg	3.4	4.2				
	bio 14	0.7	2.6				
Current without EVI	bio 19	42.6	7.3	0.888	0.005	0.825	0.2415
	bio 12	27.6	34.8				
	bio 10	10.8	44.1				
	bio 18	10.4	7.1				
	slope	7.3	3.2				
	bio 14	1.3	3.5				

4.2. SELECTION OF SUITABLE BIOCLIMATIC VARIABLES

The correlation table created with Arcgis's Species Distribution Modelling (SDM) toolbox assisted in determining the degree of association between various bioclimatic variables and in identifying variables that are essential to our species. An absolute value of 1 in the Pearson correlation denotes a perfect linear relationship. A correlation close to 0 suggests that the variables do not have a linear connection. The direction of the link is indicated by the sign of the coefficient. If both variables tend to rise or fall at the same time, the coefficient is positive, and the correlation line slopes upward. When one variable tends to rise while the other falls, the coefficient is negative, and the correlation line slopes downward. The highlighted cells are those with correlation. (Table 6)

Table 6: Pearson's correlation matric generated by SDM toolbox in Arcgis

Layer	Altitude	aspect	bio 1	bio 2	bio 3	bio 4	bio 5	bio 6	bio 7	bio 8	bio 9	bio 10	bio 11	bio 12	bio 13	bio 14	bio 15	bio 16	bio 17	bio 18	bio 19	evi avg	evi dry	evi mon	slope
---------	------------	------------	------------	------------	------																				
altitude	1	-0.05789	-0.8597	0.01057	0.21263	-0.30616	-0.3687	-0.23422	-0.0869	-0.88605	-0.35651	-0.58246	-0.29257	-0.01317	-0.07086	-0.02758	-0.4373	-0.07379	-0.04189	0.10444	0.01063	0.08614	0.07021	0.15934	0.08654
aspect	-0.05789	1	0.00165	0.02968	-0.07209	0.04911	0.01975	-0.06428	0.04839	0.05364	-0.03768	0.01587	-0.06038	0.09223	0.11022	-0.09281	0.16168	0.10726	-0.08816	0.02567	0.03689	0.0424	0.03788	0.0516	-0.00208
bio 1	-0.8597	0.00165	1	0.05977	-0.20419	0.36169	0.56594	0.34228	0.1432	**0.82062**	0.44481	**0.78569**	0.46182	-0.17165	-0.15788	0.09894	0.14502	-0.13911	0.10229	-0.20827	-0.12198	-0.18889	-0.20158	-0.25842	-0.06706
bio 2	0.01057	0.02968	0.05977	1	-0.48503	**0.817**	**0.75905**	-0.84325	**0.9336**	0.30631	-0.2628	0.50543	-0.6969	-0.59146	-0.46758	-0.48447	0.39214	-0.49414	-0.50041	-0.56204	-0.47655	-0.5012	-0.59814	-0.39529	-0.05901
bio 3	0.21263	-0.07209	-0.20419	-0.48503	1	-0.79419	-0.71185	0.58089	-0.75602	-0.34417	0.06254	-0.67225	0.4974	0.13699	0.02966	0.32074	-0.62938	0.03584	0.33584	0.60706	0.2684	0.21944	0.44523	0.03497	0.02443
bio 4	-0.30616	0.04911	0.36169	**0.817**	-0.79419	1	**0.89069**	-0.71311	**0.93814**	0.56293	-0.07292	**0.80092**	-0.61652	-0.49078	-0.38176	-0.28642	0.54805	-0.39055	-0.3066	-0.62082	-0.42243	-0.4129	-0.57166	-0.30653	-0.07292
bio 5	-0.3687	0.01975	0.56594	**0.75905**	-0.71185	**0.89069**	1	-0.46879	**0.86428**	0.56329	0.06421	**0.93039**	-0.2799	-0.45748	-0.37578	-0.26812	0.36085	-0.37413	-0.28201	-0.65245	-0.40185	-0.40557	-0.56533	-0.3074	-0.04857
bio 6	-0.23422	-0.06428	0.34228	-0.84325	0.58089	-0.71311	-0.46879	1	-0.8494	-0.05675	0.43499	-0.19281	**0.95718**	0.37738	0.24286	0.48015	-0.54167	0.27754	0.49606	0.46721	0.36651	0.33749	0.45918	0.18741	0.04093
bio 7	-0.0869	0.04839	0.1432	**0.9336**	-0.75602	**0.93814**	**0.86428**	-0.8494	1	0.36882	-0.20932	0.6656	-0.71223	-0.48818	-0.36277	-0.43359	0.524	-0.38154	-0.45095	-0.65581	-0.44876	-0.43447	-0.5992	-0.29036	-0.05231
bio 8	-0.88605	0.05364	**0.82062**	0.30631	-0.34417	0.56293	0.56329	-0.05675	0.36882	1	0.24054	0.69919	0.03028	-0.27592	-0.18299	-0.12088	0.4989	-0.19027	-0.11569	-0.22512	-0.22074	-0.32695	-0.32799	-0.36525	-0.1109
bio 9	-0.35651	-0.03768	0.44481	-0.2628	0.06254	-0.07292	0.06421	0.43499	-0.20932	0.24054	1	0.2412	0.44983	0.0275	-0.01159	0.19829	-0.14294	0.00524	0.2078	-0.00648	0.09162	0.02487	0.05204	-0.03279	-0.01847
bio 10	-0.58246	0.01587	**0.78569**	0.50543	-0.67225	**0.80092**	**0.93039**	-0.19281	0.6656	0.69919	0.2412	1	-0.03345	-0.35858	-0.30583	-0.09038	0.32253	-0.29172	-0.10146	-0.55909	-0.32282	-0.32503	-0.47364	-0.2699	-0.05082
bio 11	-0.29257	-0.06038	0.46182	-0.6969	0.4974	-0.61652	-0.2799	**0.95718**	-0.71223	0.03028	0.44983	-0.03345	1	0.30334	0.19131	0.35101	-0.49782	0.22311	0.37015	0.34913	0.29019	0.23713	0.33938	0.10934	0.03876
bio 12	-0.01317	0.09223	-0.17165	-0.59146	0.13699	-0.49078	-0.45748	0.37738	-0.48818	-0.27592	0.0275	-0.35858	0.30334	1	**0.96168**	0.09326	0.14744	**0.97634**	0.10809	0.33435	0.69156	0.5883	0.59478	0.52798	0.04652
bio 13	-0.07086	0.11022	-0.15788	-0.46758	0.02966	-0.38176	-0.37578	0.24286	-0.36277	-0.18299	-0.01159	-0.30583	0.19131	**0.96168**	1	-0.08943	0.34922	**0.99565**	-0.08359	0.20717	0.62549	0.48313	0.47474	0.4432	0.0329
bio 14	-0.02758	-0.09281	0.09894	-0.48447	0.32074	-0.28642	-0.26812	0.48015	-0.43359	-0.12088	0.19829	-0.09038	0.35101	0.09326	-0.08943	1	-0.55657	-0.05422	**0.97772**	0.35295	0.07504	0.35381	0.39521	0.22818	0.02798
bio 15	-0.4373	0.16168	0.14502	0.39214	-0.62938	0.54805	0.36085	-0.54167	0.524	0.4989	-0.14294	0.32253	-0.49782	0.14744	0.34922	-0.55657	1	0.31328	-0.55814	-0.37846	0.00163	-0.16549	-0.24696	-0.09104	-0.07822
bio 16	-0.07379	0.10726	-0.13911	-0.49414	0.03584	-0.39055	-0.37413	0.27754	-0.38154	-0.19027	0.00524	-0.29172	0.22311	**0.97634**	**0.99565**	-0.05422	0.31328	1	-0.04728	0.22644	0.6502	0.50744	0.49772	0.46359	0.03553
bio 17	-0.04189	-0.08816	0.10229	-0.50041	0.33584	-0.3066	-0.28201	0.49606	-0.45095	-0.11569	0.2078	-0.10146	0.37015	0.10809	-0.08359	**0.97772**	-0.55814	-0.04728	1	0.38966	0.07993	0.35848	0.41169	0.22827	0.02797
bio 18	0.10444	0.02567	-0.20827	-0.56204	0.60706	-0.62082	-0.65245	0.46721	-0.65581	-0.22512	-0.00648	-0.55909	0.34913	0.33435	0.20717	0.35295	-0.37846	0.22644	0.38966	1	0.35626	0.38732	0.53916	0.23704	0.03694
bio 19	0.01063	0.03689	-0.12198	-0.47655	0.2684	-0.42243	-0.40185	0.36651	-0.44876	-0.22074	0.09162	-0.32282	0.29019	0.69156	0.62549	0.07504	0.00163	0.6502	0.07993	0.35626	1	0.44782	0.57175	0.31825	0.01943
evi avg	0.08614	0.0424	-0.18889	-0.5012	0.21944	-0.4129	-0.40557	0.33749	-0.43447	-0.32695	0.02487	-0.32503	0.23713	0.5883	0.48313	0.35381	-0.16549	0.50744	0.35848	0.38732	0.44782	1	**0.87183**	**0.87431**	0.076
evi dry	0.07021	0.03788	-0.20158	-0.59814	0.44523	-0.57166	-0.56533	0.45918	-0.5992	-0.32799	0.05204	-0.47364	0.33938	0.59478	0.47474	0.39521	-0.24696	0.49772	0.41169	0.53916	0.57175	**0.87183**	1	0.66338	0.05083
evi mon	0.15934	0.0516	-0.25842	-0.39529	0.03497	-0.30653	-0.3074	0.18741	-0.29036	-0.36525	-0.03279	-0.2699	0.10934	0.52798	0.4432	0.22818	-0.09104	0.46359	0.22827	0.23704	0.31825	**0.87431**	0.66338	1	0.09034
slope	0.08654	-0.00208	-0.06706	-0.05901	0.02443	-0.07292	-0.04857	0.04093	-0.05231	-0.1109	-0.01847	-0.05082	0.03876	0.04652	0.0329	0.02798	-0.07822	0.03553	0.02797	0.03694	0.01943	0.076	0.05083	0.09034	1

Table 7: variables and variables they are correlated with

SL. NO	Variables	Variables that they are correlated with
1.	bio 1	bio 8 bio 10
2.	bio 2	bio 4 bio 5 bio 7
3.	bio 4	bio 2 bio 5 bio 7 bio 10
4.	bio 5	bio 2 bio 4 bio 7 bio 10
5.	bio 6	bio 11
6.	bio 7	bio 2 bio 4 bio 5
7.	bio 8	bio 1
8.	bio 10	bio 1 bio 4 bio 5
9.	bio 11	bio 6
10.	bio 12	bio 13 bio 16
11.	bio 13	bio 12 bio 16
12.	bio 14	bio 17

13.	bio 16	bio 12 bio 13
14.	bio 17	bio 14
15.	evi_avg	evi_dry evi_mon
16.	evi_dry	evi_avg
17.	evi_mon	evi_avg

We excluded variables from the correlation matrices based on their AIC values. The variables in the model with the lowest AIC value are chosen for future projection. (Table 8)

Table 8: Variables, model setting and AIC values

SL. NO	Variables	Model settings	RM	AIC value
1.	alt asp bio 3 bio 9 bio 10 bio 11 bio 12 bio 14 bio 15 bio 18 bio 19 evi_avg slp	LQHP	3.5	54717.75
2.	alt bio 3 bio 10 bio 11	H	3	54581.14

	bio 12 bio 14 bio 18 bio 19 evi_avg slp			
3.	bio 10 bio 12 bio 14 bio 18 evi_avg slp	H	2.5	54385.7
4.	bio 10 bio 12 bio 14 bio 18 bio 19 evi_avg slp	LQHP	3	54318.29

Table 9: A comparison between the influence of selected bioclimatic variables under the current climatic scenario and under all RCP scenarios on the potential distribution of Malabar parakeet

Variables	current	RCP 2.6 2050			RCP 4.5 2050			RCP 6 2050			RCP 8.5 2050		
		bcc	miroc	Mohc hadgem	bcc	miroc	Mohc hadgem	bcc	miroc	Mohc hadgem	bcc	miroc	Mohc hadgem
Bio 19	42.6	50	38.6	39.4	47.8	39	40.6	49.2	31.2	39.4	48.5	44.1	37.7
Bio 12	27.6	22.5	30.7	28.6	18.4	30.8	28.9	21.2	34.8	23.3	19.6	26.7	30.8
Bio 10	10.8	17.4	19.9	22.1	20.9	22.5	22.4	19.2	24	22.4	19.4	20.8	23.6

Slope	7.3	5	8.6	6	7.5	6.4	3.3	3.1	8.5	6.4	7.9	7	2.5
Bio 14	1.3	4.6	1.5	0.1	3.5	0.8	1.7	5.1	1.3	2.7	3.2	1.2	3.4
Bio 18	10.4	0.6	0.6	3.7	1.9	0.6	3	2.1	0.2	1.8	1.4	0.3	2.2

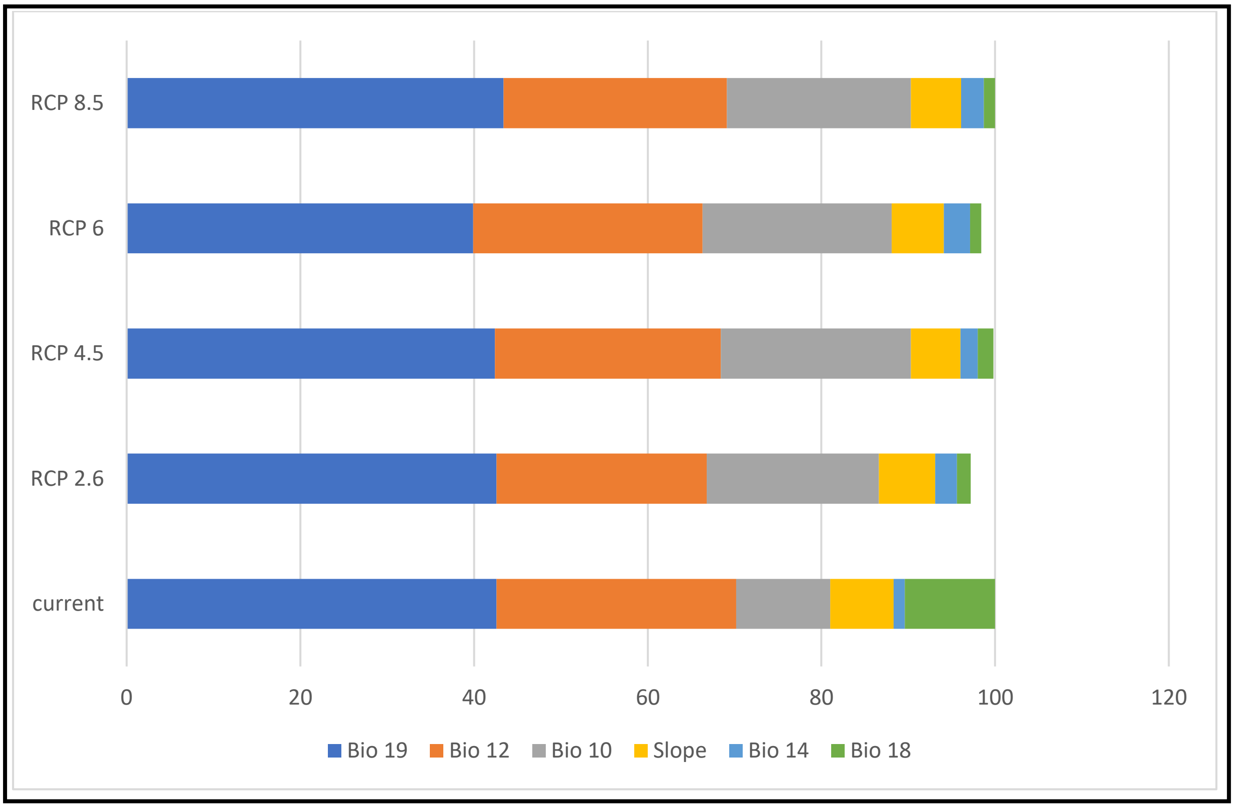


Figure 12: Chart illustrating the comparison between the influence of selected bioclimatic variables under the current climatic scenario and under all RCP scenarios on the potential distribution of Malabar parakeet

4.3 CLIMATE SPACE SUITABILITY FOR MALABAR PARAKEET UNDER CURRENT AND FUTURE SCENARIO

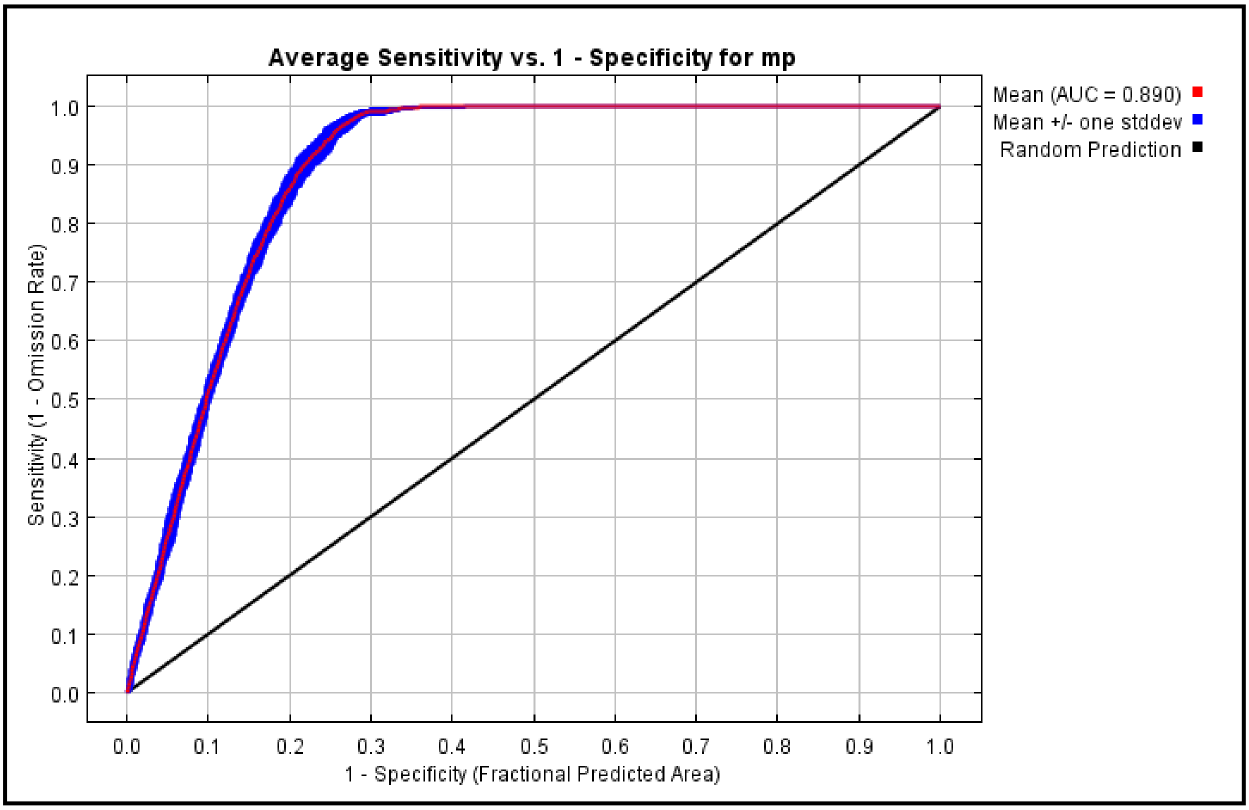


Figure 13: Receiver Operating Characteristic Curve (ROC) curve of the finalized model settings output in MaxEnt for future projection

The model's performance in terms of average test AUC value is 0. 890, with a standard deviation of 0.004 (Figure 14), according to ROC curve above (Figure 13). The TSS values for the model was 0.838, indicating that the model is better in predicting the suitable habitat area for Malabar parakeet in WG. With an overall accuracy of 0.8924, the specificity and sensitivity were 0.8778 and 0.9602, respectively.

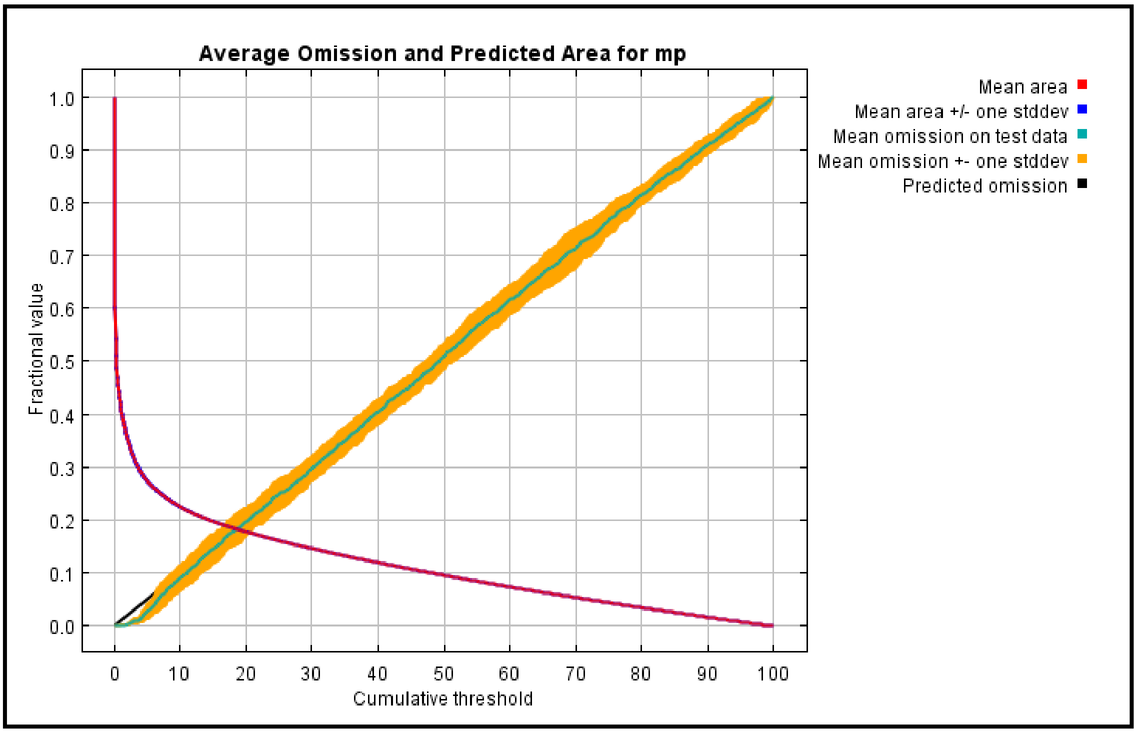


Figure 14: Average omission curve and predicted area for Malabar parakeet, an endemic bird species of Western ghats for future projection.

