IMPACT OF CLIMATE CHANGE ON THE STATUS AND DISTRIBUTION OF MALABAR BARBET (*Psilopogon malabaricus*), AN ENDEMIC SPECIES TO WESTERN GHATS

By

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THESIS

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DECLARATION

I, Alita Treevan (2016-20-032) hereby declare that this thesis entitled "**Impact of climate change on the status and distribution of Malabar Barbet (*Psilopogon malabaricus*), an endemic species to Western Ghats**" is a bonafide 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 title, of any other University or Society.

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CERTIFICATE

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Alita Treevan

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SYMBOLS AND ABBREVATIONS

|r|	Pearson correlation matrix
AKN	Avian Knowledge Network
AUC	Area under the curve
EVI	Enhanced Vegetation Index
bio1	Annual Mean Temperature
bio2	Mean Diurnal Range
bio3	Isothermality
bio4	Temperature Seasonality
bio5	Maximum Temperature of Warmest Month
bio6	Minimum Temperature of Coldest Month
bio7	Temperature Annual Range
bio8	Mean Temperature of Wettest Quarter
bio9	Mean Temperature of Driest Quarter
bio10	Mean Temperature of Warmest Quarter
bio11	Mean Temperature of Coldest Quarter
bio12	Annual Precipitation
bio13	Precipitation of Wettest Month
bio14	Precipitation of Driest Month
bio15	Precipitation Seasonality
bio16	Precipitation of Wettest Quarter
bio17	Precipitation of Driest Quarter
bio18	Precipitation of Warmest Quarter
bio19	Precipitation of Coldest Quarter
EEA	European Environment Agency
FAO	Food and Agriculture Organization of the United Nations

GCMs	General Circulation Model
GCMs	Global circulation models
IPCC	Intergovernmental Panel on Climate Change
MaxEnt	Maximum Entropy Modelling
R 2	Coefficient of determination
RCPs	Representative Concentration Pathways
ROC	Receiver Operating Characteristic Curve
WMO	World Meteorological Organization

CHAPTER 1

INTRODUCTION

Changing climate is an issue that affects the world in many ways. Biodiversity in the world is being threatened by climate change. Global warming has resulted in glaciers melting, sea levels rising, and extreme weather patterns, etc. The Full IPCC AR5 Report states that in the Northern Hemisphere, the period between 1983 and 2012 may be the hottest 30 years of the last 1400 years. The mean ocean and land surface temperatures warmed by 0.85 degrees between 1880 and 2012 (0.65 degrees to 1.06 degrees) (Allen et al., 2014). Climate change can affect many species in an ecosystem. Large populations are more vulnerable to climate change than smaller populations. A major cause of climate change is human activities, such as burning fossil fuels and emitting greenhouse gases. In addition to biodiversity loss and ecosystem services, climate change exacerbates other problems, including water scarcity, floods and droughts, desertification and land degradation, and changes in biogeochemical cycles. The world needs to implement adaptation mechanisms in order to cope with climate change. Continually updating and reviewing the knowledge about these changes is necessary. It's essential to understand climate change and its consequences. The world should take immediate action to combat climate change by reducing the global average temperature increase.

Various species in an ecosystem are susceptible to climate change. There are many ways species respond to climate change such as adaptation and migration. It has been demonstrated that climate change has affected plant and animal species distributed across a wide range of geographies. A species tolerance to temperature and precipitation is influenced by climate conditions through physiological thresholds. The climate ranges of these regions have been altered by warming trends. Some animals and birds will change their positions to find a better place where environmental conditions are conducive to their growth and reproduction.

Biological indicators, like birds, benefit from their sensitivity to environmental changes, especially since birds disperse seeds and regulate insect populations. This enables them to highlight strategies to preserve biodiversity and ecosystem services (de Moraes et al., 2020) and understand the effects of climate change. According to more recent studies, climate change has left a lasting impact on biodiversity, as evidenced by shifts in bird distribution (Gregory et al., 2009; Niven et al., 2009; Chen et al., 2011).

Western Ghats (WG) are one of the world's most fragile and beautiful ecosystems (Shameer et al. 2019), thus considered an important biodiversity hotspot (Cincotta et al. 2000; Myers et al. 2000). The Western Ghat Mountains, which extend from the Tapti River in the north to the southern end of India, is considered one of the richest areas of biodiversity on Earth. Located in a unique biogeographic region, the Western Ghats feature a unique flora and fauna. Deforestation, an extension of agriculture, urbanization, and other anthropogenic factors threaten the forests in WG. The Western Ghats are home to an extensive variety of bird species, including endemics. Due to their geographical isolation, endemic species are more vulnerable to the effects of climate change. Birds inhabiting the Western Ghats include many endemic species. Westen Ghats is home to 29 endemic bird species. The Malabar Barbet (*Psilopogon malabaricus*) is one of the endemic birds found in the Western Ghats and the IUCN status of this bird is Least Concern (LC). Due to climate change, endemic birds in the Western Ghats can experience changes in their distribution.

In understanding the effects of environmental change on species distributions, a species distribution model is very useful. Using statistical methods, they relate the field observations to environmental predictor variables. They predict future distributional changes by incorporating climate model data. Climate change impacts can be assessed by assessing species distribution models (SDMs). Grinnell's niche concept describes the ecological niche as the unit of distribution occupied by a species, whereas the distribution of individuals is ruled by both physical and climatic factors. The combination of species occurrence data with local climatic conditions, therefore, can be used to predict climatic tolerance and potential climatic suitability regions based upon their occurrence data. Further, SDMs can be used to assess climate refuge areas, which are habitats that remain relatively unchanged regardless of changes in their surroundings (de Moraes et al., 2020).

The study will use appropriate modeling techniques to examine how the distribution of Malabar Barbets in the Western Ghats has changed over time. Considering that the Western Ghats are home to many endemic species of birds, this study may shed light on the future of these species. The birds can be used to measure climate trends if the results are good.

Project objectives include examining the impact of climate change on the status and distribution of the Malabar Barbet (*Psilopogon malabaricus*), a species endemic to the Western Ghats. We can use a climate niche model to predict the distribution patterns of the Malabar Barbet based on different climate change scenarios by developing a climate niche model using current climate data.

Methodologies used in this study can also be applied to other species whose distribution is changing. This will aid in predicting future changes in the distribution of the Malabar Barbet and other species of significance will be able to be studied in a similar manner. The results of this study will help us gain an understanding of how climate change impacts the geographical distribution of the Malabar Barbet.

CHAPTER 2

REVIEW OF LITERATURE

2.1 CLIMATE CHANGE IN THE WESTERN GHATS

In order to assess how the climate of India might change in the future, PRECIS (Providing Regional Climates for Impact Studies) was used. Climate change will result in a rise in precipitation and temperature in the 21st century. Temperatures are expected to increase on the Indian subcontinent, but precipitation patterns will vary based on the region, with torrential rain primarily occurring on the west coast and in the far west of the country. Additionally, the model indicated that nighttime temperatures would rise faster than daytime temperatures (Kumar et al., 2006).

According to predictions, there will most likely occur mid-elevation evergreen forests in the central and southern parts of the Western Ghats, specifically south of the Palghat gap (Priti et al., 2016). In the case of A2 and B2 of the Special Report on Emission Scenarios (SRES), the Western Ghats will likely experience an increase in evergreen forest cover. Due to the fact that evergreen tropical forests are not fragmented, seeds can disperse widely. There are fewer dispersal agents in the forest as a result of human pressures and climate change. Western Ghats' forests are at risk from global warming. It is important to manage pests in these areas systematically, to harvest accurately, and to anticipate plantations (Chaturvedi, 2011).

2.2 IMPACTS OF CLIMATE CHANGE ON BIRD

2.2.1 Birds as bio-indicators

As bio-indicators, avian species were well understood by the public and policy makers, since they have a recognizable and iconic status throughout the world (Crick, 2004). Climate change was considered to be a widespread and dangerous threat to biological diversity (IPCC, 2007). Human activities have altered ecological systems worldwide, changed the world's climate, and reduced and fragmented habitat, according to Willis and Bhagwat (2009). In addition to birds being well-known indicators of climate change (Wormworth and Sekercioglu, 2011), birdwatchers around the globe are producing extensive datasets on birds (www.ebird.org; www.worldbirds.org).

2.2.2 Effect of climate change on physiology of birds

The weather affects the metabolic rate of birds directly and indirectly, which influenced bird behavior. When birds avoid places with unfavorable climates, important activities like breeding and feeding will be reduced (Walsberg, 1993). Hormones are released during breeding, and these hormones fluctuate depending on the weather. According to Crick (2004). Bird behavior and activity were observed to be influenced by temperature and humidity indirectly. As Gregory et al. (2009) report, climate change can both negatively and positively affect large species assemblages. However, it is plausible that the physiological reactions of birds to climate change will be significant (McKechnie, 2008; McNab, 2009).

2.2.3 Responses of birds towards climate change

The responses done by the species to climate change was generally by three methods such as movement (if the species are mobile they will track the suitable environment niches), adaptation (if the species are able to adjust to the changing conditions and have high physiological tolerances) and extirpation (when both movement and adaptation fails) (Holt, 1990; Melillo et al., 1995). In addition to climatic factors, land-use and habitat change, biotic interactions and evolutionary adaptation also influenced species distribution (Huntley et al., 2006; La Sorte and Thompson, 2007; Beale et al., 2008). According to Thomas (2010), the climate is one of the most important factors that determine range boundaries. The climate change effect on endothermic birds is indirect as it impacts the vegetation in their communities as opposed to directly affecting their physiology (Aragon et al., 2010a). Chen et al.

(2011) argued that most species' ranges are shifting into the poles and upwards because of climate warming (Chen et al., 2011).

2.2.4 Climate change and avian distributional range

Gibbons and Wotton (1996) found that the lack of severe winters in the UK since the 1960s had led to the expansion of the distribution of the Dartford Warbler (*Sylvia undata*). A number of studies have documented that shifts in distributional ranges were linked to temperature gradients and the interaction between temperatures and precipitation is also significant in determining distributions (Hawkins et al., 2003). To determine how much change has occurred for this interaction over the century, a temporal distributional study could be conducted (Hawkins et al., 2003). In another study using a community index rather than species range margins, it was revealed that in France there was a substantial northward shift in breeding bird assemblages, but it did not reflect the 9 climate warming experienced there (Devictor et al., 2008). There has already been evidence that climate change has an effect on bird distributions in multiple studies (Gregory et al., 2009; Niven et al., 2009; Chen et al., 2011). Researchers found that increasing range sizes are correlated with species whose ranges expand as reported by Gregory et al. (2009). The Alps have recently experienced an upward trend in breeding bird distribution according to (Popy et al., 2010). Tropical bird species have become increasingly vulnerable to climate change over the past few years (La Sorte and Jetz, 2010; Harris et al., 2011; Sodhi et al., 2011; Wormworth and Sekercioglu, 2011). Bradbury et al. (2011) report that Sylvia undata populations have been increasing in the northwest and upward in Northern Ireland between 1974 and 2006. Climate change has also affected bird demographics (Pautasso, 2012) and not just species distributions.

2.2.5 Importance of range distribution studies

For a better understanding of biodiversity ecological impacts and evolutionary changes that will occur in the future, it is necessary to collect information regarding species ecology and geographic distribution (Rosenzweg, 1995; Ricklefs, 2004; Graham et al, 2006), in addition to planning and forecasting for the conservation (Ferrier, 2002b; Funk and Richardson, 2002; Rushton et al, 2004). Adaptive and mitigation measures associated with climate change were eagerly anticipated by researchers and policymakers alike (Mace and Baillie, 2007; EEA, 2007).

2.3 MODELLING OF SPECIES DISTRIBUTION

2.3.1 Importance of species distribution modeling

There are statistical correlations between the abundance and distribution of 148 wintering land birds and six environmental factors, among them climatic factors. Root (1988a, 1988b) and Root and Schneider (1993) conducted similar research on these same topics. A model developed by Gates et al. (1994) related species distribution in the United Kingdom to land-use patterns of usage and climatic variables, and the results indicated a strong relationship between the climate and bird distribution, and the predicted climate change was spurring redistribution. In order to determine whether measurements have changed, climate envelopes were applied to describe the spatial distribution, and compared with the current distribution pattern. Among these factors, biotic interactions, geographic barriers, and historical circumstances were not taken into account, so species in suitable environments would become rare (Anderson et al., 2002; Svenning and Skov, 2004; Araujo and Pearson, 2005).

Models of species distributions were applied to examine spatial configuration and habitat characteristics to determine if species continuity may have been possible in landscapes (Araujo and Williams, 2000; Ferrier et al., 2002b; Scotts and Drielsma;

2003), historical distributions of species (Hugall et al., 2002; Peterson et al., 2004), 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) in conjunction with environmental and species diversity variables (Mac Nally and Fleishman, 2004).

Conservation practitioners can estimate species distribution sizes and predict the probability of their presence without systematic surveys by using distribution models (Elith, 2002). Our study of changing distributions was based on predictive modeling. It is possible to correlate climate variables and environmental variables with the presence or absence of species in accurate maps of their distribution (Crick, 2004).

