# IMPACT OF CLIMATE CHANGE ON STATUS AND DISTRIBUTION OF MALABAR GREY HORNBILL (*Ocyceros griseus*) AN ENDEMIC SPECIES TO THE WESTERN GHATS

*by*

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**THESIS**

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**COLLEGE OF CLIMATE CHANGE AND ENVIRONMENTAL SCIENCE**

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## DECLARATION

I, Devikrishna, T.R. (2016-20-031) hereby declare that this thesis entitled "**Impact of climate change on status and distribution of Malabar Grey Hornbill (*Ocyceros griseus*) an endemic species to the 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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Certified that this thesis entitled "**Impact of climate change on status and distribution of Malabar Grey Hornbill (*Ocyceros griseus*) an endemic species to the Western Ghats**" is a record of research work done independently by Ms, Devikrishna T. R under my guidance and supervision and that it has not previously formed the basis for the award of any degree, diploma, fellowship or associateship to her.

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**Devikrishna, T. R.**

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## 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 |
| IPCC | Intergovernmental Panel on Climate Change |
| MaxEnt | Maximum Entropy Modelling |
| R2 | Coefficient of determination |
| RCPs | Representative Concentration Pathways |
| ROC | Receiver Operating Characteristic Curve |
| WMO | World Meteorological Organization |

# CHAPTER 1

# INTRODUCTION

Global warming and the effect of climate change have become a significant environmental and societal problem over the past few decades. Increased level of greenhouse gases causes notable changes in temperature which are the most obvious indication of climate change. This is creating cascading effects on biotic and abiotic components of the ecosystem. The global average temperature exhibited a warming of 0.85 °C [0.65 °C to 1.06 °C] between 1880 and 2012 (IPCC, 2014). Such global temperature changes can result in a number of effects, from glacial melt to sea level rise, to unusual weather events like floods and droughts, to intense but short rainfalls, disease outbreaks, and other effects on flora and fauna (Hickling et al., 2006; Pounds et al., 2006; Nogues-Bravo et al., 2007; Kannan and James, 2009; Lawler et al., 2009; Xu et al., 2009; Acharya and Chettri, 2012). As climate change is becoming a glaring problem to our world, necessary actions and studies must be undertaken to face its effects.

Climate change threatens the entire structure and function of the biodiversity. The effects of climate change aren't all going to manifest in the same way and at the same time. Some will appear quickly, others slowly and are cumulative; and, there may be multiple impacts occurring concurrently and at different times. Impact of climate change on various ecosystems need to be studied thoroughly. Different species in distinct locations maybe affected differently and some of them many not be able to adapt to these sudden changes. Species distribution and habitat limits are commonly influenced by climate, especially when it comes to extending and defining species margins (Hill and Preston, 2015). The species which fail to adapt face the risk of extinction.

The climatic changes are a major driver of shifts in species distributions, and understanding the relative importance of climatic variables is necessary to better understand the impact of future climate change on species distributions. Change in climatic regimes has altered the geographic ranges of many species and has led to biodiversity loss across the globe. There have been numerous reports of shift in latitude or elevation of distribution of species in response to changing climate. There is a substantial body of evidence for changes in the phenology of birds, particularly of the timing of migration and of nesting as a result of changes in weather parameters. Populations that are genetically adapted to local climate are more susceptible to climate change than those that are phenologically plastic.

A major biodiversity hotspot, the Western Ghats lie in a north-south direction along the west coast of India. The endemic avifauna of Western Ghats varies in habitat preference, from generalist species in orchards and tea plantations to specialist species that exist only in high elevation shola forests and grassland patches. It is well understood that climate is a key factor determining the geographic range of bird species. So, birds are considered as good indicators of climate change.

In India there resides, nine species of hornbills (Ali & Ripley 1987). Malabar grey hornbill or *Ocyseros griseus* is a species of birds found within the Western Ghats region of India, with more abundance seen in moist forests in mid elevation ranges.

In order to reduce biodiversity loss due to climate change, quantifying the uncertainty of shifting distributions and recognizing the risk of shrinking ranges for the species are critical. As knowledge of the impact of climate change on biodiversity increases, a number of methods have been developed to assess the species vulnerability to climate change, both in the present and in the future. In ecology, species distribution models (SDMs) are widely used to identify species' habitat preferences and to predict how habitat suitability might change in space or time.

However, species distribution models have proven particularly useful in predicting species' responses to climate change. Range sizes are usually evaluated by examining the climatic characteristics of present distribution and the projections of these climatic conditions in the future.

The primary objective of this study is to find out the distribution pattern of Malabar Grey Hornbill (*Ocyceros griseus),* an avian species endemic to Western Ghats in the changing climate scenario and to determine the environmental variables that influence the distribution pattern. With regional differences in climate change expected in the future, understanding the distribution of species relative to current climatic conditions will help better understand how species distributions will likely respond to future climate change. There are not many studies which explicitly assess the effect of climate change on this endemic bird species.

The methodology followed here can be used for further probable distribution studies of various other species. This model can assist in predicting the future distributional changes of the Malabar Grey Hornbill, as well as the study of other significant similar species.

# CHAPTER 2

# REVIEW OF LITERATURE

## 2.1 CLIMATE CHANGE

There is extensive evidence showing that climate change will result in inauspicious effects for biodiversity, including changes in temperature, increasing sea level, surge in heavy rainfall, and associated heat stress and inundation damage (Byers *et al.,* 2018). According to IPCC AR5 report, the global mean surface temperature has risen by 0.78C (0.72 to 0.85C) since the late 19$^{th}$ Century. From 1901 to 2010 the sea levels rose by 0.19m due to ocean warming in addition the ice sheets in poles have reduced in mass in recent decades (average annual sea ice extent has decreased by 2.7 ± 0.6% per decade) (IPCC, 2013). Change in precipitation patterns and an increase in the frequency of occurrence of extreme events are evident in recent decades (IPCC 2013). Furthermore, climate change is spatially varied, with some places like Arctic experiencing much added dramatic climate variations than the global average (IPCC, 2007).

Human-induced climate change and different other threats like habitat destruction and pollution pose major menace to our environment (Walther et al. 2002; Brook, Sodhi & Bradshaw 2008; Pereira et al. 2010). It is possible that biodiversity losses will increase as climate change impacts interact with other factors, such as land-use change, in the future (Sala et al. 2000; Mantyka-Pringle et al. 2015). Climate change is likely to influence at the genetic, species, community and environmental levels (Thomas, Franco & Hill 2006; Foden et al. 2013; Pacifici et al. 2015). Understanding species responses to climate change is one of the most pressing challenges facing scientists today (Garcia et al. 2014).

## 2.2 SPECIES RESPONES TO CLIMATE CHANGE

Researchers have already identified profound effects, ranging from phenology changes (Menzel et al. 2006) to range shifts (Root et al. 2003) to changes in biotic interactions (Ockendon et al. 2014) as an evidence for the increased impact of altering climate in ecological system.

### 2.2.1 Adaptation and phenotypic plasticity

Adapting to or eluding adverse environmental changes (such as rising global temperature) has become more difficult as rapid changes are taking place (Valladares, Gianoli & Gomez 2007). Genetic adaptations to local climatic conditions render populations more susceptible to rapidly varying climate than phenologically plastic populations (Chevin, Lande & Mace 2010; Phillimore et al. 2010). Local adaptation and phenotypic plasticity are the two methods that will determine the ability of a population to survive climate change (Jump & Penuelas 2005; Gimeno et al. 2009).

### 2.2.2 Range shifts

Recent research has focused on the shifting ranges of species, and this is likely due to their widespread nature, and their significance for conservation and reserve selection (Araujo et al. 2004; Guisan et al. 2013). For species that have shifting climate niches, several factors will affect their ability to keep pace with this shift. Species-specific dispersal ability is particularly important (Schloss, Nuñez & Lawler 2012). Plant species may be particularly vulnerable as their lack of mobility reduce their ability to keep pace with the human induced climate variations (Neilson et al. 2005) and reptiles and amphibians are more effected by rainfall and temperature patterns changes (Bickford et al. 2010).

### 2.2.3 Biotic interactions

Different species and locations react differently to climate change. Species responds in different ways like changes in their abundance, shift in direction of range, and also variation in their geographic range size (Parmesan & Yohe 2003; Hickling et al. 2006; Mair et al. 2012; Rapacciuolo et al. 2014). The high interspecific variance in abundance trends observed in 115 Lepidoptera species over the past four decades may be explained by species-specific exposure and sensitivity to climate change throughout history (Palmer et al., 2015). Spatial pattern of species can be affected by different interactions like predation, competition, resource-consumer interactions, and host-parasite interactions, and many of these interactions may be influenced by the global climatic changes (Tylianakis et al., 2008; van Dam, 2009; Gilman et al., 2010; Wisz et al., 2013). Record provides clear evidence that some past episodes of climate variations resulted in species extinctions and speciation, and that the distribution and abundance of species were affected (Blois et al., 2013). According to Gilman et al., (2010) species interactions can profoundly influence how species respond to recent variations in climate at every scale, and if these interactions are not incorporated, it will be difficult to predict species reactions to climate change.

## 2.3 CLIMATE CHANGE IN THE WESTERN GHATS

The Western Ghats of the Indian subcontinent, consisting of six states is one of the (Kumar et al., 2011) 36 global biodiversity hotspots. An increase in temperature and rainfall was predicted for India by the 21st century by using the PRECIS model. In western coast of India and western central India, the projected rainfall changes show extreme precipitation. Another observation by the model was the faster rise in day time temperature than the night temperature (Kumar et al., 2006). It has been predicted that under the future variations in climate, the evergreen forests of mid elevation are most suitable for the Southern part of Palaghat gap of the Western Ghats region (Priti et al., 2016). Climate of India is dominated by summer monsoon rainfall and so its variability is viewed with great concern. Summer monsoon rainfall of Western Ghats shows similarity with India and the strength increases from south to north (Revadekar et al., 2018). Higher elevations are more likely to be affected by climate change and so the mountainous forests seen commonly in Western Ghats are susceptible to degradation. Such regions demand efficient management of pest and fire, scientifically correct harvesting and anticipatory plantations (Chaturvedi et al., 2011). Under the A1B scenario, the northern and central parts of the Western Ghats could be prone to climate change on a regional scale, according to a study published recently on the impacts of climate change on Indian forests (Gopalakrishnan et al., 2011). The Western Ghats may lose suitable habitat areas for five species of Myristicaceae in the future, under either scenario A1B or A2A (Priti et al., 2016) and also habitat suitability of Garcinia indica in the Western Ghats are predicted to decreases due to climate change under RCP 8.5 for 2050 and 2070 (Pramanik et al. 2018).

## 2.4 SPECIES DISTRIBUTION: FACTORS

Bio geographers have noted the relationship of distributions and abundance of species in a region with its climate from early days. Ecological factors, both biotic and abiotic were significant predictors of species distribution, but the impact of changes in the climate is not totally understood (Murray and Conner, 2009). In ecology, the factors that shape species distributions remain an unsolved issue (Araujo and Guisan, 2006). Variables within the climate system, such as number of cold and wet days, length of winter frosts and snow periods, summer drought, and spring temperatures, play an important role in bird demographics (Robinson et al., 2007). Other factors that affect bird distributions, including summer weather (Robinson et al., 2007), food availability (Conrad et al., 2006), habitat distribution and quality (Fuller et al., 2007) and nesting sites (Thaxter et al., 2010), have been assessed. Researchers in Northern Britain found that the decline of Turdus torquatus (Ring Ouzel) populations was related to summer temperatures rising and decline in rainfall

(Beale et al., 2006). According to Fasola et al. (2010), increased winter temperatures have caused a rise in the population of Ardea cinerea (Grey Heron) in Northern Italy.

## 2.5 IMPACTS OF CLIMATE CHANGE ON AVIAN SPECIES

### 2.5.1 Birds as bio-indicators

Bird populations have been studied for over half a century in order to understand the impact of weather on their behavior. As bio-indicators, avian species are a group that is easily understood by the public and policy makers since birds are popular as well as often have an iconic status around the world (Crick, 2004). Birds can be used as surrogate for understanding the wider impacts of climate change, and they can be a key indicator of what this new threat looks like. A well known indicator of climate change, birds are very important for climate research (Wormworth and Sekercioglu, 2011). Based on the study conducted on the Indian Peafowl in Kerala, they act as a great bioindicators (Sanjo and Nameer, 2020).

### 2.5.2 Effect of climate change on physiology of birds

Based on the physiology of their bodies, different species are affected by climate change differently (Acharya and Chettri, 2012). Meteorological conditions affect the metabolic rate of birds directly and indirectly, which in turn affect the birds' behavior. When birds try to avoid unfavorable climatic conditions, it will reduce various activities like breeding and feeding (Walsberg, 1993). Sekercioğlu et al. (2012) noted that birds are suffering from low reproduction and population declines around the world. Changes in weather condition can cause shift in the production of hormones, which can influence the breeding success. Temperature and humidity changes can affect bird activity and behavior indirectly (Crick, 2004). Several studies have highlighted the importance of species' physiological responses to coping with climate change (McKechnie, 2008; McNab, 2009).

### 2.5.3 Climate change and avian distributional range

The Dartford Warbler seen in the UK have shown enlargement of their distribution since 1960 and this was considered a result of not having severe winters (Gibbons and Wotton, 1996). It was shown that in many regions, the shift in distribution ranges corresponded with temperature fluctuations. Precipitation and temperature interaction also played a significant role in the range distributions (Hawkins et al., 2003). Birds in Sikkim have exhibited increased elevational range expansion/shifting (Acharya and Chettri, 2012).

### 2.5.4 Importance of range distribution studies

To better understand the ecological and evolutionary factors determining the patterns of biodiversity at various spatial scales, it was necessary to have a thorough understanding of species ecology and geographic distribution (Rosenzweg, 1995; Ricklefs, 2004; Graham et al., 2006). These types of studies are also needed for forecasting and for creating conservation plans (Ferrier, 2002; and Rushton et al., 2004). The impact of climate change was still in its infancy, so scientists and policymakers were eagerly anticipating further development to study the biological consequences of global warming and establish adaptive and mitigating measures (Mace and Baillie, 2007; EEA, 2007).

### 2.4.5 The study on birds

Avian enthusiasts, both amateur naturalists and professional scientists have studied about birds for many years, and so they are a well understood species. Globally, 13% of bird species are at risk of extinction (BirdLife International, 2015). Birds have been facing a plethora of threats during this century as a result of climate change (Thomas et al. 2004; Warren et al. 2013). However, bird population decline may also be attributed to habitat degradation, invasive species impacts, and other factors (Szabo et al. 2012; Bellard et al. 2013). Climate change may aggravate their effects further (Mac Nally et al., 2009). Studies of bird ringing and direct observations of arrivals and departures are both sources of information on bird movements (Pearce-Higgins & Green 2014). In recent years, technological advances have enabled remote tracking of birds in both time and space (Robinson et al. 2010). By using various bird data like range distribution (Orme et al. 2006) and species richness patterns (Storch et al. 2006; Rahbek et al. 2007a), broad- scale spatial patterns in biodiversity have been studied.

## 2.5 MODELLING OF SPECIES DISTIBUTION

### 2.5.1 Significance of species distribution modeling

Gates et al. (1994) noted that climate had strong relationship with bird distribution and changes in distribution were happening with the predicted climate change by using distribution models. Species distribution models were used to study past species distribution (Peterson et al., 2004) and species richness and its relation with climatic factors (Mac Nally and Fleishman, 2004). For estimating most suitable habitats, biologists used distribution models, which could predict the probability of species presence in areas in which systematic surveys had not been conducted (Elith, 2002). Predictive model was used to examine the changing distributions and having an accurate map of a species' distribution may make it possible to work out the connection between distribution and environmental variables like climate (Crick, 2004). Bio-geographical analysis methods have been used to study the distribution of species niches in relation to environmental data collected at various localities (Guisan and Thuiller, 2005). These models aim to predict species distribution through knowledge of the presence or abundance of species in relation to certain environmental factors. Ecological, evolutionary, and conservation arguments can be extensively explored with these models (Elith et al., 2006). As well as determining future species distributions (Jeschke and Strayer, 2008; Sinclair et al., 2010), these models can be used as a tool for planning of reserve (Thorn et al., 2009). These models used in various studies dealing with range shift of avian species are significant for managing protected areas and conserving threatened bird species (Aragón et al., 2010b; Araújo et al., 2011).

