MODELLING CLIMATE CHANGE IMPACT ON THE HIGH-ALTITUDE BIRDS OF WESTERN GHATS, INDIA

by

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THESIS

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DEPARTMENT OF WILDLIFE SCIENCE
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DECLARATION

I, hereby declare that this thesis entitled **"MODELLING CLIMATE CHANGE IMPACT ON THE HIGH-ALTITUDE BIRDS OF WESTERN GHATS, INDIA"** is a bonafide record of research work done by me during the course of research and the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar title, of any other University or Society.

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CERTIFICATE

Certified that this thesis entitled **"MODELLING CLIMATE CHANGE IMPACT ON THE HIGH-ALTITUDE BIRDS OF WESTERN GHATS, INDIA"** is a record of research work done independently by Mr Sreekumar, E. 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 him.

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CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF PLATES

LIST OF APPENDICES

1 INTRODUCTION

Climate change is a long-term natural change in the global weather pattern. However, human interference accelerates the natural pace of climate change. The rate of diminishing ice cover, sea-level rise, and increased global temperature provide clear indications of accelerated climate change. The period between 1983 and 2012 is likely the warmest 30-year span of the last 1400 years (IPCC, 2014). Extreme weather events have been observed more frequently since 1950. The temperature rise would exceed more than 2°C by the end of the 21st century under severe climate change projections such as RCP 6.0 and RCP 8.5 (IPCC, 2014). These changes adversely affect the global biodiversity but tend to act over a much longer timescale. Anthropogenic climate change leads to environmental degradation and puts millions of species at risk of extinction (IPBES, 2019). Widespread species extinctions, population decline (Thomas *et al.*, 2004; Malcolm *et al.*, 2006), shift in geographical range, and change in phenology of the species (Thuiller, 2007) are the immediate effects of climate change on biodiversity. The climate warming of 1.5°C to 2°C would lead to losing half of the suitable habitats of 4% to 8% of the world's vertebrates (IPCC, 2018). Therefore, climate change threatens global biodiversity and, ultimately, the structure and functioning of the ecosystem (Walther *et al.*, 2002; Thomas *et al.*, 2004; Walther, 2010).

The mountain ecosystems are the specialised habitats that are more sensitive to climate change as their temperature regime varies in a short range of elevation (Nogués-Bravo *et al.*, 2007). These montane ecosystems are generally known as sky islands due to the unique microclimatic conditions of these high-altitude habitats (McCormack *et al.*, 2009). Hence, these ecosystems could be considered valuable climate change indicators (Rogora *et al.*, 2018). The Western Ghats (WG) is one of the 36 biodiversity hotspots (Myers *et al.*, 2000; CEPF, 2021), situated in southwest India. The WG is also a World Heritage Site since 2012 (UNESCO World Heritage Committee, 2017), and two hill ranges in the WG (Nilgiri and Agasthyamalai Hills) have been recognised as Biosphere Reserves by the United Nations Educational, Scientific and Cultural Organization (UNESCO) (UNESCO, 2012, 2016). The isolated sky islands of the WG exhibits high endemism, with several species restricted to a narrow elevational range (Ricketts *et al.*, 2005). These specialised habitats are now deteriorating due to changing climatic conditions and anthropogenic activities (Robin *et al.*, 2010; Robin and Nandini, 2012; Arasumani *et al.*, 2019).

Several birds are endemic to the WG, including Wayanad Laughingthrush *Ianthocincla delesserti*, Banasura Laughingthrush *Montecincla jerdoni*, Nilgiri Laughingthrush *M. cachinnans*, Palani Laughingthrush *M. fairbanki*, Nilgiri Flycatcher *Eumyias albicaudatus* and Black-and-orange *Flycatcher Ficedula nigrorufa*. It is imperative to understand the climate change effects on these endemic species because of the restricted distribution and specific habitat requirements (Jones *et al.*, 2013). Species distribution models would be a helpful tool to understand these effects. Such models statistically develop the relationship between species occurrence and environmental factors (Root, 1988; Root and Schneider, 1993). The species distribution models also predict a given species' previously unknown suitable habitat by using specific environmental layers and species geographic locations (Allouche *et al.*, 2006; Peterson *et al.*, 2008). Understanding the spatial distribution and habitat preferences of such sensitive species would help prevent them from extinction and, thereby, long-term conservation (Peterson and Robins, 2003).

Thus, this study's primary objective is to determine the environmental and climatic variables that influence the distribution of selected endemic birds of the Western Ghats. In addition, the study also intended to analyse the suitable habitats for these selected endemic birds of the Western Ghats and predicts the future changes in the habitat suitability under different climate change scenarios such as RCP 4.5, RCP 6.0, and RCP 8.5 for the 2050s (2041-2060) by using the Maxent algorithm.

2 REVIEW OF LITERATURE

2.1 BIRDS OF THE WESTERN GHATS

The Western Ghats (WG) includes the world's biodiversity hotspots (Myers *et al.*, 2000). More than 500 birds reported from the WG, and 26 species identified as endemic species to the region (Ramesh *et al.*, 2017; eBird, 2021). The bird diversity is very high in the WG due to the availability of different types of ecosystems. The WG contain high elevated mountains, and that includes many local species, including birds. Due to various environmental and human pressures, many species become threatened. Most of the birds of WG evaluated by International Union for Conservation of Nature (IUCN) and published the threatened status. Ramesh *et al.* (2017) suggested revising IUCN threatened categories of 18 WG endemic species based on species distribution modelling studies.

2.1.1 High altitude birds of the Western Ghats

The Western Ghats consist of high species diversity and endemism. The bird communities distributed in the high-altitude regions adapted to cold temperatures and prefer dense canopy cover. Many high-altitude dependant birds are endemic to the WG (Ramesh *et al.*, 2017; eBird, 2021) and highly threatened due to restricted distribution and anthropogenic activities (Nair, 1991).

Several bird communities highly prefer montane ecosystems like *shola* and evergreen forests. All four endemic Laughingthrushes in the WG (*Montecincla* sp.), such as Banasura Laughingthrush *M. jerdoni*, Nilgiri Laughingthrush *M. cachinnans*, Palani Laughingthrush *M. fairbanki* and Ashambu Laughingthrush *M. meridionalis*, restricted to the different hill regions of the WG and limited to the montane habitats. Banasura Laughingthrush confined to the Brahmagiri Hills of SWG. As the name indicates, Nilgiri Laughingthrush and Palani Laughingthrush only found in Nilgiri and Palani (Anamalai) Hills, respectively. Agasthyamalai Hills are the home for Ashambu Laughingthrush (Robin *et al.*, 2017). Genus

Sholicola includes two species of sholakili, such as Nilgiri Sholakili *Sholicola major* and White-bellied Sholakili *Sholicola albiventris*, usually distributed above 1200m elevation and former distributed in the Nilgiri Hills and later in the Anamalai Hills and further south (Robin *et al.*, 2017). Two of the endemic flycatchers, Black-and-orange Flycatcher *Ficedula nigrorufa* and Nilgiri Flycatcher *Eumyias albicaudatus,* are frequent above 1500m elevation (Khan, 1979; Billlerman *et al.*, 2020). Both the species distributed along with the entire southern WG (south of Goa Gap). Other species like Broad-tailed Grassbird *Schoenicola platyurus* and Nilgiri Pipit *Anthus nilghiriensis* also confined to the high elevation sites of the SWG and having highly fragmented and isolated distributions (Billlerman *et al.*, 2020).

2.2 CLIMATE CHANGE

Since the early 20th century, fossil fuel burning and other human activities leading to the greenhouse gas effect and changes in the earth's climate. Climate change is a long-term change in the average weather patterns that define the earth's local, regional and global climate pattern. The land surface air temperature had risen by twice compared to the preindustrial level and increased the frequency of extreme weather events (IPCC, 2019). Climate warming is already causing impacts on natural and human systems, and many lands and ocean ecosystem services change due to global warming (IPCC, 2018).

Anthropogenic climate change and increased environmental degradation put millions of species at risk of extinction (IPBES, 2019). As per the Intergovernmental Panel for Climate Change's (IPCC) recent report, anthropogenic activities will cause global temperature to rise by 1.2°C between 2030 and 2052 compared to pre-industrial levels (IPCC, 2018). Erratic environmental conditions and widespread extinctions, and declines in species abundances are the significant predicted effects of climate change (Thomas *et al.*, 2004; Malcolm *et al.*, 2006). Therefore, climate change threatens global biodiversity and, ultimately, the structure and functioning of the ecosystem (Walther *et al.*, 2002; Thomas *et al.*, 2004; Walther, 2010).

2.2.1 Representative concentration pathways

The IPCC fifth assessment report (AR5) introduce the Representative Concentration Pathways (RCPs) as the new approach of representing the range of possible radiative forcing scenarios. The RCPs are the pathways showing greenhouse gas (GHG) and aerosol concentrations, together with land-use change, consistent with a set of broad climate outcomes used by the climate modelling community. All pathways are simulating the emission till the end of the 21st century. Due to additional GHG presence in the atmosphere, the heat gets trapped, known as radiative forcing and measured in Watts per square meter (W/m^2).

According to the IPCC future emissions classification, there are four RCPs, each covering 1850 to 2100. The RCPs include a low level (RCP 2.6), two intermediate levels (RCP 4.5 and RCP 6.0) and one very high level (RCP 8.5). The RCP 2.6 is the ambitious pathway, and it shows an early peak in atmospheric CO_2 level then fall due to various CO_2 removal activities. The RCP 8.5 predicted a high CO_2 level in the atmosphere beyond 2100 due to little effort and failure in the CO_2 removal activities. The atmospheric CO_2 equivalent of RCP 2.6 and RCP 8.5 are 490ppm and >1370ppm, respectively. For the RCP 4.5 and RCP 6.0, the CO_2 level is 650ppm and 850ppm, respectively (IPCC, 2014).