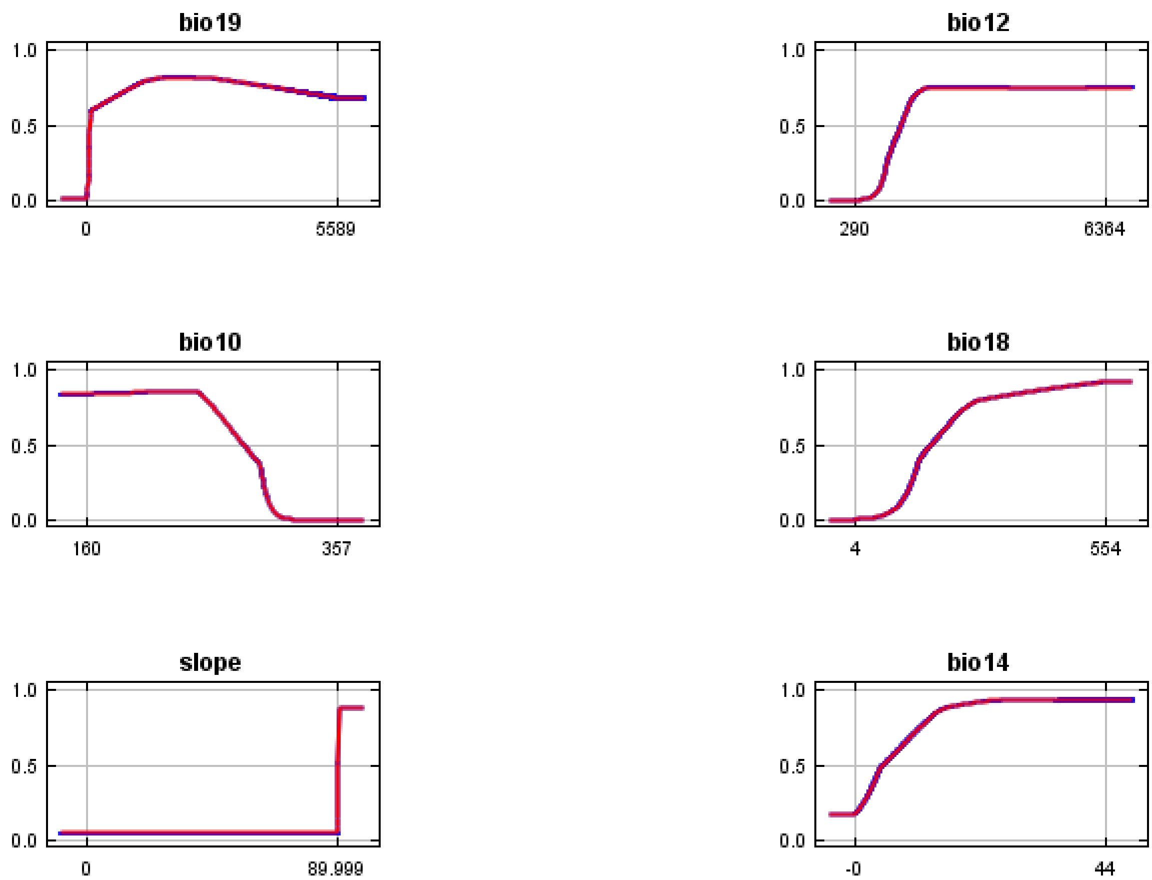


Figure 15: Response curves generated by MaxEnt for variables

The response curves of each selected bioclimatic variable, as well as other key parameters are shown in figure 11. These mainly depict the species' probability distribution in response to several bioclimatic variables. The response curve of bio 19 suggests that maximum probability can be seen when the precipitation of coldest quarter is between 1000- and 2000 mm and then decreases as amount of precipitation increases. Bio 12 (Annual precipitation) response curve shows a similar peak as bio 19 and suggests that the most ideal value range to give maximum probability is 2000 mm. For bio 10 (mean temperature of the warmest quarters) the highest probability is seen between 20℃ and 25℃ and then their distribution declines on further increment in temperature. The response curve of bio 18 clearly depicts that as precipitation of warmest quarters increases their probability also increases and peaks at between 500 and 600 mm. The response curve of slope works in agreement with the percentage contribution table as they are not likely to exert any influence on the probable distribution of species. Bio 14 (precipitation of driest month response curve have a wider range of values to which the maximum probability distribution corresponds. (Figure 15)

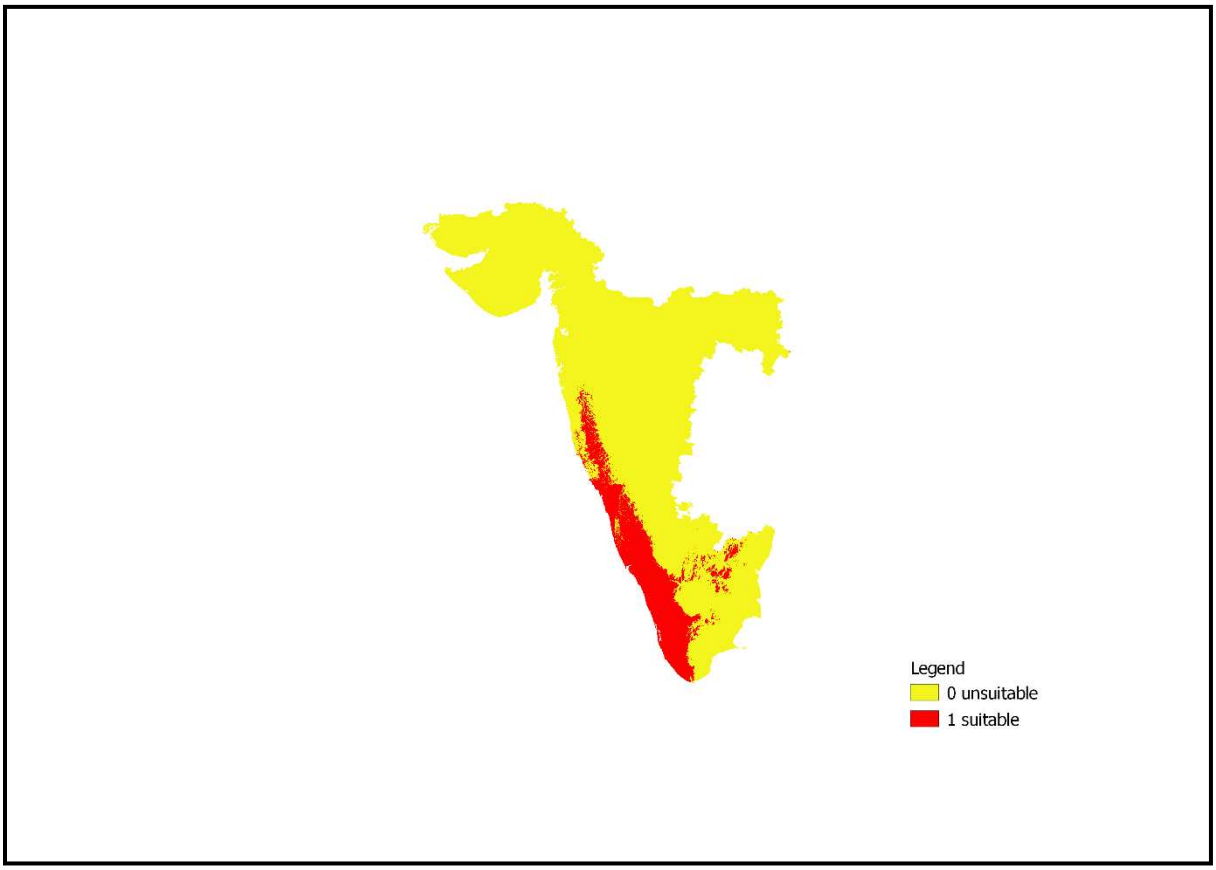


Figure 16: Distribution map showing suitability under current climatic condition

The area available as highly appropriate for Malabar parakeet in the study area under current climatic condition is 133,545 km^2 which is 12.73% of the total study area. And in the current scenario, in the study area the species were not at all present accounted for 915,133 km^2.

The area of suitability spread from Nagarcoil to Mahabaleswar covering Agastyamalai, Periyar National Park, Idukki Wildlife Sanctuary, Anamalai Tiger Reserve, Mudumalai Tiger Reserve, Bandiput Tiger Reserve and National Park, Nagarhole National Park and Tiger Reserve, Bhadhra Wildlife Sanctuary, Sharavathi valley Wildlife Sanctuary, Anshi National Park, Bhagvan Mahavir National Park, Radhanagari Wildlife Sanctuary, Chandoli National Park and their distribution finally ended within Koyna wildlife sanctuary.

Their distribution has also been identified in regions outside Western ghats like Jawahilla and Pudupalayam Reserve Forest and in Pakkamalai Reserve Forest (Figure 16)

4.3.1 FUTURE SCENARIOS

The test AUC and TSS values for the model under future scenario were 0.889 and 0.838, respectively, indicating that the model is better in predicting the suitable habitat area for Malabar parakeet in WG. With an overall accuracy of 0.8924, the specificity and sensitivity were 0.8778 and 0.9602, respectively.

The future scenarios are evaluated for four Representative Concentration Pathways (RCP) namely 2.6, RCP 4.5, RCP 6 and RCP 8.5. The average of three models viz., bcc csm1, miroc _5 and mohc_hadgem2_es was used in order to reduce the prediction bias.

In the future scenario maps, we are going to subtract the current from the respective RCPSs to obtain the percentage loss, percentage gain and no change.

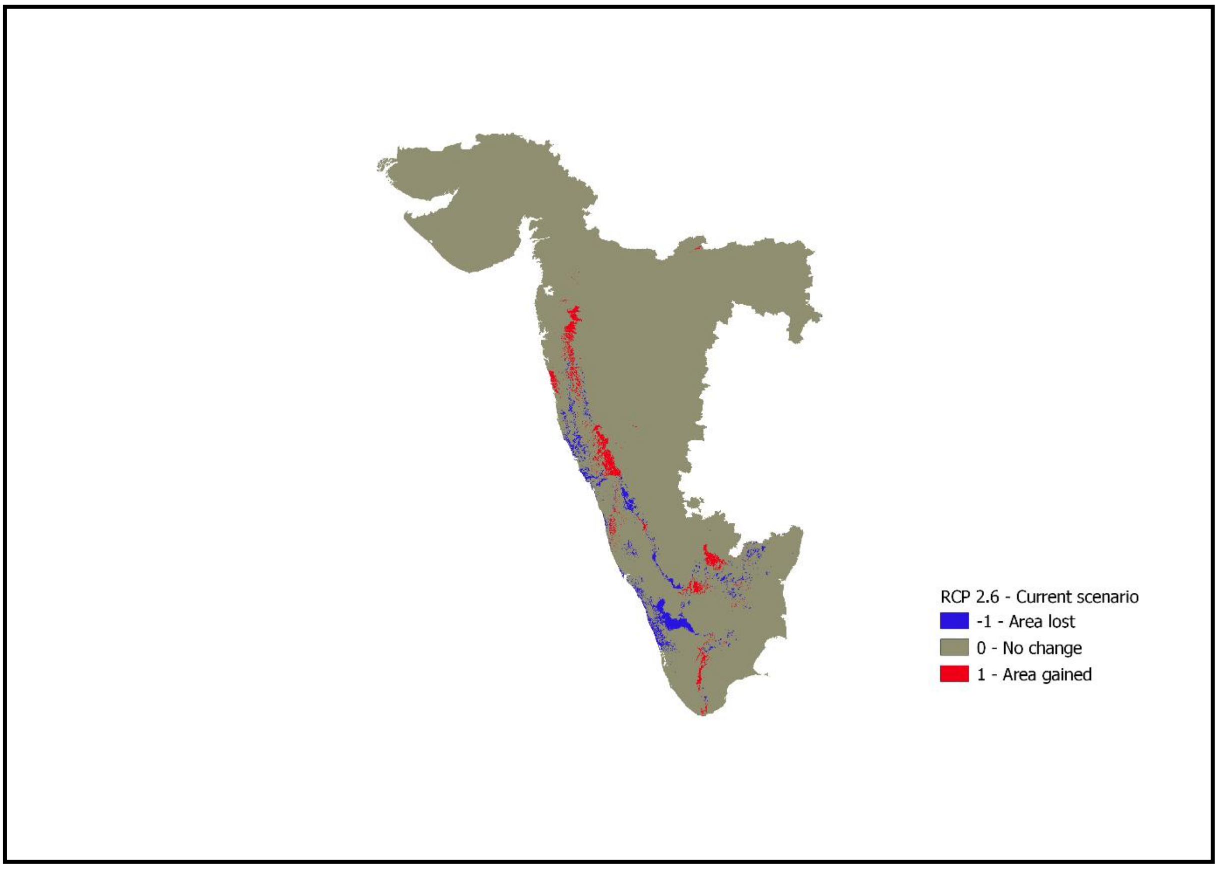


Figure 17: Distribution map showing area gained, lost and areas with no change in distribution under RCP 2.6 2050

This map is created by subtracting RCP 2.6 and current scenario. When we look at the map from top to bottom, we can see that a substantial amount of the Malabar parakeet's distribution and habitat appropriateness have remained unchanged. This value accounts for

1,008,952 km^2. This could indicate that there is no change in area where Malabar parakeet is present or absent in the earlier mentioned current scenario.

A loss of 20,764 km^2 is seen in the distribution of Malabar parakeet under RCP 2.6. This loss is observed near Singhampatti Zamindar forest near to Malayamkulam, Valliyur, near Mundanthurai Tiger reserve, in Pothai malai, in Pothai suthi, in Alangulam, near parts of Murugamalai Reserve Forest. Patches of loss can also be observed in Alagarkovil Reserve Forest. Prominent loss can be observed Palani Hills northern slope east Reserve Forest to parts of Kerala including Palakkad, Ernamkulam, Thrissur till Nilambur. Patches of habitat loss can also be observed near Bandipur Tiger reserve and national park and Nagarhole National park and tiger reserve. Some patches in the north western part of India also showed habitat loss under RCP 2.6.

Under RCP 2.6 Malabar parakeet had a gain or increment in habitat suitability of 18,450 km^2. Nagercoil, Thenkasi, Periyar National Park, Chamarajnagar, Krishnagiri, Chickmanglur showed prominent patches where Malabar parakeet showed habitat suitability. Gain in area also observes to be prominent near Shri Bhimasankar Jyotiringa wildlife, Koyna wildlife sanctuary, Chandoli National Park in the north. A patch can also be observed near the west coast region also. A tiny portion of suitable region for Malabar parakeet is also observe in Melghat tiger reserve too. Unexpectedly, regions near Bangalore also shows suitable habitat for Malabar parakeet under RCP 2.6.

The total predicted suitable habitat of Malabar parakeet accounts for 131,231 km^2. The percentage gain in area is 13.81% and the percentage loss of area accounts for 15.54%. The net gain percentage accounts for accounts -1.73%. This means that under RCP 2.6 Malabar parakeet would undergo a loss of 1.73% by 2050. (Figure 17)

Table 10: A comparison between the influence of selected bioclimatic variables under the current climatic scenario and under RCP 2.6 on the potential distribution of Malabar parakeet

Variable	Current	RCP 2.6 2050			
		bcc	miroc	Mohc hadgem	Average
Bio 19	42.6	50	38.6	39.4	42.6
Bio 12	27.6	22.5	30.7	28.6	24.2

Bio 10	10.8	17.4	19.9	22.1	19.8
Slope	7.3	5	8.6	6	6.5
Bio 14	1.3	4.6	1.5	0.1	2.5
Bio 18	10.4	0.6	0.6	3.7	1.6

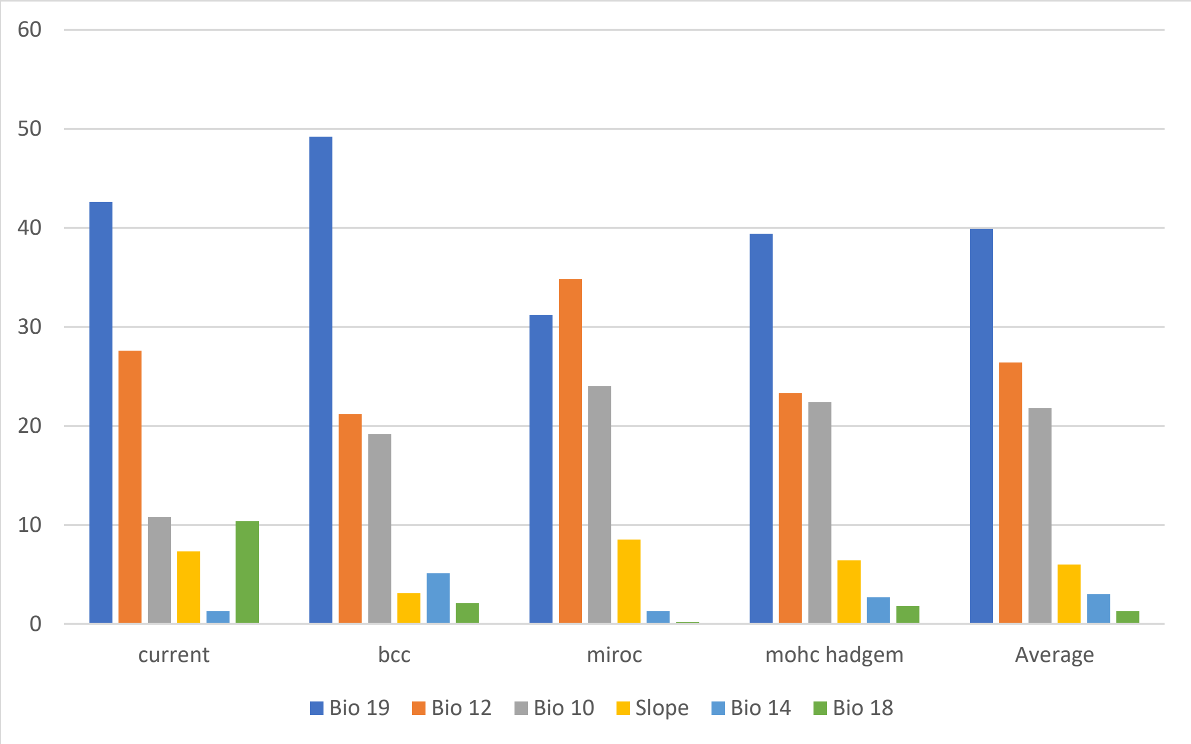


Figure 18: Chart illustrating the comparison between the influence of selected bioclimatic variables under the current scenario and under RCP 2.6

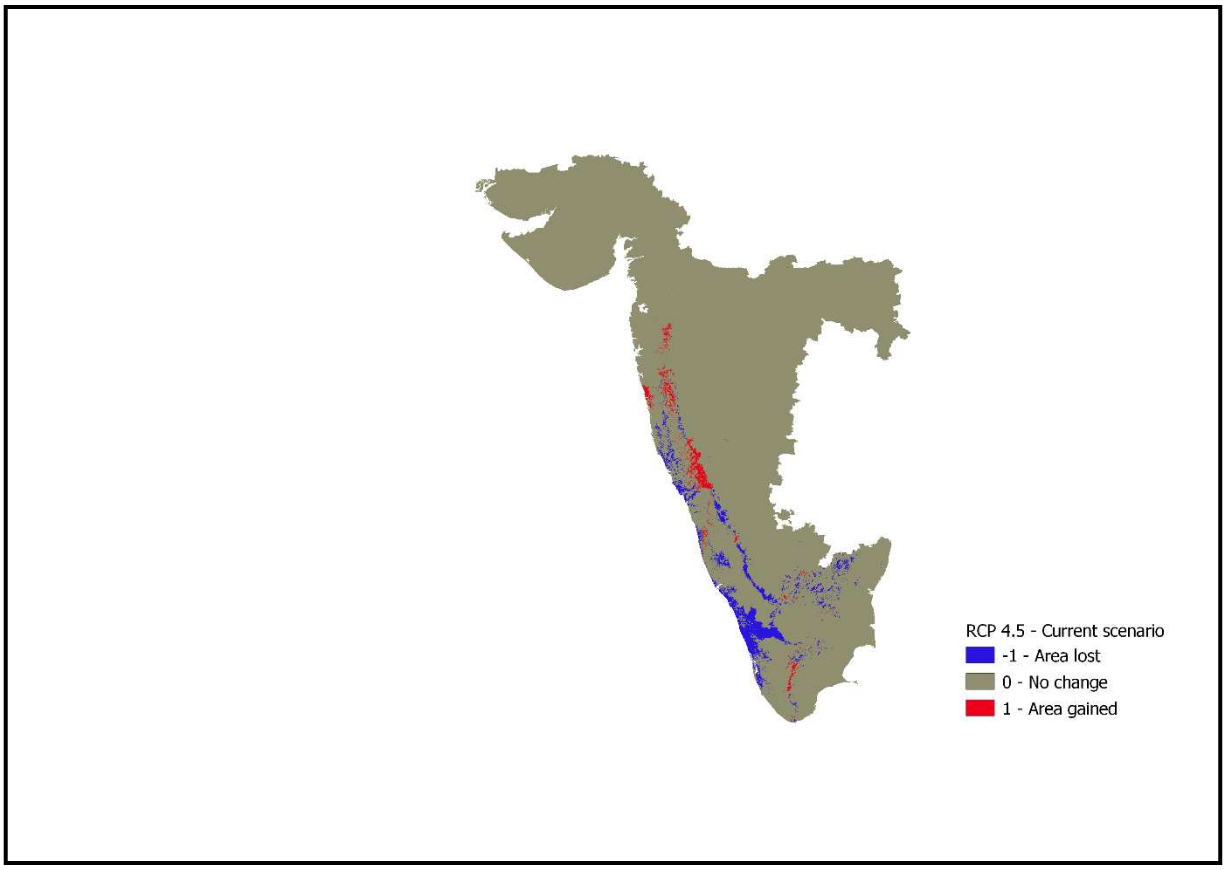


Figure 19: Distribution map showing area gained, lost and areas with no change in distribution under RCP 4.5 2050

In this scenario Malabar parakeet have lost an area of 32,962 km^2 of suitable area. Compared to RCP 2.6, there is an increment of 12,198 km^2 in unsuitable habitat in the distribution of Malabar parakeet. From the map we can see a prominent patch of habitat loss from Palani to Kannur. There are observable patches near Radhanagari wildlife sanctuary and Anshi national park. Parts of Cotigao wildlife sanctuary also showed loss of habitat suitability for Malabar parakeet under RCP 4.5. Vellur. Ambur, Dharmapuri and places near Selam also shows negative habitat suitability.

Comparing the map of RCP 2.6 and RCP 4.5 there is a clear shrinkage in habitat suitability gained. The area gained under RCP 4.5 is only 11,041 km^2. This means that the habitat suitable under RCP 4.5 have shrunk as compared to RCP 2.6 by 7,409 km^2. In the south Kadayanallur, Rajapalayam and small patches near Kodaikkanaal showed gain in habitat suitability. Small patches of habitat suitability gain can also be seen near Bhadra wildlife sanctuary and Sharavathi valley wildlife sanctuary. Prominent patches of habitat gain is seen adjacent to Bhagwan Mahavir wildlife sanctuary. Patches are also observed near Shri Bhimasankar Jyotirlinga wildlife and Koyna wildlife sanctuary. A small patch is also observed in west coast in Dapoli.