### 2.5.2 Process of species distribution modeling

#### 2.5.2.1 Steps in species distribution modeling

Several steps were involved in modelling species distributions like (1) occurrence points are created from present day data (Peterson et al., 1998; Peterson and Stockwell, 2001b); (2) the distributional data are used to test the developed ecological niche models (Guisan and Zimmerman, 2000; Kobler and Adamic, 2000); (3) Climate change models project a shift in distribution onto the landscape of interest; (4) Projecting ecological niches of specific species onto transformed landscapes to model the distributional shifts. Based on assessments of species responses to abiotic environmental factors like climate, it is possible to estimate the appropriate ecological niche (Soberon & Peterson, 2005) and the model can be used to estimate the prevalence of species for any given area or track the specific environmental conditions which suit specific species (Elith et al., 2011).

#### 2.5.2.2 Methods for testing accuracy

A variety of methods were used to model the distribution of species, each having different steps that included; choosing the most appropriate predictor variables, defining defined, setting up functions for each variable, identifying contribution of variables and attempts to predict geographic patterns of distribution of species (Guisan and Zimmerman, 2000; Burgman et al., 2005; Wintle and Bardos, 2006). Models used individual algorithms that led to landscapes being mapped within and outside ecological niches by using the data in the models (Peterson, 2001a). Comparing alternative models as well as analyzing the weight of evidence of the variables included in the model can be accomplished by hierarchy portioning (Mac

Nally, 2002). We addressed the issues of accuracy in predicting species distribution under varying climatic conditions by using climatic envelope models (Akcakaya et al., 2006; Pearson et al., 2006; Araujo and Rahbek, 2006; Zimmer, 2007). Pearson et al. (2007) concluded that the type of environment dimensions you use to define a species distribution limit plays a vital role in determining the accuracy of a model's description about the range of conditions that are suitable for a species. Due to autocorrelation among the variables among the models, they didn't reveal any causal relationship (Bahn and McGill, 2007; Currie, 2007; Beale et al., 2008), but their method had limitations due to the same source of data for all models. The use of generalized linear mixed models improved the accuracy of predictions of species distribution ranges (Swanson et al., 2013). We analyzed large geographical areas in an effort to reduce misinterpretation of the species distribution responses and therefore reduce the correlation between environmental variables and climatic variables (Maclean et al., 2008). In addition to resolving ambiguities arising from correlated predictors, it also failed to identify the spurious correlations among the environmental factors which contributed to the definition of the spatial distribution (Ashcroft et al., 2011).

### 2.5.3 Advancements in species distribution modeling

Researchers have created methods to estimate distributional areas by comparing known occurrences with environmental variables. Thousands of articles about these methodologies are now published every year as a result of the explosion of their use in recent years (Lobo et al., 2010). Ecological niche modelling was based on the presumption that climate has a major influence over terrestrial species distribution. Despite expanding predictive power for models, understanding the processes behind them is challenging (Shipley, 1999). Studies focused on modeling future distribution shifts over past distribution shifts were fewer, but the climate envelope approach was used for this (Berry et al., 2002; Thomas et al., 2004; Harrison et al., 2006). Scientific advances and technological advances led to the development of complex mathematical general circulation models (GCMs) that influenced prediction of future climate (Raper and Giorgi, 2005). The association between climate and vertebrate distribution has been used to develop predictive models based on birds (Jetz et al, 2007). Lack of data regarding the species- specific physiological parameters and processes, and correlation between climatic and nonclimatic factors still remained a problem (Kearney, 2006). Using ecological niche modelling to predict species distributions from environmental data has been well received (Pearson and Dawson, 2003).

2.5.4 Species distribution studies

It has been suggested that ecological variables, including climatic conditions could play a role in figuring out the richness and distribution patterns of the animals (Kerr, 2001; Ricklefs, 2004; Mittelbach, 2010). Studies of future distribution pattern predictions assumes that the changes in species ranges at warmer conditions are credited to the changes in the colder extremes, since both use the same climate-space (Berry et al., 2002; Thomas et al., 2004; Harrison et al., 2006). Climate data has proven useful in predicting species distributions in several studies (Pearson et al., 2002; Bakkenes et al., 2002; Burns et al., 2003; Thuiller et al., 2005; Calef et al., 2005; Rehfeldt et al., 2006; Hamann and Wang, 2006; McKenney et al., 2007; Peterson et al., 2008; Stankowski and Parker, 2010; Joyner et al., 2010; Beever et al., 2010). Numerous studies have species distributional (Iverson and Prasad, 1998; Pearson et al., 2002; Calef et al., 2005; Rehfeldt et al., 2006; Hamann and wang, 2006; McKenney et al., 2007; Peterson et al., 2008) and mass extinction of several species over the next century (Peterson et al., 2002; Bakkenes et al., 2002; Thomas et al., 2004; Malcom et al., 2006). Several analytical techniques had been developed to correlate quantifiable climatic variables with known occurrences of species due to climate change's devastating impacts on biodiversity (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). According to Goetz et al. (2014), the correlation between forest bird richness and temperature variables was observed to be strong, as was the correlation between open woodland bird richness and precipitation variables (Goetz et al., 2014). The temperature dependence of distribution changes had been studied and could be attributed to range shifts or range expansions (Maclean et al., 2008).

## 2.6 DATA USED FOR MODELLING

### 2.6.1 Type of data and performance of the model

The appraisal of model presentation was done with a variety of different test statistics or discrimination indexes (Pearce and Ferrier, 2000). Model predictions were more focused in the evaluation step, and some known occurrences were omitted (only presence data) from the development of models (Fielding and Bell, 1997; Hastie et al., 2001; Araujo et al., 2005). More predictive success was there when the independent data was not used to build the model (Fielding and Bell 1997). A measure of accuracy was based on how well the predicted outcomes were matched to the withheld data (Boyce et al., 2002; Hirzel and Guisan, 2002b). According to Anderson et al., 2002 Statistical significance of a model was calculated using the Chisquare test or upper-tailed binomial probability when data portioning was done for testing. A predicted model's performance has been highly influenced by the availability of observed absence data (Loiselle et al., 2003). The 2-2 confusion matrix is able to describe how often absences and presences are predicted correctly and incorrectly, and no absence data was required in presence only models (Anderson et al., 2003).

Several studies have suggested not including absence data because false-positive predictions would be displayed as failure rather than success (Anderson et al., 2003; Pearson and Dawson, 2003; Soberon and Peterson, 2005). With these small records, partitioning into test and training subsets as well as handling negative data was problematic (Anderson and Martinez-Meyer, 2004). The most customary and easy approach is random or spatially stratified partitioning (Peterson and Shaw, 2003). There was a reduction in predictive performance when studies used small samples (Stockwell and Peterson, 2002; Reese et al., 2005). As the use of distribution models has grown and data availability and modelling methods are improving, it became imperative that a broad scale analysis of models for presence only data be performed in order to gain high predictive ability and accuracy (Elith et al., 2006).

Many machine learning and statistical approaches have been developed that are capable of capturing complex responses, regardless of how noisy the data was. In spite of its promising results, the work did not receive any exposure in distribution modelling (Phillips et al., 2006, Leathwick et al., 2006). Spatial autocorrelation was effective at reducing biases over time, but not yet effective at reducing them spatially (Algar et al., 2009). Because absence data were rarely obtainable in surveys and it is difficult to detect by modelling techniques and validation, presence data were used only for modeling (Pearson et al., 2007). Spatial autocorrelation was effective at reducing biases over time, but not yet effective at reducing them spatially (Algar et al., 2009).

### 2.6.2 Presence and absence records

Modelling range distribution using presence/absence data was the main focal point of numerous studies (Austin and Cunningham, 1981; Hirzel and Guisan, 2002b). In ecology, presence-absence data can play a significant role, for instance in predicting the effects of changing climate, habitat destruction, and invasive species (Warren 2012). For years, presence-only data have been analysed using the envelope-based or distance-based measures that have been developed specifically for that purpose (Silverman, 1986; Busby, 1991; Carpenter et al., 1993). As a rule, breeding habitats were assumed to be saturated in most presence-absence models (Capen et al., 1986). Only presence data were analyzed according to some methodological suggestions (Nix, 1986; Carpenter et al., 1993).

According to Fielding and Bell (1997), the presence/absence models were prone to errors such as false positives and false negatives. There was a lack of absence data for a variety of reasons, including low sampling efficiency or unrecorded species occurrences during surveys so ‘pseudoabsences’ was used in place of real data (Ferrier et al., 2002a; Engler et al., 2004). Data on species occurrences are increasingly available as high-resolution environment data layers created from satellite images (Turner et al., 2003) and polished climate data (Thornton et al., 1997; Hijmans et al., 2005). Since the wildlife-habitat connection was absent, validation of absence data was difficult (MacKenzie et al., 2004; Gu and Swihart, 2004). Modeling ecological niches has been accomplished by alternative methods of different kinds, with many of them using both absence and presence records (Bourg et al., 2005). The majority of the species occurrence data were obtained from occurrence records compiled from museum or herbarium collections, many of which were digitized (Graham et al., 2004; Huettmann 2005; Soberon and Peterson, 2005). The trouble with some forms of presence data was that the purpose behind their collection and the technique employed to accumulate them were seldom discussed, and we could not infer absence data with certainty (Elith et al., 2006). Over the past decade, novel tactics have been developed that rely solely on presence data, eliminating the need for absence locations (Baldwin, 2009).

## 2.7 ASSESSMENT OF CLIMATIC CHANGES

With a comprehensive understanding of current problems and climate change assessments, it is possible to identify and emphasize regions and systems that are of particular concern (Sulzman et al., 1995). The equilibrium simulation showed warming in both hemispheres, whereas the transient simulation showed both changes in temperature distribution (Sulzman et al., 1995). Climate change rate assessment is crucial for evaluating populations' ability to adapt to climate change, so policy makers and natural resource managers need to take into account the results of transient climate experiments (Schimel et al., 1990).

Grassl (2000) noted that, southern and northern hemisphere climates have different dynamics, so models developed for one hemisphere with certain emphasis won't reproduce correct results in the other. The world climate can be projected using global circulation models (GCMs). These models provide future predictions on climate variations with regards to greenhouse gas forcing (Hannah et al., 2002). Researchers are currently conducting simulation modeling experiments to analyze the effects of human-induced climate change on natural systems using GCM-based scenarios (Sulzman et al., 1995). By using results of transient (not equilibrium) simulations, as well as models which were completely coupled with the atmosphere and ocean to the regions of interest (Hannah et al., 2002), the assessments were improved. It turns out that regional models, which depend on local forcing, do a better job of predicting local climate change than global models (Pitman et al., 2000). Cloud formation mechanisms could be represented through these models in relation to land use changes. There was, however, a lack of results of these models in many regions. Dynamic vegetation models, forest gap models, biome envelope models, and species envelope models, all used GCMs and regional climate models to shed light on different aspects of future climate change's impact on biogeography (Cramer et al., 2000).

## 2.8 MAXIMUM ENTROPY MODELLING (MAXENT)

MaxEnt is considered one of the most robust and widely used methods of species distribution prediction (Elith et al., 2006). Using location information and constraints derived from data, it approximated the most uniform distribution (Philips et al., 2004; Philips et al., 2006). Pearson et al. (2007) found MaxEnt to achieve higher success rates and to exhibit significant differences even at small sample sizes. While MaxEnt models predicted a wider area of suitable conditions, there were negative effects when sample sizes were artificially reduced (Pearson et al., 2007). According to Elith et al. (2009), MaxEnt uses only presence data and uses the environmental variables to estimate the likelihood of species' distributions. Based on these variables, MaxEnt provides a logistic output that is based on the probability distribution of species' presence.

MaxEnt had been used to inspect the distributional patterns of Geckos (*Uroplatus spp*.) for predicting the species distribution (Pearson et al., 2007), American black bear (*Ursus americanus*) for the evaluation of denning habitat (Baldwin and Bender, 2008), Bush dog (*Speothos venaticus*) to appraise the excellence of safety (DeMatteo and Loiselle, 2008), Little bustard (*Tetrax tetrax*) for modelling the seasonal distribution changes (Suárez-Seoane et al., 2008), predicting and mapping of Sage grouse's (*Centrocercus urophasianus*) nesting habitat, Asian slow lorises (*Nycticebus spp*.) was assessed to threats and species distribution analysed to find conservation urgencies (Thorn et al., 2009), Myristicaceae species for modelling impact of future climate on its distribution (Priti et al., 2016), Nilgiri tahr (*Nilgiritragus hylocrius*) for estimating suitable habitat under current and future climate change scenarios (Sony et al., 2018). There were times when there was insufficient dependable location data available to map the spreading of species and MaxEnt can still accurately build the model with fewer points and this was an advantage (Baldwin, 2009).

## 2.9. MALABAR GREY HORNBILL

The Malabar Grey Hornbill (*Ocyseros griseus)*, the subject of our research is one of the nine species found in India. Malabar Grey Hornbill is a frugivorous endemic to the forest of Western ghats hills of India (Mudappa, 2000). This species are mostly seen in the mid elevation areas (Mudappa and Raman 2009). Even though this bird is large, its length is still smaller than those of the other Asian hornbills, which ranges between 45 and 58 centimeters (Ali, 1996). Males and females are distingused by a yellow bill with black at the base of the lower mandile and sleeve along the culmen is seen on the female and reddish-brown bill with yellow tip in male. This species of hornbill is mainly found in habitats with thick vegetation. Being large frugivores, they are important seed dispersers of many species of fruit bearing forest trees either through defecation or regurgitation (Mudappa, 2000).This species is noted as vulnerable by the International Union for Conservation of Nature (IUCN).

# CHAPTER 3

# MATERIALS AND METHOS

## 3.1. STUDY AREA

The study was conducted in the Western Ghats a biodiversity hotspot in India. Western Ghats refers to the practically unbroken hill chain (with the exception of the Palakkad Gap) running roughly in a northsouth direction, for about 1500 km 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. Older than the great Himalayan Mountain chain, it contains a diverse range of ecosystems and is known for its biodiversity and endemism (Myers *et al.,* 2000). The Malabar Grey Hornbill the study subject is an endemic to this region. In the region, there are 4000 plant species, 218 fish species, 126 amphibian species, 508 bird species, and mammals, of which 137 are endemic (Das et al. 2006). At least 325 threatened species live there.

## 3.2. OCCURRENCE POINTS OF MALABAR GREY HORNBILL

The presence data for Malabar Grey Hornbill was collected from the e-Bird reference data (www.eBird.org), a free Internet-based checklist tool. These data are published in compliance with the Avian Knowledge Network (AKN) and it is run by the National Audubon Society and the Cornell Lab of Ornithology and the data is copyrighted with these organizations. The data consists of Breeding Bird Survey from 1966 onwards. It has advanced geo-referencing capability and broad user-base. It was used to get georeferenced data on the Malabar Grey Hornbill from 1964 to 2020. The compilation of place of occurrence or existence of the species is one of the main components of the Species Distribution Model (SDM) (Trisurat et al., 2011). Using

Excel, duplicate records were eliminated, and by using ArcGIS 10.8 a matching shape file was created.

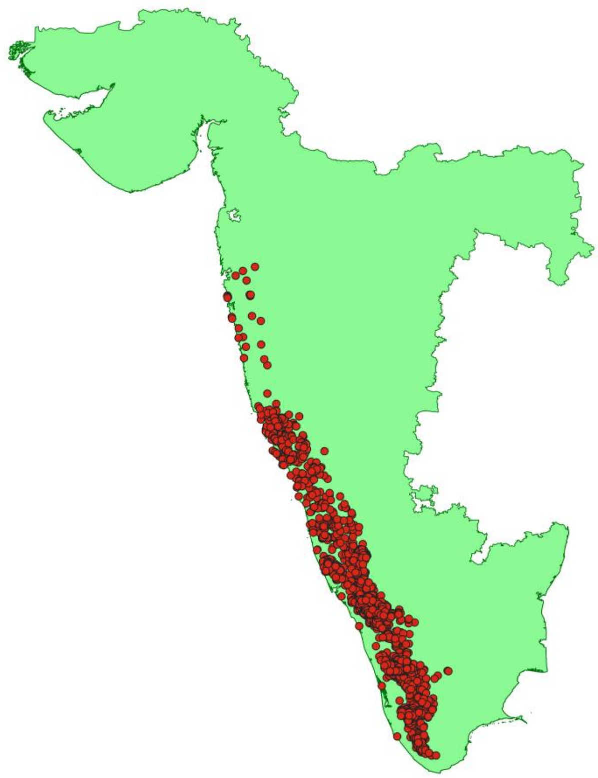

**Figure 1: Occurrence points for the Malabar Grey Hornbill from the Western Ghats**

3.3. ENVIRONMENTAL VARIABLES

The bioclimatic variables were derived by combining the monthly rainfall and temperature values and generated 19 different variables which are more meaningful. These variables represent annual trends, seasonality and extreme or limiting environmental factors. They are coded under different names such as;

**3.3.1 bio1 (Annual Mean Temperature):** The average temperature of 12 months was used to acquire the annual mean temperature. This approximated the total energy inputs for an ecosystem.