The environmental conditions were derived using the known distributional characteristics of species, thereby identifying the geographical regions with similar ecosystems and modelling the distribution of species (Pearson and Dawson, 2003). Based on bio-geographic analysis of observed localities, the distribution of species abiotic niches was extensively studied (Guisan and Thuiller, 2005). The only way to test the hypothesis or projections was by actually watching the future unfold and to overcome this difficulty, we could use past changes in the environment to test whether species and ecosystems have responded in the same way that the models (Araujo et al., 2005). Based on the abundance or presence of species in relation to a particular environment, species distribution models provide predictions of the distribution of species in the environment. In ecology, evolution, and conservation, these models were widely used in the analysis of various arguments (Elith et al., 2006).

Moreover, these models can provide estimates of the distribution of species under various climate change scenarios (Jeschke and Strayer, 2008; Sinclair et al., 2010), the potential for introduction and subsequent expansion (Jimenez-Valverde et al., 2011; Jeschke and Strayer, 2008) and could be used in reserve planning (Thorn et al., 2009). Studies of shifting bird distributions were vital for monitoring protected area networks and conserving the species of birds from becoming endangered (Aragón, 2010b; Arajo, 2011). The changes in distribution will also signal the need to conserve biodiversity throughout the landscape, resulting in the displacement of existing protected areas (Pautasso et al., 2011).

2.3.2. Process of species distribution modeling

2.3.2.1 Steps in species distribution modeling

We used several steps for modelling the distribution of species: (1) present-day data on species as points of occurrence (Peterson et al., 1998; Peterson and Stockwell, 2001b); (2) models of ecological niches have been developed and evaluated using distributional data (Guisan and Zimmerman, 2000; Kobler and Adamic, 2000); (3) the shifts in distribution are based on models of the general circulation of climate change and projected onto the landscapes of interest; (4) distributional shifts are modeled through a projection of ecological niche models of various taxa. Through the analysis of responses of species to abiotic environmental factors (Soberon and Peterson, 2005), environmental space models can estimate the ecological niche for any given area or trace the specific conditions in which the species can thrive (Elith et al., 2011).

2.3.2.2 Methods for testing accuracy

Different types of models were used to model species distributions, varying in the steps of the modelling process; selecting a suitable predictor variable, defining each predictor variable's function, weighing variable contributions, predicting species distribution by examining the interactions among the predictors and the species (Guisan and Zimmerman, 2000; Burgman et al., 2005; Wintle and Bardos, 2006). Models were built with several rules, each of which comprised an algorithm, and on the basis of that, landscapes within and outside of the ecological niches were identified (Peterson, 2001a). Comparing alternative models and including different factors in the model using hierarchical portioning would give us the ability to analyze the evidence from different factors (Mac Nally, 2002). Testing the climatic envelope models addressed concerns about the accuracy of species distribution predictions under different climate conditions (Akcakaya et al., 2006; Pearson et al., 2006; Araujo and Rahbek, 2006; Zimmer, 2007). According to Pearson et al. (2007), the degree of environmental dimensions that define a species' distribution impacts its distributional limits. A range of suitable conditions for each species was accurately described by the model as a result of this. Due to the fact that the data are derived from a single source, it is difficult to identify causal relationships between variables because autocorrelations exist among the variables (Bahn and McGill, 2007; Currie, 2007; Beale et al., 2008). The correlation between environmental variables and climatic variables can be reduced by examining large geographic areas, reducing the misinterpretation of species distribution responses (Maclean et al., 2008). Ashcroft et al. (2011) reported that models failed to detect spurious correlations among variables that determined the geographic distribution of the population in order to resolve ambiguities due to correlated predictors. We developed a generalized linear mixed model to improve the accuracy of species distribution range predictions (Swanson et al., 2013).

2.3.3. Advancements in species distribution modeling

A primary influence over terrestrial species distribution is the climate and niche modelling were based on this idea. However, the understanding of mechanisms was challenging even though predictive models had increased (Shipley, 1999). Research on the future distribution of a species was notably scarce, but the climate envelope approach was frequently used for resolution (Berry et al., 2002; Thomas et al., 2004; Harrison et al., 2006). The use of ecological niche modelling was appreciated for predicting species distributions based on environmental data (Pearson and Dawson, 2003). Science and technology advancements led to the development of very complex general circulation models (GCMs), which simulate climate changes and, in conjunction with different greenhouse gas emission scenarios, predict the future climate (Raper and Giorgi, 2005). Despite the lack of data on species-specific physiological parameters and processes, the correlation between climatic and non-climatic factors was still an issue (Kearney, 2006). Based on current climate data, the models were used to predict the distribution of bird species in the present, and the models could also be used to predict the distribution of bird species in the future based on predicted future climatic conditions (Huntley et al., 2006). There is an association between climate and vertebrate distribution, and predictive models have been developed using bird distribution data (Jetz et al., 2007).

2.3.4. Species distribution studies

Environmental variables such as climate conditions have been proposed to explain animal species richness and distribution patterns (Kerr, 2001; Ricklefs, 2004; Ceballos and Ehrlich, 2006; Mittelbach, 2010). Studies using climate data have modeled species distributions in many ways (Beever et al., 2010). According to studies of future distribution predictions, changes in the distributions of species associated with warmer climates would be reflected by similar changes in the distributions of species associated with colder climates since both occupy the same climate zone (Berry et al., 2002; Thomas et al., 2004; Harrison et al., 2006). Studies predict the future of species extinction (Peterson et al., 2002; Bakkenes et al., 2002; Thomas et al., 2004; Thuiller et al., 2005; Malcom et al., 2006), and the redistribution of ranges by species (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). Because of climate change, the location of species has been correlated with climate variables (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). A study had examined the role of temperature dependence in changing distributions and the shifts in distribution over time (MacKay et al., 2008). Prediction of species richness has been explained by various environmental factors at various levels (Coops et al., 2009; Hinsley et al., 2009; Hansen et al., 2011; Bar-Massada et al., 2012; Fitterer et al., 2012). For forest bird richness, temperature variables were strongly correlated with bird abundance, while precipitation variables were strongly associated with bird abundance in open woodlands (Goetz et al., 2014).

2.4 DATA USED FOR MODELLING

2.4.1 Type of data and performance of the model

When used withheld data for predicting species distribution, proximity-only models failed to perform well in general tests due to the biases in the geographic and environmental space (Bojorquez et al., 1995, Hijmans et al., 2000; Soberon et al., 2000; Kadmon et al., 2004). To test the performance of the model, artificial data could be used as well as the accuracy of predicted responses, or both presence and absence data could be used, along with comparing fitted functions (Austin et al., 1995). According to Fielding and Bell, (2007), 'test' data and 'training' data for training the model provided better predictive accuracy than independent data collected for building the model. An array of test statistics and discrimination indices were used to assess the performance of the model (Fielding and Bell, 1997; Pearce and Ferrier, 2000). In the evaluation stage, we observed the predictive performance and excluded some known occurrences (only its presence) from the development of the models (Fielding and Bell, 1997; Hastie et al., 2001; Araujo et al., 2005).

As a measure of accuracy, we assessed the wellness of prediction by using data withheld from the study (Boyce et al., 2002; Hirzel and Guisan, 2002b). Unlike Kappa and the area under receiver operating characteristic curve (AUC), which are commonly used indices, these cannot be used to evaluate regions with a small sample size (Boyce et al., 2002; Phillips et al., 2006). It was statistically identical to predicting a large proportion of test localities from a random prediction, so it would provide informative predictions if higher proportions of test localities were predicted (low omission rate). The Chi-square test or upper-tailed binomial probability was used for assessing the statistical significance of the model when data portioning was done for testing (Anderson et al., 2002). Observed absence data were necessary to predict the model's performance (Loiselle et al., 2003). As a result, the 2-2 confusion matrix was used to describe when the absences and presences were predicted correctly and incorrectly. However, only presence-only models without absence data were tested (Anderson et al., 2003).

Theories suggest excluding absence data (which may occur when missing data are included in the model) since inaccurate predictions will be judged as failures (Anderson et al., 2003; Pearson and Dawson, 2003; Soberon and Peterson, 2005). Typically, random or spatial stratified partitioning was used (Peterson and Shaw, 2003), but small records presented challenges, such as being too small for partitioning into training and test sets or being difficult to identify negative records (Anderson and Martinez-Meyer, 2004). When a small sample was used, the prediction performance declined (Stockwell and Peterson, 2002; Reese et al., 2005). Due to the widespread use of distribution models and the increasing advancements in available data and modelling methods, high-predictive-ability and accuracy analyses of species distribution modelling methods for presence-only data were of the utmost importance (Elith et al., 2006). A presence-absence dataset that is independent and well-structured greatly improves the evaluation of model performance (Elith et al., 2006).

The development of machine learning and statistical disciplines led to the creation of many methods which were capable of capturing complex responses despite noisy data. Despite its promise, this research has not received any exposure in distribution modelling (Phillips et al., 2006, Leathwick et al., 2006). Resampling designs revealed geographic and environmental biases as well (Elith et al., 2006). In the case of limited observational records, the jackknife approach is a valid method for assessing predictive ability. As a technique, the Jackknife (‘leave one out’) procedure was effective at assessing the model with few occurrences. Observed localities (n) were excluded once, then n-1 localities were used to construct the model. A set of n different models was built and the predictability was tested by predicting the single locality from the training set of data (Pearson et al., 2007). In the modelling techniques and validation, only presence data were used as absence data were rare or difficult to detect, respectively (Pearson et al., 2007). According to studies conducted by Algar et al., (2009), the temporal prediction was fairly accurate, but regression models could be used to reduce biases in spatial autocorrelation.

2.4.2 Presence and absence records

Distribution models developed in the past have used presence/absence or abundance data, with systematic sampling carried out within the areas of interest (Austin and Cunningham, 1981; Hirzel and Guisan, 2002b; Cawsey et al., 2002). It has been developed in the past that a number of distance-based measures can be used solely for the analysis of presence-only data (Silverman, 1986; Busby, 1991; Walker and Cocks, 1991; Carpenter et al, 1993). Most presence/absence models assume that breeding habitats are saturated (Capen et al., 1986). In some species distribution models (Nix, 1986; Carpenter et al., 1993), the only thing prescribed was to look at presence data.

If you use presence/absence models (Fielding and Bell, 1997), you can generate false positives or false negatives. In the future, adaptations could be made to use the background environment samples (produced through sampling random points over the study area) or to model presence-only data from presence-absence methods (which used a binomial response for modelling) or to use a pseudo area (Stockwell and Peters, 1999; Boyce et al., 2002; Ferrier et al., 2002b; Zaniewski et al., 2002; Keating and Cherry, 2004; Pearce and Boyce, 2006). Lack of records during surveys and poor sampling contributed to the use of pseudoabsences instead of real absences, so methods for obtaining absence data often used pseudo-absences instead (Ferrier et al., 2002a; Engler et al., 2004) or some methods used background data for the entire study area (Hirzel et al., 2002b).

We had access to occurrence data from the environmental data layers of high spatial resolution created through satellite imagery (Turner et al., 2003) and highly sophisticated climate data (Thornton et al., 1997; Hijmans et al., 2005). Validating absence data was challenging as wildlife-habitat correlations were absent, even though some species may have been spotted at a site (MacKenzie et al., 2004; Gu and Swihart, 2004).

Ecological niches were modelled using alternative methods of several kinds, using both present and absent records (Bourg et al., 2005). According to Thuiller et al., 2004 and Pearson et al. (2006), there was a wide range of predictions based on different methods, so it is imperative that the appropriate method be selected and the results verified. There were many records of species distribution in museum and herbarium collections that could be accessed electronically (Graham et al., 2004; Huettmann 2005; Soberon and Peterson, 2005). At present, there are methods that use information about members of the community as a supplement to data regarding models of rare species; specifically for rare species, this method holds promise, since information about other members of the community could reveal relationships between models (Elith et al., 2006). The problem with these types of presence data was that their intent and methods were seldom known, and therefore, the absence of data could not be inferred with certainty (Elith et al., 2006). Since the turn of the century, new approaches have been developed that have focused exclusively on presence data, thereby eliminating the need to obtain places of absence (Baldwin, 2009).

2.5 ASSESSMENT OF CLIMATIC CHANGES

A number of tools were used to assess the impacts of climate change on biodiversity, including global climate models, regional climate models, dynamic and equilibrium vegetation models, species bioclimatic envelope models, and site-specific sensitivity analyses (Sulzman et al., 1995). Transient simulations showing both ups and downs in temperature distribution showed the increasing temperatures in both hemispheres when CO2 was increased stepwise (Sulzman et al., 1995). A regional model could be used in conjunction with a Global Circulation Model (GCM) to provide greater resolution. (Sulzman et al., 1995) The two major regional models used were the MM5 (Mesoscale Model version 5) and the RAMS (Regional Atmosphere Modelling System). In the southern hemisphere, climate dynamics are different from those in the northern hemisphere, so models developed with primary emphasis on one hemisphere would not produce accurate results in the other hemisphere (Grassl, 2000).

The use of regional climate models was more useful for analyzing local changes than global models that included global forcings (Pitman et al., 2000). Models such as these could illustrate how land-use changes impact cloud formation. There was no easy way to get results from these models for all regions. Several dynamic vegetation models, forest gap models, biome envelope models, and species envelope models were used to investigate different aspects of future climate change related to biogeography (Cramer et al., 2000).

For conservation assessments of climate change, global climate models, including General Circulation Models (GCMs), provide estimates of future climate change due to greenhouse gas forcing by calculating projected climate change values at different resolutions. (Hannah et al., 2002). The assessments were enhanced by incorporating results from transient (not equilibrium) simulations of CO2 increase and models which were coupled with ocean and atmosphere in the regions of interest (Hannah et al., 2002).