100,4163 km^2 exhibited neither gain nor loss in habitat suitability under RCP 4.5. As compared to RCP 2.6, the area that remain unchanged also have decreased by 4,789 km^2.

The total predicted suitable habitat of Malabar parakeet accounts for 111,624 km^2. The percentage gain in area is 8.26% and the percentage loss of area accounts for 24.68%. The net gain percentage accounts for accounts -16.41%. This means that under RCP 4.5 Malabar parakeet would undergo a loss of 16.41%by 2050. (Figure 19)

Table 11: A comparison between the influence of selected bioclimatic variables under the current climatic scenario and under RCP 4.5 on the potential distribution of Malabar parakeet

Variables	Current	RCP 4.5 2050			
		bcc	miroc	Mohc hadgem	Average
Bio 19	42.6	47.8	39	40.6	42.4
Bio 12	27.6	18.4	30.8	28.9	26
Bio 10	10.8	20.9	22.5	22.4	21.9
Slope	7.3	7.5	6.4	3.3	5.7
Bio 14	1.3	3.5	0.8	1.7	2
Bio 18	10.4	1.9	0.6	3	1.8

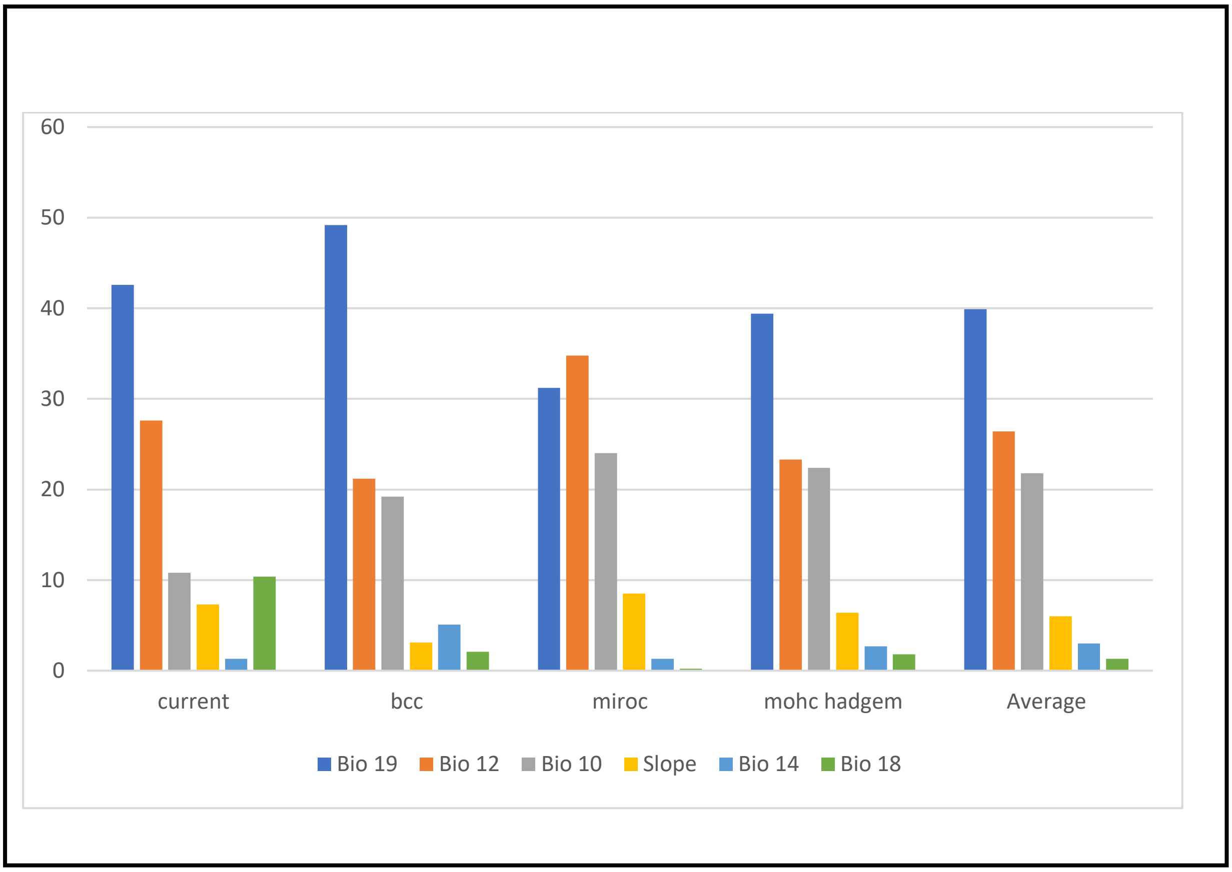


Figure 20: Chart illustrating the comparison between the influence of selected bioclimatic variables under the current scenario and under RCP 4.5

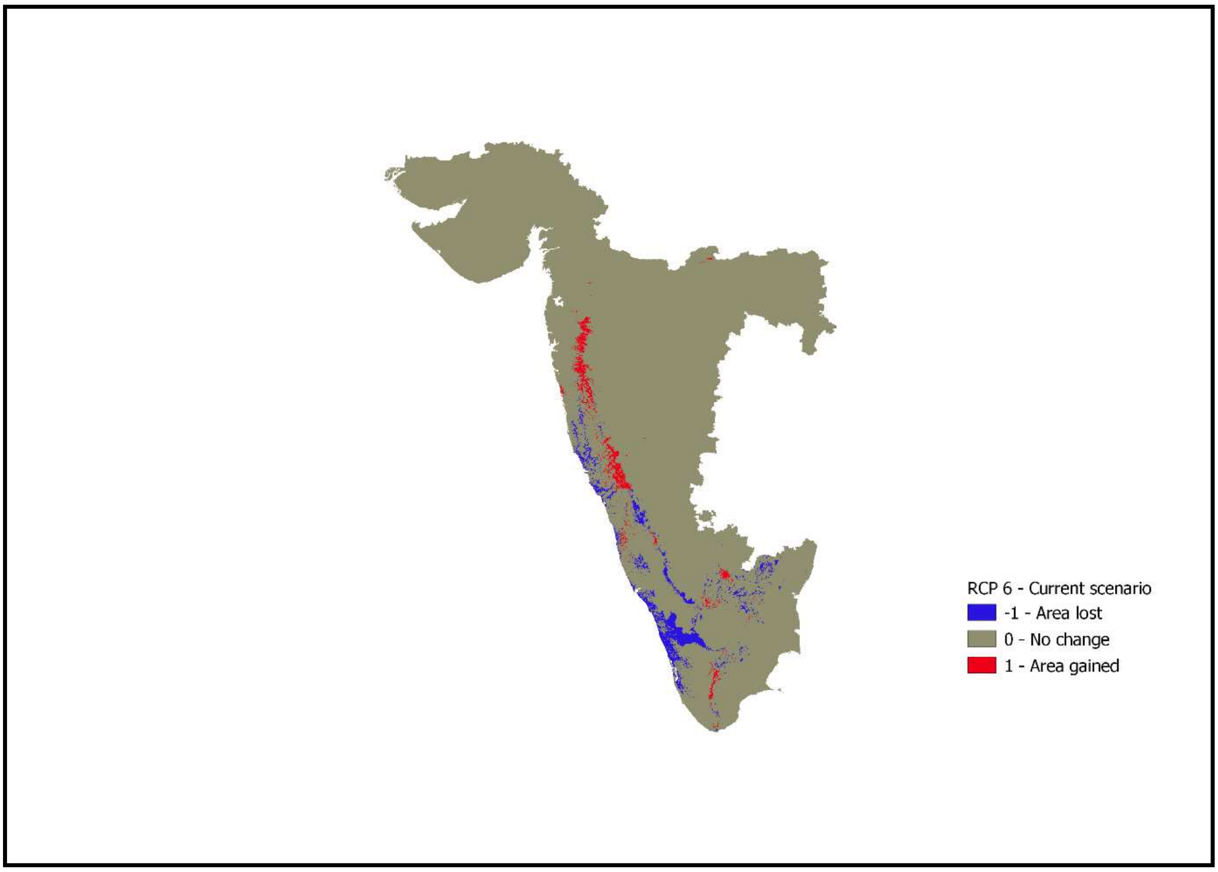


Figure 21: Distribution map showing area gained, lost and areas with no change in distribution under RCP 6 in 2050

The loss of suitable area under RCP 6 is lower when compared to RCP 4.5 2050. The area lost accounts for 27,990 km^2. A prominent patch of habitat loss can be seen from Palani hills northern slope east RF to Bekal. Many parts of Kerala showed loss of suitable habitat under RCP 6. Another patch can be observed between Bandipur Tiger Reserve and National Park and Sharavathi valley wildlife Sanctuary. Elongated patches can also be seen on north west coast of India. Ambur, Vellur, Madhurai and Salem also showed distinguishable patches which indicated habitat loss. As compared to RCP 4.5 habitat loss is reduced by 4,972 km^2 in RCP 6.

The gain in habitat under RCP 6 is increased by 4,158 km^2 as compared to RCP 4.5. Prominent patches can be seen covering Shri Bhimasankar Jyothirling Wildlife, Koyna Wildlife Sanctuary and Chandoli National Park. Similar to RCP 2.6, this scenario also showed habitat gain in Melghat Tiger Reserve. A prominent patch can be seen between Nipani and Mundgod. Bhadra Wildlife Sanctuary also promoted habitat gain under RCP 6. A circular patch of habitat gain can be seen near Manchi Reserve Forest. Overall habitat gain under RCP 6 was 15,199 km^2.

There is neither gain nor loss in habitat suitability of 1,004,977 km^2. As compared to RCP 4.5 the unchanged area have been increased by 814 km^2.

The total predicted suitable habitat of Malabar parakeet accounts for 1,20,754 km^2. The percentage gain in area is 11.38% and the percentage loss of area accounts for 20.95%. The net gain percentage accounts for accounts -9.57%. This means that under RCP 6 Malabar parakeet would undergo a loss of 9.57% by 2050. (Figure 21)

Table 12: A comparison between the influence of selected bioclimatic variables under the current climatic scenario and under RCP 6 on the potential distribution of Malabar parakeet

Variable	current	RCP 6			
		bcc	miroc	Mohc hadgem	Average
Bio 19	42.6	49.2	31.2	39.4	39.9
Bio 12	27.6	21.2	34.8	23.3	26.4
Bio 10	10.8	19.2	24	22.4	21.8
Slope	7.3	3.1	8.5	6.4	6

Bio 14	1.3	5.1	1.3	2.7	3
Bio 18	10.4	2.1	0.2	1.8	1.3

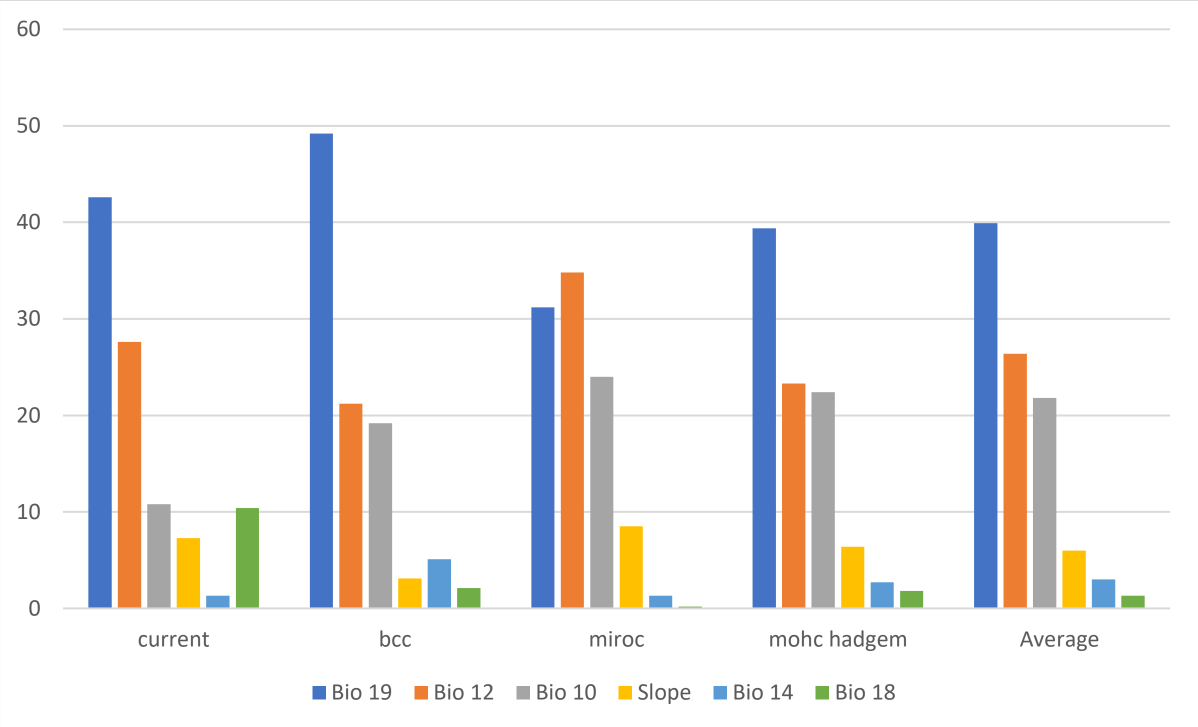


Figure 22: Chart illustrating the comparison between the influence of selected bioclimatic variables under the current scenario and under RCP 6

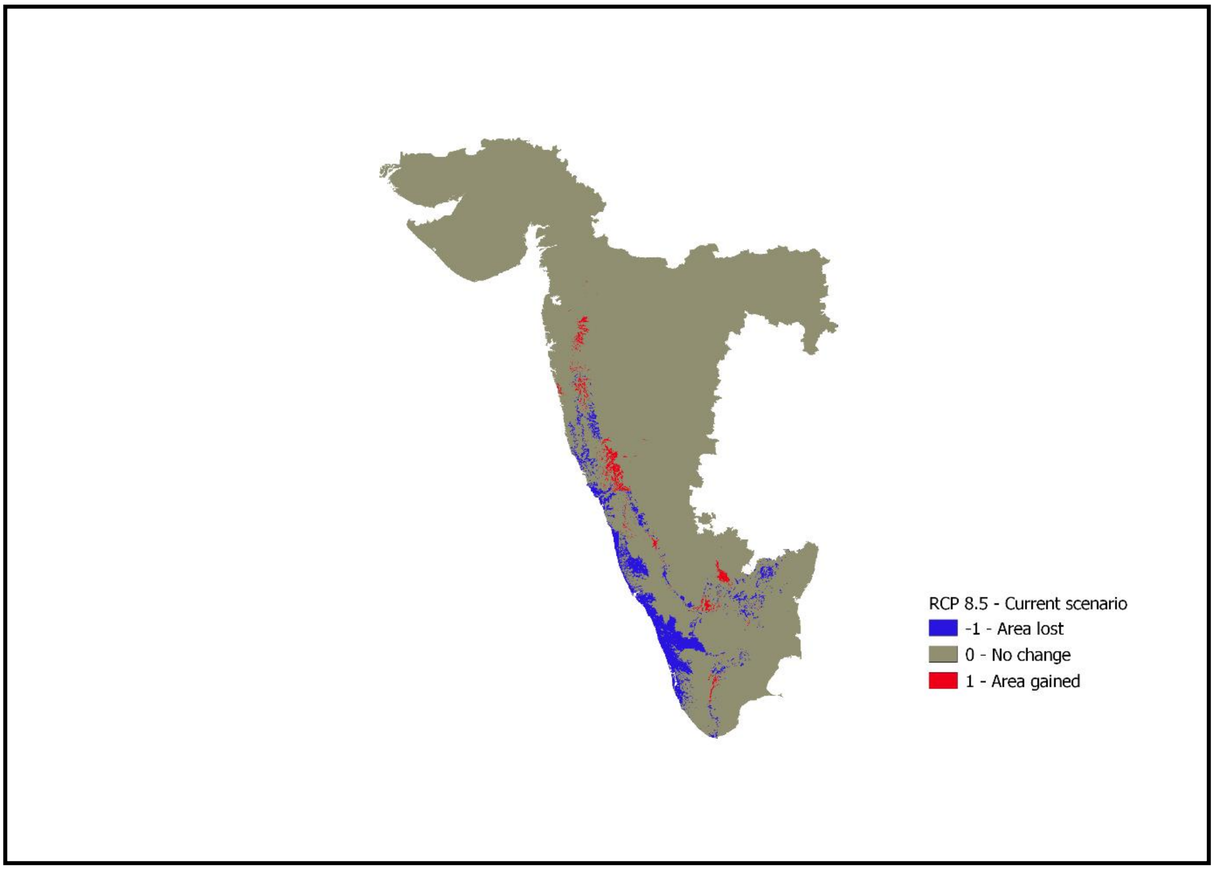


Figure 23: Distribution map showing area gained, lost and areas with no change in distribution under RCP 8.5 in 2050

As expected, being the highest emission scenario RCP 8.5 have shown overall increase in unsuitable habitats than suitable habitats. As compared to other three RCPs, RCP 8.5 have shown the highest area lost. Compared to RCP 2.6, there is an increase in unsuitable habitat by 22,213 km^2. And when compared to RCP 4.5 and RCP 6 the increase in unsuitable areas is 10,015 and 14,987 km^2 respectively. The overall habitat loss under RCP 8.5 is 42,977 km^2. A large patch from Kundapur to Kollam is clearly visible from assessing the maps. There are patches visible near Pollachi, Bandhipur Tiger Reserve, Chandoli National Park, Bhadra Wildlife Sanctuary, Vellor, Ambur, Salem and Coimbathore. Coastal regions like Panaji, Karwar and Kumta are also showing patches of habitat loss by Malabar parakeet. Anshi National Park also shows regions with no habitat suitability.

Similar to habitat loss RCP 8.5 also showed the lowest increase in habitat gain. As compared to RCP 2.6 the habitat gain has decreased by 8,021km^2. And compared to RCP 4.5 and RCP 6 the habitat gain has decreased by 612 km^2 and 4,770 km^2 respectively. The overall habitat gain under RCP 8.5 is 10,429 km^2. A patch of habitat gain can be seen from Kadayanallur to Srivilliputhur Grizzled Squirrel wildlife to Pambadumparai. A scattered patch can be seen connecting Punajur state forest, Talamalai R. F and Thamarakkarai. A circular patch is visible near Bangalore including Marichi R. F. and Bannerghatta Biological park. A patch connecting Chikmagalur and Bhadra wildlife sanctuary is also visible. There are also many scattered patches in Mookambika wildlife sanctuary and Sharavathi valley wildlife sanctuary. There is also a large patch connecting Mundgod to Chikodi. Koyna wildlife sanctuary has a patch with habitat suitability. There are also patch connecting Shri Bhimsankar jyothirlinga wildlife to Thangaon. Dapoli region in the west coast also exhibits a patch of suitable habitat.

There is neither gain nor loss in habitat suitability of 994,760 km^2. As compared to RCP 6 the unchanged area have been decreased by 814 km^2.

The total predicted suitable habitat of Malabar parakeet accounts for 100997 km^2. The percentage gain in area is 7.80% and the percentage loss of area accounts for 32.18%. The net gain percentage accounts for accounts -24.37%. This means that under RCP 8.5 Malabar parakeet would undergo a loss of 24.37% by 2050. (Figure 23)

Table 13: A comparison between the influence of selected bioclimatic variables under the current climatic scenario and under RCP 8.5 on the potential distribution of Malabar parakeet

Variable	Current	RCP 8.5			
		bcc	miroc	Mohc hadgem	Average
Bio 19	42.6	48.5	44.1	37.7	43.4
Bio 12	27.6	19.6	26.7	30.8	25.7
Bio 10	10.8	19.4	20.8	23.6	21.2
Slope	7.3	7.9	7	2.5	5.8
Bio 14	1.3	3.2	1.2	3.4	2.6
Bio 18	10.4	1.4	0.3	2.2	1.3

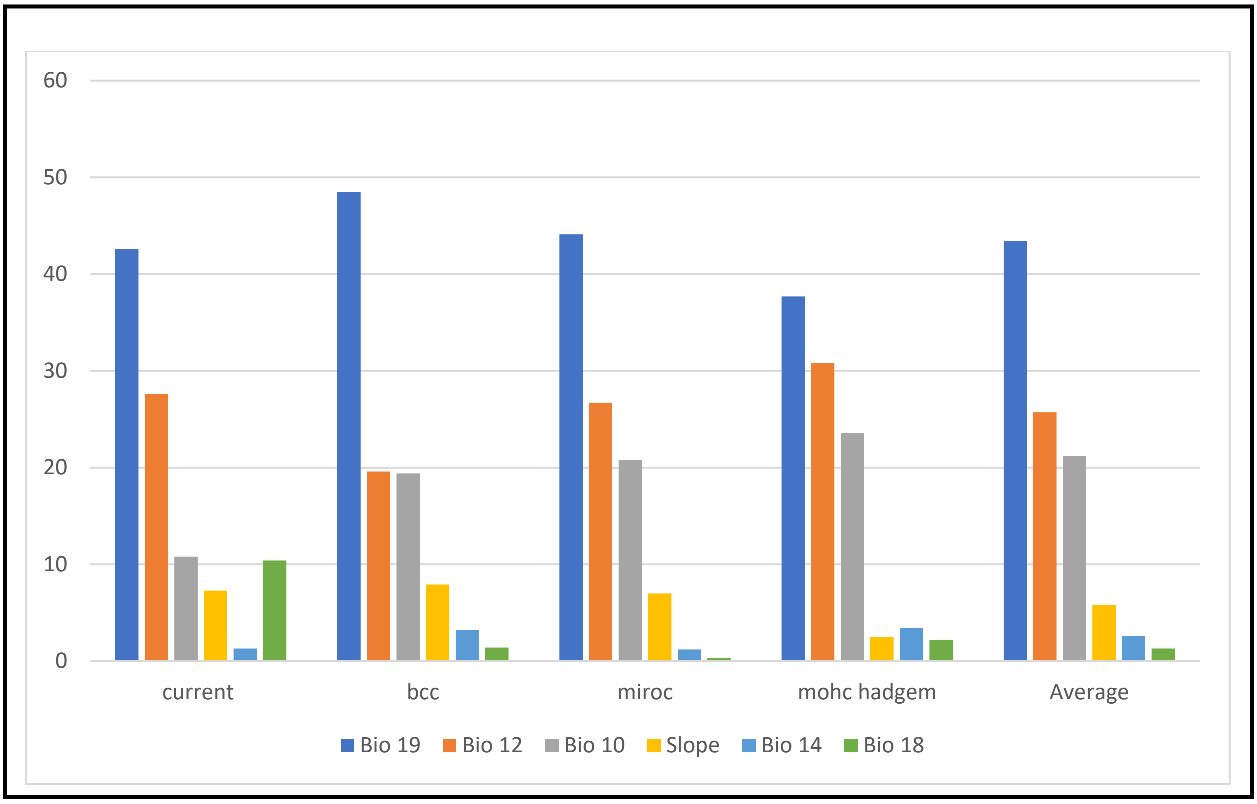


Figure 24: Chart illustrating the comparison between the influence of selected bioclimatic variables under the current scenario and under RCP 8.5

Table 14: Suitability class distribution of Malabar parakeet under various RCP scenarios with their area of extent.