**3.3.2 bio2 (Mean Diurnal Range):** Each month's diurnal range (difference between maximum and minimum temperature) was averaged for 12 months of a year. This provided information regarding the relevance of temperature fluctuation for different species.

**3.3.3 bio3 (Isothermality):** Isothermality was used to measure the oscillations of day to night temperatures relative to the annual oscillations ((bio2/bio7)x100). This could reveal the influence of larger or smaller variations in temperature of a month relative to that year.

**3.3.4 bio4 (Temperature Seasonality):** It is the temperature variation (SDx100) over a year (or averaged years) relative to the SD (variation) of monthly temperature averages. Greater variability in temperature is inferred from larger SD.

**3.3.5 bio5 (Maximum Temperature of Warmest Month):** It measures the maximum monthly temperature over a year which was useful in the determination of affects by warm temperature anomalies in species distribution.

**3.3.6 bio6 (Minimum Temperature of Coldest Month):** Measures the minimum temperature over a time period useful in the analysis of affects from cold temperatures.

**3.3.7 bio7 (Temperature Annual Range):** Quantifies the temperature variation over a period (bio5-bio6) and helps in the examination of species distribution and the effects of extreme temperature conditions on it.

**3.3.8 bio8 (Mean Temperature of Wettest Quarter):** Approximation of mean temperatures prevailing during the wettest season and its effect on species distribution can be studied.

**3.3.9 bio9 (Mean Temperature of Driest Quarter):** Mean temperature of driest quarter was measured to know the effects of it on species distribution.

**3.3.10 bio10 (Mean Temperature of Warmest Quarter):** Quantifies the mean temperature over warmest quarter and helps in the examination of species distribution.

**3.3.11 bio11 (Mean Temperature of Coldest Quarter):** Mean temperature of coldest quarter was measured to know the effects of it on species distribution.

**3.3.12 bio12 (Annual Precipitation):** It is the sum total of all the monthly precipitation and it evaluates the total water inputs which was useful in ascertaining the importance of water availability in determining the species distribution.

**3.3.13 bio13 (Precipitation of Wettest Month):** Precipitation of wettest month was measured and studies the species distribution when an extreme precipitation condition occurs.

**3.3.14 bio14 (Precipitation of Driest Month):** Total precipitation received during the driest month was measured to study the extreme conditions and its impacts on species distribution.

**3.3.15 bio15 (Precipitation Seasonality):** Variation of monthly precipitation throughout the year was measured. It is the ratio of SD of monthly total precipitation to the mean monthly total precipitation.

**3.3.16 bio16 (Precipitation of Wettest Quarter):** Precipitation of wettest quarter was measured and studies the species distribution when an extreme precipitation condition occurs.

**3.3.17 bio17 (Precipitation of Driest Quarter):** Total precipitation received during the driest quarter was measured to study the extreme conditions and its impacts on species distribution.

**3.3.18 bio18 (Precipitation of Warmest Quarter):** Precipitation of warmest quarter was measured and studies the species distribution when an extreme precipitation condition occurs.

**3.3.19 bio19 (Precipitation of Coldest Quarter):** The mean precipitation of the coldest quarter was measured to find out how it affects species distributions.

The bioclimatic variables used for the current and future conditions fed in to the species distribution model or any other ecological model was taken from CHELSA (Climatologies at high resolution for the earth's land surface areas) a very high-resolution global climate data set. 30 arc seconds (0.86 km2 at the equator) data were used for both current and future conditions. They were in the latitude/longitude coordinate reference system under the datum WGS84. The bioclimatic variables were calculated from aggregated data such as monthly precipitation, minimum, mean and maximum temperature. The unit of temperature is '°Cx10' and that of precipitation is 'mm'. According to World Meteorological Organization (WMO) climate is defined as the measurement of the mean and variability of relevant quantities of certain variables (such as temperature, precipitation or wind) over a period of time, ranging from months to thousands or millions of years. The typical period is 30 years.

In environmental and ecological sciences, high-resolution information on climate conditions is required in numerous applications. We utilised downscaled model output temperature and precipitation estimates from the ERA-Interim climatic reanalysis to a high resolution of 30 arc sec from the CHELSA (Climatologies at high resolution for the earth's land surface regions) data. CHELSA's output is often compared to other gridding algorithms as well as the Global Historical Climate Network station data. Furthermore, various studies demonstrate that CHELSA climatological data are as accurate as other temperature products, but that its precipitation pattern forecasts are superior. As it pertains to species distribution models, we provide a comparison between the new climatologies and convey that CHELSA data can improve the accuracy of species range forecasts.

**Table 1. Different RCP's and its characteristics**

| **Scenario** | **Model used** | **Radiative forcing** | **$Co_2$ equivalent (ppm)** | **Global warming until 2100 (Mean and Likely range)** |
|---|---|---|---|---|
| RCP 2.6 | IMAGE | Radiative forcing reaches its peak point at $3W/m^2$ before 2100,and then declines | 490 | 1.0 (0.3 – 1.7)℃ |
| RCP 4.5 | MiniCAM | An intermediate stabilization pathway, where the radiative forcing stabilized at around 4.5 $W/m^2$after 2100 | 650 | 1.8 (1.1 – 2.6)℃ |
| RCP 6.0 | AIM | Stabilization without overshoot pathway to ~ 6 W/m2 at stabilization after 2100 | 850 | 2.2 (1.4 – 3.1)℃ |
| RCP 8.5 | MESSAGE | Radiative forcing exceeds 8.5 $W/m^2$ by 2100 and continues to grow for some time | 1370 | 3.7 (2.6 – 4.8)℃ |

Besides 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) for the ecological niche modelling. By using the European Space Agency website (http://due.esrin.esa. int/page_globcover.php) the current land cover data (Globcover 2009) was downloaded. EVI (Enhanced Vegetation Index) from United States Geological Survey (USGS) for 10 years (2011 – 2020) was also downloaded. Since these data were downloaded on monthly basis they were obtained in different tiles. So by using ArcGIS 10.8, they were stiched 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.

## 3.4. DATA THINNING

eBird provided a total of 26,511 Malabar Grey Hornbill presence locations. The first step to data reduction was to filter the data based on the following: (1) protocol type – travelling and stationary, (2) duration minutes <300, (3) effort distance km <5, (4) number of observers - ≤ 10. Microsoft excel software was used to do all these operations. 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 4,090 occurrence points which were saved in the extension '.csv'. For superior prediction, most species distribution models require spatially independent occurrence data. The spatial autocorrelation of occurrence sites in SDMs is considered a frequent source of environmental biases (Hijmans, 2012). Model performance metrics are exaggerated as model becomes "over – fit" towards environmental biases, limiting the model's capacity to predict spatially independent data (Veloz, 2009; Hijmans, 2012; Boria et al., 2014). Then after removing the duplicates, it was the spatially thinned using R-based spThin statistical package (Aiello – Lammens et al., 2015). This was done in R studio and it removes all duplicates and decrease sampling bias. The thinning distance was taken as 1km resolution and we arrived at final “thinned” occurrence points of 2,131 (Fig.1).

### 3.5. SELECTION OF BIOCLIMATIC VARIBLES

Incorporating the correlated variables not only affects the quality of MaxEnt model prediction, but it also restricts the contribution of additional correlated variables in the output. Using a highly correlated variable in the model prevents all other correlated variables from being included, which could be quite important for our species of interest (Brown, 2014). If a correlation exists, derived response curves may not be accurate. It can be deceptive to draw conclusions based on the outputs from a model that incorporates strongly correlated variables. Variable optimization is a critical step in the model development process. There will be some variables on the list that will be more relevant to our species than others. Some factors may have a minor impact on the outcome, and it is usually recommended to remove such variables in order to improve the interpretability of the final model (epistemic sparcity) or assure better predictability (predictive sparcity) from our model (De Bin et al., 2015). For interpreting the contributions of each environmental variable to the species distribution model, highly correlated variables should be removed to avoid autocorrelation.

In autocorrelation method, if the test and training data were spatially correlated, the test omission line shrank significantly when compared to the predicted omission line, which indicates an incomplete fit. Veloz (2009) noted that spatially autocorrelated data would increase model accuracy, so it was essential to eliminate the spatially correlated variables prior to modelling.

For the current conditions, bioclimatic variables (bio1-bio19) were statistically analyzed using correlation matrix (Pearson) and coefficients of determination ($R^2$). The correlation values $|r| > 0.7$ and $R^2 > 0.7$ were used to classify the variables. The variables with the highest percentage contribution were chosen, and permutation important findings based on the MaxEnt model output were utilised to make future predictions. The percentage contribution chart showed the relative contribution of each environment variables to the MaxEnt model. In each iteration of the training algorithm, the increase in regularized gain was added to the contribution of the corresponding variable or subtracted from it if the change to the absolute value of lambda is negative. So, it depended on the path taken by the MaxEnt code to get the solution and the contribution values changed when it took a different route. There should be caution when interpreting the values of highly correlated variables. It is the MaxEnt model that affected the accuracy of the permutation importance rather than the way in which it determined its value. By random permuting the values of the variables among the presence and background (training points) and calculating the reduction in training AUC, the importance of that variable was measured. The greater the decrease, the more dependent the model is on that variable. The Jack-knife test of variable importance portrays the environment variable having the excess gain when used in seclution (having the most advantageous information) and the environment variable which decreased the gain the most when it is omitted (having the most information that isn't present in the other variables). Following the removal of the correlated variables, the remaining variables were used for further modelling.

## 3.6. MAXIMUM ENTROPY SPECIES DISTRIBUTION MODELLING (MAXENT)

The species distribution of the Malabar Grey Hornbill was studied using MaxEnt version 3.4.4. The MaxEnt software is based upon the maximum-entropy principle and used for species habitat modelling. The Maxent model can be used to synthesis the distribution of geographical species given the most important environmental factors (Phillips et al., 2004; 2006). Maxent predicts outcomes based on an insufficient amount of data using a machine-learning reaction. This method determines the "maximum entropy" of the sample points based on the data relative to the background locations while taking into account the limitations described in the data. The maximum entropy algorithm requires no prior knowledge of the probability distribution and condenses to the greatest maximum entropy distribution (Baldwin, 2009; Berger et al., 1996; Phillips et al., 2006).

According to whether a given species is present or not, a site may have been classified as present or absent category. A species' range can be determined by considering environmental features closely associated with its presence across similar habitats. Each species is given a uniform distribution at the start and, using the most important environmental variables, a series of iterations is performed until no improvement in prediction is possible. Using data from all of the environmental variables in the grid cells, the Maxent distribution is computed. As a test, we used 25% of the sample points to determine if Maxent's predictions (training data) are more accurate than random guesses. Both categorical and continuous data were employed for the method, and all variables were regarded as continuous variables. The probability of the species' occurrence was determined by analyzing a logistic output continuous map, which can differentiate between the suitability of various geographic regions.

We added 19 bioclimatic variables retrieved from the CHELSA database, slope, aspect, altitude and EVI (dry season wet season and yearly average); in total 25 predictor environmental variables, lateral to the geographical position data of Malabar Grey Hornbill occurrence. Among the different models used for ecological niche modelling and nest-site selection Maxent is a regularly utilized and it employs the area under the curve (AUC) to statistically analysis (Baldwin, 2009; Barry and Elith, 2006; Peterson and Nakazawa, 2008; Yost et al., 2008). MaxEnt can be freely downloaded online (https://biodiversityinformatics.amnh.org/open_source/maxent/). The data should be inputted into the software in the required format. Species data was made into '.csv' format and the bioclimatic layers should be of '.asc' format. As described under the settings options, the software was configured based on our requirements for the run (Philips et al., 2004; 2006).

### 3.7. MODEL OPTIMIZATION

#### 3.7.1 MODEL FEATURES

Identifying the optimal combination of model features was the first step towards optimising the model for the study requirements. Auto feature is the default setting in terms of feature setting in the MaxEnt software. MaxEnt model have five different model features that can be used separately and together. The five features in the model are linear feature (L), product feature (P), quadratic feature (Q), hinge feature (H) and threshold feature (T). The “ENMeval” R package was used for the selection of optimal model setting. This assesses models of various complexity and RM values. AIC, one of the evaluation statistics provided in ENMeval was used for the selection of model. Model having lowest AIC value is considered to be better (Warren and Seifert, 2011). Among the 48 different models, the one with the lowest AIC (LQ and RM=0.5) was chosen for future projections. So for obtaining the lowest AIC value MaxEnt was run multiple time and the variables was removed in accordance to the permutation importance. After running the Maxent and ENMeval a couple of times the lowest AIC value obtained are for LQ 0.5.

#### 3.7.2. REGULATION MULTIPLIER AND REPLICATION RUN TYPE

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

The replication run in MaxEnt was done mainly using three types: crossvalidate, bootstrap and subsampling. All three run types were configured to run three distinct models under similar conditions, with the cross validation run type proving to be the most effective. Cross-validation is a type of replication in which the occurrence data were randomly divide into several (k) groups ('folds') of equal size and leaving out a single part, it will fit the model to the other k-1 parts (combined), thus acquiring predictions for the left-out part. This procedure was reiterated for each part and the results were combined. It would be beneficial to use cross-validation when dealing with few data sets because all the data would be used for the purpose of validation. Based on this run type, the model accounts for the uncertainties in prediction and becomes more accurate by incorporating the measures into the model. Model performance can be exaggerated and standard error predictions can be miscalculated when spatially connected groups are introduced during model evaluation. In this run type, model fitting only uses a part of the data, and therefore, it is difficult to collect test data that is spatially independent of the training data (Hijmans, 2012).

## 3.8. PREDICTING THE CURRENT DISTRIBUTION OF MALABAR GREY HORNBILL

Having optimized the model for the essential and important features, we adjusted the other software settings accordingly to meet the requirements for the run under the settings option. In the method, two types of environmental data are utilized: categorical data and continuous data, and all variables have been treated as continuous variables. We set the maximum number of iterations as 5000 and left the convergence threshold (0.00001) at its default setting. For all model output to be bias-free, the random test percentage was set to 25%. Once the features of the model were configured according to our needs, environmental variables in an '.asc' format and species occurrence data in a '.csv' format were fed into the software as input, the model was ran, and the results were produced. Based on the result files from the optimized model run, visual forecasts of model predictions seemed to match quantitative evaluations previously performed, thus proving the credibility of the optimised model. The models expected area of appropriate habitat was then evaluated in a Geographic Information System (GIS) context for better understanding. The best model feature was the one with lowest AIC value 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.

## 3.9. PREDICTING THE POTENTIAL DISTRIBUTION OF MALABAR GREY HORNBILL

Future projections of environmental variables were obtained from Research Program on Climate Change, Agriculture and Food Security (CCAFS) (data available from http://www.ccafs-climate.org/data) for a time period of 2050. Three generalised circulation models from the IPCC'S CMIP5 project BSS CSM1.1, MIROC5 and Mohc HadGEM 2 ES at 30 arc-second (1 km) spatial resolutions for four representative concentration pathways (RCPs) were utilised for future climatic forecast. The four RCP scenarios; RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 encompass the complex interactions of climate systems, ecosystems, and human activities to deliver feasible descriptions of how the future might unravel. The four RCP scenarios; RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 encompass the complex interactions of climate systems, ecosystems, and human activities to deliver feasible descriptions of how the future might unravel (Moss et al. 2010; Rogelj, Meinshausen & Knutti 2012). It can be interpreted that RCP8.5 represents a high emissions scenario, while RCP2.6 represents the lowest emissions scenario (van Vuuren et al. 2011).

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. Models of different RCPs were done using a cross validation technique with 10 replicates and 25 test percentage. By assuming that the topographic features like slope are static and dynamic, prediction for future distribution was done for 2050 and omitted non-climatic variables such as EVI (Enhanced Vegetation Index).

## 3.10. MODEL EVALUATION

Two metrics were used to evaluate the model's performance: the receiver operating characteristic curve (AUC) and the true skill statistics (TSS). There isn’t any influence of thresholds on the metric. AUC measures how well a model can distinguish random and background data points whereas, TSS measures accuracy at different thresholds, TSS is the threshold-dependent measure of accuracy. AUC doesn't provide much information nor is it extremely reliable (Phillips et al. 2006; Austin 2007; Lobo 2008). TSS ratings are therefore 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) is expected to change in the future, it's data for future is not available and so we had to run the model in two ways i.e.; with EVI and without EVI. The model setting was 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 are 0.891 and 0.863, respectively, indicating that the model was better in predicting the suitable habitat area for Malabar Grey Hornbill in WG. With an overall accuracy of 0.9048, the specificity and sensitivity was 0.8905 and 0.9726, respectively.