2.3 CLIMATE CHANGE AND BIRDS

2.3.1 Birds as indicators of climate change

Bioindicators are the organisms or group of organisms that react to the changes in the environment or any environment stimuli, which can be easily recognisable (Wilson, 1994). Many studies took place on the applicability of birds as bioindicators (Becker, 2003). Weimerskirch *et al.* (2003) analysed the abundance of breeding pairs of different species of marine birds, especially penguins, in the South Atlantic Ocean. The number of individuals of all the species decreases, except King Penguin when the temperature rises. Most of the species, including birds, show some indications of climate change, including the shift in geographic ranges, fluctuations in abundance, changes in the behaviour or physiology and even extinction (Crick, 2004; Bellard *et al.*, 2012; Trautmann, 2018). Because of the birds' response to climate change, they can consider as bio-indicators of climate change. They are also popular among the public and policy makers, which can help us highlight birds as bioindicators (Crick, 2004).

2.3.2 Climate change and physiology of birds

Minor changes in the environmental conditions can alter the physiological needs of the birds. The metabolic rate directly depends on the birds' behaviour, and it may change with the local weather conditions. Significant life events like feeding and breeding may reduce unfavourable weather conditions (Walsberg, 1993). Releasing various types of hormones is a necessary condition for breeding success, and it highly depends on the environmental conditions, especially temperature and humidity (Crick, 2004). Climate change is a global phenomenon with positive and negative effects at the level of large species assemblage. Some studies confirmed that birds show pronounced physiological changes with the ongoing climate change (McKechnie, 2008; McNab, 2009).

2.3.3 Effect of climate change in bird distribution

The responses by the species to climate change was generally by three methods such as movement, adaptation and extinction (Holt, 1990; Melillo *et al.*, 1995). Apart from climatic factors, land-use and habitat change, biotic interactions and evolutionary adaptation also played a role in the species distribution (Huntley *et al.*, 2006; LA Sorte and Frank, 2007; Beale *et al.*, 2008). Temperature and precipitation played a significant role in the range distributions of a species, and climate change may lead to range shifts. Temporal distributional studies of birds also help understand climate change's effect over the century (Hawkins *et al.*, 2003). Many studies gave evidence for the shifting distribution of birds due to climate change (Gregory *et al.*, 2009; Chen *et al.*, 2011). The impacts of climate change on species distribution were significant since it also affected the demographic rates of birds (Pautasso, 2012). Thomas (2010) stated that climate plays a crucial role in shaping the range boundaries of a species. Endothermic birds were affected indirectly by climate change due to its impacts on vegetation in their communities rather than direct effects on physiology (Aragón *et al.*, 2010). Chen *et al.* (2011) argued that most of the shifts in distribution were due to climate warming, and he showed evidence for range shifting towards the pole and upwards by many species. The whole bird community will not change their distributional range due to the climate change effects. Some of the species may gain or lose their current habitat due to the impacts of climate change (Virkkala *et al.*, 2010). Tropical bird species recognized as the most vulnerable species to climate change (La Sorte and Jetz, 2010; Harris *et al.*, 2011).

Various spatial patterns of biodiversity understand by the broad knowledge regarding the geographic distribution of the species (Ricklefs, 2004; Graham *et al.*, 2006). The range distribution studies also help prescribe the conservation aspects and forecast the bird population fluctuations (Ferrier *et al.*, 2002; Funk and Richardson, 2002; Rushton *et al.*, 2004). Indicators of the impact of climate change were in the developing stage, and scientists and policy makers were looking forward to further development to understand the biological consequences of climatic warming (Mace and Baillie, 2007).

2.4 BIRD DIVERSITY AND ELEVATION

Montane ecosystems have varied in the perspective of biological diversity (Lomolino, 2001). Temperature and water availability are the key drivers that predict the elevational diversity patterns of the birds (McCain, 2009). Habitat variables or a combination of habitat and climatic variables can explain the relationship between birds and altitude (Chamberlain *et al.*, 2016). Acharya *et al.* (2011) studied the species richness, density and range size of Himalayan birds using the point count method. They also found that various habitat variables (plant species richness, shrub density and basal area of trees) have a strong relationship with the species richness of Himalaya. Kim *et al.* (2018) studied the impact of climate change and habitat variables on the species richness and density of high-altitude birds of the temperate montane forest of South Korea. They revealed that there exists correlation between bird community, micro-climatic variables and altitudinal ranges. They identified the habitat heterogeneity as the determining factor of species richness.

Some studies showed that mid-altitude has more species richness and density than the other two extremes of low and high altitudes, called the mid-domain effect (Lomolino, 2001; Lee *et al.*, 2004; Acharya *et al.*, 2011; Kim *et al.*, 2018). The mid-domain impact is not a global phenomenon and the primary driver for elevational diversity changes in the birds (McCain, 2009). Navarro (1992) studied the elevational diversity of birds in Sierra de Atoyac, Mexico and found that the species diversity declines when altitude increases. These studies show the importance of elevation in shaping species diversity and distribution.

2.5 SPECIES DISTRIBUTION MODELLING

Species distribution models (SDM) use species occurrence data with environmental data to define the niche of a given species and project that niche geographically. Interest in the SDM of plants and animals has grown in the last two decades (Guisan and Thuiller, 2005). Root (1988) and Root and Schneider (1993) found a strong statistical correlation between species distribution and environmental factors. (Root, 1988) studied the relationship between the distribution of wintering birds of North America and six environmental factors and observed that precipitation and vegetation have a reasonable correlation with bird distribution. (Gates *et al.*, 1994) used multivariate regression equations to model species distribution with land use and climatic variables. The models showed a strong correlation between bird distribution and climatic variables, and temperature is the deciding factor of redistributions of the bird population.

Many studies used SDM as a tool to draw the new distribution as well as to predict the future distribution of animal or plant species. SDM may help develop a future conservation plan for the species by predicting future distributions and extinction risk. Data quality, as well as data quantity, are crucial for doing SDMs. Jointly modelling two sets of data with high quality (but low quantity) and high quantity (but low quality) may help to improve the model (Pacifici *et al.*, 2017).

Extinction risk was studied in Australian wet tropics birds using the abundance data and revealed that 74% of the bird species become threatened within 100 years (Shoo et al., 2005). Sohl (2014) relate the climate data and land use land cover (LULC) data with the current and future distribution of 50 North American bird species. The study helps to understand that the future distribution of birds much related to projected climate change than the projected LULC pattern. Future distribution of Band-tailed Pigeon was studied and revealed 35% of suitable habitat loss by 2070 and 45% by 2100 using SDM (Coxen *et al.*, 2017). A study carried out on the birds of the Rocky Mountains and Great Plains of the United States and Canada. It studied the topographical effects on bird diversity due to climate change. The study revealed that future climate warming would reduce (about 35%) the favourable habitat of bird species in the Great Plains with the help of SDM by using presence-only data (Peterson, 2003). SDMs can give the future distribution of the species regarding future climate change. They can improve the results by applying various methodologies, choice of modelling technique, model validation, the effect of non-climatic factors and so on (Heikkinen *et al.*, 2006).

2.5.1 Types of species distribution models

2.5.1.1 Generalised Dissimilarity Models (GDM)

A generalised dissimilarity model (GDM) can be used to understand the spatial turnover in a community between pairs of sites as a function of environmental differences. Kernel regression algorithm can be used in GDM to know the probability of occurrence of a species (Lowe, 1995). Combining elements of matrix regression and generalized linear modelling allows the user to model non-linear responses of the environment, and that help to capture the ecologically realistic relationships between dissimilarity and ecological distance (Ferrier, 2002; Ferrier *et al.*, 2002).

2.5.1.2 Generalised Linear Model and Generalised Additive Models

Generalised Linear Model (GLM) used non-parametric and non-linear functions, whereas Generalised Additive Models (GAM) used parametric and combinations of linear, quadratic or cubic terms. GAM is considered more advanced than GLM in drawing complex ecological response shapes (Yee and Mitchell, 1991). Because of the solid statistical foundation and realistic ecological modelling, GLM and GAM widely used in SDM (Austin, 2002).

2.5.1.3 Multivariate Adaptive Regression Splines (MARS)

Multivariate Adaptive Regression Splines (MARS) can use for fitting non-linear responses. It used piece wise linear fits rather than smooth functions. It was straightforward to use in GIS applications to make prediction maps faster to implement than GAMs. It could analyse community data (MARS-COMM), which helped relate the variation in the occurrence of species to the environmental predictors in one analysis and later estimate the individual model coefficients for each species simultaneously (Leathwick *et al.*, 2005).

2.5.1.4 Genetic Algorithm for Rule-set Prediction (GARP)

For the approximation of species fundamental ecological niches, several approaches had been used, such as BIOCLIM (Nix, 1986), multiple logistic regression (Austin *et al.*, 1990) and Genetic Algorithm for Rule-set Prediction (GARP). The heterogeneous rules defined the GARP and the polyhedrons in the ecological niche spaces assumed to be liveable by a particular species. The model quality was assessed by dividing the occurrence points into 'training data' used for training and 'test data' used for testing models (Fielding and John, 1997). GARP had to have two versions: DK-GARP used widely for the modelling data from natural history collections and OM-GARP, a new open modeller implementation, where both these used a genetic algorithm for selecting a set of rules for adaptations of regression and range specifications, hence predicted the best species distribution (Stockwell, 1999). GARP is a machine-learning approach and also linked the occurrence records to the environment variables using envelope (variables bounded to lower and upper bounds), atomic (values assigned to each variable) and logistic regression rules. The algorithm used pseudo-absence localities since the model works on presence-absence data (Stockwell, 1999). The GARP included BIOCLIM and logistic multiple regression properties and artificial intelligence (Stockwell and Noble, 1992; Stockwell, 1999). The extensive testing done on the GARP model showed a high predictive ability for species geographic distributions (Peterson and Cohoon, 1999; Peterson *et al.*, 2001).