Scenario	No change	Loss	Gain	Total predicted suitable habitat	% area gain	% area loss	Net gain
Current	na	915133 (unsuitable)	133545 (suitable)	na	na	na	na
RCP 2.6	1008952	20764	18450	131231	13.81	15.54	-1.73
RCP 4.5	1004163	32962	11041	111624	8.26	24.68	-16.41
RCP6	1004977	27990	27990	120754	11.38	20.95	-9.57
RCP 8.5	994760	42977	422977	100997	7.80	32.18	-24.37

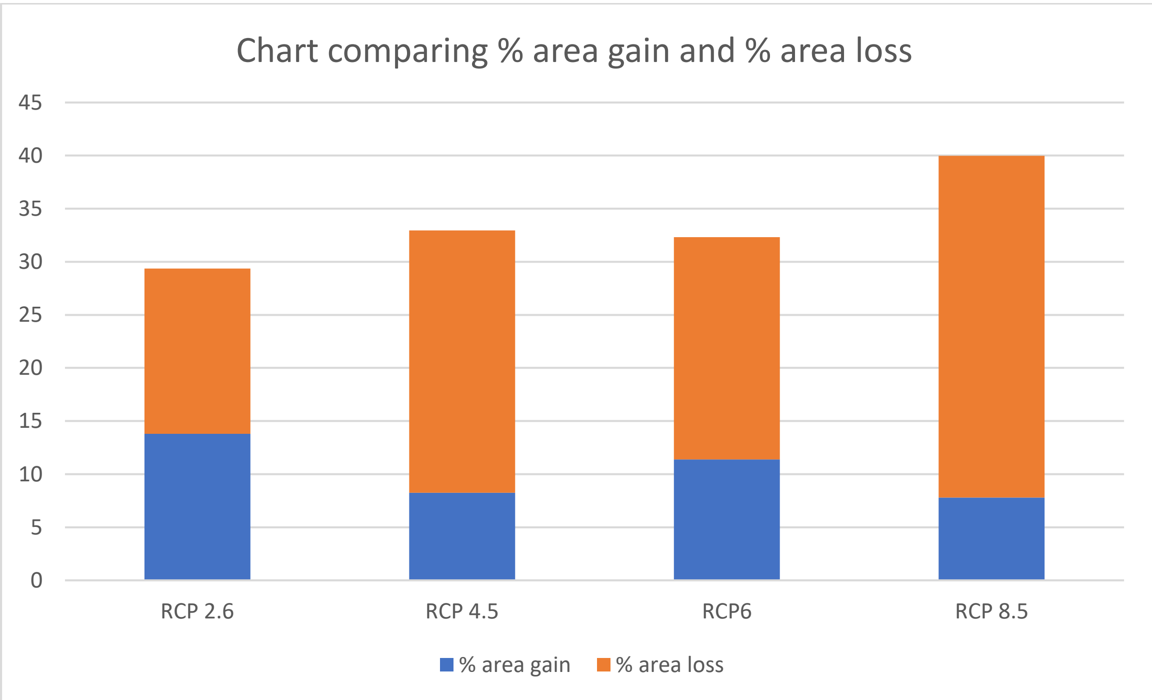


Figure: 25 Chart comparing % area gain and % area loss under different RCPs for the year 2050

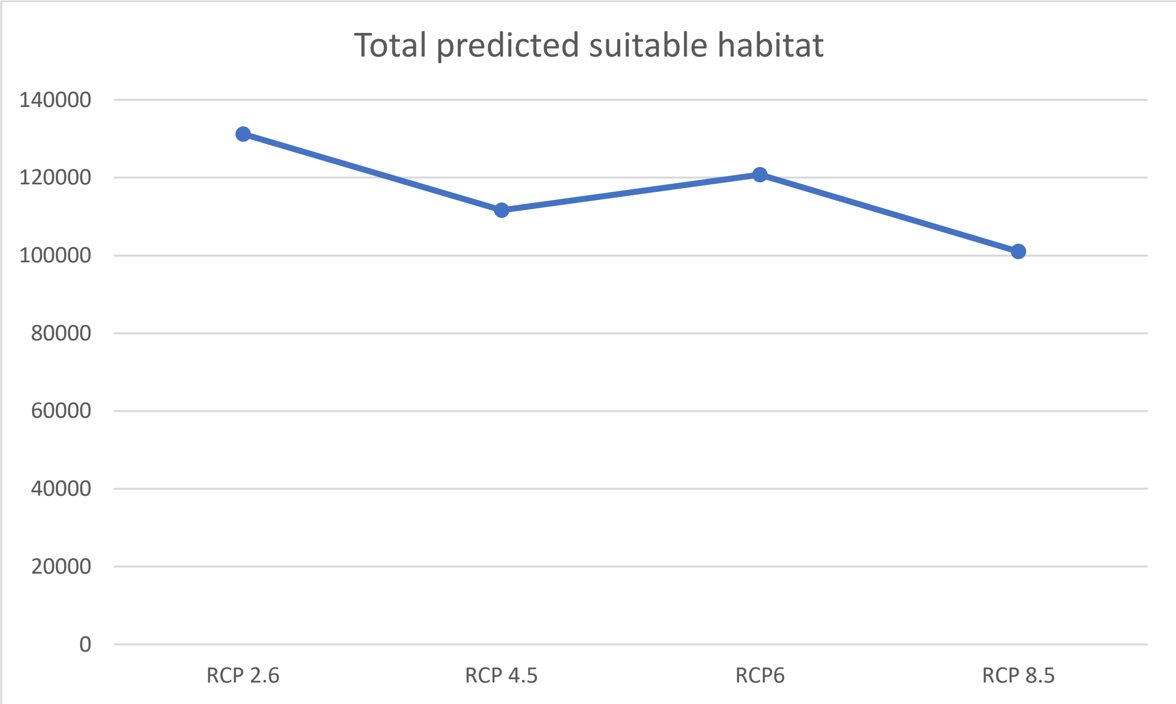


Figure: 26 Chart comparing total predicted suitable habitat under different RCPs for the year 2050

CHAPTER 5

DISCUSSION

Climate change is having an impact on every sector. The existence of life is being questioned, and some species have become extinct as a result of natural disasters. When the ecosystem is severely modified owing to harsh climatic events, intolerant species have perished and some have gone extinct. Several other species adapted by changing their habitat or displaying adaptive processes. Changes in distribution are common among avian species because they are sensitive to modest climatic fluctuations and migrate. The current study evaluates the Malabar parakeet's existing distribution patterns using climatic and other physical characteristics, as well as projecting the Malabar parakeet's distribution into the years 2050 using four Representative Concentration Pathways (RCP).

Several studies have suggested that rapid climate change will result in significant range contraction, range shifts, and local extinctions of species around the world (Parmesan 2006; Bellard et al., 2012). Knowing about the challenges that a species and its habitats face, as well as making appropriate management decisions, is crucial to the conservation of endangered species (Martin et al., 2012). Warren et al. (2013) found that if effective mitigation techniques are not implemented, the median worldwide annual mean temperature could rise to 4 °C above pre-industrial levels by 2100.

Numerous researches have been undertaken on the effects of shifting climate scenarios on the distribution of diverse species. The majority of such research findings points to either a shift in the species' range when future climatic circumstances change or a dramatic loss in the species' distribution. These changes are the outcomes of how precipitation, temperature and other derived factors change over the species' appropriate areas in the future climatic conditions.

The Western Ghats are an outstanding biodiversity hotspot, as one of Peninsular India's last contiguous tracts of tropical wet evergreen rainforests (Srinivasulu et al., 2014). This hotspot also has the highest human population density (> 300 people per square kilometre), making conservation much more difficult (Molur, 2009). Deforestation of pristine forests, as well as habitat loss and fragmentation, pose a particular hazard to the ecosystem throughout the Western Ghats range (Srinivasulu et al., 2014). As a result of their great species richness and endemism patterns, they pose a significant biodiversity conservation challenge. Predictive ecological niche modelling is a commonly used and acknowledged tool in systematic conservation planning and management (Marmion et al., 2009). However, in order to attain optimum accuracy and replicability, it is vital to understand its limitations and the statistical methodologies behind it (Elith et al., 2006; Austin, 2007; Merow et al., 2013; Feng et al., 2019).

International Union for Conservation of Nature (IUCN) have categorised Malabar parakeet as a Least Concern species. Although these species appears to be widespread in its distribution, they have very specific habitat requirements. The Malabar parakeet (*Psittacula columboides*) is an example of a bird that can be found throughout the Western Ghats, but is mostly restricted to swaths of evergreen forest on the mountain range's west facing slopes and occasionally in the well wooded sacred groves and other areas in the plains. In addition to habitat loss, research show that the inclusion of huge areas of inappropriate habitat in these species' ranges is a major driver of range overestimation. These types of range overestimation – recent habitat loss and inclusion of inappropriate habitat within a broad range – are likely to occur in other tropical birds (Hurlbert and Jetz, 2007) and taxa as well. Studies using an SDM approach will help to eliminate the inclusion of unsuitable habitats in existing species ranges and provided a foundation for tracking habitat degradation in known areas of occupancy in the future.

MaxEnt software was used to investigate the Malabar parakeet's distributional variations by linking the presence data points to the local environmental parameters. For current conditions and for the year 2050, the study used occurrence data points of the Malabar parakeet from 1979 to 2020, as well as climate data from 1979 to 2013. Climate was predicted using an ensemble of three models (BCC CSM 1.1, MIROC 5, HadGEM2 - ES of 30 second resolution) under four different Representative Concentration Pathways (RCPs). The findings are examined and analysed in depth in this chapter.

5.1. SELECTION OF REPLICATION RUN TYPE

The goal of the replication run type is to test generality, allowing the model to make sense in terms of identifying species distribution characteristics and avoiding noisy sampling processes. Cross-validation, bootstrapping, and subsampling are three types of replication types offered by MaxEnt for model evaluation. To fit the model and evaluate the model, presence locations are alienated to training and test data in cross-validation. Some studies favour it because it swiftly manages data and allows users to quickly locate statistical results such as range and standard error (Merow et al., 2013). However, when utilising cross-validation, only a portion of the data is used to fit the model, raising concerns about the statistical and spatial independence of test and training data. This will result in spatially coupled folds, which will exaggerate model performance while undervaluing prediction standard error (Anderson and Raza, 2010). Because the model takes test data in a self-contained manner, the test percentage immediately drops to zero, even if the user has chosen to test a portion of the data. The average test AUC value and SD, as well as the result outputs, are the same in all cross-validation trial models, indicating a lack of test data independence. In comparison to other models, the AUC curve's SD was relatively high. So, we chose to stick with cross validation for our study.

5.2. VARIABLE CONTRIBUTION TO THE MODEL DISTRIBUTION OF MALABAR PARAKEET

The contributions of environmental factors utilised in the building of the Malabar parakeet distribution model are given by the MaxEnt model output. Each step of the MaxEnt method modifies the coefficient of a single feature while increasing the model's gain. Precipitation of coldest quarters (bio19) had the biggest percentage contribution (44.6%) in the construction of the model, but precipitation of driest month (bio14) had negligible contribution (0.9 %), according to results. Apart from bioclimatic variables, topographical variable viz., slope have a substantial impact accounting for 7.3% of the total. When the path taken to arrive at the same solution differs due to different algorithms, the results will be different. The processing of percentage contributions should also be done with caution due to the correlations between the variables.

The importance of permutations is determined independently of the path and is only dependent on the final MaxEnt model. The drop in training AUC is calculated in line with the random permuting values of each variable among both background and presence data, and the greater the decrease in AUC, the greater the variable's reliance. The resulting numbers are then converted to percentages. As a result, measuring the contribution of each variable is preferable. For the distribution of models, mean temperature of warmest quarters (bio 10) and annual precipitation (bio 12) shows higher importance. Among other bioclimatic variables the permutation importance goes in the order: precipitation of coldest quarters (bio 19) followed by precipitation of warmest quarters (bio 18), slope and precipitation of driest month.

When the model is run in isolation, the Jackknife shows the training gain of each variable, which it then compares to the training gain of all variables. This is useful for determining which variable contributes the most. According to our results mean temperature of warmest quarters (bio 10), precipitation of coldest quarters (bio 19) and annual precipitation (bio 12) shows the most contribution.

5.3. CLIMATE CHANGE IMPACTS AND SUITABILITY CHANGES

Under a catastrophic climate change scenario, it is clear that Malabar parakeet would lose their suitable habitats. Climate change may have a negative impact on numerous species' suitable habitat, causing them to lose their probable habitat. The elevational shift could be a viable option for combating climate change (Stuhldreher and Fartmann, 2018). Even so, the Western Ghat's sky island specialists are already present in the highest elevation areas. Such an altitudinal shift in species' distribution range leads to resource competition and occupation.

Under RCP 2.6 the suitable habitat for Malabar parakeet is spread across North Sahyadri, southern end of Indian peninsula, Western coastal plain and Bangalore region. The habitat loss is expected to be in southern part of Western Ghats mainly the Kerala region and parts of Goa and Karnataka. When comparing the unsuitable area with EVI and without EVI layers there is a difference of 21,030 km^2. When converting into percentage, there is a difference of 2.29% in comparing the unsuitable area with and without EVI. When comparing the unsuitable area with and without EVI layers there is a difference of 3,382 km^2 and percentage wise difference accounts for 2.46%.

RCP 4.5 showed an increase in habitat loss than habitat gain even though being an intermediate pathway. The habitat gain in Northern Sahyadri is found to have significant reduction in area. There is a reduction in total predicted suitable area by 19,607 km^2 under RCP 4.5 when compared to RCP 2.6. In percentage wise calculation the reduction in total predicted suitable area comparing RCP 4.5 and RCP 2.6 accounts for 14.94%. There is 5.5% reduction in terms of percentage of area gained and 9.14% increase in percentage of area lost under RCP 4.5.

In RCP 6, there is reduction in percentage of area lost when compared to RCP 4.5. When compared to RCP 4.5, there is an increment of 9,130 km^2 in total predicted suitable habitat. In percentage wise calculation the increase in total predicted suitable area comparing RCP 6 and RCP 4.5 accounts for 7.56%. The percentage area that Malabar parakeet gained accounts for 3.12% when and the percentage area loss accounts for 3.73% compared with that of RCP 4.5. Comparing the total predicted suitable habitat under RCP 6 and RCP 2.6, there is a decrease of 10,477 km^2. When converting this into percentage, this accounts to 7.98% decrease than RCP

2.6. When compared with RCP 2.6, there is 5.41% increase in unsuitable habitat and 2.43% decrease in area gained.

RCP 8.5 being the highest emission scenario showed considerable increase in unsuitable area and significant decrease in suitable area. When compared to RCP 6, there is a decline of 19,757 km^2 in total predicted suitable habitat. Converting this into percentage, the decrease in total predicted suitable habitat accounts for 16.36% than RCP 6. Compared to RCP 6, there is 11.23% increase in unsuitable habitat and 3.58% decrease in area gained under RCP 8.5. When compared to RCP 4.5 the increase in percentage area loss is 7.5%. This is 3.73% lower when compared with RCP 6. And decrease in percentage area gain is 0.46%. This is 3.12% higher when compared with RCP 6. Comparing the total predicted suitable habitat under RCP 8.5 and RCP 4.5, there is a decrease of 10,627 km^2 in RCP 8.5 and this accounts to 9.52%. When comparing the least emission scenario which is RCP 2.6 and high emission scenario RCP 8.5 the increase in unsuitable area is 16.64% under RCP 8.5 and decrease in area gained is 6.01%. There is a decrease of total predicted suitable area by 30,234 km2 under RCP 8.5 compared to RCP 2.6. In percentage, this decrease accounts for 23.03%.

5.4 LIMITATIONS OF THE STUDY

The model were created using layers such as bioclimatic variables, digital elevation model, and enhanced vegetation index. However, further variables could be linked to the species habitat (Araujo and Guisan, 2006) such as insect population availability, habitat parameters, fruit tree distribution and so on. However, the majority of these layers do not exist in the format required to execute SDMs. Maximum variables that frame the habitat of selected birds were incorporated into this analysis. To construct realistic models, species to species microclimatic studies would be required. Because of the small number of weather stations in the research area, the quality of the climate models may also under dispute. To overcome this problem, high resolution climate models from various families were chosen.

CHAPTER 6

SUMMARY

All creatures' range and phenology are being affected by climate change and birds are not exception too. Birds are regarded essential bioindicators because they reflect changes in their environment. The best tool for understanding how organisms respond to climate change is species distribution modelling. Maximum entropy modelling is gaining popularity among many types of species distribution modelling studies due to its effectiveness, accuracy and ease of use. The goal of this study is to figure out what environmental and/ or climatic factors that influence the distribution of Malabar parakeet (give the scientific name here) which is an endemic bird species of Western Ghats. The study will also look at the best habitats for Malabar parakeet which is endemic to Western Ghats. Using MaxEnt algorithm, it is also proposed to forecast future changes in the habitat suitability of Malabar parakeet under various climate change scenarios such as RCP 2.6, RCP 4.5, RCP 6 and RCP 8.5 for the year 2050s (2041 – 2060).

MaxEnt models can be built using simply presence-based occurrence data and environmental factors. The presence data was acquired from eBird database. The eBird ensures data quality through a rigorous review process. The MaxEnt models were created using bioclimatic variables 1 to 19, a digital elevation model (altitude, slope and aspect), and 10 year averaged Enhanced Vegetation Index (EVI). Pearson's multicollinearity test was used to exclude variables that were highly correlated ($|R| > 0.7$). The MaxEnt features, number of background points, and regularization multiplier were determined using the ENM evaluation tool in R studio. To eliminate the model-to-model bias, future projections were made by averaging three distinct earth system models under Coupled Model Intercomparison Project 5. I choose the Western Ghats endemic species, Malabar parakeet, whose IUCN status is Least Concern.

The major findings of the study are summarized below:

- In determining the distribution of Malabar parakeet using MaxEnt, cross validate method is used with model features LQHP (Linear, Quadratic, Hinge and Product) with regularization multiplier 3.
- The occurrence points thinned at 1 km^2 gave more accurate prediction than those thinned at 5 km^2 and 10 km^2.

- Precipitation of the coldest quarters (bio19) had the biggest percentage contribution in the construction of the model for the distribution of Malabar parakeet, whereas the precipitation of the driest month (bio14) had the least influence.
- When all factors were utilized for analysis, the permutation importance in determining the probability of the Malabar parakeet was higher for mean temperature of warmest quarters (bio10) followed by annual precipitation (bio12).
- While analyzing the variables contributing to the distribution of Malabar parakeet, it is observed the precipitation related factors contributes more when compared to temperature related factors.
- One of the topographical factors that contributes to species distribution of Malabar parakeet was slope which have a percent contribution of 7.3 and permutation importance of 4.4.
- The habitat suitability for Malabar parakeet was higher in the least emission scenario which is RCP 2.6 and the lowest in the high emission scenario i.e., RCP 8.5.
- Comparing the two intermediate emission scenarios, the results of RCP 6 turned out to be more suitable than RCP 4.5.
- The total predicted suitable habitat for Malabar parakeet under RCP 2.5 was 131,231 km^2. And the % area gained, % area loss and net gain are 13.81%, 15.54% and -1.73% respectively by 2050.
- The total predicted suitable habitat for Malabar parakeet under RCP 4.5 was 111,624 km^2. And the % area gained, % area loss and net gain are 8.26%, 24.68% and -16.41% respectively by 2050.
- The total predicted suitable habitat for Malabar parakeet under RCP 6 was 120,754 km^2. And the % area gained, % area loss and net gain are 11.38%, 20.95% and -9.57% respectively by 2050.
- The total predicted suitable habitat for Malabar parakeet under RCP 8.5 was 100,997 km^2. And the % area gained, % area loss and net gain are 7.80%, 32.18% and -24.37% respectively by 2050.

- The climate change could be negatively impacting the Western Ghats endemic bird species, Malabar Parakeet, as it could be losing close to 52.08% of its suitable habitat by 2050 when combining all the RCPs.

CHAPTER 7

REFERENCES

Aiello-Lammens, M. E., Boria, R. A., Radosavljevic, A., Vilela, B., Anderson, R. P., 2015. spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography*. 38. 541–545. https://doi.org/10.1111/ecog.01132.

Akcakaya, H. R., Butchart, S. H. M., Mace, G. M., Stuart, S. N. and Hilton-Taylor, C. R. A. I. G. 2006. Use and misuse of the IUCN Red List Criteria in projecting climate change impacts on biodiversity. *Glob. Chang. Biol.* 12(11):2037-2043.

Algar, A. C., Kerr, J. T. and Currie, D. J. 2009. Evolutionary constraints on regional faunas: whom, but not how many. *Ecol. Lett*. 12(1):57-65.

Ali, S. and Ripley, S. D. (1987) Compact handbook of the birds of India and Pakistan. Delhi: Oxford University Press.

Altizer, S., R. S. Ostfeld, P. T. J. Johnson, S. Kutz & C.D. Harvell. 2013. Climate Change and Infectious Diseases: From Evidence to a Predictive Framework. *Science.* 341: 514– 519.

Anderson, R. P. and Martí , E. 2004. Modelling species' geographic distributions for preliminary conservation assessments: an implementation with the spiny pocket mice (Heteromys) of Ecuador. *Biol. Conserv*. 116(2):167-179.

Anderson, R. P. and Raza, A. 2010. The effect of the extent of the study region on GIS models of species geographic distributions and estimates of niche evolution: preliminary tests with montane rodents (genus Nephelomys) in Venezuela. *J. Biogeogr*. 37(7):1378-1393.

Anderson, R. P., Gómez-Laverde, M. and Peterson, A. T. 2002. Geographical distributions of spiny pocket mice in South America: insights from predictive models. *Glob. Ecol. Biogeogr*. 11(2):131-141.

Anderson, R. P., Lew, D. and Peterson, A.T. 2003. Evaluating predictive models of species' distributions: criteria for selecting optimal models. *Ecol. Modell*. 162(3):211-232.

Apte, S. 2004 Blue-winged Parakeet Psittacula columboides, Family Psittacidae, feeding on Loranthus leaves. *Journal of Bombay Natural History Society* .101(1): 155.