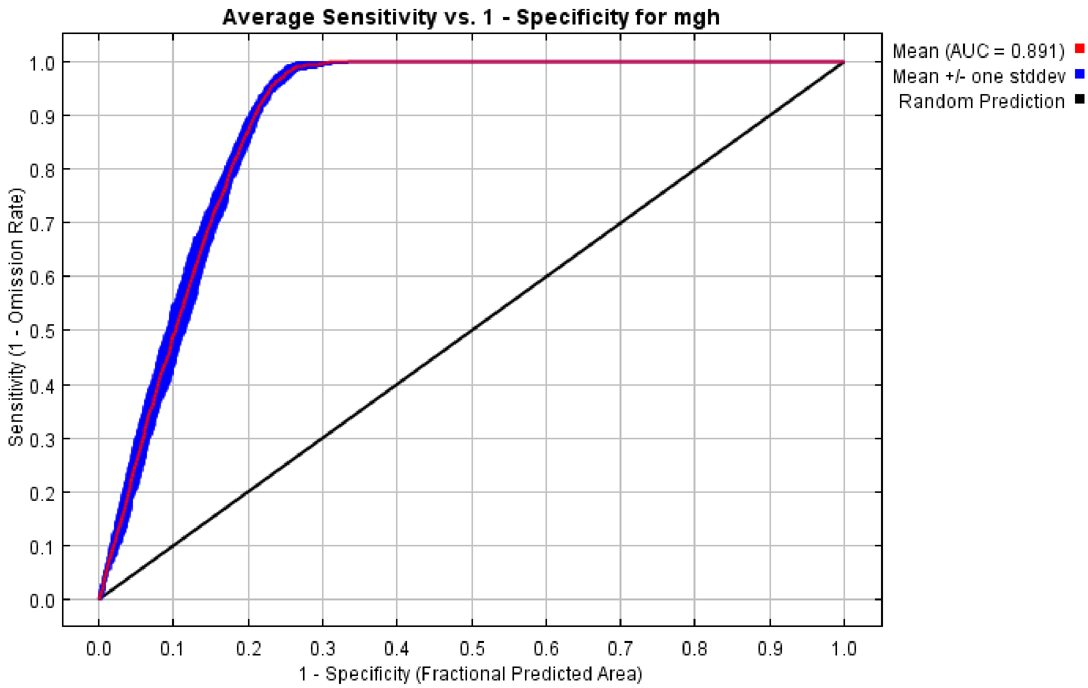


**Figure 2: Receiver Operating Characteristic Curve (ROC) curve of the finalized model settings output in MaxEnt (with EVI)**

The model's performance in terms of average test AUC value was 0. 891 as seen in Fig.2, with a standard deviation of 0.004, according to ROC curve above. AUC values range from 0 to 1, and any AUC number greater than 0.8 indicates that the model's performance was satisfactory. The average sensitivity v/s specificity graph (Fig.2) provides these values. The AUC curve curves up to the top left of the plot, indicating that the model was competent.

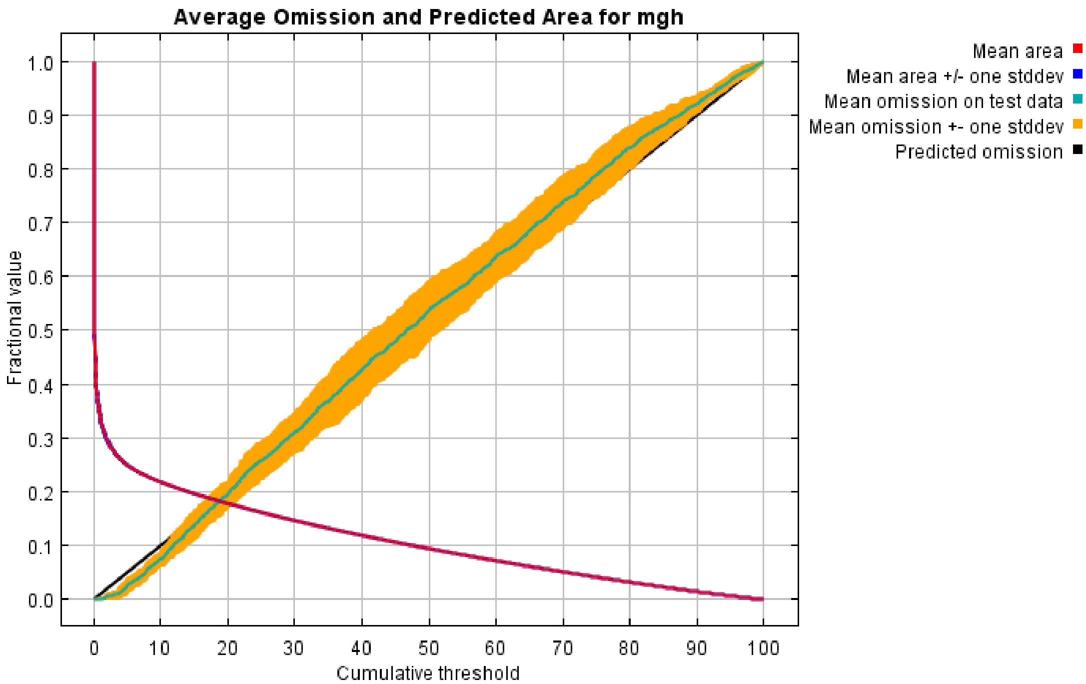


**Figure 3: Average omission curve and predicted area for Malabar Grey Hornbill, an endemic bird species of Western Ghats (With EVI).**

A metric that indicates the model's predictive capacity was the average omission and projected area curve (Fig.3) 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.

After the cross-correlation tests, the best model incorporated seven bioclimatic variables as shown in Table.2 (Mean Diurnal Range, Mean Temperature of Warmest Quarter, Precipitation of Coldest Quarter, Precipitation of Warmest Quarter, Mean Temperature of Coldest Quarter and Precipitation Seasonality), one topography layer (Slope), and EVI (Average of 10 years [2011 – 2020]). EVI average (44.2% contribution), Mean Diurnal Range (31.4% contribution), and mean temperature of the warmest quarter (13.7% contribution) were the important factors affecting the spatial distribution of Malabar Grey Hornbill among the seven variables considered for modelling. These factors combined to contribute 89.0 percent of the total. Mean temperature of warmest quarter (65.8 percent) and Mean Temperature of Coldest Quarter (24.3 percent), on the other hand, had significant permutation relevance.

**Table 2: Analysis of variable contribution (with EVI)**

| **Variable** | **Percent contribution** | **Permutation importance** |
|---|---|---|
| evi_avg | 44.2 | 2 |
| bio2 | 31.4 | 6.1 |
| bio10 | 13.7 | 65.8 |
| bio19 | 5 | 0.3 |
| bio11 | 3.4 | 24.3 |
| bio18 | 1.4 | 0.4 |
| bio15 | 0.9 | 1.1 |
| Slope | 0 | 0 |

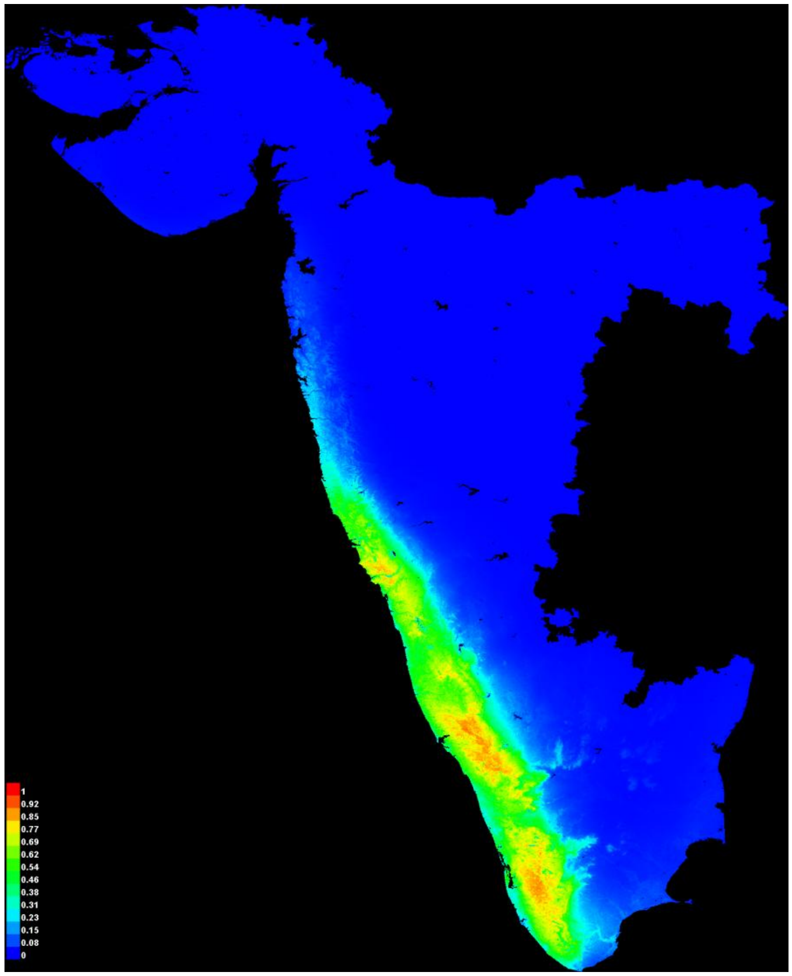


**Figure 4: Shows the current distribution of Malabar Grey Hornbill by Maxent (With EVI)**

This projection (Fig.4) goes hand in hand with the actual distribution of Malabar Grey Hornbill 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 Grey Hornbill.

Figure 5 shows the Jackknife test of selected bioclimatic variables. Mean Diurnal Range (bio2) contributes the most, followed by mean evi_avg, Precipitation of Warmest Quarter (bio18), and Mean Temperature of Warmest Quarter (bio10), Precipitation of Coldest Quarter (bio19). This finding is comparable to MaxEnt's, implying that it is trustworthy.

Figure 6 shows the response curves of each selected bioclimatic variable and other importance factors. This mainly shows the probability distribution of the species as a response to various bioclimatic predictors.

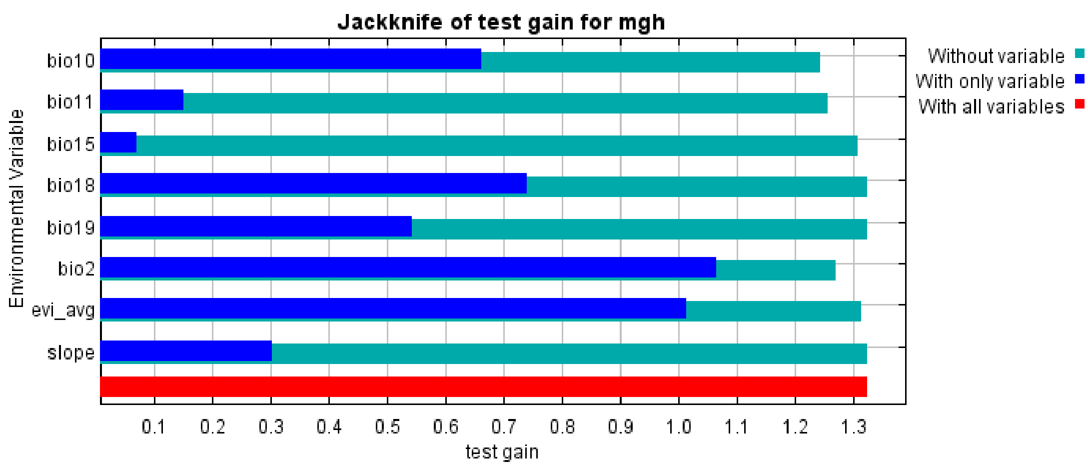


**Figure 5: Jackknife test gain for Malabar Grey Hornbill for the current distribution (with EVI)**

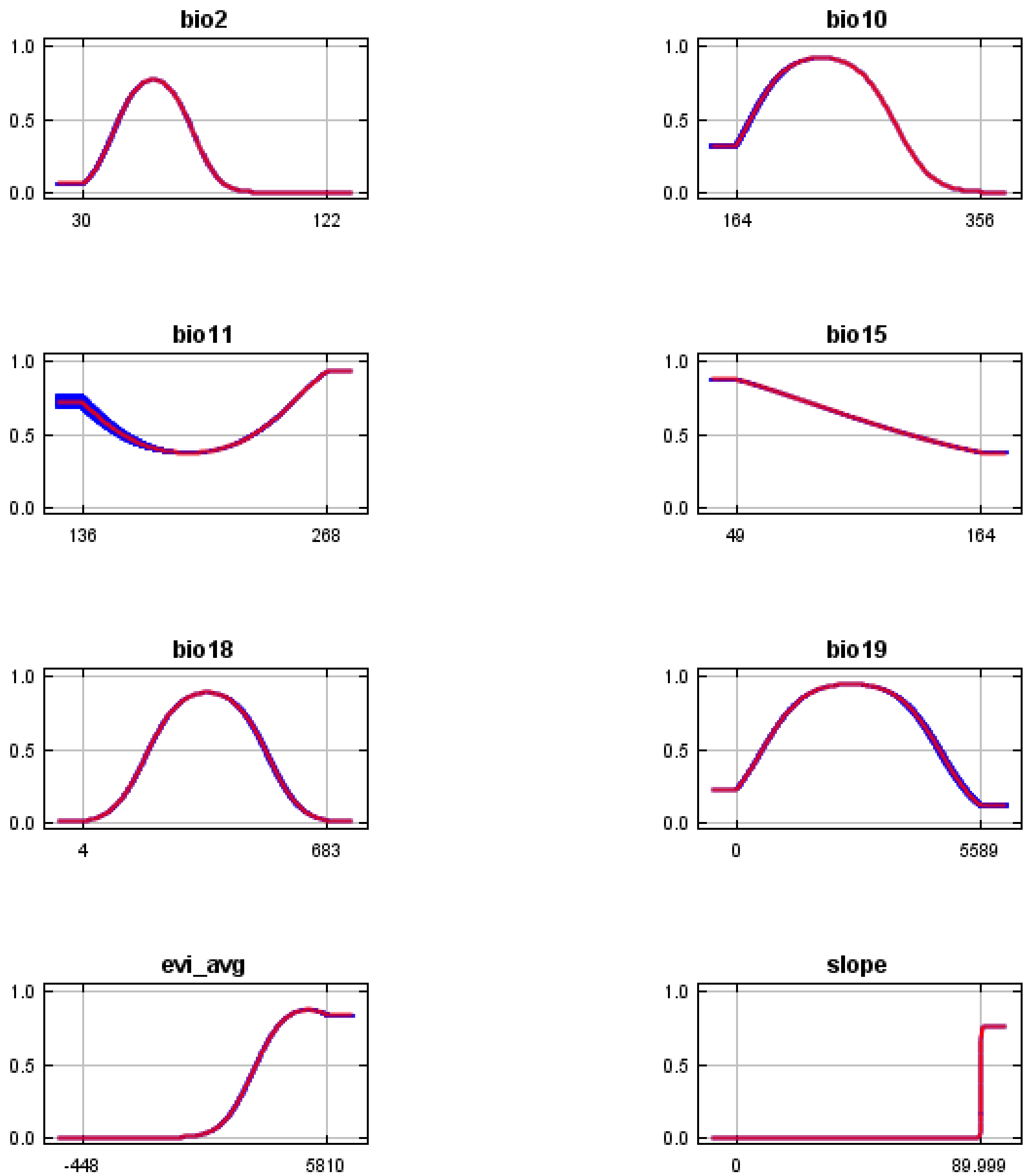


**Figure 6: Response curves generated by MaxEnt for variables (With EVI)**

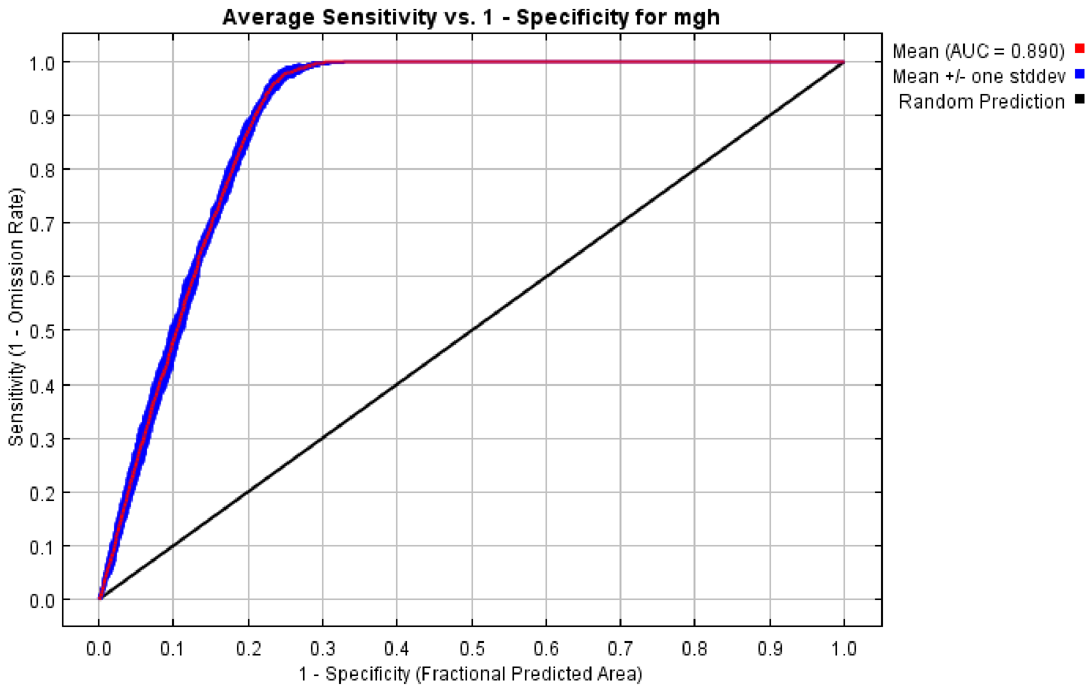


**Figure 7: Receiver Operating Characteristic Curve (ROC) curve of the finalized model settings output in MaxEnt (Without EVI)**

The test AUC (Fig.7) and TSS values for the model without EVI are 0.890 and 0.864, respectively, indicating that the model was better in predicting the suitable habitat area for Malabar Grey Hornbill in WG. With an overall accuracy of 0.9041, the specificity and sensitivity were 0.8892 and 0.9745 respectively.