2.6 MAXIMUM ENTROPY MODELLING (MaxEnt)

According to Phillips et al. (2006), MaxEnt calculates the species distribution using maximum entropy distribution under the constraint that the expected values of each environment variable (interactions) match their empirical average. It approximated the most uniform distribution by utilizing the background locations and derived constraints (Philips et al., 2004; Philips et al., 2006). If the presence data are used only as species data, the complexity of the fitted functions can be chosen. The Maximum entropy modelling (MaxEnt) technique has performed better or as well as other techniques (Elith and others, 2006; Hernandez and others, 2006; Philips et al., 2006). The MaxEnt algorithm yielded higher success rates in comparison with other algorithms, and it did so despite small sample sizes (Pearson et al., 2007). While MaxEnt models predicted broader areas of suitable conditions and could predict excluded regions when sample sizes were reduced artificially, model performance was negatively affected (Pearson et al., 2007).

MaxEnt has been applied to the prediction of distributions of geckos (*Uroplatus* spp.) (Pearson et al., 2007), denning habitat assessment of the American black bear (*Ursus americanus*) (Baldwin and Bender, 2008), Bush dog (*Speothosvenaticus)* for judging protection excellence (DeMatteo and Loiselle, 2008), modeling seasonal distribution patterns of the Little Bustard (*Tetraxtetrax*) (Suárez-Seoane et al., 2008), nesting habitat prediction and mapping for the Sage grouse (*Centrocercus urophasianus*), and a conservation plan was created for the species of Asian slow loris (*Nycticebus* spp.) (Thorn et al., 2009). MaxEnt is capable of creating accurate models even with limited data points, which proved useful when mapping the spread of species was not possible (Baldwin, 2009).

CHAPTER 3

MATERIALS AND METHODS

3.1. STUDY SPECIES

Malabar Barbets (*Psilopogon malabaricus*) are endemic to tropical evergreen mountain regions of India's western ghats (Rasmussen and Anderton, 2005). Breeding occurs during the months of December to May, making it a frugivore. Several studies have been conducted on the breeding biology of barbets *Megalaima viridis and M malabarica* in the Periyar Tiger Reserve in Kerala (Yahay, 1988). Malabar Barbet is endemic to the Western Ghats of southwestern India, where it replaces the related Coppersmith Barbet (*Psilopogon haemacephalus*) in wetter forested habitats. Within these habitats, it is generally common and vocal, although very difficult to see in the forest canopy. Largely territorial, groups often gather in fruiting trees, and pairs nest and roost in holes excavated in a rotting tree limb. It was reported in December 2012 at 0730 hrs that Malabar Barbets had been sighted in Pillur, and from April 2013 to June 2014 in Athikadavu (Manikandan and Balasubramanian, 2016).

3.2. STUDY AREA

The study was carried out in the Western Ghats, a point of high biodiversity that runs through Kerala, Tamil Nadu, Karnataka, Goa, Maharashtra and Gujarat. The Western Ghats refer to the practically unbroken hill chain (with the exception of the Palakkad Gap) or escarpment running roughly in a north-south direction, parallel to the Arabian sea coast, from the river Tapi (about 210 16’ N) down to just short of Kanyakumari (about 8019’ N) at the tip of the Indian peninsula . (Myers et al. 2000) The range has a diverse range of ecosystems, which contribute to its richness in biodiversity and endemism. 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. Mountains in Nilgiri and Anamalai rise to 2500 meters above sea level and are divided by a 22 km wide Palghat gap. There is a great deal of shola grassland in the south of WG, particularly in the high mountains. (Ramachandra and Suja 2006). Sholas are semi-evergreen plants that grew in prehistoric highlands. They are thought to be living fossils (Jose 2012)

3.3. OCCURRENCE POINTS OF MALABAR BARBET

Species Distribution Model (SDM) (Trisurat et al., 2011) is a framework for deriving information on the existence and distribution of species. The Malabar Barbet presence statistics were obtained from e-Bird references (http://www.ebird.org/), a free checklist tool available over the Internet. As well as being copyrighted by Audubon Society and Cornell Lab of Ornithology, this data is also released under Audubon Knowledge Network (AKN). Breeding Bird Survey data is drawn from a survey conducted in 1966 that continues till now. It has advanced georeferencing capabilities and an extensive user community. It was used to get georeferenced data from 1964 to 2020 on the Malabar Barbet. By utilizing Excel's capabilities, duplicate records were eliminated, and a matching shapefile was created in ArcMap 10.8(Fig. 1).

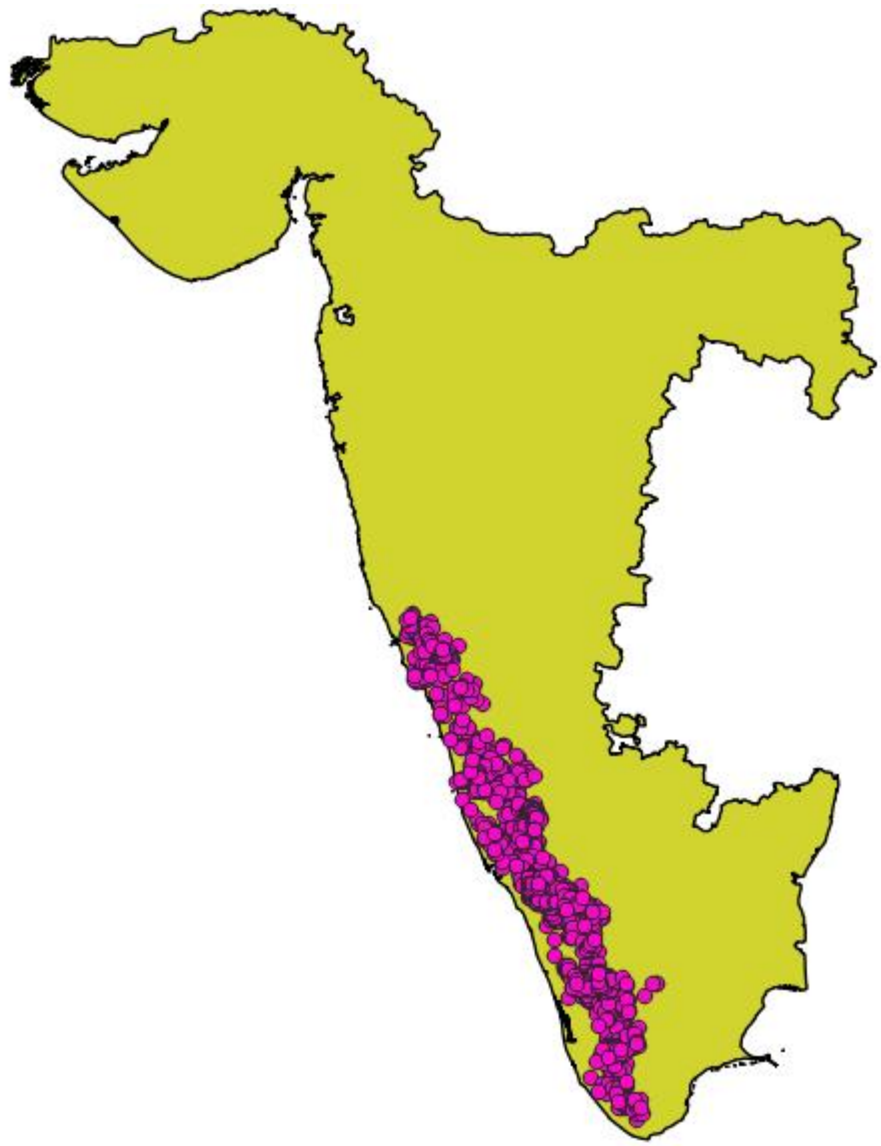


Figure 1. Occurrence points for Malabar Barbet in the Western Ghats

3.4. ENVIRONMENTAL VARIABLES

19 more relevant variables are generated by the combination of monthly rainfall data and monthly temperature data. 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): Thismakes 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. bio19 (Precipitation of Coldest Quarter): The impacts of the coldest quarter's mean precipitation on species distribution were measured.

In both current and future conditions, 30 arc seconds (0.86 km2 at the equator) were used. 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. In order to create the data layers, average monthly data from weather stations were interpolated. There are benefits and drawbacks to this information. 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.

Environmental and ecological sciences require high-resolution climate data for many applications. CHELSA (Climatologies at high resolution for Earth's land surface regions) provides downscaled estimates of temperature and precipitation based on ERA-Interim output at a high resolution of 30 arc seconds. CHELSA's output has been compared with data from the Global Historical Climate Network. According to CHELSA, species distributions can be predicted more accurately than with climatological data. In addition, several studies have shown that the CHELSA precipitation pattern forecast is as accurate as any other temperature forecast.

Table 1. 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/m2 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/m2after 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	1370	3.7 (2.6 – 4.8)°C

		and continues to grow for some time		

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). Land cover data (Globcover 2009) was downloaded from the European Space Agency site (http://due.esrin.esa.int/page_globcover.php). Besides these variables, we also downloaded EVI (Enhanced Vegetation Index) United States Geological Survey (USGS) for 10 years (2011 – 2020). Since these data were downloaded on monthly basis they were obtained in different tiles. Hence, Arcgis 10.8 was used to stitch 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.

3.5. DATA THINNING

eBird provided a total of 18,265 Malabar Barbet presence locations. 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 - $\leq$ 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 2568 occurrence points which were saved in the extension '.csv'. The majority of SDM require spatially independent occurrence data for better prediction. The spatial autocorrelation of occurrence sites in SDMs is considered a frequent source of environmental biases (Hijmans, 2012). As the model becomes overfit towards environmental biases, model metrics are exaggerated. The model can no longer predict spatially independent data (Veloz, 2009; Hijmans, 2012; Boria et al., 2014). It is important to eliminate spatially autocorrelated points from clusters of localities for better calibration and model building. We spatially thinned the occurrence data for the species using the spThin package (Aiello - Lammens et al., 2015) in R studio to remove duplicate records within a 1 km radius of each other. After thinning we acquired 1450 occurrence points.

3.6. SELECTION OF BIOCLIMATIC VARIBLES

In the process of model development, variable optimization is an essential step. The characteristics on the list will not all be equally important to our species of interest. There may be some factors that have a small impact on the outcome and they should be removed to improve the interpretability of the final model (epistemic sparcity) or make the model more predictable (predictive sparcity) (De Bin et al., 2015). To reduce the autocorrelation, highly correlated variables should be removed before evaluating the contributions of each individual environmental variable. By incorporating correlated variables, not only does MaxEnt model prediction become more accurate, but it also limits the contribution of additional correlated variables to the output. As a result, 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). A correlation might affect the accuracy of response curves derived from the presence. A model that incorporates strongly correlated variables can produce misleading results.

When there are many highly correlated variables, it is best to avoid using a percentage contribution. If the training and test data are spatially autocorrelated, it appears that the model isn't well fitted, as the test omission line is significantly lower than the predicted omission line. As geographically auto-correlated data would inflate accuracy measurements for presence-only models (Veloz, 2009), spatially correlated variables have to be eliminated beforehand.

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. On the basis of the MaxEnt model output, we selected the variables that contributed the most and used permutation-important testing to make future predictions. The contribution charts display the proportional contributions of each variable to MaxEnt. The increase in regularised gain was added to the contribution of the associated variable with each iteration of training, or removed if the changes in lambda were negative. The MaxEnt code's path to the solution was dependent on the contribution numbers, and the contribution numbers differed when it took a different approach to reach the same result. It was important to evaluate the results carefully when there were several strongly linked (correlated) variables. A permutation's importance is determined by the MaxEnt model, rather than the path it took to reach the value. To determine the significance, we arbitrarily permuted the values of that variable among training and background (training points) and calculated the reduction in training AUC. A greater drop indicates a more dependent model. According to the Jack-knife test of variable relevance, the environment variable with the highest gain when used alone (containing the most relevant information) and the environment variable with the lowest gain when omitted (containing the most information not available in the other variables). For further modeling, the selected variables were removed from the correlated variables.

3.7. MAXIMUM ENTROPY SPECIES DISTRIBUTION MODELLING (MAXENT)

In addition to considering the most important environmental conditions (Phillips et al. (2004, 2006), the Maxent model is an effective tool for simulating geographical distributions of species. Based on incomplete data, the Maxent model uses a machine-learning algorithm to predict outcomes. This method calculates the "maximum entropy" of sample points against the background locations after taking into consideration the limitations imposed by the data. Based on deterministic maximum entropy algorithms, the top probability distribution is computed at the highest maximum entropy (Baldwin, 2009; Berger et al., 1996; Phillips et al., 2006). Depending on whether a species is present or absent, a site can be classified as "present" or "absent.". Environmental characteristics similar to those of a species can be evaluated to determine which biotopes are likely to contain that species. As a starting point for the model, a uniform distribution for each species is determined, which undergoes iterations based on the most important environmental variables until no further improvement in prediction is possible. The Maxent distribution is calculated in the set of grid cells that contain all environmental variables. To determine whether Maxent's predictions (training data) are better than random guesses, we used 25% of the sample points. This method uses both categorical and continuous environmental data, and all variables are treated as continuous variables. The probability of the species occurrence was determined by using a logistic output continuous map which provides a means of discriminating between the suitability of the geographical area under consideration. In addition to the geographical location data of Malabar Barbet occurrence, we added 25 environmental predictor variables, including 19 bioclimatic variables retrieved from the CHELSA database. Maxent uses area under the curve (AUC) to statistically analyze the model, and it is one of the most commonly employed statistics when modelling ecological niches and nest site selection (Baldwin, 2009; Barry and Elith, 2006; Peterson et al., 2007; Peterson and Nakazawa, 2008; Yost et al., 2008). The model is based on a set of georeferenced occurrence sites and environmental layers obtained from CHELSA. 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), threshold (T) ,and hinge (H), and 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 AICc (LQ and rm=0.5) was chosen for future projections. In order for us to reach to the variables with lowest AICc, 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 LQ 0.5.