Aragon, P., Lobo, J. M., Olalla-Tarraga, M. A. and Rodriguez, M. A. 2010a. The contribution of contemporary climate to ectothermic and endothermic vertebrate distributions in a glacial refuge. Glob. *Ecol. Biogeogr*. 19(1):40-49.

Aragón, P., Rodríguez, M. A., Olalla-Tárraga, M. A. and Lobo, J. M. 2010b. Predicted impact of climate change on threatened terrestrial vertebrates in central Spain highlights differences between endotherms and ectotherms. *Anim. Conserv*. 13(4): 363-373.

Araujo, M. B. and Guisan, A. 2006. Five (or so) challenges for species distribution modelling, J. *Biogeogr*. 33(10): 1677 – 1688. DOI 10.1111/j.13652699.2006.01584.x.

Araújo, M. B. and Pearson, R. G. 2005. Equilibrium of species' distributions with climate. *Ecography*. 28(5):693-695.

Araújo, M. B. and Rahbek, C. 2006. How does climate change affect biodiversity? *Sci.* 313(5792): 1396-1397.

Araújo, M. B. and Williams, P. H. 2000. Selecting areas for species persistence using occurrence data. *Biol. Conserv*. 96(3):331-345.

Araújo, M. B., Alagador, D., Cabeza, M., Nogués-Bravo, D. and Thuiller, W. 2011. Climate change threatens European conservation areas. *Ecol. Lett.* 14(5):484- 492.

Araújo, M. B., Cabeza, M., Thuiller, W., Hannah, L. and Williams, P. H. 2004. Would climate change drive species out of reserves? An assessment of existing reserve-selection methods. *Glob. Chang. Biol*. 10(9):1618-1626.

Ashcroft, M. B., French, K. O. and Chisholm, L. A. 2011. An evaluation of environmental factors affecting species distributions. *Ecol. Modell*. 222(3):524- 531.

Austin, M. P. 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. *Ecol. Modell*. 157(2): 101-118.

Austin, M. P., Meyers, J. A., Belbin, L. and Doherty, M. D. 1995. *Modelling of Landscape Patterns and Processes Using Biological Data: Sub Project 5: Simulated Data Case Study.* Australian Nature Conservation Agency.

Austin, M. P., Nicholls, A. O. and Margules, C. R. 1990. Measurement of the realized qualitative niche: environmental niches of five Eucalyptus species. *Ecol. Monogr*. 60(2):161-177.

Austin, M., 2007. Species distribution models and ecological theory: a critical assessment and some possible new approaches. *Ecol. Modell*. 200:1–19. http://dx.doi.org/10.1016/j.ecolmodel.2006.07.005.

Bahn, V. and McGill, B. J. 2007. Can niche-based distribution models outperform spatial interpolation? *Glob. Ecol. Biogeogr*. 16(6):733-742.

Baker, S. 1927. The Fauna of British India, Cylone and Burma (Second Edition). *Birds*. 4: 208.

Bakkenes, M., Alkemade, J. R. M., Ihle, F., Leemans, R. and Latour, J. B. 2002. Assessing effects of forecasted climate change on the diversity and distribution of European higher plants for 2050. *Glob. Chang. Biol.* 8(4):390-407.

Baldwin, R. B. and Bender, L. C. 2008. Den-site characteristics of black bears in Rocky Mountain National Park, Colorado. *J. Wildl. Manag*. 72(8):1717-1724.

Baldwin, R.A., 2009. Use of maximum entropy modeling in wildlife research. *Entropy*.11: 854–866.

Bar-Massada, A., Wood, E. M., Pidgeon, A. M. and Radeloff, V. C. 2012. Complex effects of scale on the relationships of landscape pattern versus avian species richness and community structure in a woodland savanna mosaic. *Ecography*. 35(5):393-411.

Barnett, T. P., Adam, J. C., & Lettenmaier, D. P. (2005). Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature*, *438*(7066), 303–309. https://doi.org/10.1038/nature04141.

Barry, S., Elith, J., 2006. Error and uncertainty in habitat models. *Journal of Applied Ecology*. 43: 413–423.

Beale, C. M., Lennon, J. J. and Gimona, A., 2008. Opening the climate envelope reveals no macroscale associations with climate in European birds. *Proc. Natl Acad. Sci*, 105(39):14908-14912.

Beever, E. A., Ray, C., Mote, P. W. and Wilkening, J. L. 2010. Testing alternative models of climate-mediated extirpations. *Ecol. Appl.* 20(1):164-178.

Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W., Courchamp, F., 2012. Impacts of climate change on the future of biodiversity. *Ecol. Lett*. 15, 365–377. http://dx.doi.org/10.1111/j.1461-0248.2011.01736.x.

Berger, A.L., Della Pietra, S.A., Della Pietra, V.G., 1996. A maximum entropy approach to natural language processing. *Computer Linguistics.* 22 (1): 39–71.

Berry, P. M., Dawson, T. P., Harrison, P. A. and Pearson, R. G. 2002. Modelling potential impacts of climate change on the bioclimatic envelope of species in Britain and Ireland. *Glob. Ecol. Biogeogr*. 11(6):453-462.

Bojorquez-Tapia, L. A., Azuara, I., Ezcurra, E. and Flores-Villela, O. 1995. Identifying conservation priorities in Mexico through geographic information systems and modeling. *Ecol. Appl*. 5(1): 215-231.

Boria, R.A., Olson, L.E., Goodman, S.M., Anderson, R.P., 2014. Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. *Ecol. Modell*. 275: 73–77. http://dx.doi.org/10.1016/j.ecolmodel.2013.12.012.

Bourg, N. A., McShea, W. J. and Gill, D.E. 2005. Putting a CART before the search: successful habitat prediction for a rare forest herb. *Ecol*. 86:2793-2804.

Boyce, M. S., Vernier, P. R., Nielsen, S. E. and Schmiegelow, F. K. 2002. Evaluating resource selection functions. *Ecol. Modell*. 157(2):281-300.

Bradbury, R. B., Pearce-Higgins, J. W., Wotton, S. R., Conway, G. J. and Grice, P.V. 2011. The influence of climate and topography in patterns of territory establishment in a range-expanding bird. *Ibis*. 153(2):336-344.

Brown, J. L.2014. SDMtoolbox: a python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. *Method Ecol. Evol*.

Buermann, W., Chaves, J.A., Dudley, R., McGuire, J.A., Smith, T.B., Altshuler, D.L., 2011. Projected changes in elevational distribution and flight performance of montane Neotropical hummingbirds in response to climate change. *Global Change Biol*. 17: 1671–1680. http://dx.doi.org/10.1111/j.1365-2486.2010.02330.x.

Burgman, M., Lindenmayer, D. B. and Elith, J. 2005. Managing landscapes for conservation under uncertainty. *Ecol*. 86(8):2007-2017.

Burns, C. E., Johnston, K. M. and Schmitz, O. J. 2003. Global climate change and mammalian species diversity in US national parks. *Proc. Natl Acad. Sci*. 100(20):1474-11477.

Busby, J. R. 1991. BIOCLIM- a bioclimate analysis and prediction system. In: Margules, C. R. and Austin, M. P. (eds.), Nature conservation: cost effective biological surveys and data analysis. CSIRO, pp. 64-68.

Cahill, A.E. et al. 2013. How does climate change cause extinction? *Proceedings of the Royal Society B: Biological Sciences.* 280: 20121890.

Calef, M. P., McGuire, A. D., Epstein, H. E., Rupp, T. S. and Shugart, H. H. 2005. Analysis of vegetation distribution in Interior Alaska and sensitivity to climate change using a logistic regression approach. *J. Biogeogr.* 32(5):863-878

Capen, D. E., Fenwick, J. W., Inkley, D. B. and Boynton, A. C. 1986. On the measurement of error 47 Multivariate models of songbird habitat in New England forests. In: Wildlife 2000: Modelling Habitat Relationships of Terrestrial Vertebrates, (eds.), Verner, J. A., Morrison, M. L. and Ralph, C. J. University of Wisconsin Press, Madison, WI, USA, pp.171-75.

Carpenter, G., Gillison, A. N. and Winter, J. 1993. DOMAIN: a flexible modelling procedure for mapping potential distributions of plants and animals. *Biodiv. Conserv*. 2(6):667-680.

Cawsey, E. M., Austin, M. P. and Baker, B. L. 2002. Regional vegetation mapping in Australia: a case study in the practical use of statistical modelling. *Biodiv. Conserv*. 11(12): 2239-2274.

Ceballos, G. and Ehrlich, P. R. 2006. Global mammal distributions, biodiversity hotspots, and conservation. *Proc. Natl Acad. Sci*. 103(51):19374-19379.

Chen, I. C., Hill, J. K., Ohlemüller, R., Roy, D. B. and Thomas, C. D. 2011. Rapid range shifts of species associated with high levels of climate warming. *Sci.* 333(6045):1024-1026.

Chen, Y. 2016. Testing adaptive regime shifts for range size evolution om emdemic birds of China. *Journal of Asia – Pacific Biodiversity*. 9: 85 – 88. (doi:10.1016/j.japb.2015.11.003).

Coops, N. C., Waring, R. H., Wulder, M. A., Pidgeon, A. M. and Radeloff, V. C. 2009. Bird diversity: a predictable function of Satellitederived estimates of seasonal variation in canopy light absorbance across the United States. *J. Biogeogr.* 36(5):905-18

Cramer, W., Bondeau, A., Woodward, F. I., Prentice, I. C., Betts, R. A., Brovkin, V., Cox, P. M., Fischer, V., Foley, J. A., Friend, A. D., Kucharik, C., Lomas, M. R., Ramankutty, N., Sitch, S., Smith, B., White, A. and Young-Molling, C. 2000. Global response of terrestrial ecosystem structure and function to CO2 and climate change: results from six dynamic global vegetation models. *Glob. Chang. Biol*. 7(4):357-373.

Crick, H. Q. 2004. The impact of climate change on birds. *Ibis*. 146(1):48-56.

Currie, D.J. 2007. Disentangling the roles of environment and space in ecology. *J. Biogeogr*. 34(12):2009-2011.

Das A, Krishnaswamy J, Bawa JK, et al (2006) Prioritisation of conservation areas in the Western Ghats, India. *Biol Conserv* .133(1):16–31.

Daufresne, M., Lengfellner, K. & Sommer, U. 2009 Global warming benefits the small in aquatic ecosystems. *Proc. Natl Acad. Sci*. USA (doi:10.1073/pnas.090208 0106).

De Bin, R., Janitza, S., Sauerbrei, W. and Boulesteix, A.L. 2016. Subsampling versus bootstrapping in resampling – based model selection for multivariable regression. *Biometrics*.72:272- 280.

Deb, J.C., Phinn, S., Butt, N., McAlpine, C.A., 2017a. The impact of climate change on the distribution of two threatened Dipterocarp trees. *Ecol. Evol*. 7: 2238–2248.

DeMatteo, K. E. and Loiselle, B. A. 2008. New data on the status and distribution of the bush dog (Speothos venaticus): Evaluating its quality of protection and directing research efforts. *Biol. Conserv*. 141(10):2494-2505.

Devictor, V., Julliard, R., Couvet, D. and Jiguet, F. 2008. Birds are tracking climate warming, but not fast enough. *Proc. R. Soc. Lond. B: Biol Sci*. 275:2743-2748.

Edwards, M. & Richardson, A. J. 2004 Impact of climate change on marine pelagic phenology and trophic mismatch. *Nature.* 430: 881–884. (doi:10.1038/nature02808).

Elith H., J., Graham P., C., Anderson, R., Dudík, M., Ferrier, S., Guisan J., A., Hijmans, R., Huettmann R., F., Leathwick, J., Lehmann, A., Li G., J., Lohmann A., L., Loiselle, B., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., McC, M., Overton, J., Townsend Peterson J., A., Phillips, S., Richardson, K., ScachettiPereira E., R., Schapire, R., Soberon, ´ J., Williams S., S., Wisz E., M., Zimmermann, N., 2006. Novel methods improve prediction of species' distributions from occurrence data. *Ecography*. 29: 129–151. https://doi.org/10.1111/j.2006.0906-7590.04596.x.

Elith, J. and Burgman, M. 2002. Predictions and their validation: Rare plants in the Central Highlands, Victoria, Australia. In: Predicting Species Occurrences: Issues of Accuracy and Scale. *Washington, USA: Island Press*. pp. 303-313.

Elith, J., Graham, C. H., Anderson, R. P., Dudı´k, M., Ferrier, S., Guisan, A., Hijmans, R. J., Huettmann, F., Leathwick, J. R., Lehmann, A., Li, J., Lohmann, L. G., Loiselle, B. A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J. McC., Peterson, A. T., Phillips, S. J., Richardson, K. S., Scachetti-Pereira, R., Schapire, R. E., Sobero´n, J., Williams, S., Wisz, M. S. and Zimmermann, N. E. 2006. Novel methods improve prediction of species' distributions from occurrence data. *Ecography.* 29(2): 129-151.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E. and Yates, C.J. 2011. A statistical explanation of MaxEnt for ecologists. *Divers. Distrib*. 17(1):43-57.

Engler, R., Guisan, A. and Rechsteiner, L. 2004. An improved approach for predicting the distribution of rare and endangered species from occurrence and pseudoabsence data. *J. Appl. Ecol.* 4(2):263-274.

Enquist, C. A. F. 2002. Predicted regional impacts of climate change on the geographical distribution and diversity of tropical forests in the Costa Rica. *Journal of Biogeography.* 29: 519 – 534.

European Environment Agency (EEA). 2007. Halting the Loss of Biodiversity by 2010: Proposal for a First Set of Indicators to Monitor Progress in Europe.

Feeley, K. J. and Silman, M. R. 2010. Modelling the responses of Andean and Amazonian plant species to climate change: the effects of georeferencing errors and the importance of data filtering. *J. Biogeogr*. 37(4):733-740.

Feng, X., Park, D.S., Walker, C., Peterson, A.T., Merow, C., Papes, M., 2019. A checklist for maximizing reproducibility of ecological niche models. *Nat. Ecol. Evol*. 3: 1382–1395. https://doi.org/10.1038/s41559-019-0972-5.

Ferrier, S. 2002a. Mapping spatial pattern in biodiversity for regional conservation planning: where to from here? *Syst. Biol*. 51(2): 331-363.

Ferrier, S., Watson, G., Pearce, J. and Drielsma, M. 2002b. Extended statistical approaches to modelling spatial pattern in biodiversity in northeast New South Wales. I. Species-level modelling. *Biodiv. Conserv*. 11(12):2275-2307.

Ferrier, S., Watson, G., Pearce, J. and Drielsma, M. 2002c. Extended statistical approaches to modelling spatial pattern in biodiversity: the north-east New South Wales experience. II. Community-level modelling. *Biodiv. Conserv*. 11(12): 2309-2338.

Fielding, A. H. and Bell, J. F. 1997. A review of methods for the assessment of prediction errors in conservation presence/ absence models. *Environ. Conserv*. 24(01):38-49.

Friedman, J. H., Hastie, T. and Tibshirani, R. 2000. Additive logistic regression: a statistical view of boosting. *Ann. Stat*. 28(2):337-407.

Funk, V. and Richardson, K. 2002. Systematic data in biodiversity studies: use it or lose it. *Syst. Biol*. 51(2):303-316.

Gaston, A. J. and Zacharias, V. J. (1996) The recent distribution of endemic and disjunct birds in Kerala State: preliminary results of an ongoing survey. *J. Bombay Nat. Hist. Soc*. 93: 389–400.

Gates, S., Gibbons, D. W., Lack, P. C. and Fuller, R. J. 1994. Declining farmland bird species: modelling geographical patterns of abundance in Britain. In: Edwards, P.J., May, R.M. and Webb, N.R. (eds.*) Large Scale Ecology and Conservation Biology.* Oxford: Blackwell. pp 153-177.

Gibbons, D. W. and Wotton, S. 1996. The Dartford Warbler in the United Kingdom in 1994. *Br. Birds*. 89(5):203-212.

Goetz, S. J., Sun, M., Zolkos, S., Hansen, A. and Dubayah, R. 2014. The relative importance of climate and vegetation properties on patterns of North American breeding bird species richness. *Environ. Res. Lett*. 9(3): 034013.

Gokula, V. and C. Venkatraman. 2003. Foraging and breeding biology of the Malabar Parakeet Psittacula columboides in the Siruvani foothills, Tamil Nadu, India. *Forktail* .19(2003): 138-139.

Graham, C. H., Elith, J., Hijmans, R. J., Guisan, A., Peterson, A. T. and Loiselle, B. A. 2008. The influence of spatial errors in species occurrence data using in distribution models. *J. Appl. Ecol*. 45(1):239-247.

Graham, C. H., Ferrier, S., Huettman, F., Moritz, C. and Peterson, A. T. 2004. New developments in museum-based informatics and applications in biodiversity analysis. *Trends Ecol. Evol.* 19(9):497-503.

Graham, C. H., Moritz, C. and Williams, S. E. 2006. Habitat history improves prediction of biodiversity in a rainforest fauna. *Proc. Natl. Acad. Sci. USA*. 103(3):632-636.

Grassl, H. 2000. Status and improvements of coupled general circulation models. *Sci*. 288(5473):1991-1997.

Gregory, R. D., Willis, S. G., Jiguet, F., Voříšek, P., Klvaňová, A., van Strien, A., Huntley, B., Collingham, Y. C., Couvet, D. and Green, R. E. 2009. An indicator of the impact of climatic change on European bird populations. *PloS one.* 4(3):p.e4678.

Gu, W. and Swihart, R. K. 2004. Absent or undetected? Effects of non-detection of species occurrence on wildlife–habitat models. *Biol. Conserv*. 116(2):195-203.

Guisan, A. and Thuiller, W. 2005. Predicting species distribution: offering more than simple habitat models. *Ecol. Lett*. 8(9):993-1009.

Guisan, A. and Zimmerman, N. E. 2000. Predictive habitat distribution models in ecology. *Ecol. Modell.* 135(2):147-186.

Guisan, A., Graham, C. H., Elith, J. and Huettmann, F. 2007. Sensitivity of predictive species distribution models to change in grain size. *Divers. Distrib.* 13(3):332- 340.

Hamann, A. and Wang, T. 2006. Potential effects of climate change on ecosystem and tree species distribution in British Columbia. *Ecol.* 87(11):2773-2786.

Hannah, L., Midgley, G. F. and Millar, D. 2002. Climate change-integrated conservation strategies. *Glob. Ecol. Biogeogr*. 11(6):485-495.

Hannah, L., Midgley, G. F. and Millar, D. 2002. Climate change-integrated conservation strategies. *Glob. Ecol. Biogeogr.* 11(6):485-495.

Hansen, A. J., Phillips, L. B., Flather, C. H. and Robison-Cox, J. 2011. Carrying capacity for species richness as a context for conservation: a case study of North American breeding birds. *Glob. Ecol. Biogeogr*. 20(6):817-831.

Harris, J .B. C., Sekercioglu, C. H., Sodhi, N. S., Fordham, D. A., Paton, D.C. and Brook, B.W. 2011. The tropical frontier in avian climate impact research. *Ibis*. 153(4):877-882.

Harris, J.B.C., Putra, D.D., Gregory, S.D., Brook, B.W., Prawiradilaga, D.M., Sodhi, N.S., Wei, D., Fordham, D.A., 2014. Rapid deforestation threatens mid-elevational endemic birds but climate change is most important at higher elevations. *Divers. Distrib*. 1–13. http://dx.doi.org/10.1111/ddi.12180.

Harrison, P. A., Berry, P. M., Butt, N. and New, M. 2006. Modelling climate change impacts on species' distributions at the European scale: implications for conservation policy. Environ. *Sci. policy*. 9(2):116-128.

Hastie, T., Tibshirani, R., Friedman, J. and Franklin, J. 2001. The elements of statistical learning: data mining, inference and prediction. *Math. Intelligencer*. 27(2):83- 85.

Hawkins, B. A., Field, R., Cornell, H. V., Currie, D. J., Guégan, J .F., Kaufman, D. M., Kerr, J. T., Mittelbach, G. G., Oberdorff, T., O'Brien, E. M. and Porter, E. E. 2003. Energy, water, and broad-scale geographic patterns of species richness. *Ecol.* 84(12):3105-3117.

Heikkinen, R .K., Luoto, M., Araújo, M. B., Virkkala, R., Thuiller, W. and Sykes, M.T. 2006. Methods and uncertainties in bioclimatic envelope modelling under climate change. *Prog. Phys. Geogr*. 30(6):751-777.

Hernandez, P. A., Graham, C. H., Master, L. L. and Albert, D. L. 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods. *Ecography*. 29(5):773-785.

Hijmans, R. J. 2012. Cross-validation of species distribution models: removing spatial sorting bias and calibration with a null model. *Ecol*. 93(3):679-688.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. and Jarvis, A. 2005. Very high resolution interpolated climate surfaces for global land areas. *Int. J. Climatol.* 25(15):1965-1978.

Hijmans, R. J., Garrett, K. A., Huaman, Z., Zhang, D. P., Schreuder, M. and Bonierbale, M. 2000. Assessing the geographic representativeness of genebank collections: the case of Bolivian wild potatoes. *Conserv. Biol.* 14(6):1755-1765.

Hinsley, S., Hill, R., Fuller, R., Bellamy, P. and Rothery, P. 2009. Bird species distributions across woodland canopy structure gradients. *Community Ecol.* 10(1):99-110.

Hirzel, A. H., Hausser, J., Chessel, D. and Perrin, N. 2002b. Ecological-niche factor analysis: how to compute habitat suitability map without absence data. *Ecol.* 83(7):2027-2036.

Holt, R. D. 1990. The microevolutionary consequences of climate change. *Trends Ecol. Evol*. 5(9): 311-315.

Huettmann, F. 2005. Databases and science-based management in the context of wildlife and habitat: towards a certified ISO standard for objective decisionmaking for the global community by using the internet. *J. Wildl. Manage*. 69:466-472.

Hugall, A., Moritz, C., Moussalli, A. and Stanisic, J. 2002. Reconciling paleodistribution models and comparative phylogeography in the Wet Tropics rainforest land snail Gnarosophia bellendenkerensis (Brazier 1875). *Proc. Natl Acad. Sci*. 99(9):6112-6117.

Huntley, B., Collingham, Y. C., Green, R. E., Hilton, G. M., Rahbek, C. and Willis, S. G. 2006. Potential impacts of climatic change upon geographical distributions of birds. *Ibis*. 148(s1):8-28.

Hurlbert, A.H., Jetz, W., 2007. Species richness, hotspots, and the scale dependence of range maps in ecology and conservation. *Proc. Natl. Acad. Sci*. 104 (33), 13384–13389.

Ibisch, P., Mérida, G., 2003. Biodiversidad: La Riqueza de Bolivia. Estado de Conocimiento y Conservación. Editorial FAN, Santa Cruz de la Sierra, Bolivia. IPCC, 2007. Climate Change 2007: Synthesis Report. Cambridge University Press, Cambridge.