2.5.1.5 Maximum Entropy Modelling (Maxent)

Maxent uses maximum entropy distribution, which was subjected to the constraint that the expected value of each environment variable (interactions) in the estimated distribution matched its empirical average for counting the species distribution (Phillips *et al.*, 2006). Using the background locations and data derived constraints approximated the most uniform distribution (Phillips *et al.*, 2004, 2006). The MaxEnt had done better than other modelling techniques even though it needs presence-only occurrence data (Elith *et al.*, 2006; Hernandez *et al.*, 2006; Phillips *et al.*, 2006). MaxEnt achieved a higher success rate, and it marked the differences even at low sample sizes compared to other algorithms (Pearson *et al.*, 2007). MaxEnt models predicted a broader area of suitable conditions, but the artificial reduction of sample size would negatively impact the model performance (Pearson *et al.*, 2007).

Maxent had used to predict the species distribution patterns of Geckos *Uroplatus* spp. (Pearson *et al.*, 2007). To find the denning sites of American Black Bear *Ursus americanus* (Baldwin and Bender, 2008), Maxent was helpful. DeMatteo and Loiselle (2008) used Maxent to appraise the excellence of protection of the Bush Dog *Speothos venaticus*. The seasonal distribution changes of the Little Bustard (*Tetrax tetrax*) identified by Maxent's help (Suárez-Seoane *et al.*, 2008). Maxent can precisely build the model even though there are a smaller number of locations. It was an advantageous feature since frequently there is a deficiency of dependable sites obtainable for mapping the spreading of species (Baldwin, 2009).

2.5.1.6 Boosted Regression Trees (BRT)

BRT used a combination of algorithm such as regression-tree algorithm (boosting algorithm) to construct an ensemble of trees. The use of regression trees helped in selecting relevant variables, and it could model interactions. It was upon the weighted versions of the data set where the observation was poorly fitted in the preceding model and was accounted for by adjusting the weights (Elith *et al.*, 2006).

2.5.2 Basic steps in species distribution modelling

Different steps included in the SDM of a given species. Current occurrence data of species of interest required in the form of geographical coordinates, and that should well represent the range of the species of interest (Peterson *et al.*, 1998, 2002). Another important consideration for a SDM is the selection of background. The background should contain the entire distribution of the species and limit the boundaries by considering dispersal capacity of the species. Scientists already developed the environmental and climate variables, and that can be used to build the SDM. The above inputs help to develop SDM by using appropriate modelling method or algorithm. The accuracy of the model that dipects the current distribution can be verified with the already known distribution of the species under consideration (Guisan and Zimmermann, 2000; Kobler and Adamic, 2000) and also with the several other indices. A well-fitted model can help to identify the key environmental variables that determine the distribution of the species. We can identify the suitable ecological niche or probability of species presence through species suitability models by analysing species' response to abiotic environmental factors (Soberon and Peterson, 2005; Elith *et al.*, 2011).

2.5.3 Accuracy of species distribution models

The better utility of species distribution models requires knowledge about the accuracy of the model. Two aspects should consider when we discuss model accuracy; discrimination capacity and reliability. The power of the model to differentiate presences from absences is that discrimination capacity and reliability refer to the predicted probabilities' capability to reflect the observed proportion of sites occupied by the subject species (Pearce and Ferrier, 2000). Generally, the discrimination capacity is important than reliability (Ash and Shwartz, 1999).

In ecology, generally using two groups of methods for measuring accuracy; threshold-dependent and threshold-independent, based on indices. Threshold-dependent methods used for binary predictions and threshold-independent for continuous predictions. Continuous predictions transformed to binary ones if a specific threshold is employed.

2.5.3.1 Threshold-dependent indices

Many threshold-dependent indices are using to calculate the accuracy of the models. Conditional probabilities like sensitivity and specificity used in many disciplines, including SDM. The former is the probability that the model correctly predicts an observation of a species at a site. The latter is the probability that a known absence site correctly predicted. Positive predict value (PPV) and negative predictive value (NPV) are the other indices conditional on the predictive pattern. PPV is the probability that a site predicted as present is present, and NPV is the probability that a site expected as absent is absent. Although these two indices widely used in medical diagnostic tests, they rarely applied to SDM. The pair sensitivity and specificity and the pair PPV and NPV complement each other (Hand, 2001).

Researchers generally prefer a single global measure for calculating the accuracy of models. Overall accuracy (OA) is one of the preferred measures in different fields, including ecology (Fielding and John, 1997), which is the probability that a site, either presence or absence correctly predicted. Another widely used measure is Cohen's kappa (Cohen, 1960). This index helps to overcome the problem of over estimating accuracy by OA. It measures the extent to which the agreement between observed and predicted is higher than that expected by chance alone. It used in meteorology, known as Heidke's skill score (Stephenson, 2000).

The odds ratio is another index mainly used in epidemiological studies (Glas *et al.*, 2003), which defined as the ratio of the odds of positivity in the presences relative to the odds of positivity in the absences, or the ratio of the odds of positivity in predicted presences relative to the odds of positivity in predicted absences. This index has also been introduced to SDM (Fielding and John, 1997) and has used in a few studies (Manel *et al.*, 2001). Another index is the 'true skill statistic' (TSS). Some people also referred to it as 'Pierce skill score' about its original discovery (Stephenson, 2000). It has been introduced to SDM by Allouche *et al.* (2006). TSS is equivalent to Youden's index J, developed by Youden (1950) and widely used in medical diagnostic tests. It defined as the average of the net prediction success rate for present sites and that for absent sites. It has gained considerable theoretical interest over many years (Böhning *et al.*, 2008), and it is the best available summary measure of model performance in medical diagnostic tests (Biggerstaff, 2000). This index is closely related to the arithmetic mean of sensitivity and specificity.

2.5.3.2 Threshold-independent indices

Many threshold-independent indices are available for measuring the accuracy of different models. One of the popular indices is the 'area under the receiver operating curve' (AUC). It widely used in many fields, including ecology, but it has received some criticism (Lobo *et al.*, 2008). In the context of SDM, the AUC of a model is equivalent to the probability that the model will rank a randomly chosen species presence site higher than a randomly chosen absence site (Pearce and Ferrier, 2000). Some researchers have criticized AUC to give a misleading picture of model performance since it covers parts of the prediction range of no practical use (Briggs and Zaretzki, 2008). Therefore, partial AUC (PAUC) (McClish, 1989) proposed the average sensitivity over a fixed range of the false positive rate. The choice of such "regions" has to make on a case-by-case basis, and the PAUC does not possess a probabilistic interpretation (Lee and Hsiao, 1996).

The maximum overall accuracy and maximum kappa are frequently used in SDM in a threshold-independent way to indicate a model's predictive capacity (Guisan *et al.*, 1998; Liu *et al.*, 2005). Point biserial correlation coefficient also used in SDM (Elith *et al.*, 2006). It is the Pearson product-moment correlation coefficient calculated under the condition that one variable (i.e., the observed species occurrence) is binary and the other (i.e., the predicted probability) is ordinal (Kraemer, 2006).

2.5.4 Selection of background in species distribution modelling

The background is the landscape of interest used to perform the SDM. The background can be suggested based on a problem and defined by the ecologist (Elith *et al.*, 2011). One should be careful about selecting background because it will affect the performance and accuracy of the model (Merow *et al.*, 2013). It will not be suitable to choose a large area as background where species doesn't inhabit (Anderson and Raza, 2010). The landscape of interest can be limited by the geographical barriers or by considering the dispersal ability of the focal species (Elith *et al.*, 2011; Radosavljevic and Anderson, 2014). Species presence area regarded as the subset of the background area.

This study only considering the birds that are endemic to the Western Ghats. Different species distributed in diverse landscapes of the WG. So, the background area would be unique for each species. The species and subspecies distribution of WG depend on geographical and climatic factors. Significant geographical and climatic barriers that limit the distribution of different taxa were studies and identified by Ramachandran *et al.* (2017). They identified six significant breaks from south to north in the WG; Shenkottah Gap, Palakkad Gap, Chaliyar River, Kaveri River, Goa Gap and Narmada River. The Agasthyamalai Hills (Ashambu Hills) situated to the south of the Shenkottah Gap. South of the Palakkad Gap, Anamalai and Pandalam Hills distributed. The Nilgiri Hills spread to the south of Chaliyar River and Brahmagiri Hills situated between Chaliyar River and Goa Gap. Biligirirangana Hills identified as a different landscape, and that connects the WG with the Eastern Ghats. Landscapes of the south of northern Maharashtra and south of Narmada River considered as a separate group from other landscapes of the WG in terms of subspecies dissimilarity indices. Some of the endemic species of the

WG restricted in the high montane *shola* forests. South of the Bhadra WLS, Karnataka identified as the northern limit of the *shola* forest (Robin *et al.*, 2010).

2.5.5 Variables used in species distribution modelling

Species distribution is closely associated with environmental factors. Understanding the ecological niche of a species is very important to deciding the environmental variables used in SDMs. Many variables positively and negatively affect the distribution of a given species (Sexton *et al.*, 2009; Wiens, 2011). Environmental variables are usually chosen based on past predictive performance, known relationship with the species of interest, or a variable selection process (Synes and Osborne, 2011). Variable used in SDMs should have an ecological relationship with the species and allow the model's transferability between regions (Mac Nally, 2000; Elith and Leathwick, 2009; Elith *et al.*, 2011).