3.8.2. REGULATION MULTIPLIER AND REPLICATION RUN TYPE

Model overfitting is prevented by using regulation multipliers (Philips, 2008). In order to fine-tune the model, different multipliers were experimented with, which are settings that control 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. Other numbers were 1.5, 2, 2.5, 3, 4 and 5. However, model fitting seemed to be significantly improved with the default value 1 and generally setting one as the regulatory multiplier value produced the highest test Area Under the Curve (AUC) among numerous experiments (Warren and Seifer, 2011).

Cross validation involves randomly partitioning the species location data into groups (k) of comparable size, leaving one part out, and evaluating the model based on k - 1 parts. Each part of the model is processed independently in this run type, and the results are merged to create the final output. With this type of run, no data is left unvalidated, which is especially useful when dealing with data sets with a 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 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 AICc 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

RCP2.6, 4.5, 6.0, and 8.5 available from the BSS CSM1.1, MIROC5 AND MohcHadGEM 2 ES at a spatial resolution of 30 arc-seconds (100 meters) for climate forecasting. This is consistent with the scenario put forth by the Intergovernmental Panel on Climate Change (IPCC) in its fifth assessment report (AR5), according to which greenhouse gas concentrations follow a range of radiative forcing as they increase. 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 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 a distinct layer. Future forecasts were made for 2050, assuming static features such as aspect will be the same in the 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 where same for both the models with EVI and without EVI which is LQ 0.5, 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 0.915 and 0.886, respectively, indicating that the model is better in predicting the suitable habitat area for Malabar Barbet in WG. With an overall accuracy of 0.9117, the specificity and sensitivity were 0.9011 and 0.9854, respectively. After the cross-correlation tests, the best model incorporated seven bioclimatic variables (Mean Temperature of Warmest Quarter, Mean Diurnal Range, Precipitation of Coldest Quarter, Annual Precipitation, Precipitation of Warmest Quarter, Mean Temperature of Coldest Quarter, Precipitation Seasonality), topography layers (Slope and aspect) and EVI (Average of 10 years [2011 – 2020]). EVI_avg (46.2% contribution), Mean Temperature of Warmest Quarter (23.8 % contribution), and Mean Diurnal Range (10.6% contribution) were the important factors affecting the spatial distribution of Malabar barbet among the seven variables considered for modelling. These factors combined to contribute 80.6 percent of the total. Mean temperature of warmest quarter (74.8 percent) and Mean Temperature of Coldest Quarter (16.6 percent), on the other hand, had significant permutation relevance (Table 2)

Table 2: Analysis of variable contribution (with EVI)

Variable	Percent contribution	Permutation importance
Evi_avg	46.2	0.8
bio10	23.8	74.8
bio2	10.6	5.8
bio19	6.2	0
bio12	4.1	0.5
bio18	3.9	0.2
bio11	3.3	16.6
slope	1.5	1.1
bio15	0.2	0.2
aspect	0.2	0

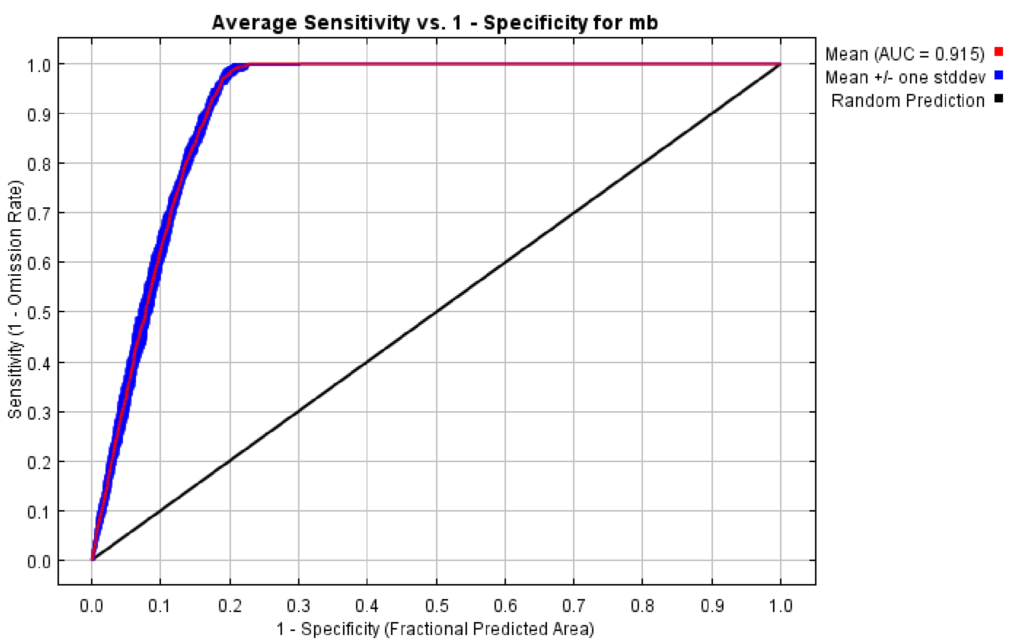


Figure 2 : Receiver Operating Characteristic Curve (ROC) curve of the finalized model settings output in MaxEnt (with EVI)

The model's performance in terms of average test AUC value is 0. 915, with a standard deviation of 0.005, according to ROC curve above (Figure 2). 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.

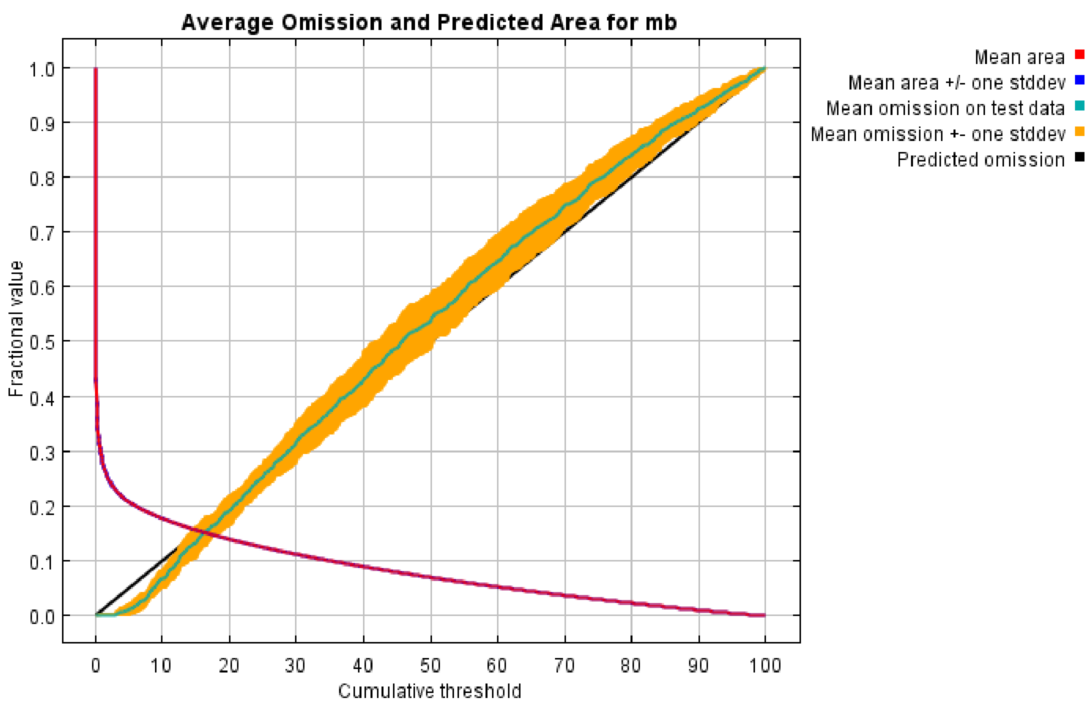


Figure 3 : Average omission curve and predicted area for Malabar Barbet, an endemic bird species of Western ghats (With EVI).

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.

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.

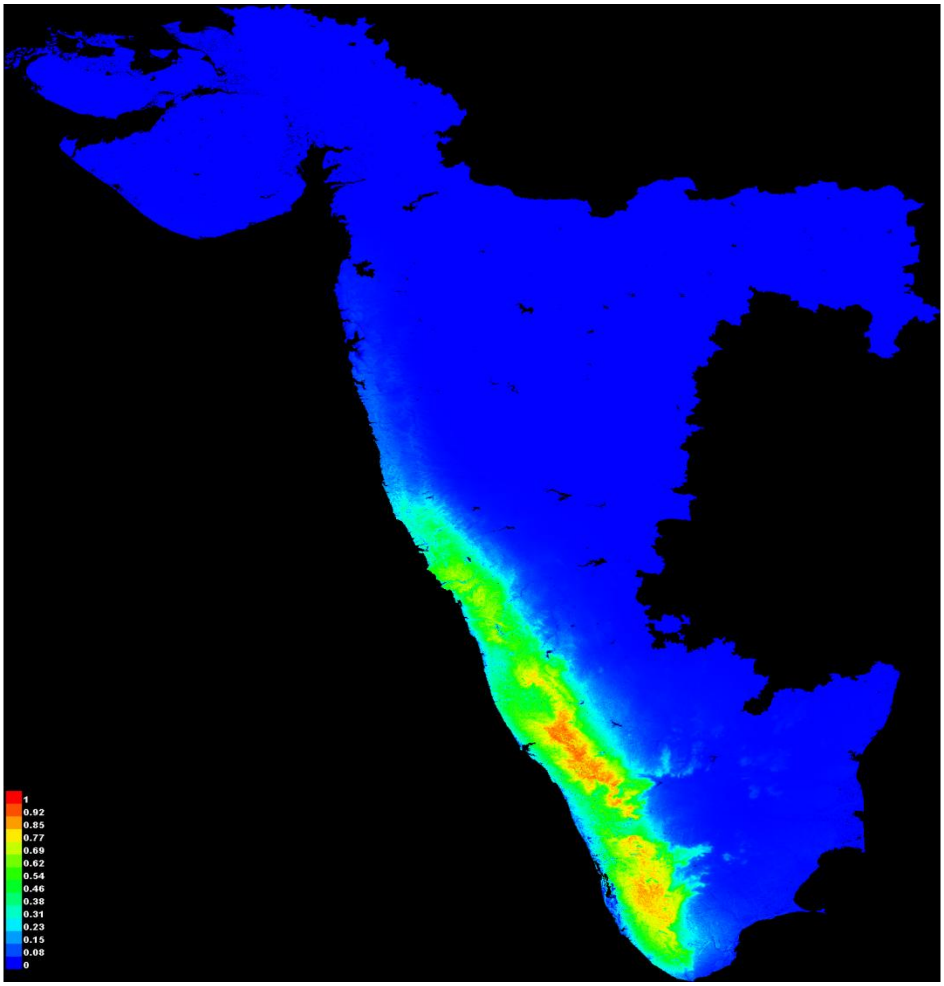


Figure 4: Shows the current distribution of Malabar Barbet by Maxent (With EVI)

This projection goes hand in hand with the actual distribution of Malabar Barbet hence we can say that this projection provided by MaxEnt with the setting LQ 0.5 can be used to project the future distribution of Malabar Barbet

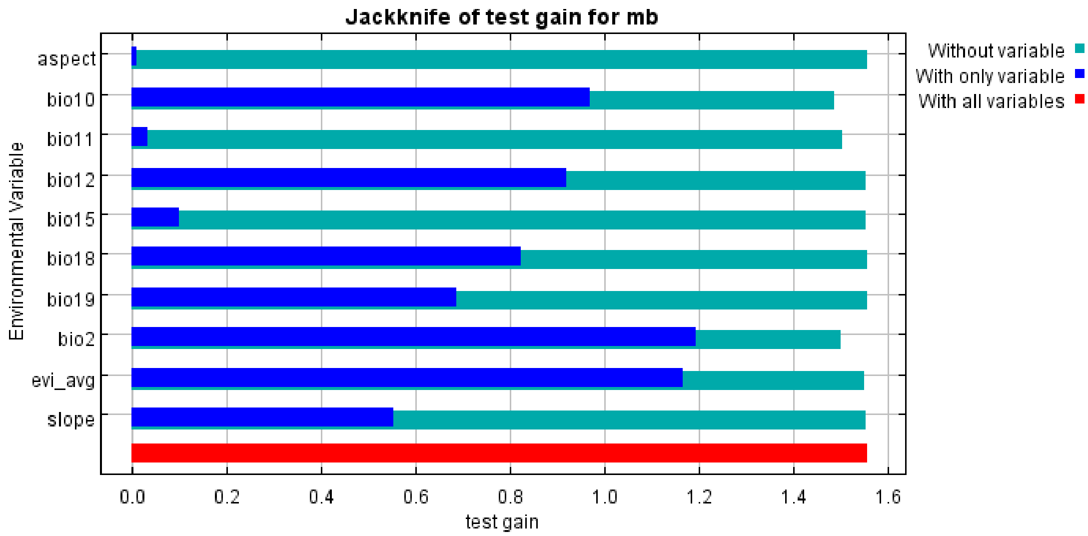
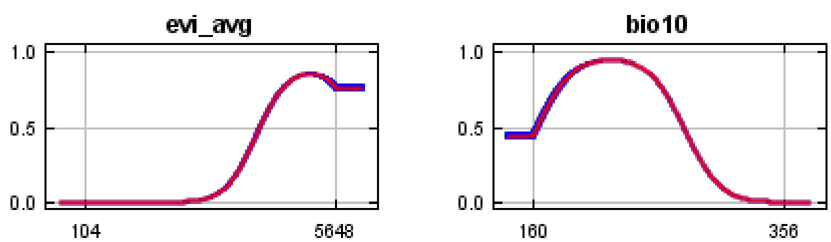


Figure 5 : Jackknife test gain for Malabar Barbet for the current distribution (with EVI)

According to the results of the Jackknife test, Mean Diurnal Range contributes the most, followed by Evi_avg, Mean Temperature of Warmest Quarter, and Annual Precipitation. This finding is comparable to MaxEnt's, implying that it is trustworthy(Figure 5).