Intergovernmental Panel on Climate Change (IPCC), 2007. *Fourth Assessment Report: Climate Change 2007, The Physical Science Basis.* Cambridge University Press, Cambridge

Iverson, L. R. and Prasad, A. M. 1998. Predicting abundance for 80 tree species following climate change in the Eastern United States. *Ecol. Monogr.* 68(4):465-485.

Jeschke, J. and Strayer, D. 2008. Usefulness of bioclimatic models for studying climate change and invasive species. *Ann. N. Y. Acad. Sci.* 1134(1):1-24.

Jetz, W., Wilcove, D. S. and Dobson, A. P. 2007. Projected impacts of climate and land-use change on the global diversity of birds. *PLoS Biol*. 5(6):1211-1219.

Jiménez-Valverde, A., Peterson, A. T., Soberón, J., Overton, J. M., Aragón, P. and Lobo, J. M. 2011. Use of niche models in invasive species risk assessments. *Biol. Invasions*.13(12):2785-2797.

Jose FC (2012) The 'living fossil'shola plant community is under threat in upper Nilgiris. *Curr Sci*. 102(8):1091.

Kadmon, R., Farber, O. and Danin, A. 2004. Effect of roadside bias on the accuracy of predictive maps produced by bioclimatic models. *Ecol. Appl*. 14(2):401-413.

Kearney, M. 2006. Habitat, environment and niche: what are we modelling? *Oikos*. 115(1):186-191.

Keating, K. A. and Cherry, S. 2004. Use and interpretation of logistic regression in habitat-selection studies*. J. Wildl. Manag*. 68(4):774-789.

Keenan, T., J. Maria Serra, F. Lloret, M. Ninyerola & S. Sabate. 2011. Predicting the future of forests in the Mediterranean under climate change, with niche- and process-based models: CO2 matters! *Global Change Biology.* 17: 565–579.

Kerr, J. 2001. Global biodiversity patterns: from description to understanding. *Trends Ecol. Evol*. 16(8):424-425.

Kobler, A. and Adamic, M. 2000. Identifying brown bear habitat by a combined GIS and machine learning method*. Ecol. Modell*. 135(2):291-300.

La Sorte, F. A. and Jetz, W. 2010. Projected range contractions of montane biodiversity under global warming*. Proc. R. Soc. B: Biol. Sci.* 277:3401-3410.

La Sorte, F.A. and Thompson, F.R. III. 2007. Poleward shifts in winter ranges of North American birds. *Ecol*. 88:1803-1812.

Leathwick, J. R., Elith, J., Francis, M. P., Hastie, T. and Taylor, P. 2006. Variation in demersal fish species richness in the oceans surrounding New Zealand: an analysis using boosted regression trees. *Mar. Ecol. Prog. Ser.* 321:.267-281.

Leathwick, J. R., Rowe, D., Richardson, J., Elith, J. and Hastie, T. 2005. Using multivariate adaptive regression splines to predict the distributions of New Zealand's freshwater diadromous fish. *Freshw. Biol*. 50(12):2034-2052.

L. El Zein, A. (2015). The Effect of Greenhouse Gases on Earth's Temperature. *International Journal of Environmental Monitoring and Analysis*, *3*(2), 74. https://doi.org/10.11648/j.ijema.20150302.16

Lobo, J.M., Jiménez-valverde, A., Real, R., 2008. AUC: a misleading measure of the performance of predictive distribution models. *Ecol. Biogeogr. Glob*. 10.1111/j.1466-8238.2007.00358.x.

Loiselle, B. A., Howell, C. A., Graham, C. H., Goerck, J. M., Brooks, T., Smith, K. G. and Williams, P. H. 2003. Avoiding pitfalls of using species distribution models in conservation planning. *Conserv. Biol*. 17(6):1591-1600.

Loiselle, B. A., Jørgensen, P. M., Consiglio, T., Jiménez, I., Blake, J. G., Lohmann, L. G. and Montiel, O. M. 2008. Predicting species distributions from herbarium collections: does climate bias in collection sampling influence model outcomes? *J. Biogeogr*. 35(1):105-116.

Lowe, D.G. 1995. Similarity metric learning for a variable-kernel classifier. *Neural Comput*. 7(1):72-85.

M. P. and Cunningham, R. B. 1981. Observational analysis of environmental gradients. In Proc. *Ecol. Soc. Aust*. 11: 109-119.

Mac Nally, R. 2002. Multiple regression and inference in ecology and conservation biology: further comments on identifying important predictor variables. *Biodivers. Conserv.* 11(8):1397-1401.

Mace, G. M. and Baillie, J. E. 2007. The 2010 biodiversity indicators: challenges for science and policy. *Conserv. Biol*. 21(6):1406-1413.

Maclean, I., Austin, G. E., Rehfisch, M. M., Blew, J. A. N., Crowe, O., Delany, S., Devos, K., Deceuninck, B., Guenther, K., Laursen, K. and Van Roomen, M. 2008. Climate change causes rapid changes in the distribution and site abundance of birds in winter. *Glob. Chang. Biol*. 14(11):2489-2500.

Malcolm, J. R., Liu, C., Neilson, R. P., Hansen, L. and Hannah, L. E. E. 2006. Global warming and extinctions of endemic species from biodiversity hotspots. *Conserv. Biol*. 20(2):538-548.

Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R.K., Thuiller, W., 2009. Evaluation of consensus methods in predictive species distribution modelling. *Divers. Distrib*. 15, 59–69. https://doi.org/10.1111/j.1472-4642.2008.00491.x.

Martin, T.G., Nally, S., Burbidge, A.A., Arnall, S., Garnett, S.T., Hayward, M.W., Lumsden, L.F., Menkhorst, P., McDonald-Madden, E., Possingham, H.P., 2012. Acting fast helps avoid extinction. *Conserv. Lett*. 5: 274–280. http://dx.doi.org/10.1111/j.1755-263X. 2012.00239.x.

McKechnie, A. E. 2008. Phenotypic flexibility in basal metabolic rate and the changing view of avian physiological diversity: a review. *J. Comp. Physiol*. 178(3):235- 247

McKenney, D. W., Pedlar, J. H., Lawrence, K., Campbell, K. and Hutchinson, M.F. 2007. Potential impacts of climate change on the distribution of North American trees. *Biosci.* 57(11):939-948.

McNab, B. K. 2009. Ecological factors affect the level and scaling of avian BMR. *Comparative Biochemistry and Physiology Part A: Molecular & Integrative Physiology*. 152(1):22-45.

Melillo, J. M., Prentice, I. C., Farquhar, G. D., Schulze, E. D. and Sala, O. E. 1995. Terrestrial biotic responses to environmental change and feedbacks to climate. In: Houghton, J. T., Meira Filho, L. G., Callander, B. A., Harris, N., Kattenberg, A., Maskell, K. (eds.), Climate Change 1995: The Science of Climate Change.

Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography.* 36: 1058–1069. https://doi.org/10.1111/j.1600-0587.2013.07872.x.

Midgley, G. F., Hannah, L., Millar, D., Rutherford, M. C. and Powrie, L. W. 2002. Assessing the vulnerability of species richness to anthropogenic climate change in a biodiversity hotspot. *Glob. Ecol. Biogeogr*. 11(6):445-451.

Mittelbach, G.G. 2010. Understanding species richness–productivity relationships: the importance of meta-analyses. *Ecol*. 91(9):2540-2544.

Molur, S., 2009. Habitat and Status Assessment of Mammals with Special Reference to Rodents and Bats in Western Ghats of Karnataka. Department of Zoology, University of Mysore, Manasagangotri, Mysore (PhD thesis).

Molur, S., Smith, K.G., Daniel, B.A., Darwall, W.R.T., 2011. The Status and Distribution of Freshwater Biodiversity in the Western Ghats. International Union for Conservation of Nature (IUCN), Gland, Switzerland and Zoo Outreach Organization (ZOO), Coimbatore, India.

Moran, X. A. G., Urrutia, A´. L., Calvo-Dı´az, A. & Li, W. K. W. 2010. Increasing importance of small phytoplankton in a warmer ocean. *Global Change Biol*. 16: 1137–1144. (doi:10.1111/j.1365-2486.2009. 01960.x).

Myers, N., Mittermeier, R.A., Mittermeier, C.G., da Fonseca, G.A.B., Kent, J., 2000. Biodiversity hotspots for conservation priorities. Nature 403, 853–858. Nayar, T.S., Beegam, A.R., Sibi, M., 2014. Flowering Plants of the Western Ghats, India. vol. 1 Jawaharlal Nehru Tropical Botanic Garden and Research Institute, Thiruvananthapuram x+934pp.

Nally, R. M. and Fleishman, E. 2004. A successful predictive model of species richness based on indicator species. *Conserv. Biol*. 18(3):646-654.

Niven, D. K., Butcher, G. S. and Bancroft, G. T. 2009. *Birds and Climate Change: Ecological Disruption in Motion.* National Audubon Society, New York.

Nix, H. A., 1986. A biogeographic analysis of Australian elapid snakes. In: *Atlas of Australian Elapid Snakes. Bureau Flora Fauna*, Canberra, pp. 4-15.

Oswald, S. A., & Arnold, J. M. (2012). Direct impacts of climatic warming on heat stress in endothermic species: Seabirds as bioindicators of changing thermoregulatory constraints. In *Integrative Zoology* (Vol. 7, Issue 2, pp. 121–136). https://doi.org/10.1111/j.1749-4877.2012.00287.x.

Parmesan, C. 2006 Ecological and evolutionary responses to recent climate change. *Annu. Rev. Ecol. Evol*. Syst. 37: 637–669. (doi:10.1146/annurev.ecolsys.37.091305. 110100).

Pautasso, M. 2012. Observed impacts of climate change on terrestrial birds in Europe: an overview. *Ital. J. Zool.* 79(2):296-314.

Pautasso, M., Böhning-Gaese, K., Clergeau, P., Cueto, V. R., Dinetti, M., Fernández-Juricic, E., Kaisanlahti-Jokimäki, M. L., Jokimäki, J., McKinney, M. L., Sodhi, N. S. and

Storch, D. 2011. Global macroecology of bird assemblages in urbanized and semi-natural ecosystems. *Glob. Ecol. Biogeogr*. 20(3):426-436.

Pearce, J. and Ferrier, S. 2000. Evaluating the predictive performance of habitat models developed using logistic regression. *Ecol. Modell.* 133(3):225-245.

Pearce, J. L. and Boyce, M. S. 2006. Modelling distribution and abundance with presence-only data. *J. Appl. Ecol.* 43(3):405-412.

Pearson, R. G. and Dawson, T. P. 2003. Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? *Glob. Ecol. Biogeogr*. 12(5):361-371.

Pearson, R. G., Dawson, T. P., Berry, P. M. and Harrison, P. A. 2002. SPECIES: a spatial evaluation of climate impact on the envelope of species. *Ecol. Modell*. 154(3):289-300.

Pearson, R. G., Raxworthy, C. J., Nakamura, M. and Peterson, A. T. 2007. Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *J. Biogeogr*. 34(1):102-117.

Pearson, R. G., Thuiller, W., Araújo, M. B., Martinez-Meyer, E., Brotons, L., McClean, C., Miles, L., Segurado, P., Dawson, T. P. and Lees, D. C. 2006. Model-based uncertainty in species range prediction. *J. Biogeogr.* 33(10):1704-1711.

Peterson, A. T. and Cohoon, K. P. 1999. Sensitivity of distributional prediction algorithms to geographic data completeness. *Ecol. Modell*. 117(1):159-164.

Peterson, A. T. and Shaw, J. 2003. Lutzomyia vectors for cutaneous leishmaniasis in Southern Brazil: ecological niche models, predicted geographic distributions, and climate change effects. *Int. J. Parasitol.* 33(9):919-931.

Peterson, A. T., Martínez-Meyer, E. and González-Salazar, C. 2004. Reconstructing the Pleistocene geography of the Aphelocoma jays (Corvidae). *Divers. Distrib*. 10(4):237-246.

Peterson, A. T., Navarro-Sigüenza, A. G. and Benítez-díaz, H. E. S. I. Q. U. I. O. 1998. The need for continued scientific collecting; a geographic analysis of Mexican bird specimens. *Ibis.* 140(2):288-294.

Peterson, A. T., Ortega-Huerta, M. A., Bartley, J., Sánchez-Cordero, V., Soberón, J., Buddemeier, R. H. and Stockwell, D. R. 2002. Future projections for Mexican faunas under global climate change scenarios. *Nat*. 416(6881):626-629.

Peterson, A. T., Sánchez-Cordero, V., Soberon, J., Bartley, J., Buddemeier, R. W. and Navarro-Sigüenza, A. G., 2001a. Effects of global climate change on geographic distributions of Mexican Cracidae. *Ecol. Modell*. 144(1):21-30.

Peterson, A. T., Stewart, A., Mohamed, K. I. and Araújo, M. B. 2008. Shifting global invasive potential of European plants with climate change. *PLoS one.* 3(6):e2441.

Peterson, A., Nakazawa, Y., 2008. Environmental data sets matter in ecological niche modelling: an example with Solenopsis invicta and Solenopsis richteri. *Glob. Ecol. Biogeogr*. 17, 135–144.

Peterson, A.T. and Stockwell, D. R. B. 2001. Distributional prediction based on ecological niche modeling of primary occurrence data. In: Scott, J.M. (ed.), *Predicting Species Distributions*. Island Press, Washington, DC.

Phillips, S. J., Anderson, R. P. and Schapire, R. E., 2006. Maximum entropy modeling of species geographic distributions. *Ecol. Modell*. 190(3):231-259.

Phillips, S. J., Dudík, M. and Schapire, R. E. 2004. A maximum entropy approach to species distribution modeling. In: *Proceedings of the 21st International Conference on Machine Learning.* ACM Press: New York, NY, USA. pp. 655- 662.

Phillips, S.J., Dudik, M., Elith, J., Graham, C.H., Lehmann, A., Leathwick, J., Ferrier, S., 2009. Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. *Ecol. Appl*. 19: 181–197.

Pitman, A., Pielke, R., Avissar, R., Claussen, M., Gash, J. and Dolman, H. 2000. The role of land surface in weather and climate: does the land surface matter? *IGBP Newsletter*. 4-24.

Poloczanska, E.S. et al. 2013. Global imprint of climate change on marine life. *Nature Clim. Change*. Published online 04 August 2013. doi:10.1038/nclimate1958

Popy, S., Bordignon, L. and Prodon, R. 2010. A weak upward elevational shift in the distributions of breeding birds in the Italian Alps. *J. Biogeogr*. 37(1):57-67.

Radosavljevic, A., and Anderson, R. P. 2014. Making better MaxEnt models of species distributions: complexity, overfitting and evaluation. *J. Biogeogr*. 41(4): pp. 629-643.

Raper, S.C.B. and Giorgi, F. 2005. Climate Change Projections and Models in Climate Change and Biodiversity. *Yale University Press, New Haven.* pp.199-210.

Reese, G. C., Wilson, K. R., Hoeting, J. A. and Flather, C.H. 2005. Factors affecting species distribution predictions: a simulation modeling experiment. *Ecol. Appl*. 15(2):554-564.

Rehfeldt, G. E., Crookston, N. L., Warwell, M. V. and Evans, J. S. 2006. Empirical analyses of plant-climate relationships for the western United States. *Int. J. Plant Sci.* 167(6):1123-1150.

Reif, J., Št'astný, K. and Bejček, V. 2010. Contrasting effects of climatic and habitat changes on birds with northern range limits in central Europe as revealed by an analysis of breeding bird distribution in the Czech Republic. *Acta Ornithologica*. 45(1):83-90.

Ricklefs, R. E. 2004. A comprehensive framework for global patterns in biodiversity. *Ecol. lett*. 7(1):1-15.

Root, T. L. 1988a. Environmental factors associated with avian distributional boundaries. *J. Biogeogr.* 15:489-505.

Root, T. L. 1988b. Energy constraints on avian distributions and abundances. *Ecol.* 69(2): 330-339.

Root, T. L. and Schneider, S.H. 1993. Can Large-Scale Climatic Models Be Linked with Multiscale Ecological Studies*? Conserv. Biol*. 7(2):256-270.

Root, T. L., Price, J. T., Hall, K. R., Schneider, S. H., Rosenzweig, C. & Pounds, J. A. 2003 Fingerprints of global warming on wild animals and plants. *Nature*. 421: 57–60. (doi:10.1038/nature01333).

Rosenzweig, M. 1995. Species diversity in space and time. Cambridge Univ. Press.

Rosenzweig, C., Karoly, D., Vicarelli, M., Neofotis, P., Wu, Q., Casassa, G., Menzel, A., Root, T. L., Estrella, N., Seguin, B., Tryjanowski, P., Liu, C., Rawlins, S., & Imeson, A. (2008). Attributing physical and biological impacts to anthropogenic climate change. *Nature*, *453*(7193), 353–357. https://doi.org/10.1038/nature06937.

Rowe RJ, Terry RC (2014) Small mammal responses to environmental change: integrating past and present dynamics. *J Mammal* .95:1157–1174. https://doi.org/10.1644/13-mamm-s-079

Rubidge, E.M., W.B. Monahan, J.L. Parra, S.E. Cameron & J.S. Brashares. 2011. The role of climate, habitat, and species co-occurrence as drivers of change in small mammal distributions over the past century. *Global Change Biology* 17: 696–708.

Rushton, S. P., Ormerod, S. J. and Kerby, G. 2004. New paradigms for modelling species distributions? J. *Appl. Ecol.* 41(2):193-200.

Sala, O. E., Chapin, F. S., Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., HuberSanwald, E., Huenneke, L. F., Jackson, R. B., Kinzig, A. and Leemans, R. 2000. Global biodiversity scenarios for the year 2100. *Sci*. 287(5459):1770-1774.

Scotts, D., Fulton, G. R. and Drielsma, M. 2003. Developing landscape frameworks for regional conservation planning; an approach integrating fauna spatial distributions and ecological principles. *Pac. Conserv. Biol.* 8(4):235-254.

Şekercioğlu, Ç.H., Primack, R.B., Wormworth, J., 2012. The effects of climate change on tropical birds. *Biol. Cons*. 148: 1–18. http://dx.doi.org/10.1016/j.biocon.2011.10.019.

Scheffers, B. R., De Meester, L., Bridge, T. C. L., Hoffmann, A. A., Pandolfi, J. M., Corlett, R. T., Butchart, S. H. M., Pearce-Kelly, P., Kovacs, K. M., Dudgeon, D., Pacifici, M., Rondinini, C., Foden, W. B., Martin, T. G., Mora, C., Bickford, D., & Watson, J. E. M. (2016). The broad footprint of climate change from genes to biomes to people. *Science*, *354*(6313). https://doi.org/10.1126/science.aaf7671

Shipley, B. 1999. Testing causal explanations in organismal biology: causation, correlation and structural equation modelling. *Oikos*. 86:374-382.

Shoo, L.P., Williams, S.E., Hero, J.-M., 2005. Climate warming and the rainforest birds of the Australian Wet Tropics: Using abundance data as a sensitive predictor of change in total population size. *Biol. Cons*. 125: 335–343. http://dx.doi.org/10.1016/j.biocon.2005.04.003.

Shugart, H. H. 1990. Using ecosystem models to assess potential consequences of global climatic change. *Trends Ecol. Evol*. 5(9):303-307.

Silverman, B. W. 1986. *Density estimation for statistics and data analysis*. Vol. 26. CRC press.

Sinclair, S. J., White, M. D. and Newell, G. R. 2010. How useful are species distribution models for managing biodiversity under future climates. *Ecol. Soc*. 15(8).

Singh, H., Kumar, N., Kumar, M., Singh, R. 2020. Modelling habitat suitability of western tragopan(*Tragopan Melanocephalus*) a range- restricted vulnerable bird species of the Himalayan region, in response to climate change. *Climate risk Management*. 29(2020): 100241.

Skov, F. and Svenning, J. C. 2004. Potential impact of climatic change on the distribution of forest herbs in Europe. *Ecography*. 27(3):366-380.

Soberón, J. M. and Peterson, A. T. 2005. Interpretation of models of fundamental ecological niches and species' distributional areas. Biodiv. *Inform.* 2:1-10.

Soberón, J. M., Llorente, J. B. and Oñate, L. 2000. The use of specimen-label databases for conservation purposes: an example using Mexican Papilionid and Pierid butterflies. *Biodiver. Conserv*. 9(10):1441-1466.

Sodhi, N. S., Sekercioglu, C. H., Barlow, J. and Robinson, S. K. 2011.Conservation of tropical birds. John Wiley & Sons.

Srinivasulu, C., Srinivasulu, B., Molur, S. (Compilers), 2014. The Status and Distribution of Reptiles in the Western Ghats, India. Conservation Assessment and Management Plan (CAMP). Wildlife Information Liaison Development Society., Coimbatore, Tamil Nadu.

Stattersfield, A., Crosby, M., Long, A., Wedge, D., 1998. Endemic Bird Areas of the world : Priorities for Biodiversity Conservation. BirdLife International, Cambridge.

Stockwell, D. and Peters, D. 1999. The GARP modelling system: problems and solutions to automated spatial prediction. Int. *J. Geogr. Inform*. Sci. 13:143- 158.

Stockwell, D. and Peters, D. 1999. The GARP modelling system: problems and solutions to automated spatial prediction. *Int. J. Geogr. Inform. Sci*. 13:143- 158.

Stockwell, D. R. and Noble, I. R. 1992. Induction of sets of rules from animal distribution data: a robust and informative method of data analysis. Math. *Comput. Simulat*. 33(5):385-390.

Stuhldreher, G. and Fartmann, T. 2018. Threatened grassland butterflies as indicators of microclimatic niches along an elevational gradient – Implications for conservation in times of climate change, *Ecol. Indic*. 94: 83-98. DOI: 10.1016/j.ecolind.2018.06.043.

Suárez-Seoane, S., de la Morena, E. L. G., Prieto, M. B. M., Osborne, P. E. and de Juana, E. 2008. Maximum entropy niche-based modelling of seasonal changes in little bustard (Tetrax tetrax) distribution. *Ecol. Modell*. 219(1):17-29.

Sulzman, E. W., Poiani, K. A. and Kittel, T. G. 1995. Modeling human-induced climatic change: A summary for environmental managers. *Environ. Manag*. 19(2):197-224.

Svenning, J. C. and Skov, F. 2004. Limited filling of the potential range in European tree species. *Ecol. Lett.* 7(7):565-573.

Swanson, A. K., Dobrowski, S. Z., Finley, A. O., Thorne, J. H. and Schwartz, M. K., 2013. Spatial regression methods capture prediction uncertainty in species distribution model projections through time. *Glob. Ecol. Biogeogr.* 22(2):242- 251.

Thomas, C. D. 2010. Climate, climate change and range boundaries. *Divers. Distrib*. 16:488-495.