Temperature and precipitation are significant predictor variables for most of the species in the world. Bioclimatic predictors are derived from two primary climate data, temperature and precipitation, and represent the seasonal trends pertinent to the physiological constraints of different species (Nix, 1986; Hijmans *et al.*, 2005). Better to use bioclimatic variables instead of standard climatic variables to get useful outputs (Saatchi *et al.*, 2008). Bioclimatic variables may have high multicollinearity problem when it operates for small regions. Multicollinearity may overfit the model, and predictions become meaningless. So, avoiding multicollinearity is a mandatory step in SDM (Zurell *et al.*, 2020). Different statistical methods are there for detecting multicollinearities. Pearson correlation coefficient (*r*-value), Principal Component Analysis (PCA) and Variance Inflation Factor (VIF) are some of the approaches used to deal with the multicollinearity problems.

2.5.6 Occurrence data used in species distribution modelling

The SDM developed by using presence-absence data or presence-only data. The data used for the SDM studies taken from secondary sources like museum or herbarium without knowing the sampling techniques if the primary sources are not available (Graham *et al.*, 2004; Huettmann, 2005). Presence-only data may not be sufficient to develop the excellent performing SDM if not taken appropriate method (Bojorquez-Tapia *et al.*, 1995; Hijmans *et al.*, 2000; Kadmon *et al.*, 2004). The absence of data of a species in a given location may be questionable. The researcher should collect absence data of a species through systematic surveys (Austin and Cunningham, 1981; Cawsey *et al.*, 2002; Hirzel and Guisan, 2002). Including absence data in SDM may cause prediction failures such as false-positive and false-negative (Anderson *et al.*, 2003; Pearson and Dawson, 2003). Most presence-absence data-based models assumed that breeding habitats were saturated (Capen *et al.*, 1986). In presence-only models, pseudo-absence points created by using the respective algorithm in the background area. Using pseudo-absence data gives more reliability than real-absence data because collecting such data could be very difficult or missing species occurrences during surveys (Ferrier *et al.*, 2002; Hirzel *et al.*, 2002; Engler *et al.*, 2004).

Random or spatially stratified portioning of the occurrence data is simple, but if the occurrence data is minimal, then partitioning the data into test and training may be tricky and error-prone (Peterson and Shaw, 2003; Anderson and Martinez-Meyer, 2004). The predictive performance of models may be highly affected when using the small number of occurrence records (Stockwell and Peterson, 2002; Reese *et al.*, 2005). When the occurrence data is minimal (<50 points), the jackknife or leave-one-out approach can be the best replication method. Novel techniques introduced over the last decade exploited only presence data, thus removing the necessity of absence locations (Baldwin, 2009). Techniques such as machine learning and development in statistical disciplines help develop complex responses, even though the data was very noisy. But it doesn't receive any exposure in SDM even though the work was promising (Leathwick *et al.*, 2006; Phillips *et al.*, 2006).

2.5.7 Selection of threshold value for raster classification

The species distribution model outputs provide the probabilities of species presence. But habitat suitability represented as species presence/absence would be better than the usage of probability value. Species presence/absence data would be more beneficial for better conservation and management prescriptions. A proper threshold value derived to classify suitability data into presence/absence data would help correctly interpret model results (Manel *et al.*, 2001). Liu *et al.* (2005) studied 12 threshold approaches, and the sensitivity-specificity sum maximisation approach identified as a promising approach for presence-absence models. The exact threshold approach could be better for a presence-only model like Maxent (Liu *et al.*, 2013).

2.6 CLIMATE CHANGE PREDICTION

The General Circulation Models (GCM) defined as the physical process in the atmosphere (Atmospheric GCM), ocean (Oceanic GCM), cryosphere and land surface. These models are the most advanced tools for simulating the response of the global climate system to increasing greenhouse gas concentrations. Regional Climate Models (RCM) used as a tool to understand the regional or local climate system. Both GCM and RCM are essential tools in climate change-related research works.

Earth System Models (ESM) are more complicated mathematical models that consider the atmospheric CO_2 level, ocean ecology and biogeochemistry and plant ecology and land use patterns compared to GCM. ESM provides the relationship between biological processes and climate. Many organisations and regional government institutions developed ESMs to understand the future climate change and associated impacts on biodiversity. Based on radiating force simulations in the IPCC reports, ESM to become updated periodically.

The Coupled Model Intercomparison Project (CMIP) is a collaborative framework under World Climate Research Programme (WCRP). The programme aims to understand the past, present and future climate based on the changes in radiative forcing (Meehl *et al.*, 2000). They are working for the better development of ESM under different IPCC Representative Concentration Pathways (RCP). Based on the CMIP framed codes, many organisations release the different ESM (e.g., HadGEM2-ES). The CMIP update their model suggestions periodically, and the latest release is CMIP6 (Eyring *et al.*, 2016).

Different ESM is available for understanding the future habitat suitability of any species. It is always better to use multiple ESM for predicting the future habitat suitability of a species. Based on the model-to-model variations, we have to select less overlapped ESM for reducing the bias between different models (Sanderson *et al.*, 2015). The selection of various models for a specific region is tricky, and some of the studies attempted to evaluate the model selection for different areas (McSweeney *et al.*, 2015). Anyway, there is no much clarity on model selection for a specific region.

2.7 SPECIES DISTRIBUTION MODEL STUDIES FROM THE WESTERN GHATS

A few studies on the species distribution modelling get published on the Western Ghats species. Wordley *et al.* (2015) attempted to do the habitat suitability models of ten species of bats in a tea-dominated landscape. Small (100–500 m) scale habitat variables (e.g., percentage tea plantation cover) and distances to habitat features (e.g., distance to water) identified as the most substantial predictor variables of bat occurrence. Most bat species positively correlate with the coffee plantations and negative correction to highly modified tea plantations.

Nilgiri Tahr *Nilgiritragus hylocrius* is an endemic and endangered ungulate in the Western Ghats. Sony *et al.* (2018) simulate the distribution of Nilgiri Tahr based on the ESMs by using the Maxent algorithm. They developed the models based on two IPCC scenarios (RCP 4.5 and RCP 8.5) for three time periods (2030, 2050 and 2080). Their study identified the current potential distributional range of Nilgiri Tahr and 63% of habitat loss predicted under extreme climate change scenarios.

Jose and Nameer (2020) studied the effect of climate change on the distribution of Indian Peafowl in Kerala. They used the Maxent algorithm for identifying current suitable habitat and future change in distribution. The study considered two IPCC scenarios such as RCP 4.5 and RCP 8.5, for the 2050s and 2070s and predicted a 50% expansion of suitable habitat compared to current habitat availability.

Raman *et al.* (2020) developed the Maxent model of Western Ghats endemic Brown Mongoose *Herpestes fuscus*. The outcomes predicted the habitat loss of 20%, 18%, and 55% in RCP 4.5, 6.0, and 8.5, respectively. Isothermality, precipitation of the coldest quarter and elevation are the most influencing factors of species distribution. The study suggests the immediate action on the conservation strategy of the lesser-known animal, the Brown Mongoose.

Yellow-throated Bulbul *Pycnonotus xantholaemus* is an endemic species to peninsular India. A study attempted to predict the current habitat availability and climate change impacts on the species. The study indicated 6.5 to 42% of loss of habitat under different climate change scenarios. The jackknife analysis and permutation importance suggested the variables like topographic ruggedness index and precipitation of the wettest month identified as the crucial factors shaping the species habitat (Jha and Vasudevan, 2019).

Some of the plant species also studied based on the SDM approach. Giriraj *et al.* (2008) mapped the potential distribution of *Rhododendron arboreum nilagiricum*, an endemic plant in the Western Ghats, Priti *et al.* (2016) studied the future climate impacts on the distribution of Myristicaceae species. Pramanik *et al.* (2018) developed the species distribution model and future simulations of *Garcinia indica* about the effects of climate change.

2.8 SELECTED BIRDS FOR THE STUDY

Based on the data availability, six species selected for the current study. The distribution range and ecology of the species are essential to decide the background and selection of variables for the modelling. The chosen species include Wayanad

Laughingthrush (WLT) *Ianthocincla delesserti*, Banasura Laughingthrush (BLT) *Montecincla jerdoni*, Nilgiri Laughingthrush (NLT) *M. cachinnans*, Palani Laughingthrush (PLT) *M. fairbanki*, Nilgiri Flycatcher (NIF) *Eumyias albicaudatus* and Black-and-orange Flycatcher (BOF) *Ficedula nigrorufa.*

Distribution of the WLT limited in between the southern tip of the WG and south of Goa Gap. The species evenly distributed throughout the extent except in the Biligirirangana Hills (Collar and Robson, 2020; eBird, 2021). Broadleaved evergreen and semi-evergreen forests are the preferred habitats of WLT. It also likes thorny-cane brakes, *Strobilanthes* spp. and Black Cardamom *Amomum subulatum*. WLT distributed from 155m to 1220m elevation, but mostly between 455m and 760m (Collar and Robson, 2020).

BLT, NLT and PLT confined to the high elevation montane forests of the WG. BLT has a very restricted distribution, in between north of Chaliyar River and south of Kaveri River. It distributed in the elevation range of 1600m and 2400m, but most frequent in between 1400m and 1600m (Praveen, 2020). NLT also has a very narrow distribution range between Chaliyar River and Palakkad Gap (Nilgiri Hills). It prefers the elevation band of 1400m and 2600m (Collar *et al.*, 2020a) and restricted in the landscape between south of Palakkad Gap and north of Shenkottah Gap (Anamalai and Pandalam Hills). PLT preferred the elevation band of 1200m and 2600m (Collar *et al.*, 2020b). Broadleaved evergreen forest has identified as the primary habitat for all *Montecincla* species. However, NLT and PLT also prefer semi-evergreen forests, plantations, gardens and secondary forests (Collar *et al.*, 2020b, 2020a; Praveen, 2020).