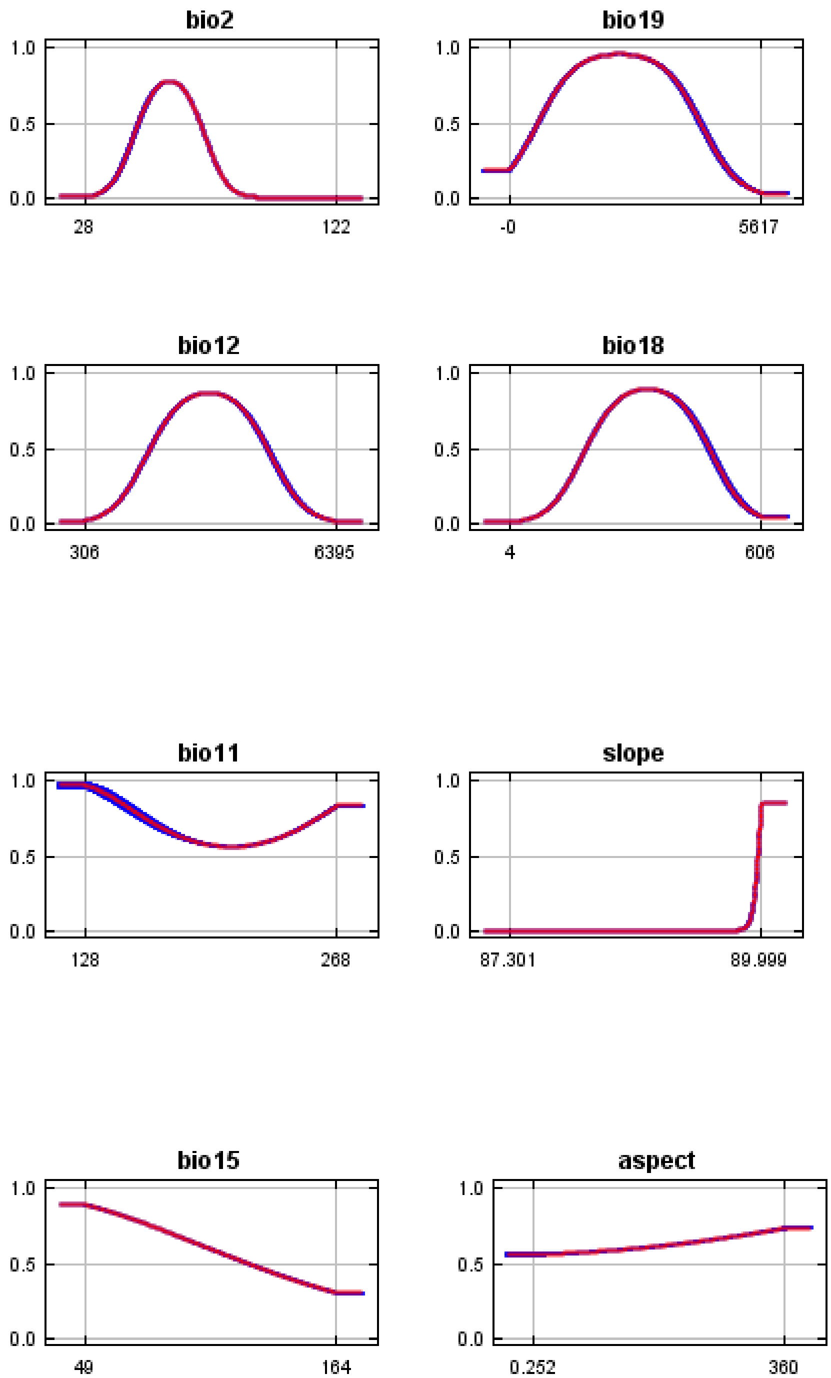


Figure 6 : Response curves generated by MaxEnt for variables (With EVI)

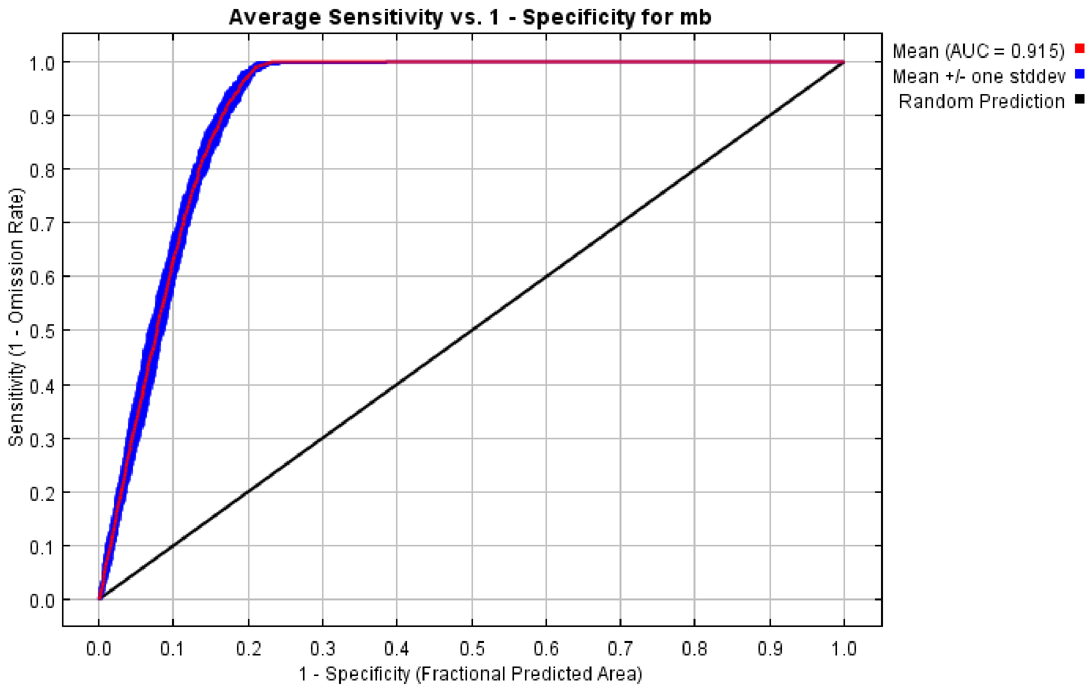


Figure 7: Receiver Operating Characteristic Curve (ROC) curve of the finalized model settings output in MaxEnt (Without EVI)

The test AUC and TSS values for the model without EVI were 0.915 and 0.875, respectively, indicating that the model is better in predicting the suitable habitat area for Malabar Barbet in WG. With an overall accuracy of 0.9083, the specificity and sensitivity were 0.8984 and 0.9771 respectively. Mean Diurnal Range (34.1% contribution), Mean Temperature of Warmest Quarter (32.80 % contribution), and Precipitation of Coldest Quarter (13.30% contribution) were the important factors affecting the spatial distribution of Malabar Barbet among the nine variables considered for modelling. These factors combined to contribute 80.20 percent of the total. Mean Temperature of Warmest Quarter (74.2 percent) and Mean Temperature of Coldest Quarter (16.60 percent), on the other hand, had significant permutation relevance (Table 3). The model's performance in terms of average test AUC value is 0.915, with a standard deviation of 0.006, according to ROC curve above.(Figure 7)

Table 3:Analysis of variable contribution (without EVI)

variable	Percent contribution	Permutation importance
bio2	34.1	5.6
bio10	32.8	74.2
bio19	13.3	0.2
bio18	6.8	0.3
slope	5.4	2.3
bio11	4.1	16.6
bio12	2.9	0.8
bio15	0.4	0.1
aspect	0.1	0

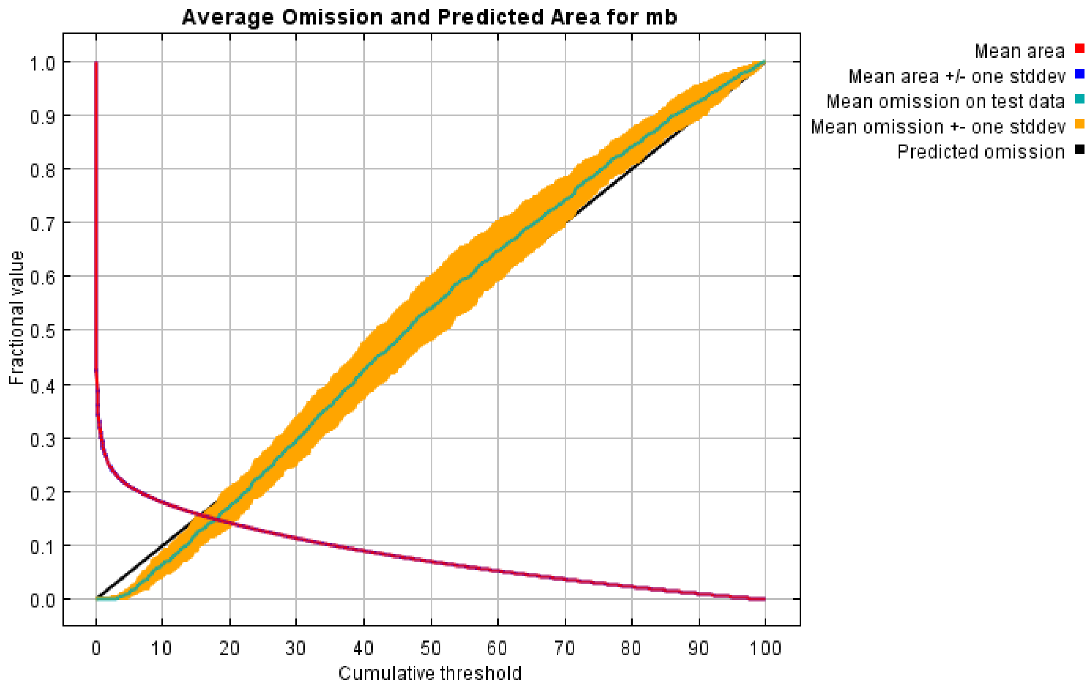


Figure 8: Average omission curve and predicted area for Malabar barbet, an endemic bird species of Western ghats (Without EVI).

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.

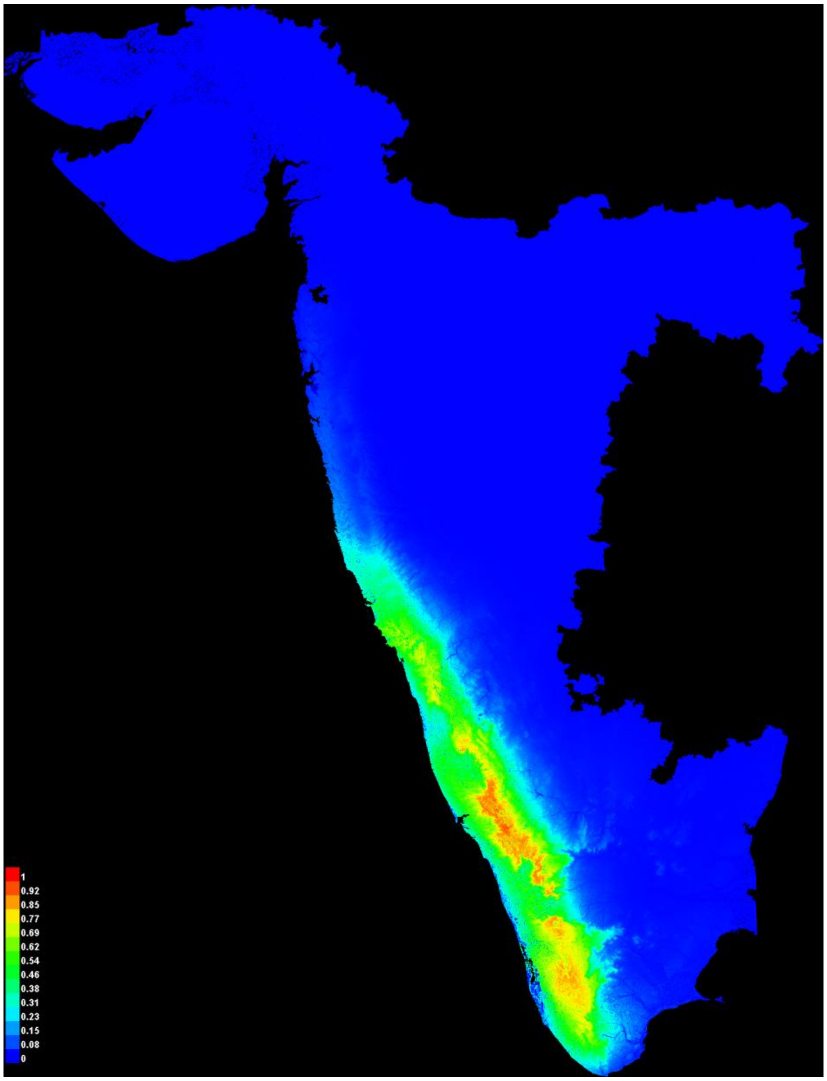


Figure 9: Shows the current distribution of Malabar Barbet by Maxent (Without EVI)

This projection depicts the current Malabar Barbet 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 LQ 0.5. The current distribution of Malabar Barbet and Maxent's projection go hand in hand.