Thomas, C. D., Bodsworth, E. J., Wilson, R. J., Simmons, A. D., Davies, Z. G., Musche, M. & Conradt, L. 2001 Ecological and evolutionary processes at expanding range margins. *Nature.* 411: 577–581. (doi:10.1038/ 35079066).

Thomas, C. D., Bodsworth, E. J., Wilson, R. J., Simmons, A. D., Davies, Z. G., Musche, M. & Conradt, L. 2004 Extinction risk from climate change. *Nature*. 427: 145–148. (doi:10.1038/nature02121).

Thomas, C. D., Cameron, A., Green, R. E., Bakkenes, M., Beaumont, L. J., Collingham, Y. C., Erasmus, B. F., De Siqueira, M. F., Grainger, A., Hannah, L. and Hughes, L. 2004. Extinction risk from climate change. *Nat.* 427(6970):145-148.

Thorn, J. S., Nijman, V., Smith, D. and Nekaris, K. A. I. 2009. Ecological niche modelling as a technique for assessing threats and setting conservation priorities for Asian slow lorises (Primates: Nycticebus*). Divers. Distrib.* 15(2):289-298.

Thornton, P. E., Running, S. W. and White, M. A., 1997. Generating surfaces of daily meteorological variables over large regions of complex terrain. *J. Hydrol*. 190(3):214-251.

Thuiller, W., Araújo, M. B., Pearson, R. G., Whittaker, R. J., Brotons, L. and Lavorel, S. 2004. Biodiversity conservation: uncertainty in predictions of extinction risk. *Nat.* 430(6995).

Thuiller, W., Lavorel, S., Araújo, M. B., Sykes, M. T. and Prentice, I. C. 2005. Climate change threats to plant diversity in Europe. *Proc. Natl. Acad. Sci. USA*. 102(23):8245-8250.

Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E. and Steininger, M. 2003. Remote sensing for biodiversity science and conservation. *Trends Ecol. Evol*. 18(6):306-314.

Vedder, O., S. Bouwhuis & B.C. Sheldon. 2013. Quantitative Assessment of the Importance of Phenotypic Plasticity in Adaptation to Climate Change in Wild Bird Populations. *PLoS Biol.* 11: e1001605.

Venkatraman, C. and V. Gokula. 1996. Some observations on mating in the Bluewinged Parakeet Psittacula columboides. *Newsletters for Birdwatchers*. 36: 79.

Vieira de Souza, T., Lorini, M.L., Alves, M.A.S., Cordeiro, P., Vale, M.M., 2011. Redistribution of threatened and endemic Atlantic forest birds under climate change. *Nat. Conserv*. 9: 214–218. http://dx.doi.org/10.4322/natcon.2011.028.

Vigors. 1835. *Zoological Journal*. 5: 274.

Virkkala, R., Marmion, M., Heikkinen, R. K., Thuiller, W. and Luoto, M. 2010. Predicting range shifts of northern bird species: influence of modelling technique and topography. *Acta Oecologica*. 36(3):269-281.

Walker, P. A. and Cocks, K. D. 1991. HABITAT: a procedure for modelling a disjoint environmental envelope for a plant or animal species. *Glob. Ecol. Biogeogr. Lett.* pp. 108-118.

Walsberg, G. E. 1993. Thermal consequences of diurnal microhabitat selection in a small bird. *Ornis Scandinavica.* pp. 174-182.

Walther, G.-R. 2010. Community and ecosystem responses to recent climate change. *Phil. Trans. R. Soc. B* .365: 2019–2024. (doi:10.1098/rstb.2010.0021).

Walther, G.-R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T. J. C., Fromentin, J.-M., Hoegh-Guldberg, O. & Bairlein, F. 2002 Ecological responses to recent climate change. *Nature.* 416: 389–395. (doi:10.1038/ 416389a).

Warren, D. L., and Seifert, S. N. 2011. Ecological niche modelling in MaxEnt: the importance of model complexity and the performance of model selection criteria. *Ecol. Appl.* 21(2): pp. 335-342.

Warren, R., VanDerWal, J., Price, J., Welbergen, J.A., Atkinson, I., Ramirez-Villegas, J., Osborn, T.J., Jarvis, A., Shoo, L.P., Williams, S.E., Lowe, J., 2013. Quantifying the benefit of early climate change mitigation in avoiding biodiversity loss. *Nat. Clim. Chang*. 3: 1–5. http://dx.doi.org/10.1038/nclimate1887.

Willis, K. J. and Bhagwat, S .A. 2009. Biodiversity and climate change. *Sci.* 326(5954):806-807.

Wintle, B. A. and Bardos, D. C. 2006. Modeling species–habitat relationships with spatially autocorrelated observation data. *Ecol. Appl*. 16(5):1945-1958.

Woodward, F. I. and Beerling, D. J. 1997. The dynamics of vegetation change: health warnings for equilibrium 'dodo' models. *Glob. Ecol. Biogeogr*. Lett. pp. 413- 418.

Wormworth, J. and Sekercioglu, C.H. 2011. *Winged sentinels: birds and climate change.* Cambridge University Press.

Yee, T. W. and Mitchell, N. D., 1991. Generalized additive models in plant ecology. *J. Veg. sci*. 2(5):587-602.

Yost, A.C., Petersen, S.L., Gregg, M., Miller, R., 2008. Predictive modeling and mapping sage grouse (Centrocercus urophasianus) nesting habitat using Maximum Entropy and a long-term dataset from Southern Oregon. *Ecology Information*. 3: 375–386.

Zaniewski, A. E., Lehmann, A. and Overton, J. M. 2002. Predicting species spatial distributions using presence-only data: a case study of native New Zealand ferns. *Ecol. Modell*. 157(2):261-280.

Zimmer, C. 2007. Predicting oblivion: Are existing models up to the task? *Sci.* 317:892-893.

Impact of climate change on the status and distribution of Malabar Parakeet (*Psittacula columboides*), an endemic bird species of Western Ghats.

by

KEERTHANA M. J.

(2016-20-027)

THESIS

Submitted in partial fulfilment of the

requirements for the degree of

B.Sc – M.Sc. (Integrated) Climate Change Adaptation

Faculty of Agriculture

Kerala Agricultural University

COLLEGE OF CLIMATE CHANGE AND ENVIRONMENTAL SCIENCE

VELLANIKKARA, THRISSUR – 680 656

KERALA, INDIA

2021

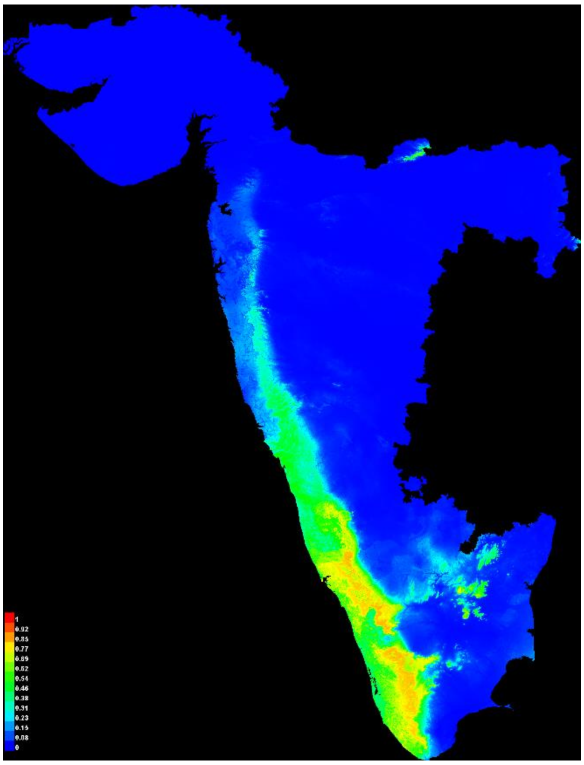
CHAPTER 8

ABSTRACT

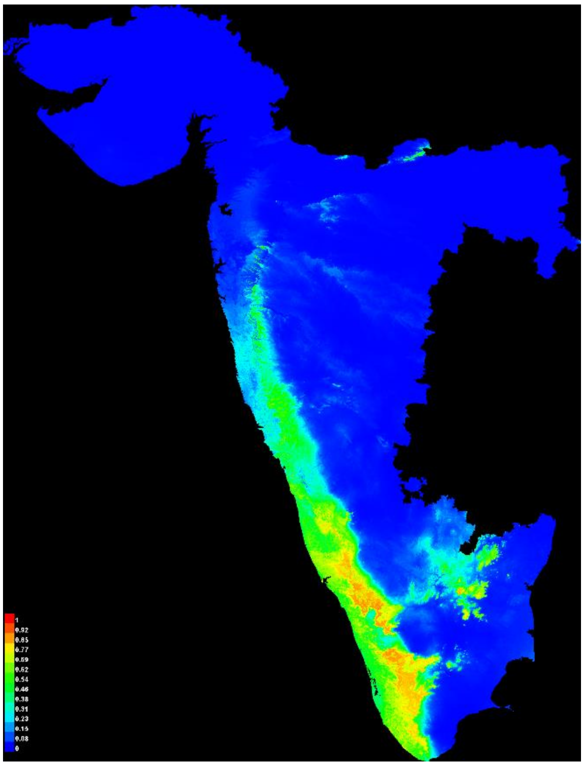
Finding the elements that controlled the distributions of species has been critical for the researchers. They want to determine the current and future distribution patterns of endangered species so that conservation strategies can be implemented. Some invasive species are spreading their territory into new places, which necessitates accurate identification. Avian species are thought to be a useful bio-indicator of the environment's devastation. Because these ecosystems' habitat specialist species are vulnerable to climate change, they could be employed as bioindicators. This research was based on the spatial and temporal distribution of the Malabar parakeet in the Western Ghats, which could help determine environmental changes at various locations. During recent years, Malabar parakeet has been seen spotting in locations outside Western ghats. The study's theory was that this growth was caused by climatic changes. MaxEnt was used to map out species distributions and habitat relationships. The distribution of the Malabar parakeet was modelled using current presence data from the e-Bird data source and 19 bioclimatic factors from CHELSA V. 1.2. The MaxEnt model settings were determined using the ENM Evaluate tool, and the best – performing model was chosen based on the Akaike Information Criterion (AIC) value. It would project the Malabar parakeet distribution into the future using the current distribution analysis by converging it to the highest entropy probability distribution. The study only employed uncorrelated variables, which were chosen based on their percent contribution, permutation relevance, and R^2 value. The study demonstrated the Malabar parakeet's actual and anticipated distribution patterns for the year 2050, based on several RCP estimates. The projected model shows a declining geographical distribution of Malabar parakeet across Western ghats. Precipitation of the coldest quarters (bio 19) is found to be the most contributing variable in the distribution of Malabar parakeet. Total predicted suitable habitat is the highest under RCP 2.6 and lowest under RCP 8.5. In this projected distribution of the Malabar parakeet, the combined effects of precipitation and temperature fluctuation alongside slope are critical.

APPENDIX - I

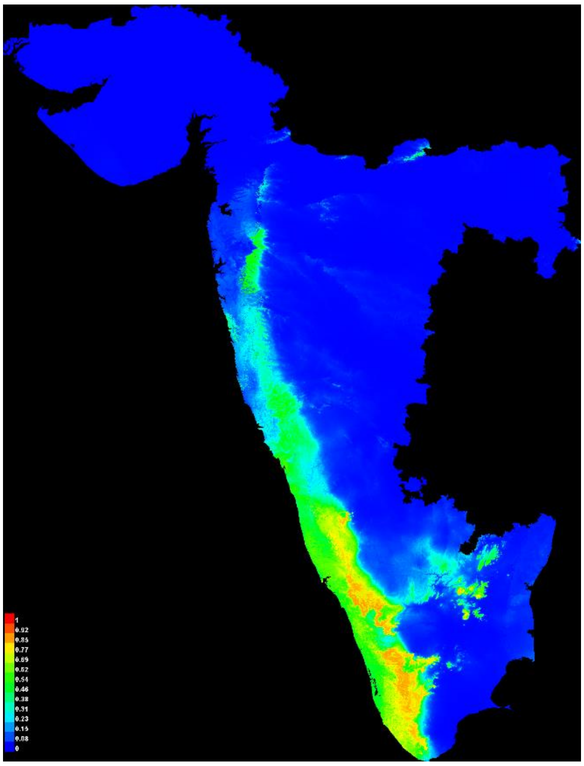
The prediction of distribution of the Malabar parakeet for the year 2050 under RCP 2.6 prediction by BCC CSM 1.1, MIROC5 and HadGEM2-ES



BCC CSM 1.1

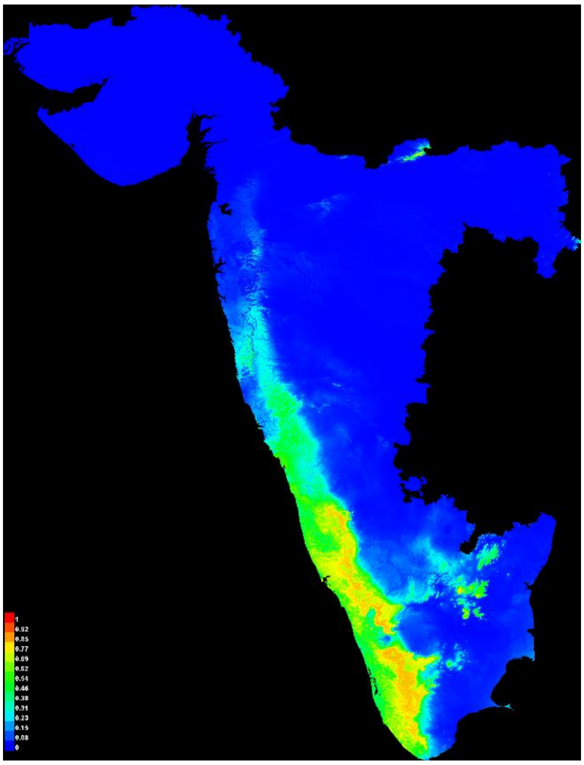


MIROC5

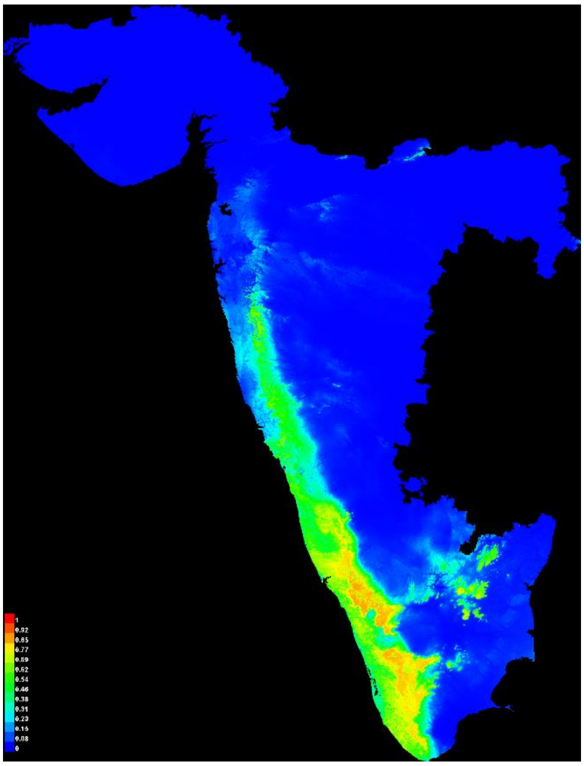


HadGEM2-ES

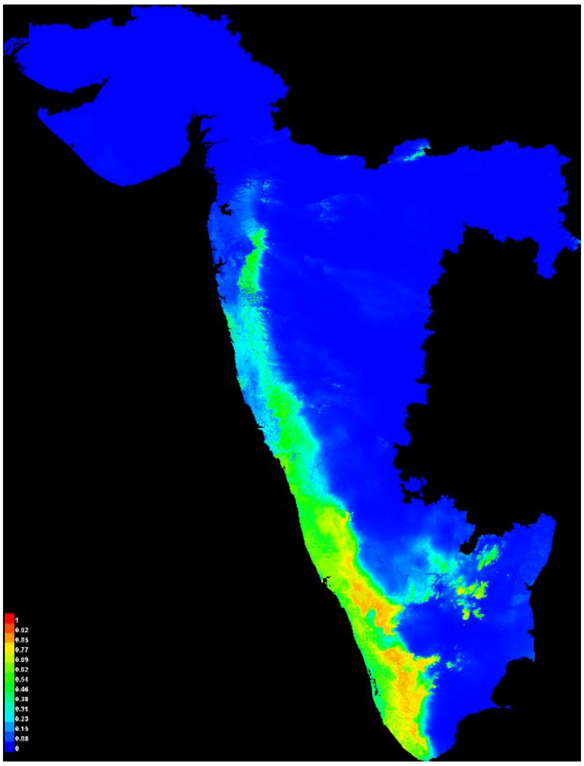
The prediction of distribution of the Malabar parakeet for the year 2050 under RCP 4.5 prediction by BCC CSM 1.1, MIROC5 and HadGEM2-ES



BCC CSM 1.1

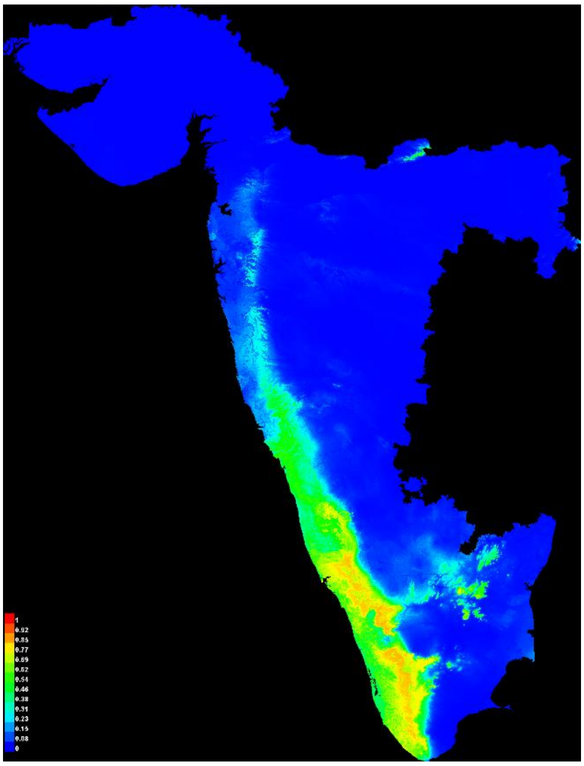


MIROC5

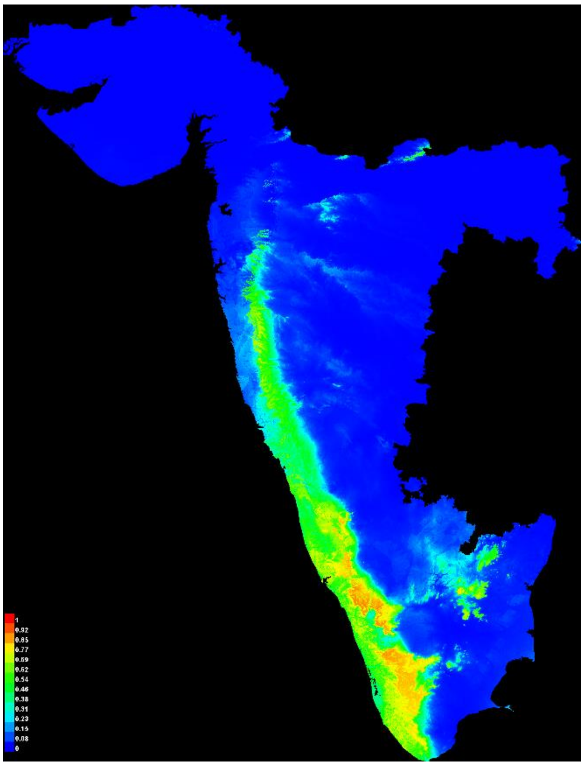


HadGEM2-ES

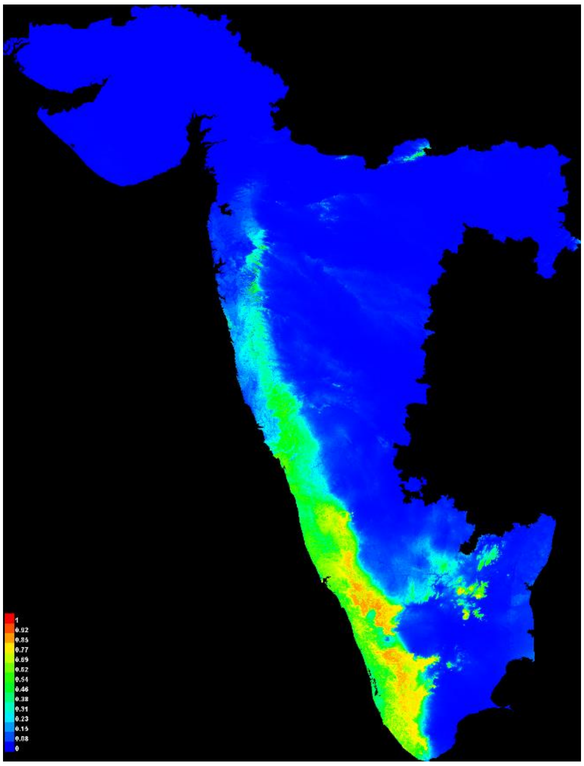
The prediction of distribution of the Malabar parakeet for the year 2050 under RCP 6 prediction by BCC CSM 1.1, MIROC5 and HadGEM2-ES