The NIF and BOF restricted to the high elevation forests of the WG. Both species distributed from the southern tip of the WG to the south of Bhadra WLS, the northern limit of the *shola* habitat. Sudden elevation change (become <500m) may be the other reason for limiting the distribution. Some of the isolated records of NIF can also see in Biligirirangana Hills. Both species preferred the broadleaved evergreen and *shola* forests and distributed above 600m elevation (Clement, 2020a, 2020b). NIF is most frequent above 1200m elevation (Clement, 2020b) and BOF above 1500m (Khan, 1979).

3 MATERIALS AND METHODS

3.1 SPECIES

Based on the availability of occurrence data and ecological information, six Western Ghats endemic bird species selected for the current study. Selected species include Wayanad Laughingthrush (WLT) *Ianthocincla delesserti*, Banasura Laughingthrush (BLT) *Montecincla jerdoni*, Nilgiri Laughingthrush (NLT) *M. cachinnans*, Palani Laughingthrush (PLT) *M. fairbanki*, Nilgiri Flycatcher (NIF) *Eumyias albicaudatus* and Black-and-orange Flycatcher (BOF) *Ficedula nigrorufa* (Plate 1). The BLT and NLT categorised as *Endangered* according to the IUCN Red List assessment, and both having *High* conservation concern in the State of India's Birds (SoIB) report (SoIB, 2018; IUCN, 2021) (Table 1).

Table 1. Birds selected for the current study with IUCN and SoIB categories

Common Name	**Species**	**Malayalam Name**	**IUCN**	**SoIB Status**
Wayanad Laughingthrush	*Ianthocincla delesserti*	പതുങ്ങൻ ചിലപ്പൻ	LC	
Banasura Laughingthrush	*Montecincla jerdoni*	ബാണാസുര ചിലുചിലുപ്പൻ	EN	High
Nilgiri Laughingthrush	*Montecincla cachinnans*	നീലഗിരി ചിലുചിലുപ്പൻ	EN	High
Palani Laughingthrush	*Montecincla fairbanki*	വടക്കൻ ചിലുചിലുപ്പൻ	NT	Moderate
Nilgiri Flycatcher	*Eumyias albicaudatus*	നീലക്കിളി പാറ്റപിടിയൻ	LC	Moderate
Black-and-orange Flycatcher	*Ficedula nigrorufa*	കരിഞ്ചെമ്പൻ പാറ്റപിടിയൻ	LC	Moderate

IUCN: International Union for Conservation of Nature Red List (LC: Least Concern; EN: Endangered; NT: Near-Threatened); SoIB: State of India's Birds Report (SoIB, 2018; IUCN, 2021)

3.2 LANDSCAPE OF INTEREST (BACKGROUND)

The background is the geographical area or landscape of interest used to perform the species distribution modelling of a given species. The background selection is a critical step in SDM and affects the model predictive power and accuracy. The background should contain suitable habitats of species in question, and species dispersal ability also is considered. Each species required a different background based on the extent of distribution and dispersion capacity (Elith *et al.*, 2011; Merow *et al.*, 2013).

All selected species for the study are endemic to the WG. Each species distributed in different landscapes due to the geographic and climatic barriers present in the WG (Ramachandran *et al.*, 2017) (Figure 1). Background for each species selected based on the birds' distribution and dispersion capacity concerning the biogeographic and climatic barriers present.

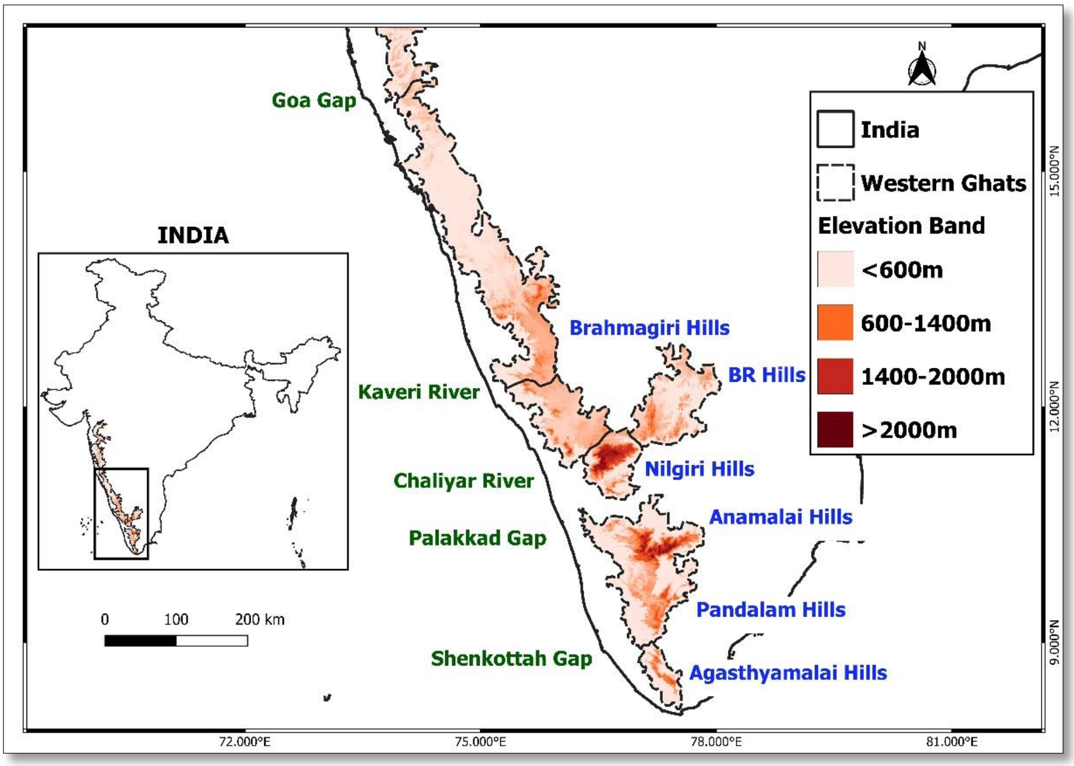


Figure 1. Significant landscapes and elevation bands of the Western Ghats, India

Wayanad Laughingthrush

Banasura Laughingthrush

Nilgiri Laughingthrush

Palani Laughingthrush

Nilgiri Flycatcher

Black-and-orange Flycatcher

Plate 1. Photographs of the species selected for the current study

3.3 OCCURRENCE DATA

Occurrence data is one of the inevitable inputs to the SDM process. It should be including species name, latitude and longitude, additionally date, time and location.

3.3.1 Collection of occurrence data

The point count method collects high-altitude birds' occurrence data by visiting various protected areas and other high elevation locations. Each stationary count was taken for 15 minutes and collected the following information; species name, date, time, place, geocoordinates by using Global Positioning System (GPS) and habitat. The survey was conducted from January 2019 to December 2020 by visiting various locations like Agasthyamalai Biological Park, Periyar Tiger Reserve, Eravikulam National Park, Chinnar Wildlife Sanctuary, Munnar territorial division, Marayur sandal division, Vazhachal reserve forest, Silent Valley National Park and Wayanad Wildlife Sanctuary. All collected data uploaded to the eBird (www.ebird.org) database.

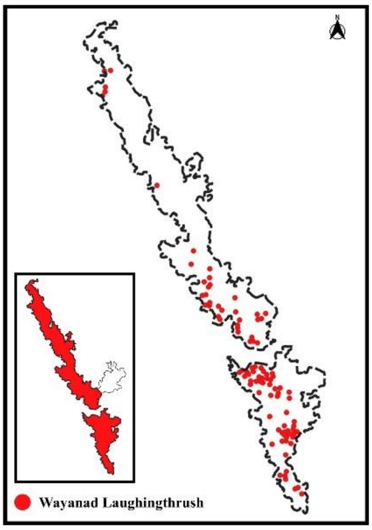
Additional occurrence data help to frame the full extent of the species. For that, other data downloaded from eBird basic dataset. eBird is a freely available citizen science-based bird data accumulating webtool (Sullivan *et al.*, 2009). A proper multi-level rigorous review process (Sullivan *et al.*, 2009) makes the eBird data available for research and conservation programmes, including the development of species distribution models (Coxen *et al.*, 2017; Pacifici *et al.*, 2017; Sullivan *et al.*, 2017; Robinson *et al.*, 2018). Other sources like iNaturalist, India Biodiversity Portal, etc., also provide the birds' occurrence data, but they lack the proper vetting process.

The occurrence points downloaded from eBird, including personally collected data. eBird basic dataset version 'EBD_relJan-2021' used to extract occurrence data. The details of the occurrence data provided under Appendix I.

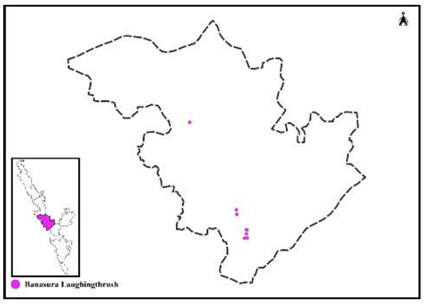
3.3.2 Processing of occurrence data

There should be some pre-processing needed for the occurrence data before they used for SDM. As mentioned above, eBird data is citizen science-based data, and it has some limitations. The quality of eBird data would highly depend on the identification skills of the observer, spatial and temporal coverage by participants, detectability of a species, rare bird recording method and care is given by the reviewer to vet the data (Isaac *et al.*, 2014; Kamp *et al.*, 2016). So, one should follow the proper filtering method to overcome the limitation of the eBird data for scientific use. The following filtering method was adopted to standardise the data; (a) included all checklists having *traveling* and *stationary* protocols (b) excluded all checklist with more than or equal to 300 minutes of duration (c) excluded all checklists if the travelled distance was 5km or more (d) also excluded those checklists with more than ten observers (Strimas-Mackey *et al.*, 2020).