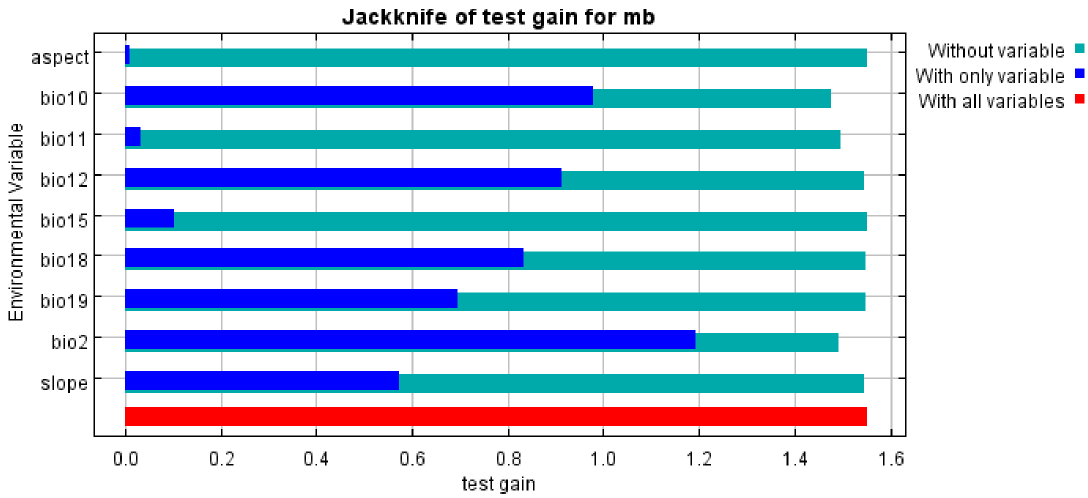
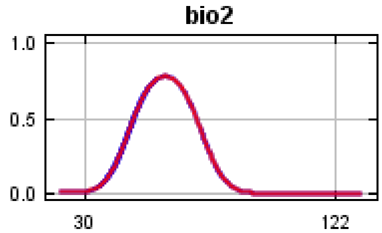
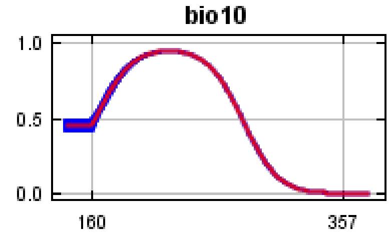
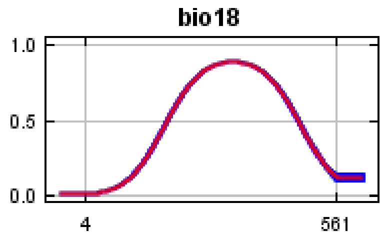


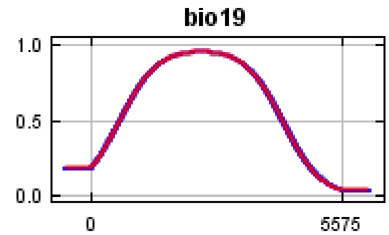
Figure 10: Jackknife test gain for Malabar Barbet for the current distribution (without EVI)

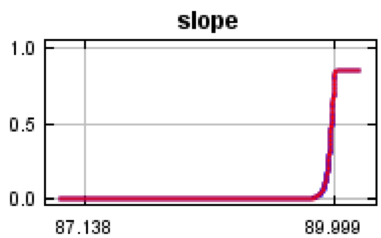
The jackknife test gain without EVI implies that the most contributing variable is mean diurnal range followed by mean temperature of warmest quarter and annual precipitation. These results are comparable to those produced by MaxEnt thus making them a reliable finding.

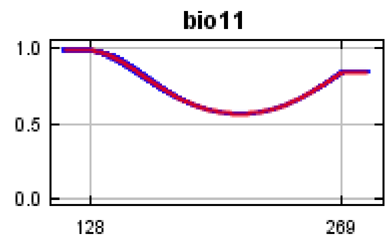

bio2
1.0
0.5
0.0
30
122


bio10
1.0
0.5
0.0
160
357


bio18
1.0
0.5
0.0
4
561


bio19
1.0
0.5
0.0
0
5575


slope
1.0
0.5
0.0
87.138
89.999


bio11
1.0
0.5
0.0
128
269

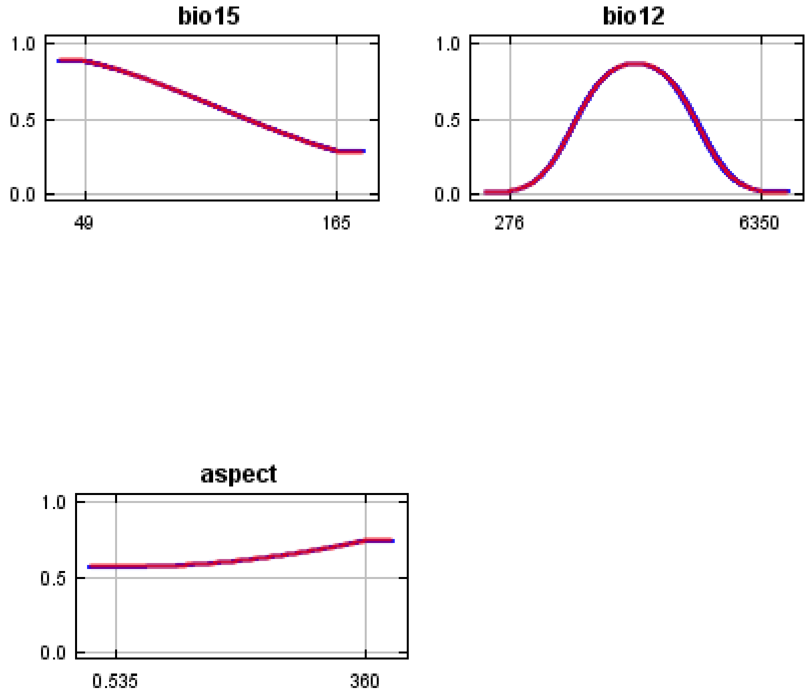


Figure11 . Response curves generated by MaxEnt for variables (Without EVI)

4.2. SELECTION OF SUITABLE BIOCLIMATIC VARIABLES

The table below (Table 4)shows the pearson correlation metrix generated by SDM toolbox in Arcgis. That is used for the selection of suitable bioclimatic variables.

Table 4: Pearson's correlation metrics 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 5 : 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 Barbet

The below table shows the variable contribution for current and also for RCP 2.6 2050 , RCP 4.5 2050 , RCP 6 2050 ,RCP 8.5 2050. In this table we can see thet bio2 and bio10 has more variable contribution.

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
bio2	34.1	50	45.4	50.2	48.8	46.8	52.3	50.5	45.8	51.2	52.7	41.2	48.1
bio10	32.8	24.9	30.9	29.7	27.3	29.7	27.5	24.8	30.7	28.8	23.5	33.9	31.4
bio19	13.3	10.8	0.9	1.3	10.5	0.8	0.9	10.2	0.8	0.7	10.1	2.7	1
bio18	6.8	2	3.2	3.3	1.9	3.3	3.1	1.9	4.1	3.7	1.7	4.2	3.7
slope	5.4	4.2	3.2	3.2	3.9	3.6	3.8	5.3	3.9	4.7	4.6	3.5	3.1
bio11	4.1	1.9	4.7	2.9	3.2	4.1	3.1	2.7	4	3.6	2.4	3.8	3.4
bio12	2.9	4.4	11	8.2	2.6	11.1	8.8	2.9	10	6.9	3.4	9.9	8.7
bio15	0.4	1.6	0.4	1	1.6	0.4	0.4	1.5	0.5	0.2	1.3	0.3	0.5
aspect	0.1	0.2	0.2	0.2	0.2	0.3	0.1	0.3	0.3	0.2	0.4	0.3	0.2

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

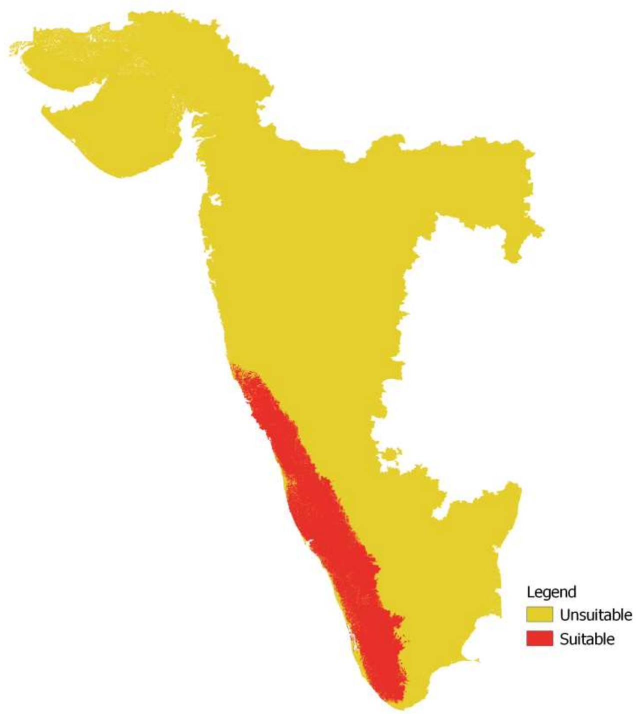


Figure 12: Distribution map showing suitability under current climatic condition

The area available as highly appropriate for Malabar Barbet in the study area under current climatic condition is 104,928km^2. And in the current scenario, in the study area the species were not at all present accounted for 937,897 km^2.

The area of suitability spread from Thuckalay to Kinjawade covering Agasthyamalai, Periyar National Park, Idukki Wildlife Sanctuary, Anamalai Tiger reserve, Nelliyampathy Forest reserve, Mudumalai Tiger Reserve, Bandipur Tiger Reserve and National Park, Nagarahole National Park and Tiger Reserve, Sharavathi valley wildlife Sanctuary, Anshi National Park, Bhagvan Mahavir National park, and Bhimghad wildlife Sanctuary.

4.3.1 FUTURE SCENARIOS

The test AUC and TSS values for the model under future scenario were 0.916 and 0.879, respectively, indicating that the model is better in predicting the suitable habitat area for Malabar Barbet in WG. With an overall accuracy of 0.9103, the specificity and sensitivity were 0.9005 and 0.9785, respectively.

The future scenarios are evaluated for four Representative Concentration Pathways (RCP) namely RCP 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 were 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.

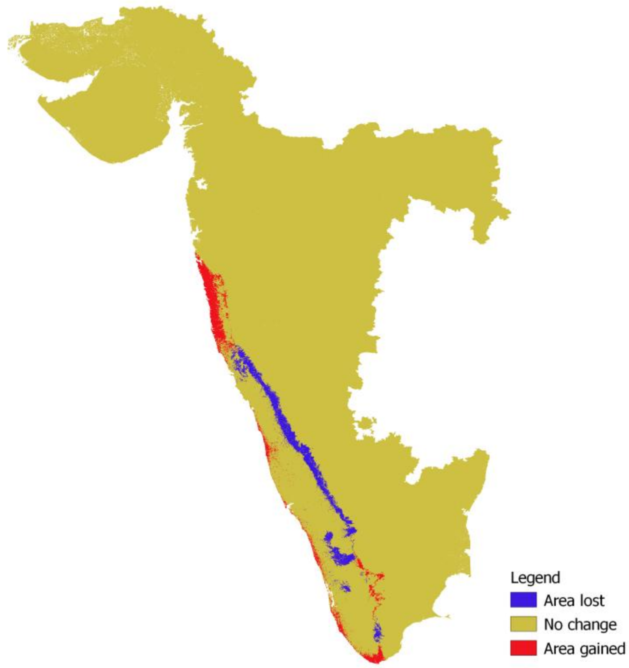


Figure 13: Distribution map showing area gained, lost and areas with no change in distribution under RCP 2.6 by 2050

This map is created by subtracting RCP 2.6 from current scenario. When we look at the map from top to bottom, we can see that a substantial amount of the Malabar Barbet's distribution and habitat appropriateness have remained unchanged. This value accounts for 10,06,757km^2. This could indicate that there is no change in area where Malabar Barbet is present or absent in the earlier mentioned current scenario.