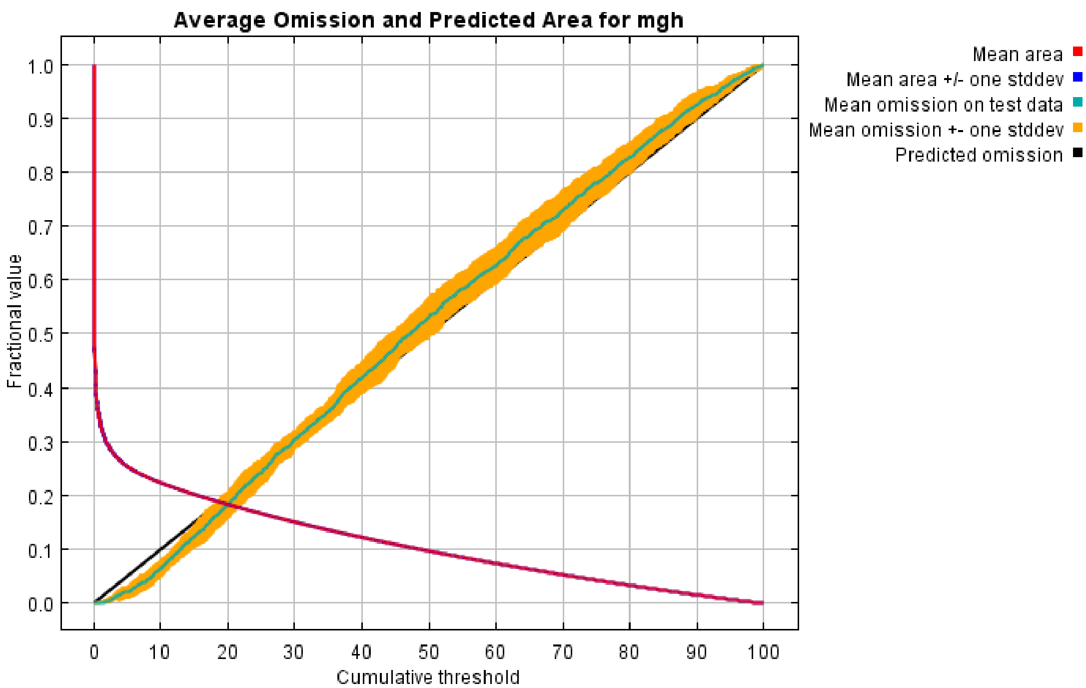


**Figure 8: Average omission curve and predicted area for Malabar Grey Hornbill, an endemic bird species of Western Ghats (Without EVI).**

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.

Mean Diurnal Range (54.8% contribution), Mean Temperature of Warmest Quarter (18.7% contribution), and Precipitation of warmest Quarter (10.8% contribution) were the important factors affecting the spatial distribution of Malabar Grey Hornbill among the nine variables considered for modeling and it was shown in Table.3. These factors combined to contribute 84.3 percent of the total. Mean temperature of warmest quarter (64.8percent) and Mean Temperature of Coldest Quarter (27.1 percent), on the other hand, had significant permutation relevance. The model’s performance in terms of average test AUC value is 0. 890, with a standard deviation of 0.003, according to ROC curve above.

**Table 3:Analysis of variable contribution (without EVI)**

| **Variable** | **Percent contribution** | **Permutation importance** |
|---|---|---|
| bio2 | 54.8 | 6.1 |
| bio10 | 18.7 | 64.8 |
| bio18 | 10.8 | 0.5 |
| bio19 | 9.5 | 0.4 |
| bio11 | 5.6 | 27.1 |
| bio15 | 0.5 | 1.1 |
| Slope | 0.1 | 0 |

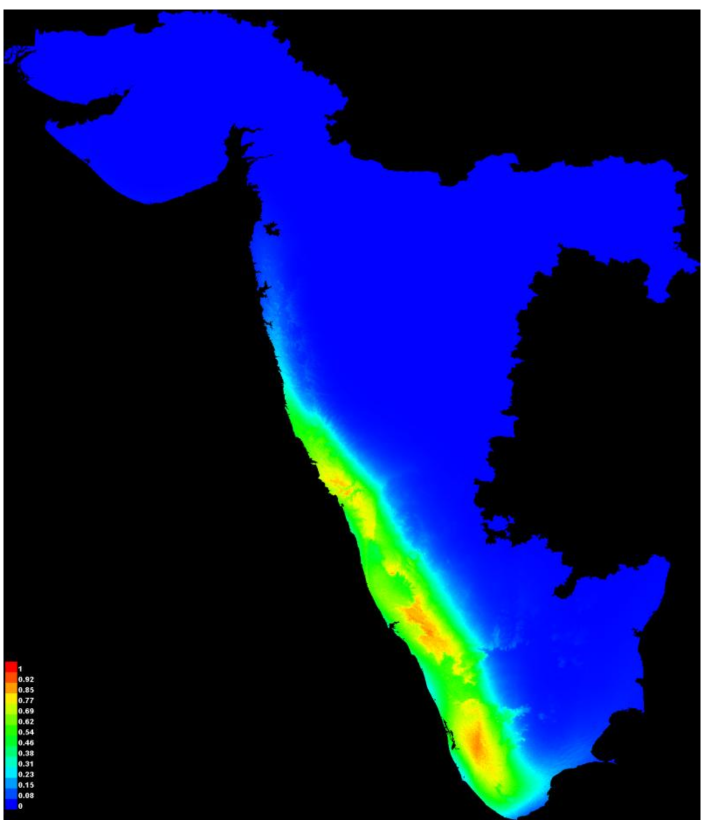

**Figure 9: Shows the current distribution of Malabar Grey Hornbill by Maxent (Without EVI)**

In Figure 9 projection depicts the current Malabar Grey Hornbill distribution, which is similar to the previous one but does not include EVI. The model settings for this projection were the same as for the previous one, namely LQ 0.5. The current distribution of Malabar Grey Hornbill and Maxent's projection go hand in hand.

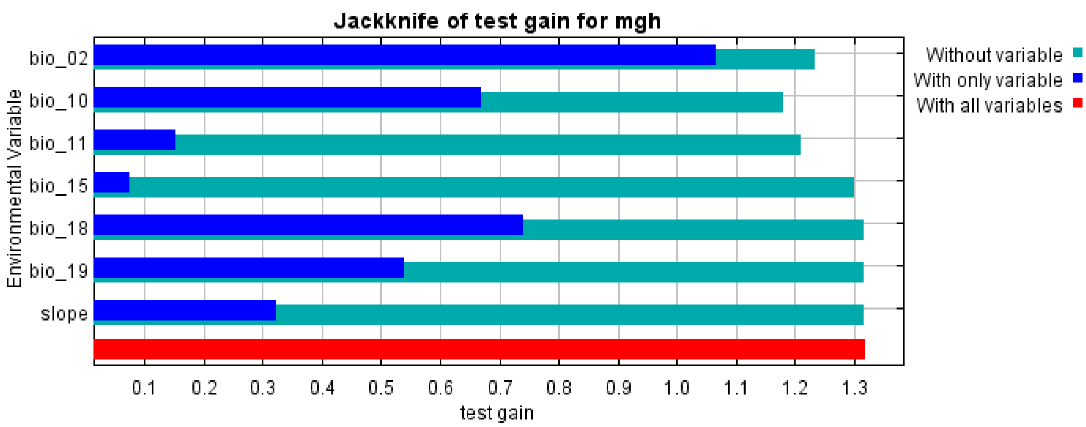


**Figure 10: Jackknife test gain for Malabar Grey Hornbill for the current distribution (without EVI)**

Figure 10 shows jackknife test gain without EVI implies that the most contributing variable was Mean Diurnal Range (bio2) followed by Precipitation of Warmest Quarter (18) and Mean Temperature of Warmest Quarter (bio10). These results were comparable to those produced by MaxEnt thus making them a reliable finding.

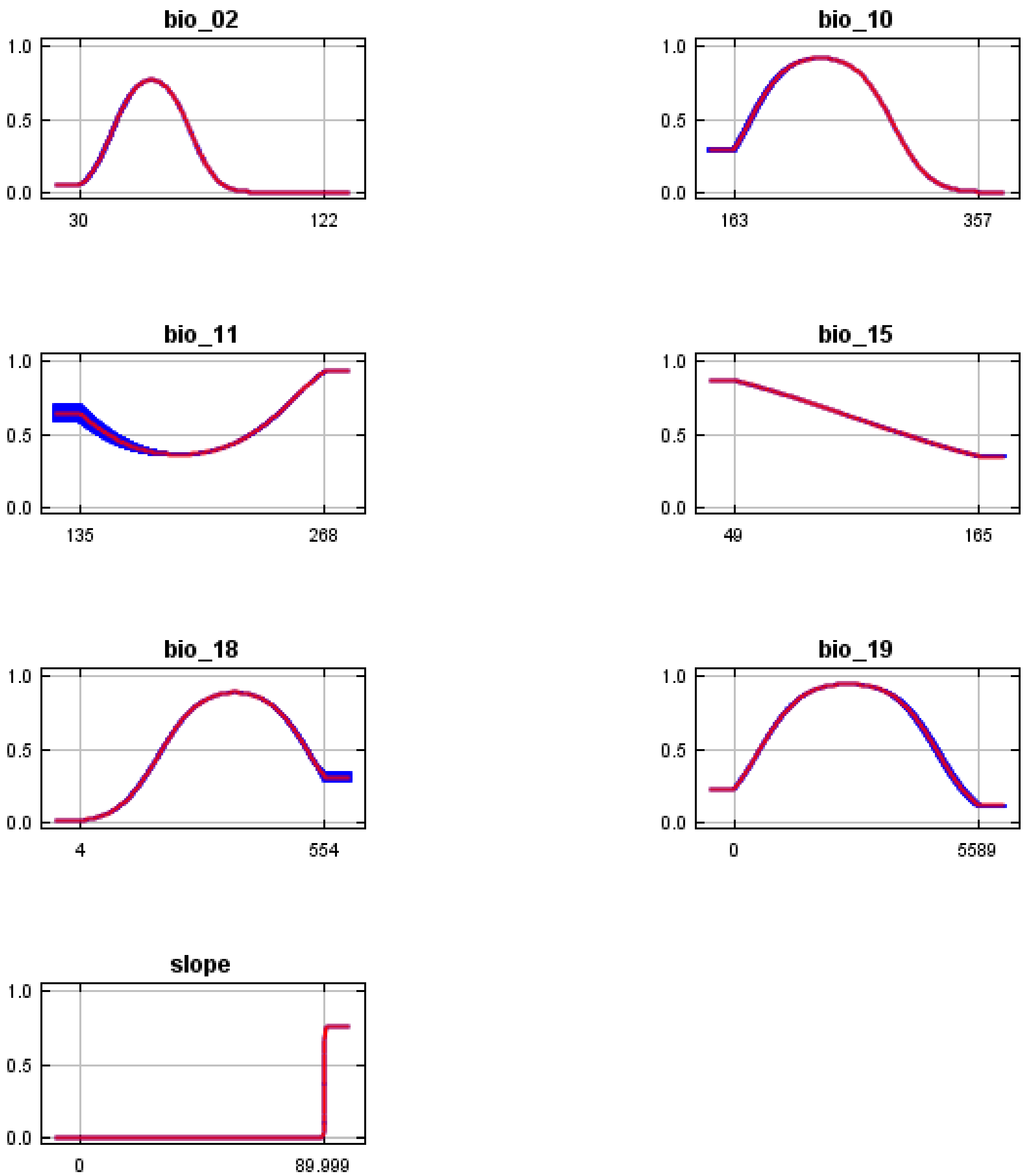


**Figure 11: Response curves generated by MaxEnt for variables (Without EVI)**

4.2. SELECTION OF SUITABLE BIOCLIMATIC VARIABLES

| 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 4: Pearson's correlation metrics generated by SDMToolbox in ArcGIS**

**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 Grey Hornbill.**

| 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 | | miroc | Mohc hadgem | bcc | miroc | Mohc hadgem |
| bio2 | 54.8 | 67 | 67.4 | 71 | 71.2 | 65.9 | 68.7 | 65.7 | 66.7 | 70.9 | 70.6 | 64 | 68.1 |
| bio10 | 18.7 | 13.5 | 20.3 | 19.5 | 15.2 | 22 | 20.6 | 16.2 | 21 | 18.1 | 15.4 | 20.9 | 21.6 |
| bio19 | 9.5 | 11.6 | 1.2 | 0.3 | 6.3 | 1 | 0.7 | 10.1 | 1.3 | 1.9 | 7.5 | 3.8 | 1 |
| bio11 | 5.6 | 5.2 | 9.5 | 7.8 | 5.2 | 7.7 | 7.5 | 5.7 | 8.2 | 7.6 | 5.4 | 8.1 | 7.8 |
| bio18 | 10.8 | 2.1 | 1.1 | 0.8 | 1.7 | 2.9 | 2 | 1.8 | 1.7 | 1.1 | 0.8 | 2.3 | 1 |
| bio15 | 0.5 | 0.5 | 0.5 | 0.5 | 0.4 | 0.3 | 0.6 | 0.6 | 0.9 | 0.4 | 0.3 | 0.9 | 0.5 |
| slope | 0.1 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 |

4.3CLIMATE SPACE SUITABILITY FOR MALABAR GREY HORNBILL UNDER CURRENT AND FUTURE SCENARIO

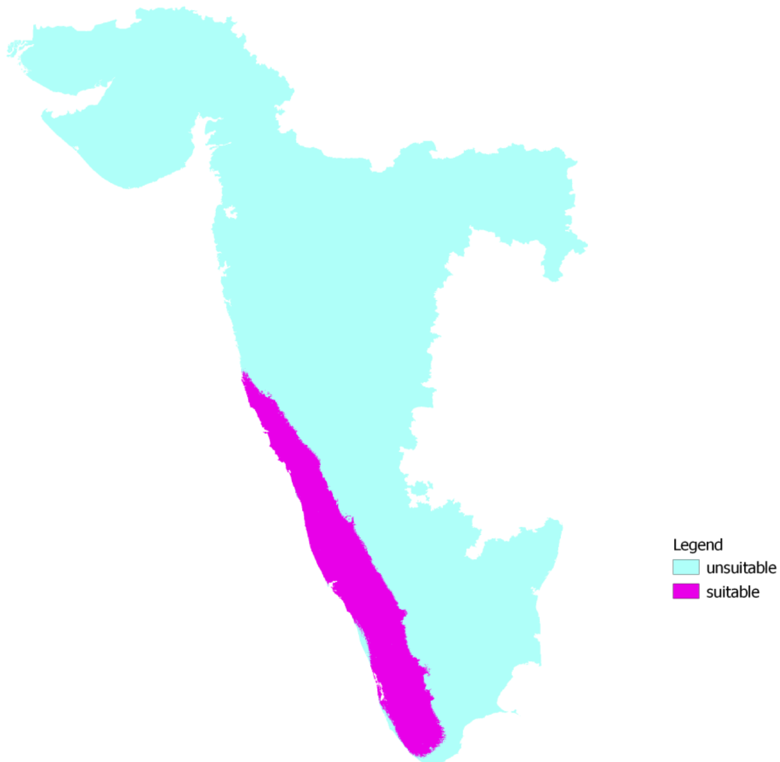


**Figure 12: Distribution map showing suitability under current climatic condition**

The habitat available as highly appropriate for Malabar Grey Hornbill in the study area under current climatic condition is 1,08,480 km$^2$. And in the current scenario, in the study area the species were not at all present accounted for 9,37,362 km$^2$.