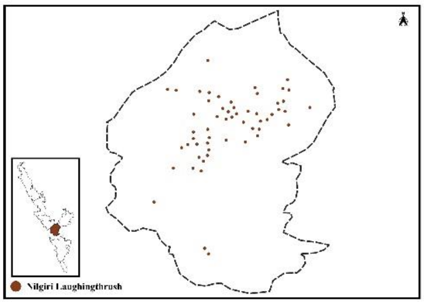
Spatial clustering of data may cause overfitting of the model (Williams *et al.*, 2002; Kadmon *et al.*, 2004). Spatial thinning was adopted to avoid the spatial clustering of occurrence data. Properly filtered occurrence data thinned by using SDMtoolbox (Brown, 2014) in ArcGIS. Occurrence data of each species thinned at a different spatial distance according to the number of available occurrence points and extent of background. The occurrence data of WLT thinned at 5km, and due to the limited number of occurrence points and very restricted distribution of the BLT, the occurrence points not thinned. The spatial thinning of both NLT and PLT performed at a 1km distance. A 2km spatial thinning distance was selected for both NIF and BOF (Plate 2).



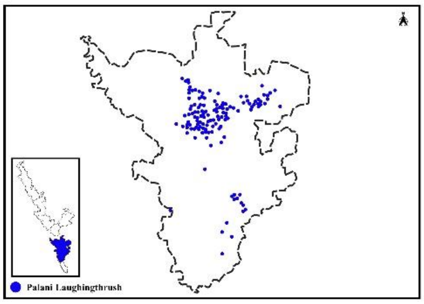
Wayanad Laughingthrush



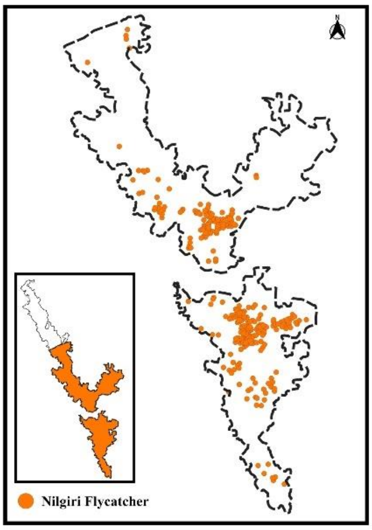
Banasura Laughingthrush



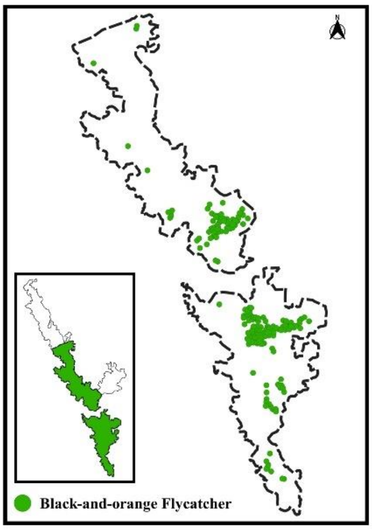
Nilgiri Laughingthrush



Palani Laughingthrush



Nilgiri Flycatcher



Black-and-orange Flycatcher

Plate 2. Background and occurrence data distribution of selected species

3.4 ENVIRONMENTAL VARIABLES

Environmental variables determined a species' niche requirement and considered the essential inputs for performing SDM (Root and Schneider, 1993; Root, 2006). Generally, the climate system determines the distribution of any species, including birds. So, variables used in any modelling should have a proper ecological connection with the species in question (Araújo and Guisan, 2006).

Based on the ecological information of the species and variable availability, the following variables considered; bioclimatic variables (BIO 1-19), Digital Elevation Model (DEM) and Enhanced Vegetation Index (EVI) (Appendix II). Bioclimatic variables (Fick and Hijmans, 2017) help to determine the climate suitability of a species. The dataset obtained from the Climatologies at high resolution for the earth's land surface areas (Chelsa) climate dataset (Karger *et al.*, 2017). The DEM (GTOPO30) downloaded from United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre. Topographic variables like slope, aspect, and elevation are calculated from the downloaded DEM file using Quantum GIS (QGIS) version 3.16. Enhanced vegetation index layers represent the greenness of a region and help to understand the vegetation cover. A 10-year (2011-2020) EVI layers obtained from the USGS Landsat imagery dataset. By using that layer 10-year average EVI by considering all months (2011-2020) (evi_avg), 10-year average EVI in peak monsoon (June-August) (evi_mon) and 10-year average EVI in peak summer (March-May) (evi_dry), were calculated and used in SDM process. All variables mentioned above were downloaded at the spatial resolution of 30 arc seconds (~1 km) and projected to World Geodetic System 84 EPSG:4326 (WGS 1984).

3.4.1 Multicollinearity test

There may be existing multicollinearity between variables in consideration. So, it is better to perform a multicollinearity analysis to eliminate highly correlated variables. In this study, variables with high correlation, that is, Pearson correlation coefficient $|r| > 0.75$, were calculated using SDMtoolbox and eliminated before use in the model building of each species. If the value $|r|>0.75$ between two variables, then remove one of the ecologically less significant variables. So, variables with low multicollinearity selected for the model building of each species. The multicollinearity results suggested eight variables for the WLT and BLT model building. Seven and ten variables chosen for the NLT and PLT, respectively and nine variables used for model development of the NIF and BOF (Appendix III).

3.5 MAXIMUM ENTROPY (MAXENT) MODELLING

Maximum entropy (Maxent version 3.4.4) (Phillips *et al.*, 2006, 2017) algorithm used to develop the species distribution models. Presence-only occurrence data needed for Maxent modelling instead of presence-absence data. Maxent would gibe better performing models when provided with specific settings and background (Merow *et al.*, 2013).

The ENM Evaluate (ENMeval) (Muscarella *et al.*, 2014) R package used to understand the model settings like the selection of Maxent features, regularization multiplier (RM) and the number of background points for the building of the Maxent model. It would also provide the bias file for Maxent model building. The output of ENMeval provided the value of Akaike Information Criterion (AIC), a measure of model performance, and associated model suggestions. The lowest AIC value indicates the highest performing model. The model with the lowest AIC value was selected from the ENMeval results and considered the preliminary model. The initial model was developed by using the Maxent algorithm and analyse the variable contribution, permutation importance and jackknife test output to understand the importance of each variable in the model building. By discarding the less significant variables, recalculate the AIC value by using the ENMeval tool. Similarly, identified the best performing model with the lowest AIC value by multiple running of ENMeval and Maxent.

Different types of outputs are available in Maxent and selected complementary log-log (cloglog) output for the current study. Cloglog type of output recently released by the Maxent development team and considered as the most appropriate output for explaining the species habitat suitability and probability of species presence (Phillips *et al.*, 2017). Maxent replication run type selected as cross-validation and number of iterations set as 5000. The number of background points, features and rm were adjusted by the recommendations of ENMeval output. All other settings kept as default (Figure 2).

3.6 FUTURE SIMULATIONS

By using the Maxent algorithm, future habitat suitability predictions of each species developed. The projections developed under different Representative Concentration Pathways (RCPs) like RCP 4.5, RCP 6.0 and RCP 8.5 for 2041 – 2060 (the 2050s). Bioclimatic variables associated with future climate models and static topographic variables used to build prediction outputs. The EVI layers exempted from the prediction models because of the unavailability of such layers.

Four different ESMs such as the Beijing Climate Centre Climate System Model 1.1 (BCC CSM1.1), Model for Interdisciplinary Research on Climate version 5 (MIROC5), Norwegian Earth System Model 1 (NorESM1-M) and Hadley Centre Global Environmental Model 2 – Earth System (HadGEM2-ES) downloaded. Three models, such as BCC CSM1.1, MIROC5 and HadGEM2-ES, were used for determining future habitat suitability changes for all species except NLT. The combination of BCC CSM1.1, MIROC5 and NorESM1-M were utilised for the NLT (Figure 2).