A loss of 18,904 km^2 is seen in the distribution of Malabar Barbet under RCP 2.6. 18% habitat loss can seen here. Loss of habitat can be seen in Ambasamudram, Alangulam, Keezhapavur and Surandai near Singampatti Zamindar forest(Fig. 13). Loss of patch can be seen in Thodupuzha, Neriamangalam, Vannapuram, Kothamangalam and Malayattoor. Small loss of patches can be seen in Anamalai

Tiger Reserve, Kanthalloor and Vattavada.Loss of habitat can be seen in Kollengode, Nenmara, Chittur-Thathamangalam near Nelliyambathi Forest Reserve and loss can be seen in Palakkad, Mundur, Mannarkkad near Silent Valley National Park. In eastern side of Western Ghats there is a large loss of habitat seen from south to north that are Coonoor, Kotagiri, Kodanad, Sri Hangala, Gundlupete near Bandipur Tiger Reserve and National Park.Sargur, Heggadadevankote near Nagarahole National Park and Tiger Reserve. Hunsur, Echalapura, Belur and also near Bhadra Wildlife Sanctuary, Kankumbi, Bhimgad Wildlife Sanctuary and ends in Amboli. Loss habitat can be seen in Voldemol Cacora, Satari, Valpoi, Sanquelim, Sawantwadi and also near Bhagwan Mahavir wildlife Sanctuary.

Under RCP 2.6 Malabar Barbet had a gain or increment in habitat suitability of 16,494 km^2.15.7% habitat gain can be seen here. Increase in habitat gain can be seen in the southern region that are Kanyakumari, Nagercoil, Marthandam, Valliyur, Nanguneri. Habitat gain can be seen near coastal areas of Thiruvanathapuram, Kollam, Kayamkulam, Alappuzha, Thrissur, Kozhikode, Kannur. Habitat patch gain can be seen near the coastal areas of Udupi, Bramavara, Baindur, Bhatkal, Murdeshwar and Kumta.Habitat gain can also be see in patches of region that are in Rajapalayam near Periyar National Park, Varusanadu, Theni, Anamalai reserve Forest, Chinnar Wildlife Sanctuary, Kodaikkanal, Thirumoorthy and Pollachi.Northern extension of habitat gain can be seen in Kudal, Malvan, Oros, Rajpur, Ratnagiri, Ganpatipule, Sangameshwar, Guhagar, Mandangad, Shrivardhan, Diveagar, Murud and in Phansad Wildlife Sanctuary. Habitat patch gain can be seen in Vishalgad and near Chandoli National Park and Koyna Wildlife Sanctuary.

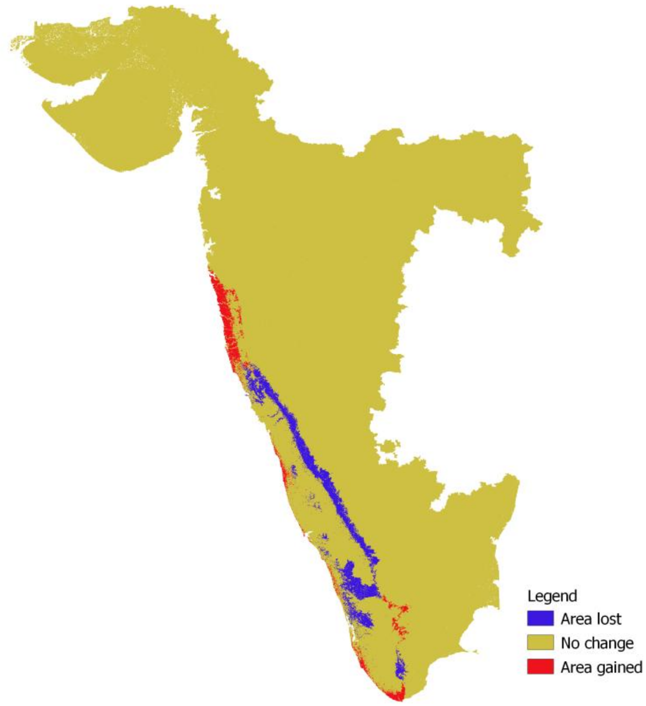


Figure 14: Distribution map showing area gained, lost and areas with no change in distribution under RCP 4.5 by 2050

This map (Figure 14) is created by subtracting RCP 4.5 from current scenario. When we look at the map from top to bottom, we can see that a substantial amount of the Malabar Barbet's distribution and habitat appropriateness have remained unchanged. This value accounts for 10,02,693km^2. This could indicate that there is no change in area where Malabar barbet is present or absent in the earlier mentioned current scenario.

A loss of 26,583 km^2 is seen in the distribution of Malabar Barbet under RCP 4.5 by 2050. 25.3% habitat loss can be seen here. Loss of habitat can be seen in Thirunelveli, Tenkasi, Alangulam and Sankarankoil. Habitat loss can be seen in

Thodupuzha, Muvattupuzha and Thrissur. Habitat loss can be seen in Pollachi, Palakkad, Mannarkkad, Silent Valley National Park, Perinthalmanna, Nilambur, Edakkara and Amarambalam Wildlife Sanctuary.Small patch loss in Kuttiadi, Iritti, Kadaba and Dharmasthala. Small patch loss in Someshwara Wildlife Sanctuary and Siddapura. In eastern side of Western Ghats there is a large loss of habitat seen from south to north that are Coimbatore, Mettupalayam, Coonoor, Kotagiri, Kodanad, Sri Hangala, Gundlupete near Bandipur Tiger Reserve and National Park.Sargur, Heggadadevankote near Nagarahole National Park and Tiger Reserve. Hunsur, Echalapura, Belur and also near Bhadra Wildlife Sanctuary, Kankumbi, Bhimgad Wildlife Sanctuary and ends in Amboli. Loss habitat can be seen in Voldemol Cacora, Satari, Valpoi, Sanquelim, Sawantwadi and also near Bhagwan Mahavir Wildlife Sanctuary. Small patch loss in Bellipal and Ulavi.

Under RCP 4.5 Malabar Barbet had a gain or increment in habitat suitability of 12,879 km^2.12.2% habitat gain can be seen here. Increase in habitat gain can be seen in the southern region that are Kanyakumari, Nagercoil, Marthandam. Habitat gain can be seen near coastal areas of Thiruvanathapuram, kollam, Karunagapilli, Kayankulam, Thirur, Kozhikode, Kannur, Payyannur. Habitat patch gain can be seen near the coastal areas of Udupi, Bramavara, Kundapura, Baindur, Bhatkal, Murdeshwar. Habitat gain can also be see in patches of region that are in Rajapalayam near Periyar National Park, Theni, Thirumoorthy, Anamalai Tiger reserve, Chinnar Wildlife Sanctuary, Kodaikkanal and Kolarpatti. Northern extension of haitat gain can be seen in Kudal, Malvan, Oros, Rajpur, Ratnagiri, Ganpatipule, Sangameshwar, Guhagar, Mandangad, Shrivardhan, Diveagar, Murud and in Phansad Wildlife Sanctuary. Habitat patch gain can be seen in Vishalgad and near Chandoli National Park and Koyna Wildlife Sanctuary. Small patches can be seen in Shirgaon, Vihali and Vinhere. Small patches can be seen in Prabhanvalli.

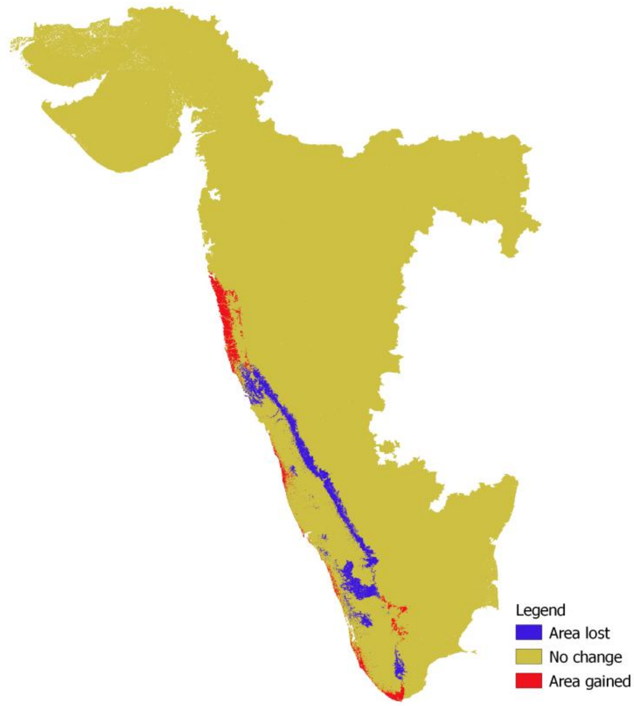


Figure 15: Distribution map showing area gained, lost and areas with no change in distribution under RCP 6 by 2050

This map (Figure 15) is created by subtracting RCP 6 from current scenario. When we look at the map from top to bottom, we can see that a substantial amount of the Malabar Barbet's distribution and habitat appropriateness have remained unchanged. This value accounts for 10,05,675km^2. This could indicate that there is no change in area where Malabar barbet is present or absent in the earlier mentioned current scenario.

A loss of 23,757 km^2 is seen in the distribution of Malabar Barbet under RCP 6. 22.6% habitat lose can be seen here. Loss of habitat can be seen in Ambasamudram, Tenkasi, Alangulam and Sankarankoil. habitat loss can be seen in

Thodupuzha, Muvattupuzha and small patch loss in Thrissur.Patch loss can be seen in Nelliyambathy Forest Reserve, Alathur, Palakkad, Mannarkadu, Nilambur and Edakkara.Small patch loss can be seen in Iritti. Small patch loss can be seen in Agumbe, Siddapura near Someshwara wildlife Sanctuary. Small habitat patch loss in Thudiyalur and Mettupalayam. In eastern side of Western Ghats there is a large loss of habitat seen from south to north that are Mettupalayam, Ooti, Mudumalai Tiger Reserve, Gundlupete, Bandipur Tiger Reserve and National Park, Sargur, Hunsur, Krishnarajanagara, Echalapura, Belur and also Bhadra Wildlife Sanctuary, Anandapura, Soraba, Sirsi, Yellapur, Kankumbi, Bhimgad Wildlife Sanctuary and ends in Amboli. Loss habitat can be seen in Satari ,Voldemol Cacora, Margao, Mapusa, Niravade, Sawantwadi and Bhagwan Mahavir wildlife Sanctuary.small habitat patch loss in Kudal and Oros.small patch loss in Kodlagadde and Artibail. Small habitat patch loss in Birkhol and Devakar near Anshi Wildlife Sanctuary.

Under RCP 6 Malabar Barbet had a gain or increment in habitat suitability of 12,723 km^2.12.1% habitat gain can be seen here. Increase in habitat gain can be seen in the southern region that are Kanyakumari, Nagercoil, Marthandam. Habitat gain can also be see in patches of region that are in Theni, Kodaikkanal, Anamalai Tiger reserve. Small habitat gain patches can be seen near coastal areas of Thiruvanathapuram,Varkkala, kollam, Karunagapilli, Kayankulam.Very small patches in Alappuzha and Thiruvalla. Very small patches in Kunnamkulam, Thirur, Kozhikode and Kannur. Small patches in Baindur, Bhatkal, Murdeshwar and very small patches in Kumta. Northern extension of haitat gain can be seen in Malvan, Devgad, Rajpur, Ratnagiri, Dapoli, Guhagar, Mandangad, Shrivardhan, Diveagar, Murud and in Phansad Wildlife Sanctuary. Very small patches can be seen in Pangrad. Very small patches in Ghonsari, Harkul, Prabhanvalli, Vishalgad.small habitat patch gain can be seen in Gothane and Pofali and also in Vinhere and

Ambavali, Talvat Khed.

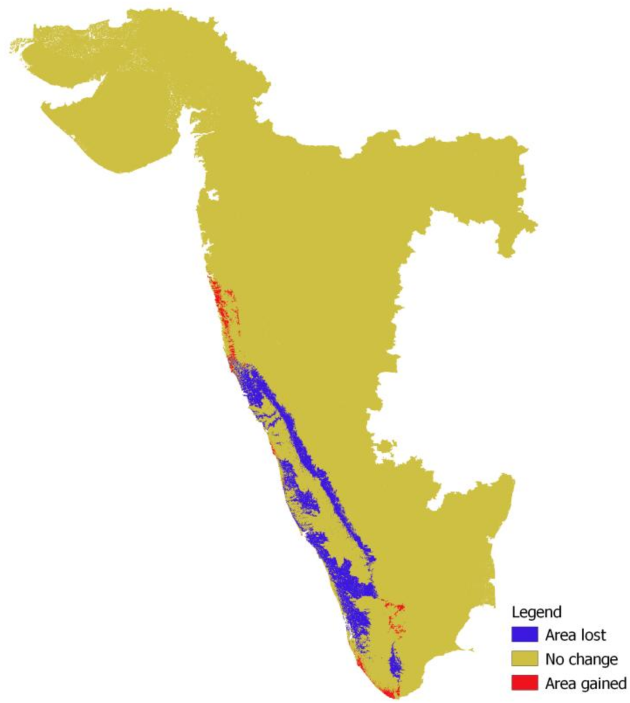


Figure 16: Distribution map showing area gained, lost and areas with no change in distribution under RCP 8.5 by 2050

This map (Figure 16) is created by subtracting RCP 8.5 from current scenario. When we look at the map from top to bottom, we can see that a substantial amount of the Malabar Barbet's distribution and habitat appropriateness have remained unchanged. This value accounts for 9,92,408km^2. This could indicate that there is no change in area where Malabar barbet is present or absent in the earlier mentioned current scenario.