The area of suitability spread from Marthandam in Thiruvananthapuram to bhalvali covering Agastyamalai, Neyyar Wildlife Sanctuary, Periyar National Park, Idukki Wildlife Sanctuary, Anamalai Tiger Reserve, Nelliyampathy Forest Reserve, Mudumalai Tiger Reserve, BandipurTiger Reserve and National Park, Nagarhole

National Park and Tiger Reserve, Bhadhra Wildlife Sanctuary, Sharavathi Valley Wildlife Sanctuary, Anshi National Park, Bhagvan Mahavir Wildlife Sanctuary and Bhimgad Wildlife Sanctuary (Fig.12).

### 4.3.1 FUTURE SCENARIOS

The test AUC and TSS values for the model under future scenario were 0.891 and 0.868, respectively, indicating that the model is better in predicting the suitable habitat area for Malabar Grey Hornbill in WG. With an overall accuracy of 0.9111, the specificity and sensitivity were 0.8988 and 0.9693, respectively.

The future scenarios are evaluated for the 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.

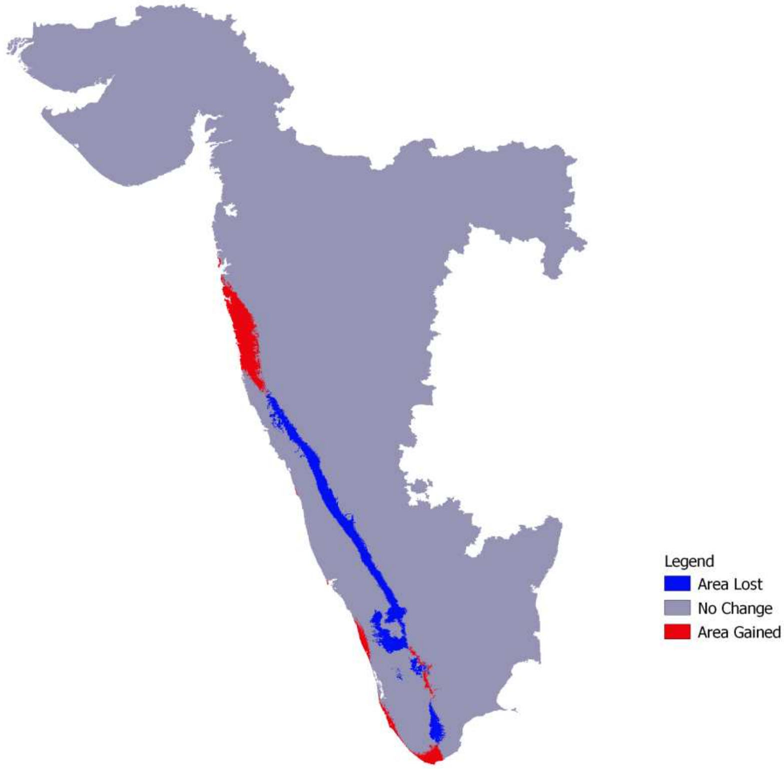


**Figure 13: Distribution map showing area gained, lost and areas with no change in distribution under RCP 2.6 in 2050**

Figure 13 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 Grey Hornbill distribution and habitat appropriateness have remained unchanged. This value accounts for 10,02,782km$^2$. This could indicate that there was no change in area where Malabar Grey Hornbill is present or absent in the earlier mentioned current scenario.

A loss of 25,180 km$^2$ was seen in the distribution of Malabar Grey Hornbill under RCP 2.6. A patch of habitat loss was observed near Singhampatti Zamindar forest near to Ambasamudram, Madiyarm and Sivagir. Another loss was seen near Idamalayar and near Anamali Tiger Reserve, Marayur, Pampadam SholaNational Park, Eravikulam National Park, Kurinjimala Wildlife Sanctuary and Mathikettan

Shola National Park. A loss was also seen in Palakkad region near Silent Valley National Park and New Amarambalam Wildlife Sanctuary. In the eastern side of WG there was a large stretch of loss of habitat seen from north to south including Ooty, Mudumalai Tiger Reserve, Bandipur Tiger Reserve and National Park, near Nagarhole National Park, near Sharavati Valley Wildlife Sanctuary, Bhagawan Mahavir Wildlife Sanctuary, Bhimgad Wildlife Sanctuary and ending near Amboli.

Under RCP 2.6 Malabar Grey Hornbill had a gain or increment in habitat suitability of 17,174 $km^2$. In Marthandam, Nagarcoil, Kanyakumari and Koodankulam region show an increase in the habitat of Malabar Grey Hornbill. Near coastal areas of Thiruvananthapuram, Kollam, Ambalapuzha and in Guruvayur, Ponnani and Kozhikode there was a light increase in habitat. And near Agamalai Forest Reserve, Chinnar Wildlife Sanctuary, Pallani hill Conservation Area and in Srivilliputhur Grizzled Squirrel Wildlife Sanctuary a gain in area is observed. A large gain in habitat can be seen in the north part near Radhanagari Wildlife Sanctuary, Rajapur, near Chandoli National Park, Sangameshwar Phansad Wildlife Sanctuary and in Mumbai area.

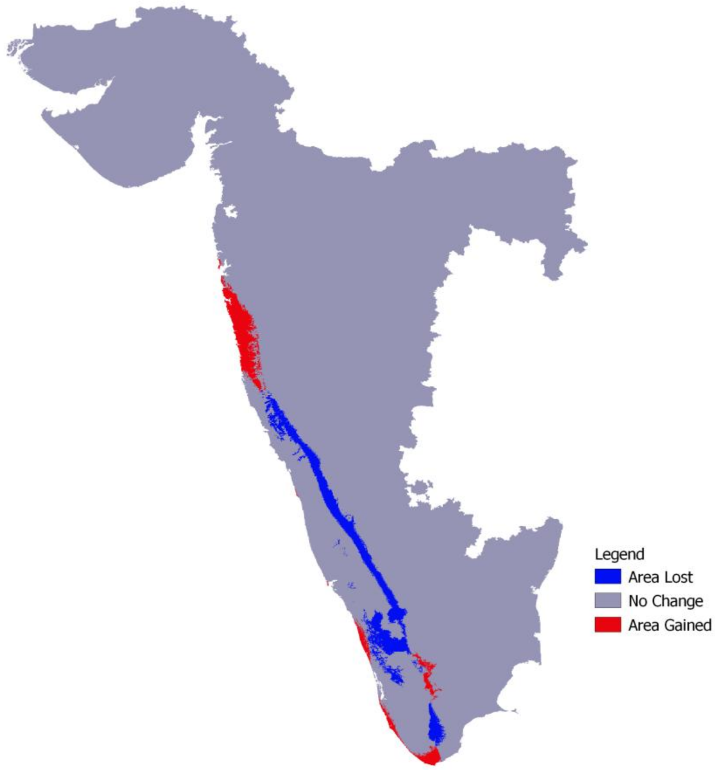


**Figure 14: Distribution map showing area gained, lost and areas with no change in distribution under RCP 4.5 in 2050**

This map was 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 Grey Hornbill distribution and habitat appropriateness have remained unchanged. This value accounts for 10,01,144 km$^2$.

A loss of 27,592 km$^2$ was seen in the distribution of Malabar Grey Hornbill under RCP 4.5. This loss was observed near Singhampatti Zamindar forest near to Ambasamudram, Madiyarm and Sivagir. Near Grass hill National Park, Anamudi SholaNational Park, Pampadam Shola National Park, Kurinjimala Sanctuary and Munnar Reserved Forest a small loss is seen. A patch of loss of habitat of Malabar Grey Hornbill was seen from Thodupuzha, Angamaly, Thrissur and in Chimmoni Wildlife Sanctuary. A loss was also seen in Palakkad region near Silent Valley

National Park and New Amarambalam Wildlife Sanctuary and near Thamarassery part. In the eastern side of WG there is a large stretch of loss of habitat seen from north to south including Ooty, Mudumalai Tiger Reserve, Bandipur Tiger Reserve and National Park, near Nagarhole National Park, near Sharavati Valley Wildlife Sanctuary, Bhagawan Mahavir Wildlife Sanctuary, Bhimgad Wildlife Sanctuary, Banda and ending near Sivdav.

Under RCP 4.5 Malabar Grey Hornbill had a gain or increment in habitat suitability of 16,400 $km^2$. In Marthandam, Nagarcoil, Kanyakumari and Valliyur region show an increase in the habitat of Malabar Grey Hornbill. Near coastal areas of Thiruvananthapuram, Kollam, Ambalapuzha and in Guruvayur, Ponnani and Kozhikode there shows a gain in the suitable habitat for Malabar Grey Hornbill (Fig. 14). And near Agamalai Forest Reserve, Chinnar Wildlife Sanctuary, Pallani hill Conservation Area, Saptur Reserved Forest and in Srivilliputtur Grizzled Squirrel Wildlife Sanctuary a gain in area is observed. A large gain in habitat can be seen in the north part near Radhanagari Wildlife Sanctuary, Rajapur, near Chandoli National Park, Sangameshwar Phansad Wildlife Sanctuary and in Mumbai area.

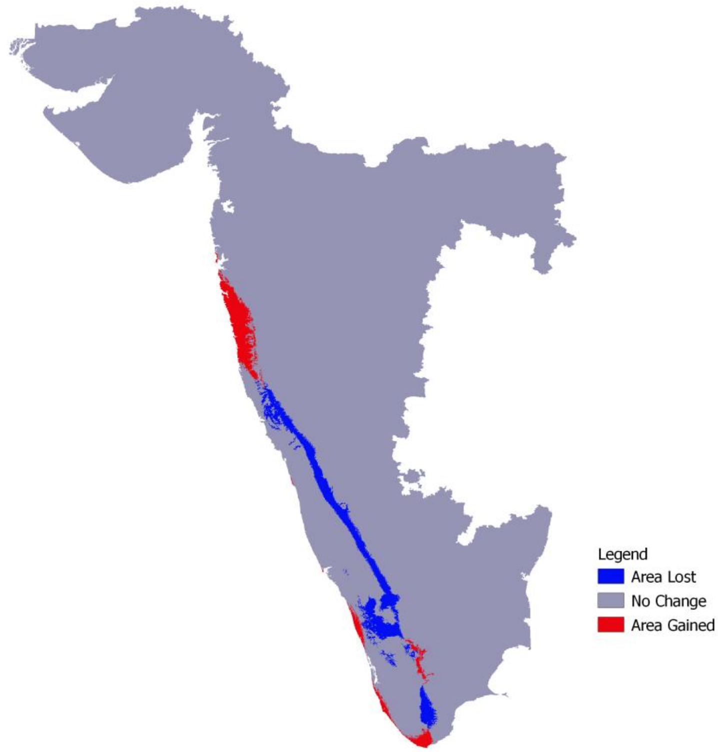


**Figure 15: Distribution map showing area gained, lost and areas with no change in distribution under RCP 6 in 2050**

This map was created by subtracting RCP 6.0 from current scenario. When we look at the map from top to bottom, we can see that a substantial amount of the Malabar Grey Hornbill distribution and habitat appropriateness have remained unchanged. This value accounts for 10,02,914km$^2$.

A loss of 26,168 km$^2$ was seen in the distribution of Malabar Grey Hornbill under RCP 4.5 in 2050. This loss was observed near Singhampatti Zamindar forest near to Ambasamudram, Surandai, Madiyarm and Rajapalayam. Near Grass hill National Park, Anamudi Shola National Park, Pampadum Shola National Park, Kurinjimala Wildlife sanctuary and Munnar Reserve Forest a small loss was seen. A patch of loss of habitat of Malabar Grey Hornbill was seen in Neriyamangalam and Thattekad Bird Sanctuary and also in Thirssur, Chimmoni Wildlife Sanctuary and

Wadakkanchery. A loss was also seen in Palakkad region near Silent Valley National Park and New Amarambalam Wildlife Sanctuary, Malappuram and near Thamarassery part. In the eastern side of WG there is a large stretch of loss of habitat seen from north to south including Ooty, Mudumalai Tiger Reserve, Bandipur Tiger Reserve and National Park, near Nagarhole National Park, near Sharavati Valley Wildlife Sanctuary, Bhagawan Mahavir Wildlife Sanctuary, Bhimgad Wildlife Sanctuary, Banda and ending near Kankavli (Fig.15).

Under RCP 6.0 in 2050 Malabar Grey Hornbill had a gain or increment in habitat suitability of 16,054 $km^2$. In Marthandam, Nagarcoil, Kanyakumari and Valliyur region show an increase in the habitat of Malabar Grey Hornbill. Near coastal areas of Thiruvananthapuram, Kollam, Ambalapuzha and in Guruvayur, Ponnani and Kozhikode there is a light increase in habitat. And near Agamalai Forest Reserve, Chinnar Wildlife Sanctuary, Pallani hill Conservation Area, Saptur Reserve Forest and in Srivilliputtur Grizzled Squirrel Wildlife Sanctuary a gain in area is observed. A large gain in habitat can be seen in the north part in Talere, Rajapur, Sangameshwar, Phansad Wildlife Sanctuary, Alibag and in Mumbai area.

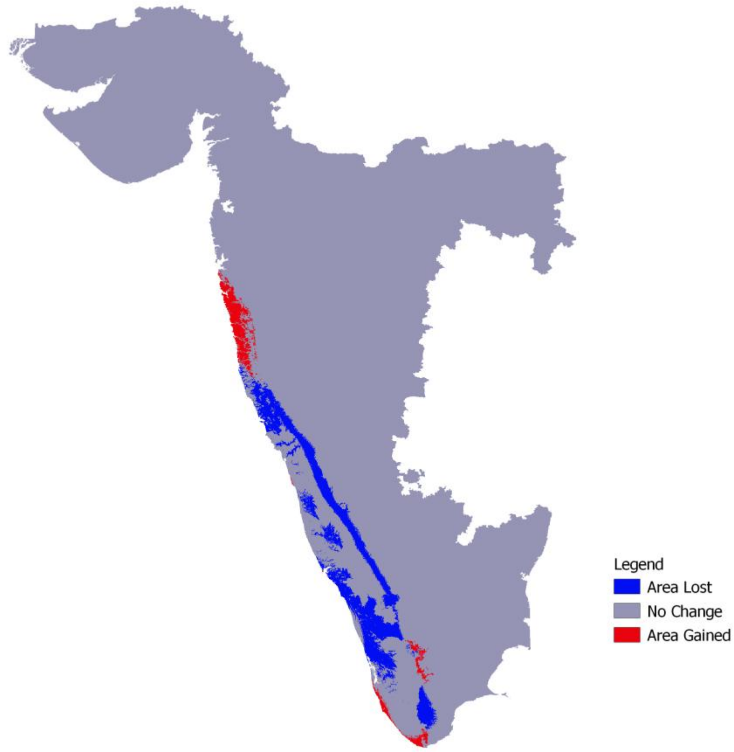


**Figure 16: Distribution map showing area gained, lost and areas with no change in distribution under RCP 8.5 in 2050**

This map was 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 Grey Hornbill distribution and habitat appropriateness have remained unchanged. This value accounts for 9,89,188km$^2$.