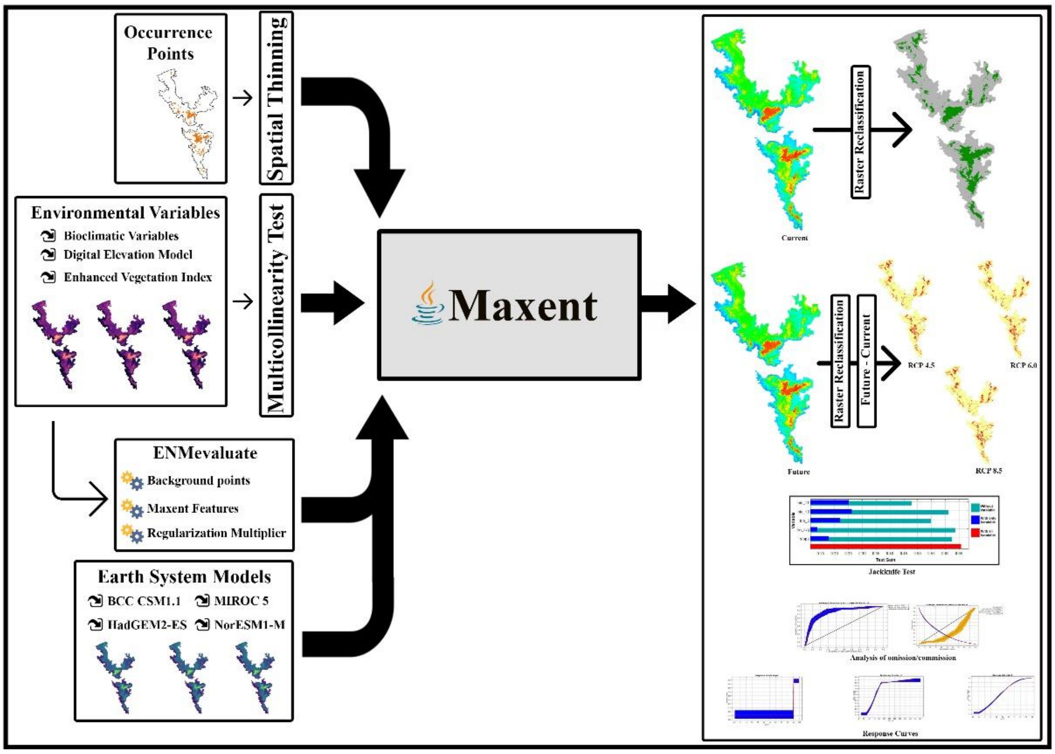


Figure 2. Steps involved in Maxent modelling

3.7 MODEL PERFORMANCE EVALUATION

Model performance evaluation would be an essential step in the SDM process. Several indices are available for assessing model performance, and Area Under the Receiver Operating Characteristic Curve (AUC) value assessment is one method. AUC measures how well a parameter can distinguish between two diagnostic groups (random and background points). It calculated from the receiver operating characteristic (ROC) curve by plotting the sensitivity against '1-specificity' across the range of possible thresholds. The AUC ranges from 0 to 1, and the model's goodness indicated by values close to one or one. This measure of model performance provided the results of Maxent out. It is not good to evaluate the model performance alone with the AUC value because it is not entirely reliable and informative (Phillips *et al.*, 2006). Another model evaluation measurement is the True Skill Statistic (TSS), defined as 'sensitivity + specificity – 1'. TSS ranges from –1 to +1, and values near one or one indicate a high accuracy model. Model robustness understood by calculating the AIC value. We used AIC, AUC and TSS for model performance evaluation.

3.8 HABITAT SUITABILITY ASSESSMENT

The output from Maxent provides prediction maps in raster, '.asc' as default, format. The raster files converted into the binary format by using a threshold value. Maximum test sensitivity plus specificity (maxSSS) cloglog considered the best threshold for Maxent output reclassification for habitat suitability assessment (Liu *et al.*, 2013). The values below the threshold limit can be regarded as unsuitable habitat and above the threshold as suitable. Current and future outputs would be reclassified to binary raster from 0 (unsuitable) to 1 (suitable) with the respective maxSSS threshold values by using ArcGIS or QGIS tools. Suitability changes calculated by using the raster calculator tool in QGIS 3.16 by subtracting the current binary map from the future binary maps. A value of 0 indicates no change in suitability (both future and current maps having the same value overlapping cells). A value of 1 means the areas change to suitable habitat in the future, and –1 suggest that the area changes to unsuitable.

The suitable habitat of the species coming under the protected area network also calculated. The maps of the protected area network were developed by using ENVIS Centre on Wildlife and Protected Areas database (ENVIS Centre on Wildlife and Protected Areas, 2020).

4 RESULTS

4.1 MODEL SELECTION AND IMPORTANT ENVIRONMENTAL VARIABLES

The contribution and permutation importance of the variables used in the final model, the model with the lowest AIC value, were assessed. The significance of variables also evaluated based on the jackknife test, and a different set of variables appeared in the finally suggested models. The response curves of each gave the best suitable conditions of the species concerning the variable.

4.1.1 Wayanad Laughingthrush

Five models developed for the WLT based on the importance of variables in the model and AIC value. Out of these models, Model 2 selected as the final model with five variables and Maxent features as Linear (L), Quadratic (Q), Hinge (H), Product (P) and Threshold (T) with 1.5 as regularization multiplier (RM). A high AUC value and moderately good TSS value show the final model's robustness (Table 2).

Table 2. Different model suggestions and associated accuracy indices of the Wayanad Laughingthrush

Model	Variables	Features/RM	AIC	TSS	AUC
Model 1	BIO 2, BIO 11, BIO 14, BIO 16, BIO 18, aspect, slope, evi_avg	H/3.5	2026.62	0.460	0.78
Model 2	BIO 2, BIO 11, BIO 18, slope, evi_avg	LQHPT/1.5	1987.42	0.536	0.82
Model 3	BIO 2, BIO 11, BIO 18, slope	LQHPT/2	1993.10	0.549	0.8
Model 4	BIO 2, BIO 11, BIO 18, evi_avg	LQ/0.5	1988.86	0.501	0.82
Model 5	BIO 2, BIO 11, BIO 18	LQ/0.5	1992.62	0.485	0.81

All five variables contributed to the model building with noticeable permutation importance. BIO 11 has the highest percentage of contribution and permutation importance, and slope identified as the least important variable (Table 3).

Table 3. Variables included in the final model of Wayanad Laughingthrush and associated calculations

Variable	PC	PI	Mean	Max	Min	SD
BIO 2	12.3	31.9	6.0	9.2	2.8	1.9
BIO 11	38.3	38.5	19.5	28.0	11.0	4.9
BIO 18	16.9	10.9	300.5	596.3	4.7	171.0
EVI_avg	21.7	12.3	3047.5	6168.1	-73.1	1804.4
Slope	10.8	6.4	88.7	90.3	87.0	0.9

PC: Percent Contribution; PI: Permutation Importance; Max: Maximum; Min: Minimum; SD: Standard Deviation

Jackknife analysis also shows the importance of the BIO 11 in model testing. The evi_avg has a minor test gain in the jackknife analysis (Figure 3). When referring to the response curves of the variables, the best suitable conditions of the WLT defined around 19.5°C of BIO 11 and 6°C of BIO 2 (Figure 4).

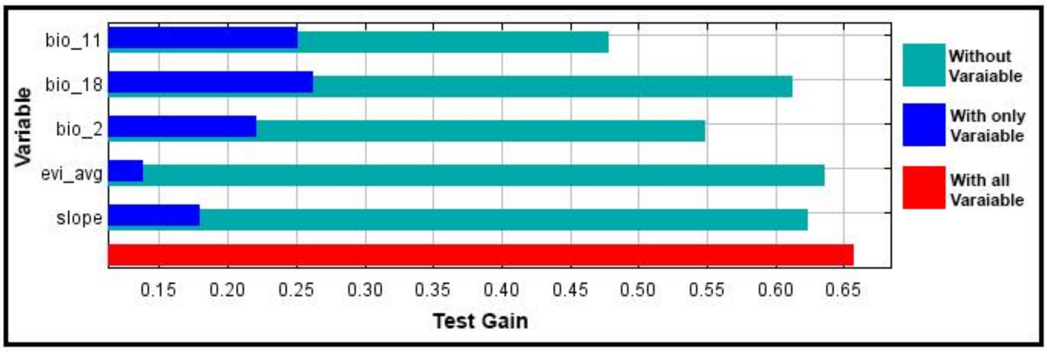


Figure 3. Jackknife test graphs showing the test gain of different variables used in the model building of Wayanad Laughingthrush

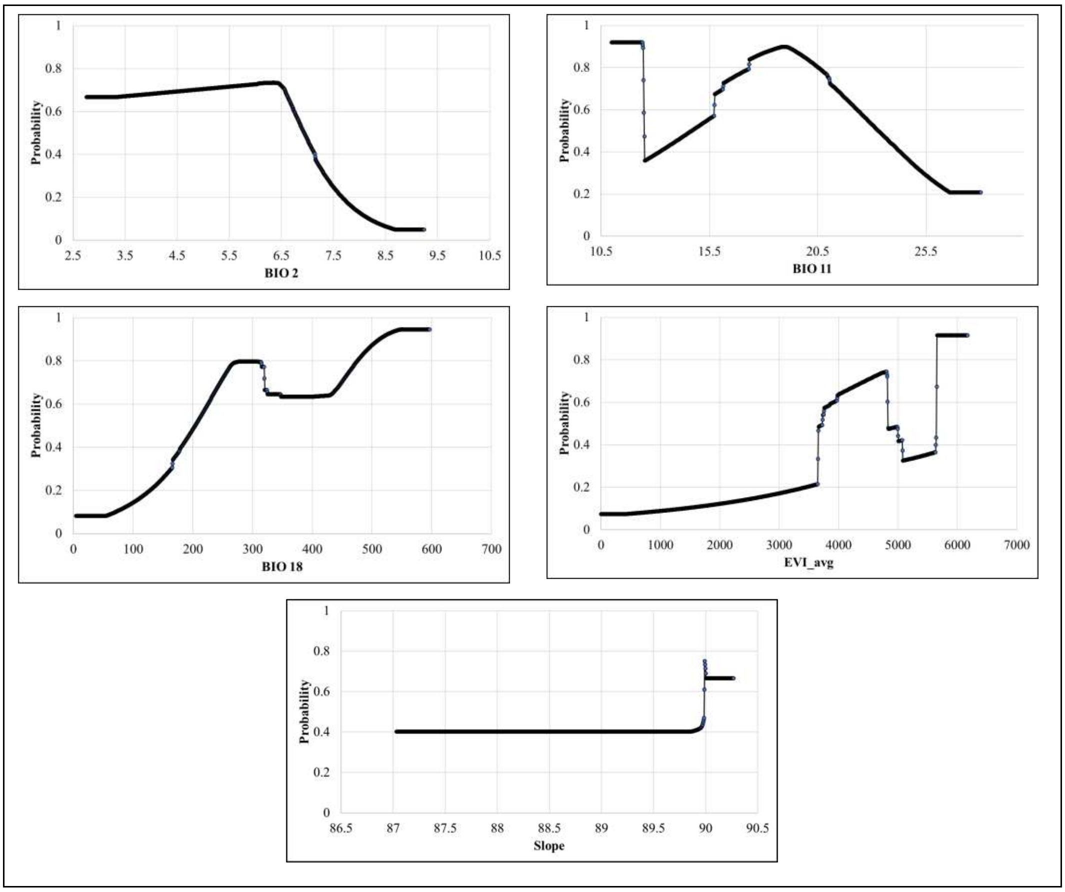


Figure 4. Response curves of the variables used for the model building of Wayanad Laughingthrush

4.1.2 Banasura Laughingthrush

Four models developed for the BLT and Model 3 selected as the best performing model with five environmental variables. The final model created by the Maxent features of L and Q and RM as 0.5. The values of the AUC and TSS indicate the high accuracy of the final model (Table 4).