A loss of 43, 985 km^2 is seen in the distribution of Malabar Barbet under RCP 8.5.41.9% habitat loss can be seen here.Habitat loss can be seen in Thirunelveli, Tenkasi, Periyar National Park. Habitat loss can be seen near areas of Pathanamthitta, Thiruvalla, Kottayam, Thodupuzha, Muvattupuzha, Kochi, Thrissur, Peechi-Vazhani Wildlife Sanctuary, Palakkad, Nelliyampathy Forest Reserve, Mannarkkad, Silent Valley National Park, Malappuram, Edakkara, Thamarassery, Kannur, Kasargode. . In eastern side of Western Ghats there is a large loss of habitat seen from south to north that are Mettupalayam, Ooti, Mudumalai Tiger Reserve, Gundlupete, Bandipur Tiger Reserve and National Park.Sargur. Hunsur, Krishnarajanagara, Echalapura, Belur and also Bhadra Wildlife Sanctuary, Anandapura, Soraba, Sirsi, Yellapur, Kankumbi, Bhimgad Wildlife Sanctuary and ends in Amboli. Loss habitat can be seen in Neturlim, Satari, Voldemol Cacora, Margao, Mapusa, Niravade, Sawantwadi and Bhagwan Mahavir wildlife sanctuary.small patch loss in Oros and Kudal. Habitat patch loss can be seen in Dharmasthala, Puttur, Karkala, Agumbe, Udupi, Kundapura and Baindur.small habitat patch loss in Kasanabail and Bellipal. Small patch loss in Kadra, Karwar, Ulavi, Anshi National Park, Cotigao Wildlife Sanctuary. Small habitat patch loss can also be seen in Canacona and Agonda.

Under RCP 8.5 Malabar Barbet had a gain or increment in habitat suitability of 5,762 km^2. Only 5.4% habitat gain can be seen here. Habitat gain can be seen in Marthandam, Nagercoil and Thuckalay.smallpatches can be seen near coastal areas of Thiruvanandhapurm, Varkkala, Karunagapalli, chavara.very small patches can be seen in Alappuzha.small habitat gain patch can be seen in Varusanadu, Chinnamanur , Agamalai Reserved Forest, Kodaikkanal, Chinnar Wildlife Sanctuary, Anamalai Tiger Reserve.small habitat patches in Bhatkal, Murdeshwar, Honnavar. Northern extension of haitat gain can be seen in very small patches in Malvan. Small patches in Talebazar, Kumbhavade.Very small patches in Rajpur, Ratnagiri, Ganpatipule.Very small patches in Dapoli, Mandangad, Shrivardhan and Diveagar. Small patches in Vishalgad. Small habitat patch gain in Devrukh, Sangameshwar near Chandoli National Park. Small patch in Gothane and Pofali. Small habitat patch gain near Koyna Wildlife Sanctuary.

CHAPTER 5

DISCUSSION

All sectors are being affected by climate change. There have been devastating incidents that have happened to nature that have caused life to be questioned and several species have gone extinct. When the habitat is dramatically altered due to extreme climate events, intolerant species have perished and some have gone extinct. Another group of species adapted to new environments or changed their habitats. Among avian species, changes in distribution are widely seen since they are sensitive to small climatic shifts and due to their migration. Taking current distribution and environmental factors into account, climate change can have a significant impact on the distribution of a single bird species. According to Virkkala et al. (2010), it is based on current distributions and climate variables. Reduced habitat is causing some species to experience range reductions at high latitudes and high altitudes, according to Reif et al. (2010).

Malabar Barbet is an endemic species to western ghats. Climate change has the greatest effect on biodiversity in endemic species, such as the Malabar Barbet.Thus, the present study examines the current distribution patterns of the Malabar Barbet based on climatic variables and other physical variables and also the distribution of the Malabar Barbet is being projected for the year 2050 under four Representative Concentration Pathways (RCP).

MaxEnt software was used to study the distributional changes of the Malabar Barbet by relating the presence data points to the climatic conditions prevailing there. The study used the occurrence data points of the Malabar Barbet from 1964 to 2020 and climate data from CHELSA for current conditions. . In determining the distribution of Malabar Barbet using MaxEnt, cross validate method is used with model features LQ (Linear & Quadratic) with regularization multiplier 0.5. Future climate was predicted by using the coupled model BSS CSM1.1, MIROC5 and MohcHadGEM 2 ES at a spatial resolution of 30 arc-seconds resolution under four different Representative Concentration Pathways (RCPs).

The result obtained shows that the current distribution of the species depends on 9 variables without EVI. Among these variables bio2 (Mean Diurnal Range) and bio10 (Mean Temperature of Warmest Quarter) are two major bioclimatic variables influencing the species distribution.

Using the representative concentration pathways RCP 2.6, RCP 4.5, RCP 6, RCP 8.5 future distribution of Malabar Barbet was predicted for the year 2050. Future prediction shows that the area of habitat loss, habitat gain and no change in area under RCP 2.6 accounts for 18,904 km^2, 16494 km^2 and 1,006,757 km^2 respectively and 18% habitat loss can be seen. Under RCP 4.5, area of habitat loss, habitat gain and no change in area accounts for 26,583 km^2, 12,879 km^2 and 1,002,693 km^2 respectively and 25.3% habitat loss can be seen. For RCP 6, area of habitat loss, habitat gain and no change in area were 23,757 km^2, 12,723 km^2 and 1,005,675 km^2 respectively and 22.6% habitat loss can be seen. And finally for 8.5 area of habitat loss, habitat gain and no change in area accounts for 43,985 km^2, 5,762 km^2 and 992,408 km^2 respectively and a habitat loss of 41.9% can be seen. The habitat suitability for Malabar Barbet 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.

Under RCP 2.6 the suitable habitat for Malabar Barbet is spread across North Sahyadri, southern end of Indian peninsula, Western coastal plain and also near Agamalai Forest Reserve. The habitat loss is seen mainly in eastern side of western Ghats, Palakkad, Idukki, Malappuram and also in southern part of Western Ghats.

RCP 4.5 showed an increase in habitat loss than habitat gain even though being an intermediate pathway 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 12,879 km^2. This means that the habitat suitable under RCP 4.5 have shrunk as compared to RCP 2.6 by 3615 km^2

In RCP 6, there is reduction in percentage of area lost when compared to RCP 4.5. RCP 8.5 being the highest emission scenario showed considerable increase in unsuitable area and significant decrease in suitable area. The area lost under RCP 8.5 is more than double as compared to RCP 2.6.

The overall results of the study take us into the conclusion that Malabar Barbet's population is declining under different scenarios.There is 18% of habitat loss can be seen in RCP 2.6, 25.3% in RCP 4.5, 22.6% in RCP 6, 41.9% in RCP 8.5 and habitat loss is more than habitat gain This means that in the future, conservations strategies must be taken in order to sustain the life of Malabar Barbet.

CHAPTER 6

SUMMARY

Climate change affects the range and phenology of all creatures. It includes birds as well. Since birds reflect changes in their environment, they are regarded as vital bio-indicators.The goal of this study is to figure out what environmental and or climatic factors influence the distribution of Malabar Barbet which is an endemic bird species of Western Ghats and provide projection for different RCPs namely RCP 2.6, 4.5, 6 and 8.5 for the year 2050.

The Malabar Barbet occurrence data from eBird and the current climate conditions from CHELSA were used as bioclimatic layers in this study. In determining the distribution of Malabar Barbet using MaxEnt, cross validate method is used with model features LQ (Linear & Quadratic) with regularization multiplier 0.5. The habitat suitability for Malabar Barbet 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. Future prediction shows that the area of habitat loss under RCP 2.6 accounts for 18,904 km^2 and 18% habitat loss can be seen.RCP 4.5 has a habitat loss of 26,583 km^2 and 25.3% habitat loss can be seen.RCP 6 has a habitat loss of 23,757 km^2 and 22.6% habitat loss can be seen. RCP 8.5 has a habitat loss of 43,985 km^2 and 41.9% habitat loss can be seen.The climate change could be negatively impacting the Western Ghats endemic bird species, Malabar Barbet, as it is losing its suitable habitat by 2050 .

CHAPTER 7

REFERENCE

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.

Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Church, J.A., Clarke, L., Dahe, Q., Dasgupta, P., Dubash, N. K. and Edenhofer, O. 2014. IPCC Fifth Assessment Synthesis Report-Climate Change 2014 Synthesis Report.

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., 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.

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.

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

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.

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

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. 2009. Use of maximum entropy modeling in wildlife research, Entropy, 11 (2009), pp. 854-866

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.

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.

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.

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.

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*.

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.

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.

Chaturvedi, R.K., Gopalakrishnan, R., Jayaraman, M., Bala, G., Joshi, N.V., Sukumar, R. and Ravindranath, N.H., 2011. Impact of climate change on Indian forests: a dynamic vegetation modeling approach. Mitigation and adaptation strategies for global change, 16(2), pp.119-142.

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.

Cincotta RP, Wisnewski J, Engelman R .2000.Human population in the biodiversity hotspots. Nature 404:990–992. https://doi. org/10.1038/35010105

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.

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.

de Moraes, K.F., Santos, M.P.D., Gonc¸alves ,G.S.R., de Oliveira, G.L., Gomes, L.B., Lima, M.G.M. (2020) Climate change and bird extinctions in the Amazon. PLoS ONE 15(7): e0236103. https://doi.org/ 10.1371/journal.pone.023610

DeMatteo, K. E. and Loiselle, B. A. 2008. New data on the status and distribution of the bush dog (Speothosvenaticus): 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.

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.

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.

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.

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.

Fourcade, Y., Engler, J.O., Rodder, D., Secondi, J., 2014. Mapping species distributions with MaxEnt using a geographically biased sample of presence data: a performance assessment of methods for correcting sampling bias. *PLoS One*. 9: e97122.

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

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.

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.

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.

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 Gnarosophiabellendenkerensis (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.

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.

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.

Kumar, K.R., Sahai, A.K., Kumar, K.K., Patwardhan, S.K., Mishra, P.K., Revadekar, J.V., Kamala, K. and Pant, G.B., 2006. High-resolution climate change scenarios for India for the 21st century. Current Science, 90(3), pp.334-345.

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.

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.

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.

Manikandan, P. and Balasubramanian, P.2018. Sequential Use of Tree Cavities by Birds and Nest Web in a Riparian Forest in Southwest India. Acta Ornithologica53(1):49-60. https://doi.org/10.3161/00016454AO2018.53.1.005

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.

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

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.

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.

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 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.T. and Stockwell, D. R. B. 2001b. 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.

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.

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.

Priti, H., Aravind, N.A., Shaanker, R.U. and Ravikanth, G., 2016. Modeling impacts of future climate on the distribution of Myristicaceae species in the Western Ghats, India. Ecological Engineering, 89, pp.14-23.

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.

Ramachandra TV, Suja A (2006) Sahyadri: Western Ghats biodiversity information system. In: Ramakrishnan N (ed) Biodiversity in Indian scenarios. Daya Publishing House, New Delhi, p 22.

Raman,S.,shameer,T.T.,Sanil,R.P.,Usha,P.,Kumar,S.2020. Protrusive infuence of climate change on the ecological niche of endemic brown mongoose (Herpestesfuscusfuscus): a MaxEnt approach from Western Ghats. Modeling Earth Systems and Environment.https://doi.org/10.1007/s40808-020-00790-1

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.

Rasmussen, P. and Anderton, J. 2005. Birds of South Asia The Ripley Guide. Lynx Edicions. London.Yahay, H.S.A. 1988.Breeding biology of Barbets

Megalaimaspp. (Capitonidae:Piciformes) at Periyar tiger reserve, Kerala. *J. Bombay Nat. Hist. Soc.*, 85 (4) 493-511.

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., Šť'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.

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

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

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

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.

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

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).

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.

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.

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 (Tetraxtetrax) 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., 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.

Veloz, S.D., 2009. Spatially autocorrelated sampling falsely inflates measures of accuracy for presence-only niche models. *J. Biogeogr*. 36: 2290–2299. http://dx.doi.org/10. 1111/j.1365-2699.2009.02174.x.

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.

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.

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.

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

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.

ABSTRACT

Identifying the factors that influence the distribution of the species has been challenging for researchers. To develop conservation strategies, they want to find out the current distribution patterns and the future patterns among the threatened species. There are some invasive species that are spreading their territory into new areas, making accurate identification very important. Avian species are considered to be valuable bio-indicators of the environment's destruction. The habitat specialist species in these ecosystems are vulnerable to climate change, which makes them potential bioindicators. This research was based on the spatial and temporal distribution of the Malabar Barbet in the Western Ghats, which could help determine environmental changes at various locations. MaxEnt was used to map the species distributions and habitat relationships.The distribution of the Malabar Barbet was modelled using current occurrence data from the eBird 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 Barbet 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 Barbet'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 Barbet across Western Ghats. Mean Diurnal Range (bio 2) is found to be the most contributing bioclimatic variable in the distribution of Malabar Barbet. Future prediction shows that the area of habitat loss under RCP 2.6 accounts for 18% .RCP 4.5 has a loss of 25.3% habitat loss.RCP 6 has a habitat loss of 22.6% . RCP 8.5 has a highest loss of 41.9% habitat loss. As per the present study, the projected distribution of the Malabar Barbet, is influenced by the

combined effects of precipitation and temperature fluctuation alongside slope and aspect.