A loss of 44,494 km$^2$ was seen in the distribution of Malabar Grey Hornbill under RCP 8.5 in 2050. This loss was observed near Singhampatti Zamindar forest near to Ambasamudram, Surandai, Madiyarm, Sivagiri Reserve Forest and Rajapalayam. Near Grass hill National Park, Anamudi Shola National Park, Pampadam Shoal national park, Kurinjimala sanctuary and Munnar Reserve Forest a small loss was seen. A large patch of loss of habitat of Malabar Grey Hornbill is seen from Pala, Muvattupuzha, Idamalayar, Thattekad Bird Sanctuary, Sholayar Reserve

Forest, Chimmoni Wildlife Sanctuary, Peechi-Vazhani Wildlife Sanctuary, Thirssur, Silent Valley National Park, Malappuram, Kozhikode, Kannur and finally ending near Kanhangad. In the eastern side of WG there was a large stretch of loss of habitat seen from north to south including Ooty, Mudumalai Tiger Reserve, Bandipur Tiger Reserve and National Park, near Nagarhole National Park, near Sharavati Valley Wildlife Scantuary, Anshi National Park, Cotigao Wildlife Sanctuary, Bhagawan Mahavir Wildlife Sanctuary, Bhimgad Wildlife Sanctuary and it then spreads towards west including Margoa, Mollem, Devgad and Vijavdurg. Two loss patches seen in Dharmasthula, Puttur, Kadaba and near Someshwara Wildlife Sanctuary, Siddapur near Mookambika Wildlife Sanctuary (Fig.16).

Under RCP 8.5 in 2050 Malabar Grey Hornbill had a gain or increment in habitat suitability of 11,454 $km^2$. In Marthandam, Nagarcoil, Panakudi, Kalakadu RF and near coastal areas of Thiruvananthapuram, Kollam, Ambalapuzha. And near Agamalai Forest Reserve, Chinnar Wildlife Sanctuary, Palani Hill Conservation Area, Saptur Reserve Forest and in Srivilliputtur Grizzled Squirrel Wildlife Sanctuary a gain in area is observed. A gain in habitat can be seen in the north part in Talere, Rajapur, Sangameshwar, Phansad Wildlife Sanctuary and kihim.

# CHAPETR 5

# DISCUSSION

Climate change is impacting each and every sector**.** Several species have gone extinct due to the devastation nature has endured. Many more are on the verge of extinction. Several intolerant species have disappeared or become extinct as the habitat is drastically altered by severe climatic events. Others have adapted their habitats to more suitable spaces. Changes in avian distribution are most commonly seen due to their sensitivity to small climatic shifts and their ability to migrate. There are numerous studies conducted on various species distribution changes under changing climate scenario. Most results of such studies suggest either a range shift of the species as climate conditions of the future changes or great decline in the distribution of species. These changes are results of how the temperature, precipitation and other variables over the suitable area for the species.

Malabar Grey Hornbill (*Ocyceros griseus)* is an endemic avian species seen in the Western Ghats region of India.The present study examines the current distribution patterns of the Malabar Grey Hornbill based on climatic variables and other physical variables and also the distribution of the Malabar Grey Hornbill is being projected for the year 2050 under four Representative Concentration Pathways (RCP).

MaxEnt version 3.4.4 software was used to study the distributional changes of the Malabar Grey hornbill by relating the presence data points to the climatic conditions prevailing there. The study used the occurrence data points of the Malabar Grey Hornbill from 1964 to 2020 and climate data from CHELSA for current conditions. For the study, the occurrence points were thinned for 1 $km^2$. Climate was predicted by using the models BSS CSM1.1, MIROC5 and Mohc HadGEM 2 ES of 30 second resolution under four different Representative Concentration Pathways (RCPs). For determining the distribution of Malabar Grey Hornbill using MaxEnt, cross validate method was used with model features LQ (Linear, Quadratic) with regularization multiplier 0.5. TSS and AUC were the methods used for validating the performance of the model.

The study shows that the current distribution of Malabar Grey Hornbill depends mainly on eight variables including EVI and seven variables without EVI. From the analysis of Table.2 when including EVI, it has the highest percentage contribution of 44.4% followed by Mean Diurnal Range (bio2) of 31.4%, Mean Temperature of Warmest Quarter (bio10) of 13.7%, Precipitation of Coldest Quarter (bio19) of 5% and so on. And in the case without EVI in Table.3, Mean Diurnal Range (bio2) of 54.8% and Mean Temperature of Warmest Quarter (bio10) of 18.8% show more importance in percentage contribution to the distribution of species. But these percentage contributions are heuristically defined. They will differ when the path used to get the same solution changes according to different algorithms. The determination of permutation importance (Table.2 and Table.3) is path independent and it depends only on the final MaxEnt model. So it is more preferable for estimating the contribution of each variable. So in Table.2 when EVI is considered the permutation importance was highest for Mean Temperature of Warmest Quarter (bio10) 65.8% followed by Mean Temperature of Coldest Quarter (bio11) of 24.3%. Then in the case where EVI was not used (Table.3), the Mean Temperature of Warmest Quarter (bio10) 64.8% followed by Mean Temperature of Coldest Quarter (bio11) of 27.1% had the highest importance again. In both cases the slope showed no importance at all. By conducting analysis of the variables contributing to the distribution of Malabar Grey Hornbill, it is observed that the temperature related factors contribute more when compared to precipitation related factors. The topographical factor slopes contribution is only seen in the jackife test.

Models prepared using the optimized variables under four different Representative Concentration Pathways (RCP) ie: RCP2.6, RCP4.5, RCP6 and RCP8.5 gave the prediction for future distribution of the Malabar Grey Hornbill for the year 2050. Under RCP 2.6 the suitable habitat for Malabar Grey Hornbill is spreading towards North, Southern end of India, South-Western coastal areas and a small gain near Chinnar Wildlife Sanctuary Forest Reserve area. The loss of habitat is largely seen in the Eastern side of Western Ghats and in the Palakkad. Small loss is also seen in Idukki and Southern end of India. The area of habitat loss, habitat gain and no change in area under RCP 2.6 accounts for 25,180 $km^2$, 17,174 $km^2$ and 10,02,782 $km^2$ respectively. Under RCP 4.5, area of habitat loss, habitat gain and no change in area accounts for 27,592 $km^2$, 164,00$km^2$ and 10,01,144 $km^2$ respectively. In RCP 4.5 decrease of habitat loss is higher than the habitat gain. The habitat suitability under 4.5 has shrunken compared to RCP 2.6 by 774 $km^2$. For RCP 6, area of habitat loss, habitat gain and no change in area were 26,168 $km^2$, 16,054 $km^2$ and 10,02,914 $km^2$ and it shows reduction in the area lost when compared to RCP 4.5 by 1,424 $km^2$. RCP 8.5 being the highest emission scenario showed great increase in habitat loss and a decrease in suitable area. For RCP 8.5 area of habitat loss, habitat gain and no change in area accounts for 44,494 $km^2$, 11,454 $km^2$ and 989,188 $km^2$ and this scenario shows the largest loss of habitat. The area lost under RCP 8.5 is almost double as compared to RCP 2.6. There is an increase in loss of habitat from RCP 2.6 to RCP 4.5, RCP 6 and RCP 8.5 of about 2,412 $km^2$, 988 $km^2$ and 19,314$km^2$.

According to the IUCN red list of threatened species Malabar Grey Hornbill is showing a decreasing trend in population and the result from our study shows a conclusion that Malabar Grey Hornbill population declining under various scenarios. These results suggest that different conservation strategies should be undertaken for the protection and conservation of Malabar Grey Hornbill.

# CHAPTER 6

# SUMMARY

Climate change can affect biodiversity and ecosystems in a variety of ways. Several studies have been undertaken to study the effects of climate change on both plant and animal species and it revealed the changes occurring in the phenology, distribution and abundance of species. Birds are considered as an important bio indicator, which reflect the changes happening in their environment. These changes can affect the bird distribution and it is the field where predictive modelling can be applied. The results obtained here can be used especially in the conservation practices, where the potential places of occurrences can be identified and measures can be taken to protect them in the changed habitat.

The goal of this study was to find out what environmental or climatic factors influence the distribution of Malabar Grey Hornbill 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. For this study I used the occurrence data on the Malabar Grey Hornbill from eBird and the current climatic data from CHELSA as bioclimatic layers. The correlation and probability was calculated for current distribution of the Malabar Grey Hornbill using MaxEnt software using Maximum Entropy method. Using the results obtained from these, future prediction was made. In determining the distribution of Malabar Grey Hornbill using MaxEnt, cross validate method was used with model features LQ (Linear, Quadratic) with regularization multiplier 0.5. The variable which showed highest percentage contribution in the construction of model for the distribution of Malabar Grey Hornbill was Mean Diurnal Range (bio2). Permutation importance was higher for Mean

Temperature of Warmest Quarter (10) which can be useful for examining or understanding how the environmental variable is affecting the species seasonal distribution. The habitat suitability for Malabar Grey Hornbill as higher in the least emission scenario which is RCP 2.6 and the lowest in the high emission scenario i.e., RCP 8.5.The area of habitat loss under RCP 2.6 accounts for 25,180 $km^2$, under RCP 4.5 loss accounts for 27,592 $km^2$, under RCP 6 habitat loss accounts for 26,168 $km^2$ and finally for RCP 8.5 area of habitat loss accounts for 44,494 $km^2$.

The climate change will negatively impact the Western Ghats endemic bird species, Malabar Grey Hornbill, as it would be losing close to 23.23% under RCP 2.6, 25.44%under RCP 4.5, 24.12% under RCP 6 and 41.02% under RCP 8.5 scenarios of its suitable habitat by 2050. So we can clearly say that the Malabar Grey Hornbill will be experiencing a wide range of habitat loss in the future.

# CHAPTER 7

# REFERENCES


Acharya, B. K., and B. Chettri. 2012. Effect of climate change on Birds, Herpetofauna and Butterflies in Sikkim Himalaya: A preliminary investigation. In: M. L. Arrawatia and S. Tambe, (eds), Climate Change in Sikkim Patterns, Impacts and initiatives, Information and Public Relations Department, Government of Sikkim, Gangtok, pp. 141-160.

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

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

Ali, S. and S. D. Ripley. 1987. Compact book of the birds of India, Pakistan together with those of Bangladesh, Nepal, Bhutan and Sri Lanka ($2^{nd}$ Ed.). Oxford University Press, New Delhi. 737 p.

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

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 Guisan, A. 2006. Five (or so) challenges for species distribution modelling. *J. Biogeogr*. 33(10):1677-1688.

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

Araújo, M. B., Alagador, D., Cabeza, M., Nogués-Bravo, D. and Thuiller, W. 2011. Climate change threatens European conservation areas. *Ecol. Lett.* 14(5):484492.

Araujo, 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. Change Biol*. 10: 1618-1626.

Araújo, M. B., Pearson, R. G., Thuiller, W. and Erhard, M. 2005. Validation of species– climate impact models under climate change. *Glob. Chang. Biol*. 11(9):15041513.

Ashcroft, M. B., French, K. O. and Chisholm, L. A. 2011. An evaluation of environmental factors affecting species distributions. *Ecol. Modell*. 222(3):524531.

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.

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.

Beale, C. M., Burfield, I. J., Sim, I. M., Rebecca, G. W., Pearce-Higgins, J. W. and Grant, M.C. 2006. Climate change may account for the decline in British ring ouzels Turdus torquatus. *J. Anima. Ecol*. 75(3):826-835.

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

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

Bellard, C., Thuiller, W., Leroy, B., Genovesi, P., Bakkenes, M. and Courchamp, F. 2013. Will climate change promote future invasions? *Glob. Change Biol.* 19:3740-3748.

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.

Bickford, D., Howard, S. D., Ng, D. J. J. and Sheridan, J. A. 2010. Impacts of climate change on the amphibians and reptiles of Southeast Asia. *Biodivers. Conserv.* 19:1043-1062.

Birdlife International. 2015. One in eight of all species is threatened with global extinction. Presented as part of the BirdLife State of the world's birds website.

Blois, J. L., Zarnetske, P. L., Fitzpatrick, M. C, Finnegan, S. 2013. Climate change and the past, present, and future of biotic interactions. *Science*. 341:499–504.

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.

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.

Brook, B.W., Sodhi, N.S. and Bradshaw, C.J.A. 2008. Synergies among extinction drivers under global change. *Trends Ecol. Evol.* 23:453-460.

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

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.

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

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.

Byers, E., Gidden, M., Leclère, D., Balkovic, J., Burek, P., Ebi, K., Greve, P., Grey, D., Havlik, P., Hillers, A., Johnson, N., Kahil, T., Krey, V., Langan, S., Nakicenovic, N., Novak, R., Obersteiner, M., Pachauri, S., Palazzo, A., Parkinson, S., Rao, N., Rogelj, J., Satoh, Y., Wada, Y., Willaarts, B. and Riahi, K., 2018. Global exposure and vulnerability to multi-sector development and climate change hotspots. *Environ. Res. Lett.* 13(5):055012.

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.

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):119-142.

Chevin, L. M., Lande, R. and Mace, G. M. 2010. Adaptation, Plasticity, and Extinction in a Changing Environment: Towards a Predictive Theory. *Plos Biology*. 8.

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.

Conrad, K. F., Warren, M. S., Fox, R., Parsons, M. S. and Woiwod, I.P. 2006. Rapid declines of common, widespread British moths provide evidence of an insect biodiversity crisis. *Biol. Conserv.* 132(3):279-291.

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

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

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.

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

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. and Leathwick, J. R. 2009. Conservation prioritization using species distribution models. Spatial Conservation Prioritization: Quantitative Methods ans Computational Tools (eds A. Moilanen, K.A. Wilson & H.P. Possingham), pp. 70-93. Oxford University Press, Oxford.

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.

Fasola, M., Rubolini, D., Merli, E., Boncompagni, E. and Bressan, U. 2010. Long-term trends of heron and egret populations in Italy, and the effects of climate, humaninduced mortality, and habitat on population dynamics. *Popul. Ecol*. 52(1):5972.

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., Watson, G., Pearce, J. and Drielsma, M. 2002a. 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.

Foden, W., Butchart, S., Stuart, S., Vié, J., Akçakaya, H., Angulo, A., DeVantier, L., Gutsche, A., Turak, E., Cao, L., Donner, S., Katariya, V., Bernard, R., Holland, R., Hughes, A., O'Hanlon, S., Garnett, S., Şekercioğlu, Ç. and Mace, G., 2013. Identifying the World's Most Climate Change Vulnerable Species: A Systematic Trait-Based Assessment of all Birds, Amphibians and Corals. *PloS one*. 8(6):e65427.

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.

Fuller, R. J., Smith, K. W., Grice, P. V., Currie, F. A. and Quine, C. P. 2007. Habitat change and woodland birds in Britain: implications for management and future research. *Ibis* 149(s2):261-268.

Garcia, R. A., Cabeza, M., Rahbek, C. and Araújo, M. B. 2014. Multiple Dimensions of Climate Change and Their Implications for Biodiversity. *Science.* 344(6183).

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.

Gilman, S. E., Urban, M. C., Tewksbury, J., Gilchrist, G. W. and Holt, R. D. 2010. A framework for community interactions under climate change. Trends Ecol. Evol. 25: 325-331.

Gimeno, T. E., Pías, B., Lemos-Filho, J. P. and Valladares, F. 2009. Plasticity and stress tolerance override local adaptation in the responses of Mediterranean holm oak seedlings to drought and cold. *Tree Physiol*. 29:87-98.

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.

Gopalalkrishnan. R., Jayaraman. M., Bala. G., and Ravindranath. N. H. 2011. Climate change and Indian forests. *Curr. Sci.* 101(3):348–355.

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*. 103(3):632-636.

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

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., Graham, C. H., Elith, J. and Huettmann, F. 2007. Sensitivity of predictive species distribution models to change in grain size. *Divers. Distrib*. 13(3):332340.

Guisan, A., Petitpierre, B., Broennimann, O., Daehler, C. and Kueffer, C. 2013. Unifying niche shift studies: insights from biological invasions. *Trends Ecol. Evol*. 29: 260-269.

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.

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.

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):8385.

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.

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.

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.

Hickling, R., Roy, D. B., Hill, J. K., Fox, R. and Thomas, C. D. 2006. The distributions of a wide range of taxonomic groups are expanding polewards. *Glob. Chang. Biol.* 12(3):450-455.

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.

Hill, M. and Preston, C. 2015. Disappearance of boreal plants in southern Britain: habitat loss or climate change? *Biol. J. Linn. Soc.* 115(3):598-610.

Hirzel, A. H. and Guisan, A. 2002a. Which is the optimal sampling strategy for habitat suitability modelling? *Ecol. Modell*. 157(2):331-341.

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.

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.