BCC CSM 1.1

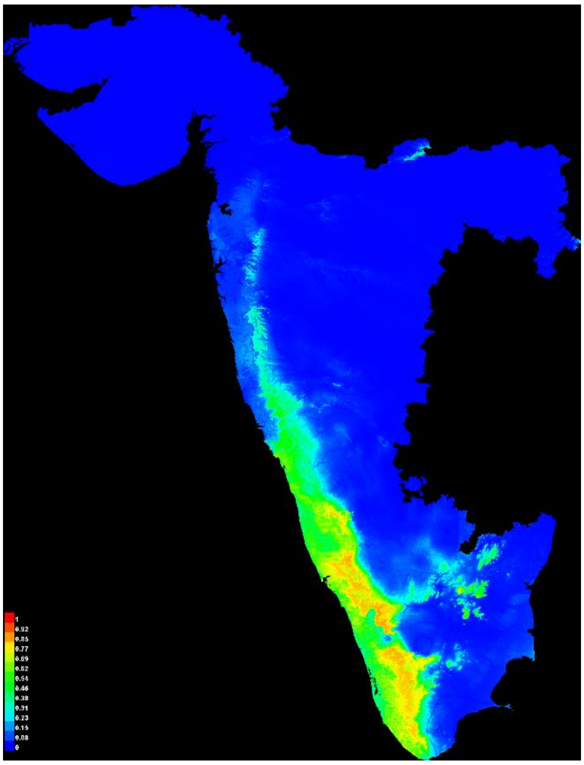


MIROC5

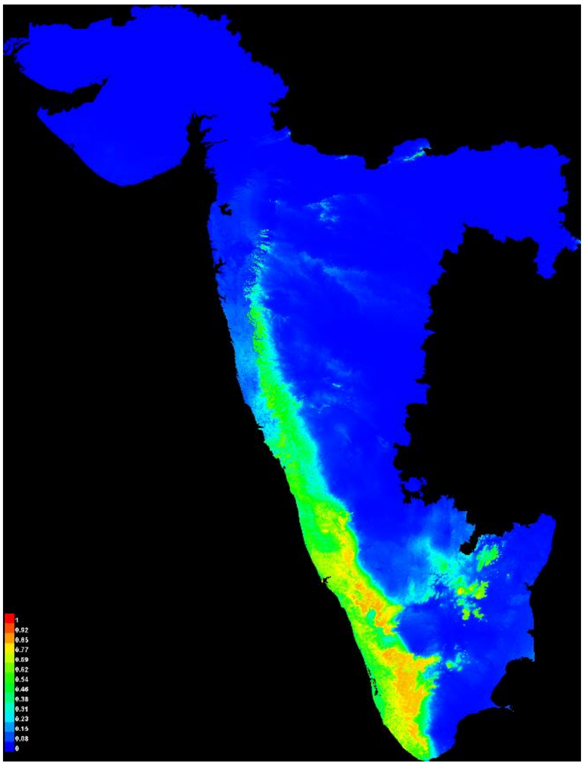


HadGEM2 - ES

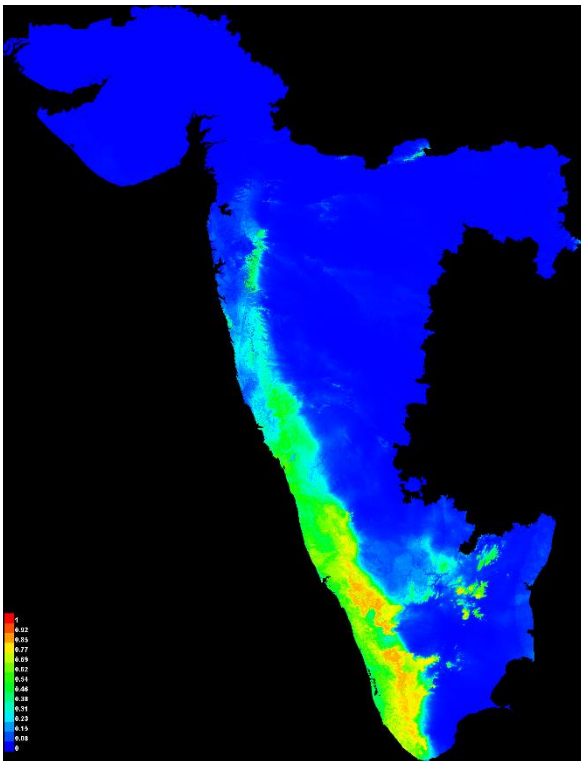
The prediction of distribution of the Malabar parakeet for the year 2050 under RCP 8.5 prediction by BCC CSM 1.1, MIROC5 and HadGEM2-ES



BCC CSM 1.1



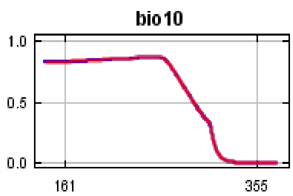
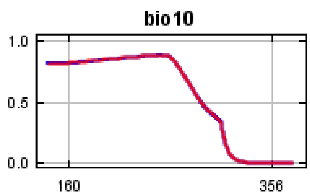
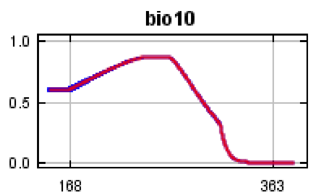
MIROC5

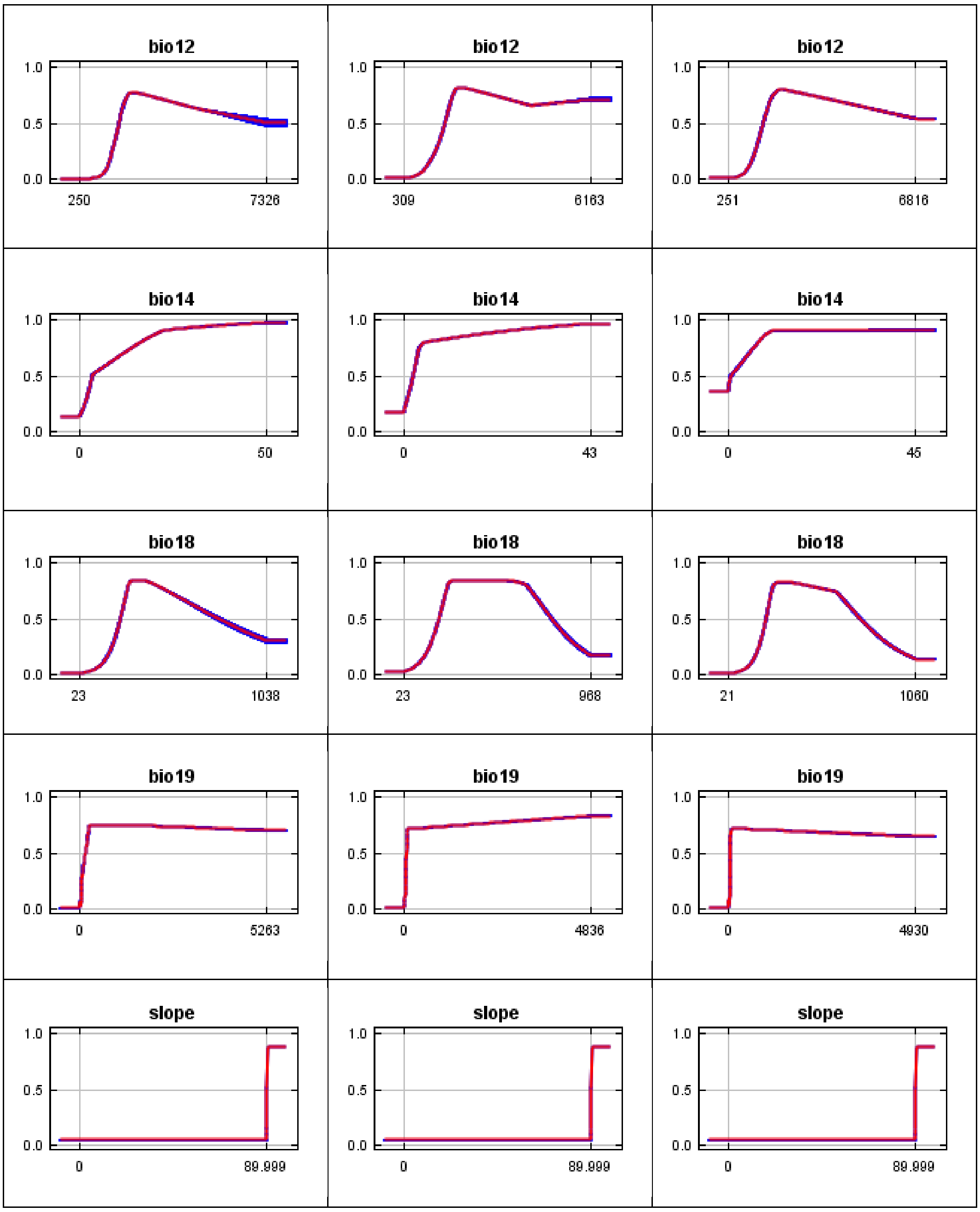


HadGEM2-ES

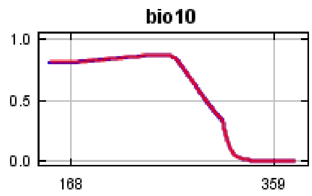
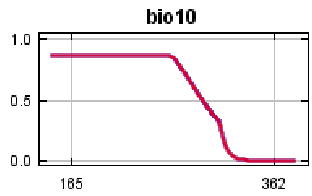
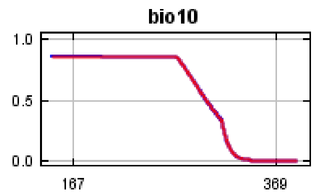
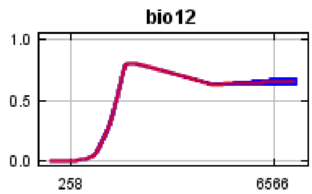
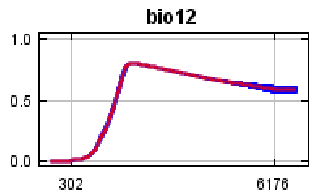
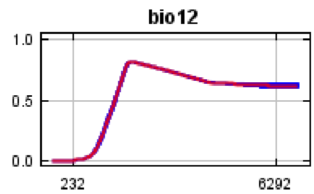
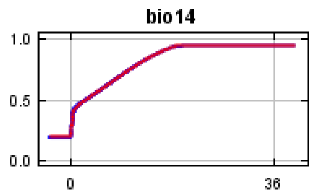
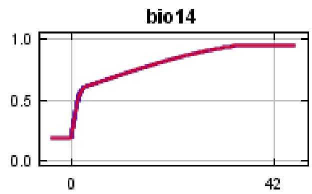
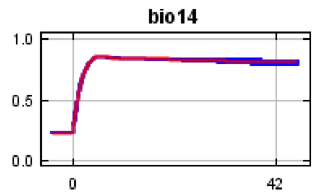
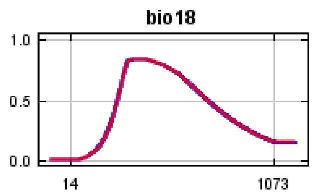
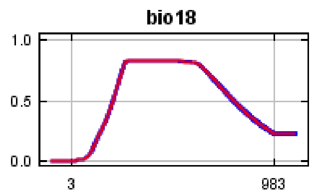
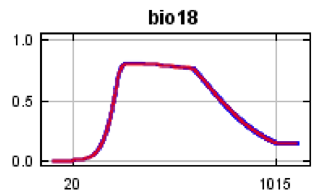
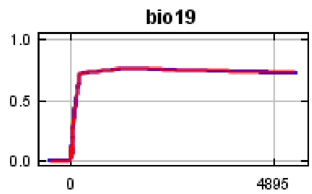
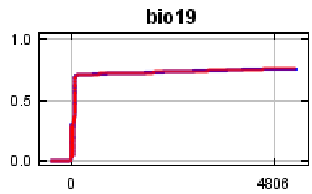
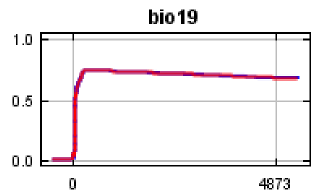
APPENDIX- II

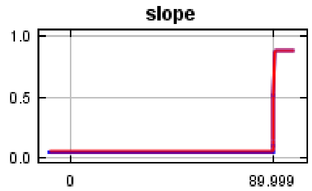
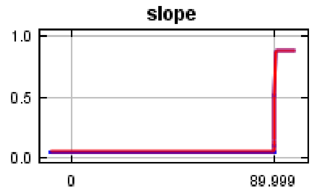
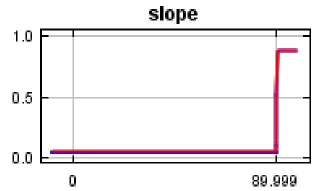
Response curves of each variable under RCP 2.6 by BCC CSM 1.1, MIROC5 and HadGEM2-ES

BCC CSM 1.1	**MIROC5**	**HadGEM2-ES**
		

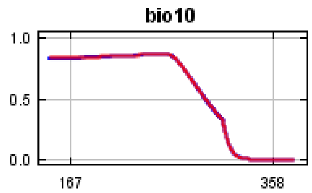
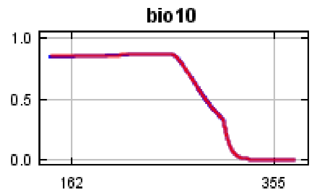
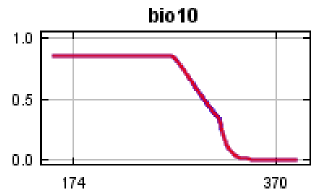
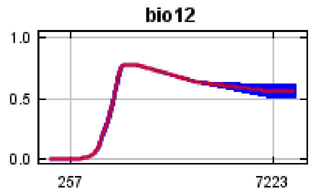
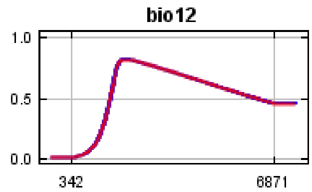
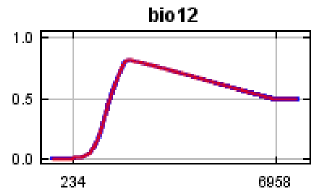
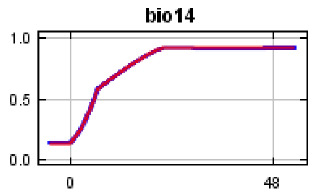
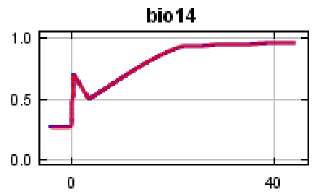
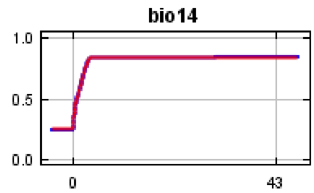
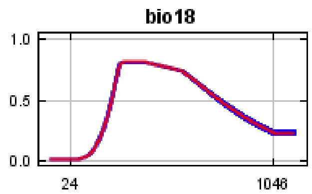
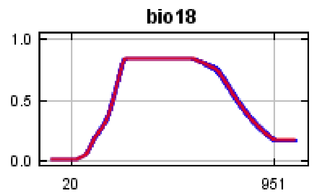
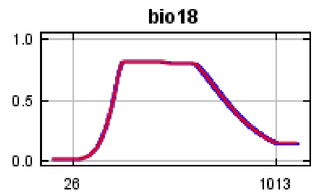

bio12
1.0
0.5
0.0
250
7326
bio12
309
6163
bio12
251
6816
bio14
0
50
bio14
0
43
bio14
0
45
bio18
23
1038
bio18
23
968
bio18
21
1060
bio19
0
5263
bio19
0
4836
bio19
0
4930
slope
0
89.999
slope
0
89.999
slope
0
89.999

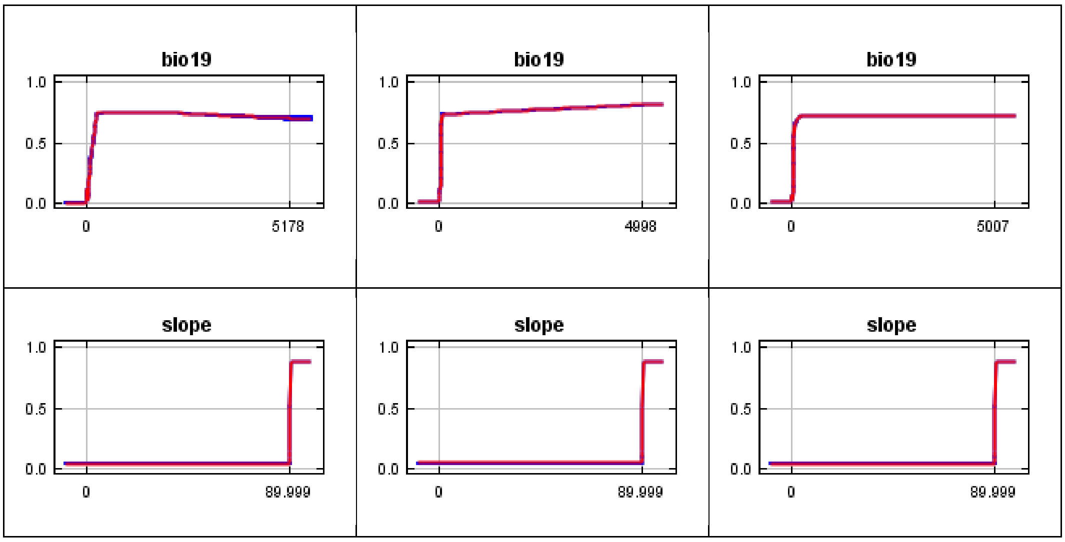
Response curves of each variable under RCP 4.5 by BCC CSM 1.1, MIROC5 and HadGEM2-ES

BCC CSM 1.1	**MIROC5**	**HadGEM2-ES**
		
		
		
		
		

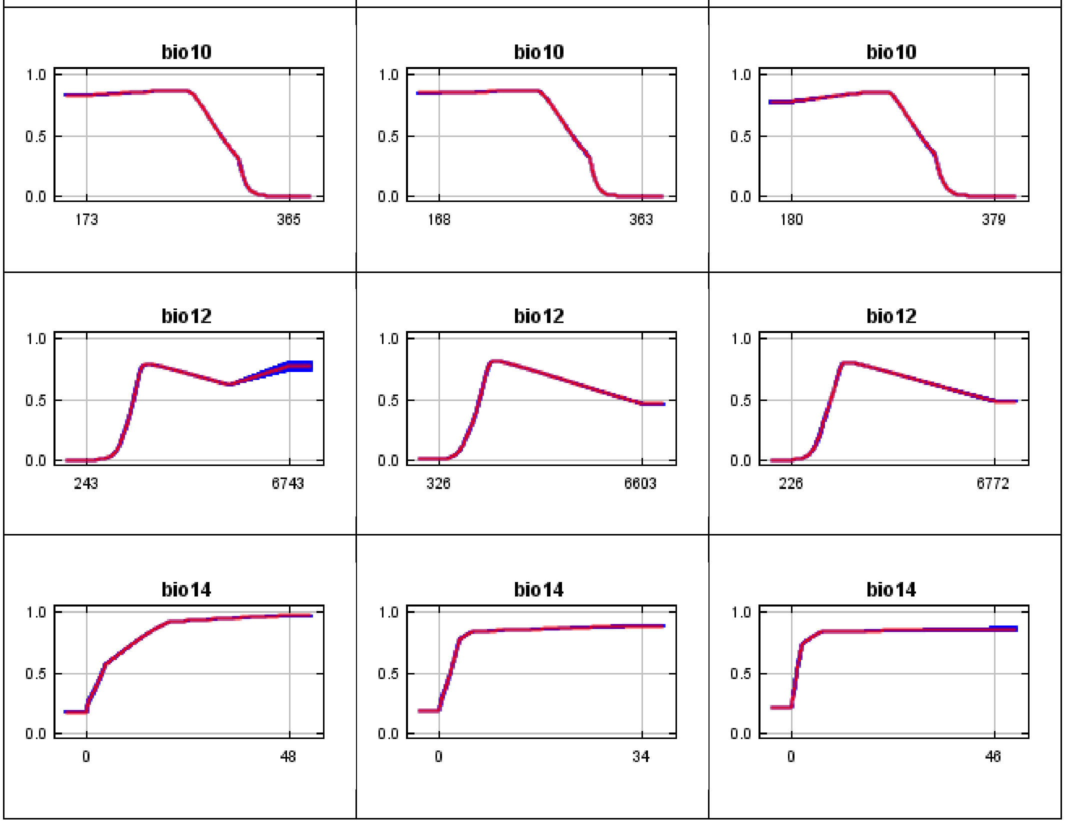
Response curves of each variable under RCP 6 by BCC CSM 1.1, MIROC5 and HadGEM2-ES

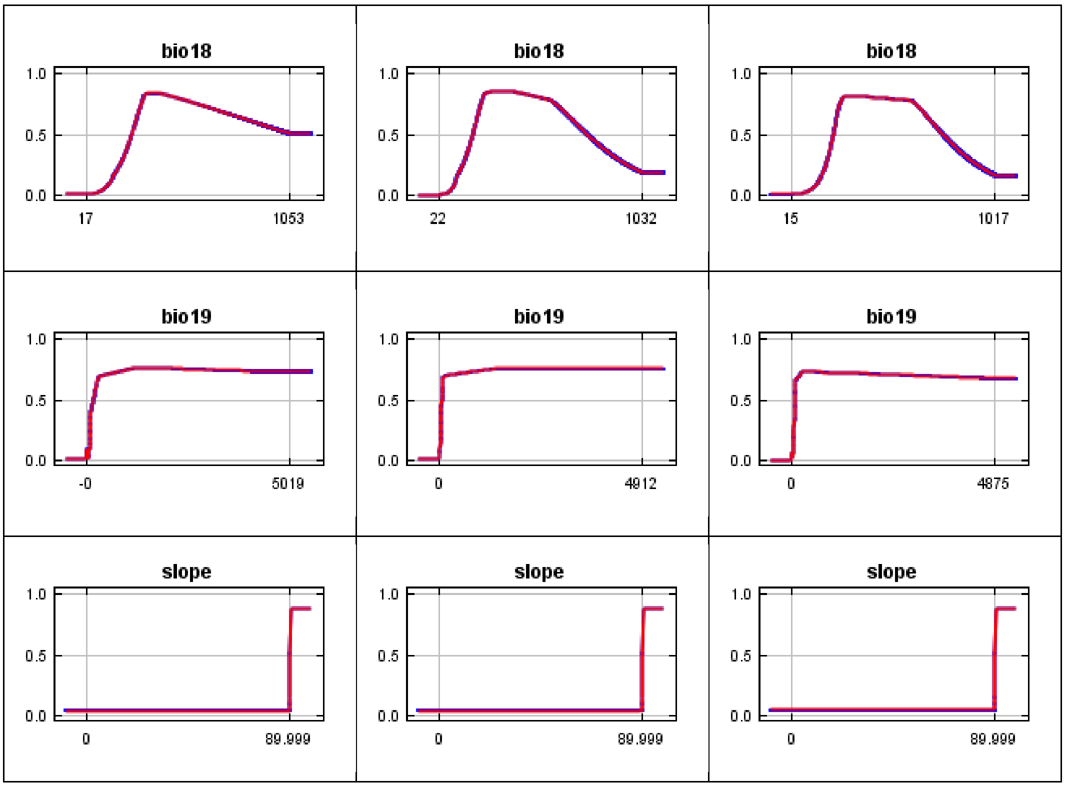
BCC CSM 1.1	MIROC5	HadGEM2-ES
		
		
		
		



Response curves of each variable under RCP 8.5 by BCC CSM 1.1, MIROC5 and HadGEM2-ES

BCC CSM 1.1	MIROC5	HadGEM2-ES




bio18
1.0
0.5
0.0
17
1053
bio18
1.0
0.5
0.0
22
1032
bio18
1.0
0.5
0.0
15
1017
bio19
1.0
0.5
0.0
-0
5019
bio19
1.0
0.5
0.0
0
4912
bio19
1.0
0.5
0.0
0
4875
slope
1.0
0.5
0.0
0
89.999
slope
1.0
0.5
0.0
0
89.999
slope
1.0
0.5
0.0
0
89.999