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

Intergovernmental Panel on Climate Change (IPCC), 2013. Summary for Policymakers: Climate Change 2013, *The Physical Science Basis*. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. T.F. Stocker, D. Qin, G.K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex & P.M. Midgley, (eds), Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1-30.

IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change R.K. Pachauri and L.A. Meyer, (eds), Geneva, Switzerland, 151p.

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.

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

Joyner, T. A., Lukhnova, L., Pazilov, Y., Temiralyeva, G., Hugh-Jones, M. E., Aikimbayev, A. and Blackburn, J. K. 2010. Modeling the potential distribution of Bacillus anthracis under multiple climate change scenarios for Kazakhstan. *PloS one*. 5(3):e9596.

Jump, A. S. and Penuelas, J. 2005. Running to stand still: adaptation and the response of plants to rapid climate change. *Ecol. Lett.* 8:1010-1020.

Kannan, R. and James, D. A. 2009. Effects of climate change on global biodiversity: a review of key literature. *Trop. Ecol.* 50:31-39.

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

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.K., Patwardhan, S.K., Kulkarni, A., Kamala, K., Rao, K.K. and Jones, R., 2011. Simulated projections for summer monsoon climate over India by a high-resolution regional climate model (PRECIS). *Current Science*, 101(3), pp.312-326.

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):334-345.

Lawler, J., Shafer, S., White, D., Kareiva, P., Maurer, E., Blaustein, A. and Bartlein, P., 2009. Projected climate-induced faunal change in the Western Hemisphere. *Ecol.* 90(3):588-597.

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. and Hortal, J. 2010. The uncertain nature of absences and their importance in species distribution modelling. *Ecography*, 33:103-114.

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.

Mac Nally, R., Bennett, A. F., Thomson, J. R., Radford, J. Q., Unmack, G., Horrocks, G. and Vesk, P. A. 2009. Collapse of an avifauna: climate change appears to exacerbate habitat loss and degradation. *Divers. Distrib*. 15:720-730.

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

MacKenzie, D. I., Nichols, J. D., Lachman, G. B., Droege, S., Andrew Royle, J. and Langtimm, C. A. 2002. Estimating site occupancy rates when detection probabilities are less than one. *Ecol.* 83(8):2248-2255.

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.

Mair, L., Thomas, C. D., Anderson, B. J., Fox, R., Botham, M. and Hill, J. K. 2012. Temporal variation in responses of species to four decades of climate warming. *Glob. Change Biol.* 18:2439-2447.

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.

Mantyka-Pringle, C. S., Visconti, P., Di Marco, M., Martin, T. G., Rondinini, C. and Rhodes, J. R. 2015. Climate change modifies risk of global biodiversity loss due to land-cover change. *Biol. Conserv*. 187:103-111.

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):235247.

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.

Menzel, A., Sparks, T. H., Estrella, N., Koch, E., Aasa, A., Ahas, R., Alm-Kubler, K., Bissolli, P., Braslavska, O., Briede, A., Chmielewski, F. M., Crepinsek, Z., Curnel, Y., Dahl, A., Defila, C., Donnelly, A., Filella, Y., Jatcza, K., Mage, F., Mestre, A., Nordli, O., Penuelas, J., Pirinen, P., Remisova, V., Scheifinger, H., Striz, M., Susnik, A., Van Vliet, A.J.H., Wielgolaski, F.E., Zach, S. & Zust, A. 2006. European phenological response to climate change matches the warming pattern. *Glob. Change Biol*. 12: 1969-1976.

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.

Mudappa, D .2000.Breeding biology of the Malabar Grey Hornbill (Ocyceros griseus) in southern Western Ghats, India. *J. Bombay Nat. Hist. Soc*. 97 (1): 15–24.

Mudappa, D. and Raman, T. R. S. 2009. A conservation status survey of hornbills (Bucerotidae) in the Western Ghats, India. *Indian Birds*, 5: 90–102

Murray, K. and Conner, M. M. 2009. Methods to quantify variable importance: implications for the analysis of noisy ecological data. *Ecol*. 90(2):348-355.

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.

Neilson, R. P., Pitelka, L. F., Solomon, A. M., Nathan, R., Midgley, G. F., Fragoso, J. M. V., Lischke, H. and Thompson, K. 2005. Forecasting regional to global plant migration in response to climate change. *BioScience*, 55:749-759.

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

Nogués-Bravo, D., Araújo, M., Errea, M. and Martínez-Rica, J., 2007. Exposure of global mountain systems to climate warming during the 21st Century. *Glob. Environ. Change*. 17(3-4):420-428.

Ockendon, N., Baker, D.J., Carr, J.A., White, E.C., Almond, R.E.A., Amano, T., Bertram, E., Bradbury, R.B., Bradley, C., Butchart, S.H.M., Doswald, N., Foden, W., Gill, D.J.C., Green, R.E., Sutherland, W.J., Tanner, E.V.J. & Pearce-Higgins, J.W. (2014) Mechanisms underpinning climatic impacts on natural populations: altered species interactions are more important than direct effects. *Glob. Change Biol*. 20: 2221-2229.

Orme, C. D. L., Davies, R. G., Olson, V. A., Thomas, G. H., Ding, T. S., Rasmussen, P. C., Ridgely, R. S., Stattersfield, A. J., Bennett, P. M., Owens, I., Blackburn, T. M. and Gaston, K. J. (2006) Global patterns of geographic range size in birds. PLoS Biol. 4:1276-1283.

Pacifici, M., Foden, W. B., Visconti, P., Watson, J. F. M., Butchart, S. H. M., Kovacs, K. M., Scheffers, B. R., Hole, D. G., Martin, T. G., Akcakaya, H. R., Corlett, R. T., Huntley, B., Bickford, D., Carr, J. A., Hoffmann, A. A., Midgley, G. F., Pearce-Kelly, P., Pearson, R. G., Williams, S. E., Willis, S. G., Young, B.

and Rondinini, C. 2015. Assessing species vulnerability to climate change. *Nat. clim.change*. 5:215-225.

Palmer, G., Hill, J. K., Brereton, T. M., Brooks, D. R., Chapman, J. W., Fox, R., Oliver, T. H. and Thomas, C. D. 2015. Individualistic sensitivities and exposure to climate change explain variation in species' distribution and abundance changes. *Sci. Adv*. 1.

Parmesan, C. and Yohe, G. 2003. A globally coherent fingerprint of climate change impacts across natural systems. *Nature*, 421:37-42.

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

Pearce-Higgins, J. W. and Green, R. E. 2014. Birds and climate change: impacts and conservation responses. Cambridge University Press, Cambridge.

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.

Pereira, H.M., Leadley, P.W., Proença, V., Alkemade, R., Scharlemann, J.P.W., Fernandez-Manjarrés, J.F., Araújo, M.B., Balvanera, P., Biggs, R., Cheung, W.W.L., Chini, L., Cooper, H.D., Gilman, E.L., Guénette, S., Hurtt, G.C., Huntington, H.P., Mace, G.M., Oberdorff, T., Revenga, C., Rodrigues, P., Scholes, R.J., Sumaila, U.R. and Walpole, M. 2010. Scenarios for Global Biodiversity in the 21st Century. *Science*. 330:1496-1501.

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., 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. 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.

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., 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.

Phillimore, A. B., Hadfield, J. D., Jones, O. R. and Smithers, R. J. 2010. Differences in spawning date between populations of common frog reveal local adaptation. *Proc. Natl. Acad. Sci. USA*. 107:8292-8297.

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. 655662.

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.

Pounds, J. A., Bustamante, M. R., Coloma, L. A., Consuegra, J. A., Fogden, M. P. L., Foster, P. N., La Marca, E., Masters, K. L., Merino-Veteri, A., Puschendorf, R., Ron, S. R., Sanchez-Azofeifa, G. A., Still, C. J. and Young, B. E. 2006. Widespread amphibian extinctions from epidemic disease driven by global warming. *Nature*. 439(7073):161-167.

Pramanik M, Paudel U, Mondal B, Chakraborti S, Deb P. 2018. Predicting climate change impacts on the distribution of the threatened Garcinia indica in the Western Ghats, India. *Clim. Risk Manag*. 19:94–105.

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. *Ecol. Eng*. 89:14-23.

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.

Rahbek, C., Gotelli, N. J., Colwell, R. K., Entsminger, G. L., Rangel, T. F. and Graves, G. R. 2007. Predicting continental-scale patterns of bird species richness with spatially explicit models. *Proc. Biol. Sci*. 274:165-174.

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

Rapacciuolo, G., Maher, S. P., Schneider, A. C., Hammond, T. T., Jabis, M. D., Walsh, R. E., Iknayan, K. J., Walden, G. K., Oldfather, M. F., Ackerly, D. D. and Beissinger, S. R. 2014. Beyond a warming fingerprint: individualistic biogeographic responses to heterogeneous climate change in California. *Glob. Change Biol*. 20:2841-2855.

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

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

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

Revadekar, J. V., Varikoden, H., Murumkar. P. K., and Ahmed, S. A. 2018. Latitudinal variation in summer monsoon rainfall over Western Ghat of India and its association with global sea surface temperatures. *Sci. Total. Environ*. 613:88–97.

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

Robinson, R. A., Baillie, S. R. and Crick, H. Q., 2007. Weather-dependent survival: implications of climate change for passerine population processes. *Ibis*. 149(2):357-364.

Robinson, W. D., Bowlin, M. S., Bisson, I., Shamoun-Baranes, J., Thorup, K., Diehl, R. H., Kunz, T. H., Mabey, S. and Winkler, D. W. 2010. Integrating concepts and technologies to advance the study of bird migration. *Front. Ecol. Environ*. 8:354-361.

Root, T. L., Price, J. T., Hall, K. R., Schneider, S. H., Rosenzweig, C. and Pounds, J. A. 2003. Fingerprints of global warming on wild animals and plants. *Nature*, 421: 57-60.

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

Rowe, R. J and Terry, R. C. 2014. Small mammal responses to environmental change: integrating past and present dynamics. *J Mammal*.95:1157–1174.

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

Sala, O. E., Chapin, F. S., Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., Huber-Sanwald, E., Huenneke, L. F., Jackson, R. B., Kinzig, A., Leemans, R., Lodge, D. M., Mooney, H. A., Oesterheld, M., Poff, N. L., Sykes, M. T., Walker, B. H., Walker, M. and Wall, D. H. 2000. Biodiversity - Global biodiversity scenarios for the year 2100. *Science*. 287:1770-1774.

Schloss, C. A., Nuñez, T. A. and Lawler, J. J. 2012. Dispersal will limit ability of mammals to track climate change in the Western Hemisphere. *Proc. Natl. Acad. Sci*. 109:8606-8611.

Schimei, D. S., W. J. Parton, T. G. F. Kittel, D. S. Ojima, and C. V. Cole. 1990. Grassland biogeochemistry: Links to atmospheric processes. *Clim. Change* 17:13-25.

Sekercioğlu, C. H., Primack, R. B. and Wormworth, J. 2012. The effects of climate change on tropical birds. *Biol. Conserv.* 148:1-18.

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).

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

Sony, R. K., Sen, S., Kumar, S., Sen, M., Jayahari, K. M. Niche models inform the effects of climate change on the endangered Nilgiri Tahr (*Nilgiritragus hylocrius*) populations in the southern Western Ghats, India. 2018. *Ecol Eng*. 120: 355–363.

Souza, T., Lorini, M., Alves, M., Cordeiro, P. and Vale, M. 2011. Redistribution of Threatened and Endemic Atlantic Forest Birds Under Climate Change. *Natureza & Conservação*. 9(2):214-218.

Stankowski, P. A. and Parker, W. H. 2010. Species distribution modelling: Does one size fit all? A phytogeographic analysis of Salix in Ontario. *Ecol. Modell*. 221(13):1655-1664.

Stockwell, D. and Peters, D. 1999. The GARP modelling system: problems and solutions to automated spatial prediction. *Int. J. Geogr. Inform. Sci*. 13:143158.

Storch, D., Davies, R. G., Zajícek, S., Orme, C. D., Olson, V., Thomas, G. H., Ding, T. S., Rasmussen, P. C., Ridgely, R. S., Bennett, P. M., Blackburn, T. M., Owens, I. P. and Gaston, K. J. 2006. Energy, range dynamics and global species richness patterns: reconciling mid-domain effects and environmental determinants of avian diversity. *Ecol. Lett*. 9:1308-1320.

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

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

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):242251.

Szabo, J. K., Khwaja, N., Garnett, S. T. and Butchart, S. H. M. 2012. Global Patterns and Drivers of Avian Extinctions at the Species and Subspecies Level. *PLoS One*, 7.

Thaxter, C. B., Joys, A. C., Gregory, R. D., Baillie, S. R. and Noble, D. G. 2010. Hypotheses to explain patterns of population change among breeding bird species in England. *Biol. Conserv.* 143(9):2006-2019.

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.

Thomas, C. D., Franco, A. M. A. and Hill, J. K. 2006. Range retractions and extinction in the face of climate warming. *Trends Ecol. Evol.* 21:415-416.

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., 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.

Tylianakis, J. M., Didham, R. K., Bascompte, J. and Wardle, D. 2008. Global change and species interactions in terrestrial ecosystems. *Ecol. Lett*. 11:1351–1363.

van Dam, N. M. 2009. How plants cope with biotic interactions. *Plant Biol*. 11:1–5.

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.

Valladares, F., Gianoli, E. and Gomez, J. M. 2007. Ecological limits to plant phenotypic plasticity. *New Phytol*. 176: 749-763.

Walsberg, G. E. 1993. Thermal consequences of diurnal microhabitat selection in a small bird. *Ornis Scandinavica*. 24:174-182.

Walther, G.R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T. J. C., Bairlein, F. 2002. Ecological responses to recent climate change. *Nature.* 416(6879):389–395.

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

Warren, D. L. 2012. In defense of 'niche modeling'. *Trends Ecol. Evol.* 27:497-500.

Warren, R., VanDerWal, J., Price, J., Welbergen, J. A., Atkinson, I., Ramirez-Villegas, J., Osborn, T. J., Jarvis, A., Shoo, L. P., Williams, S. E. and Lowe, J. 2013. Quantifying the benefit of early climate change mitigation in avoiding biodiversity loss. *Nat. Clim. Change*, 3:678-682.

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

Wisz, M. S., Pottier, J., Kissling, W. D., Pellissier, L., Lenoir, J., Damgaard, C. F. et al. 2013. The role of biotic interactions in shaping distributions and realised assemblages of species: implications for species distribution modelling. *Biol. Rev*. 88:15–30.

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

Xu, J., Grumbine, R. E., Shrestha, A., Eriksson, M., Yang, X., Wang, Y. and Wilkes, A. 2009. The Melting Himalayas: Cascading Effects of Climate Change on Water, Biodiversity, and Livelihoods. *Conserv. Biol.* 23(3):520-530.

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

**ABSTRACT**

Climate change has influenced many species and ecosystems. Researchers have given great importance to identifying the factors that influenced species distribution so as to determine the current and future distribution patterns of endangered species and conservation strategies can be implemented. Climate change poses negative impacts on bird species, particularly for those of restricted ecology and distribution range. Avian species are thought to be a bio-indicator of the environment's devastation. Since habitat specialist species are vulnerable to climate change, they could be employed as bio-indicators. This research was based on the spatial and temporal distribution of the Malabar Grey Hornbill in the Western Ghats, which could help determine environmental changes at various locations. MaxEnt was used to map out species distributions and habitat relationships. The distribution of the Malabar Grey Hornbill was modelled using current presence data from the e-Bird data source and 19 bioclimatic factors from CHELSA V. 1.2. The MaxEnt model settings were determined using the ENM Evaluate tool, and the best – performing model was chosen based on the Akaike Information Criterion (AIC) value. It would project the Malabar Grey Hornbill 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 Grey Hornbills actual and anticipated distribution patterns for the year 2050, based on several RCP estimates. The projected model shows a declining geographical distribution of Malabar Grey Hornbill across Western Ghats. Mean Diurnal Range (bio 2) is found to be the most contributing bioclimatic variable in case of percent contribution whereas Mean Temperature of Warmest Quarter (bio10) and Mean Temperature of Coldest Quarter (bio11) showed most permutation importance in the distribution of Malabar Grey Hornbill. Total predicted suitable habitat is the highest under RCP 2.6 and lowest under RCP 8.5. In this projected distribution of the

Malabar Grey Hornbill, the combined effects of precipitation and temperature fluctuation and topographic feature like slope are important. So this study results suggest that for the management of this species, protective measures needs to be taken and climate change models should be considered when planning the management.