Table 4. Different model suggestions and associated accuracy indices of the Banasura Laughingthrush

Model	Variables	Features/RM	AIC	TSS	AUC
Model 1	BIO 3, BIO 11, BIO 14, BIO 16, aspect, slope, evi_avg, evi_mon	L/0.5	125.74	0.570	0.96
Model 2	BIO 3, BIO 11, BIO 14, BIO 16, aspect, slope, evi_mon	L/0.5	125.74	0.849	0.96
Model 3	BIO 3, BIO 11, BIO 14, aspect, slope	LQ/0.5	115.98	0.709	0.95
Model 4	BIO 3, BIO 11, BIO 14, slope	L/0.5	126.09	0.707	0.96

Among the variables in the model, BIO 11 has the highest percentage of contribution (39.6%) to the model building, but slope has the highest permutation importance (83.6%) (Table 5).

Table 5. Variables included in the final model of Banasura Laughingthrush and associated calculations

Variable	PC	PI	Mean	Max	Min	SD
BIO 3	28.6	0.0	4.8	4.92	4.68	0.1
BIO 11	39.6	10.4	20.5	27.6	13.3	4.1
BIO 14	8.2	4.4	7.0	13.0	1.0	3.5
Aspect	16.9	1.6	180.1	396.0	-35.8	124.8
Slope	6.7	83.6	88.6	90.3	87.0	0.9

PC: Percent Contribution; PI: Permutation Importance; Max: Maximum; Min: Minimum; SD: Standard Deviation

Jackknife analysis also shows the importance of BIO 11 in model testing. Aspect found to be the variable with minor test gain (Figure 5). When referring to the response curves of the variables, the best suitable conditions of the BLT defined around 15°C of BIO 11, 4.8°C of BIO 3 and 11kg/m^2 of BIO 14 (Figure 6).

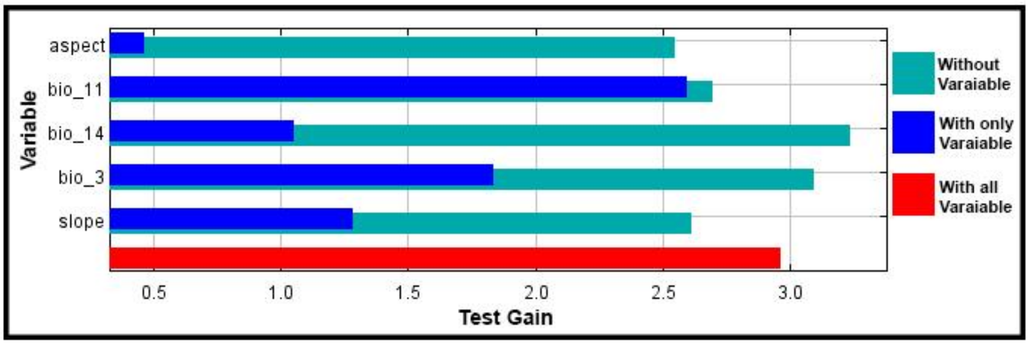


Figure 5. Jackknife test graphs showing the test gain of different variables used in the model building of Banasura Laughingthrush

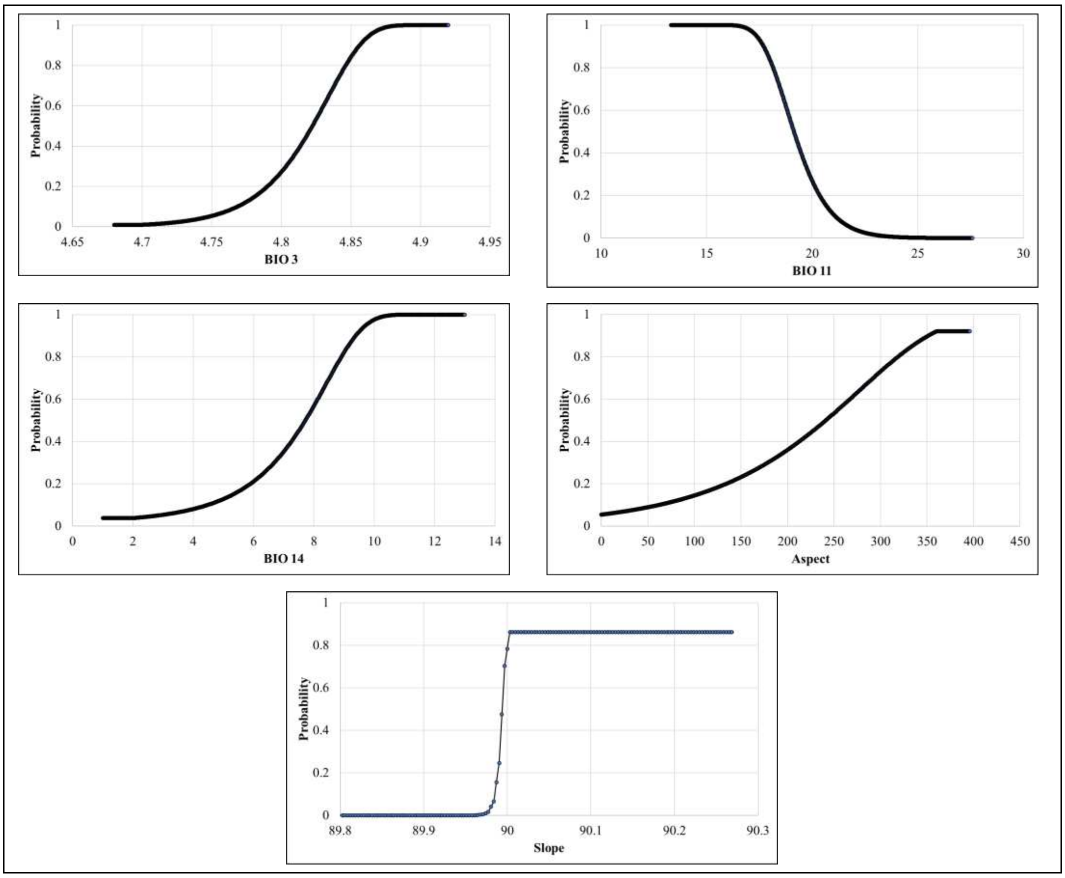


Figure 6. Response curves of the variables used for the model building of Banasura Laughingthrush

4.1.3 Nilgiri Laughingthrush

Three models developed for the NLT and Model 4 selected the final model. The final model has three variables, and L and Q selected as Maxent features with

RM as 2. Moderately good TSS (0.540) and high AUC (0.906) values indicate the robustness of the model (Table 6).

Table 6. Different model suggestions and associated accuracy indices of the Nilgiri Laughingthrush

Model	Variables	Features/RM	AIC	TSS	AUC
Model 1	BIO4, BIO 11, BIO14, BIO 16, aspect, evi_dry, slope	LQ/3	681.40	0.519	0.903
Model 2	BIO4, BIO 11, BIO14, BIO 16	LQ/2	680.82	0.559	0.908
Model 3	BIO4, BIO 11, BIO14	LQ/0.5	685.60	0.515	0.903
Model 4	BIO 11, BIO14, BIO 16	LQ/2	680.82	0.540	0.906

BIO 11 found to be the most critical variable with 83.6% of contribution to the model building and 92.7% of permutation importance. BIO 16 found to be the least contributed to the model building, and BIO 14 has the lowest permutation importance (Table 7). Jackknife analysis also indicates a good test gain for BIO 11 (Figure 7). Between 10°C and 15°C of BIO 11 gives the best suitable habitat for the NLT (Figure 8).

Table 7. Variables included in the final model of Nilgiri Laughingthrush and associated calculations

Variable	PC	PI	Mean	Max	Min	SD
BIO 11	83.6	92.7	19.5	27.9	11.0	4.9
BIO 14	14.5	3.1	15.5	25.7	5.3	5.9
BIO 16	1.8	4.2	1399.0	2633.8	164.2	714.0

PC: Percent Contribution; PI: Permutation Importance; Max: Maximum; Min: Minimum; SD: Standard Deviation

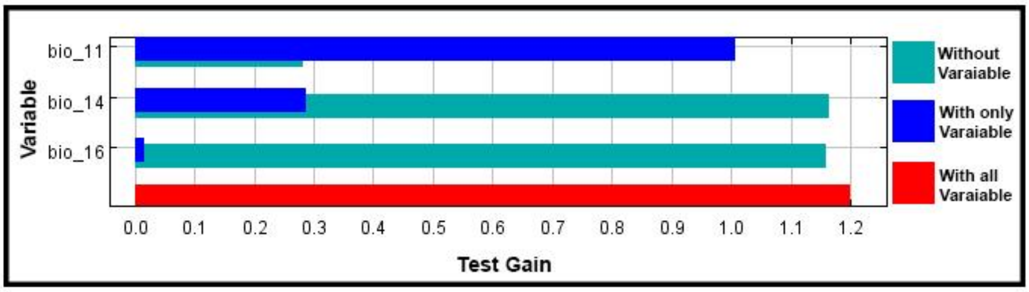


Figure 7. Jackknife test graphs showing the test gain of different variables used in the model building of Nilgiri Laughingthrush

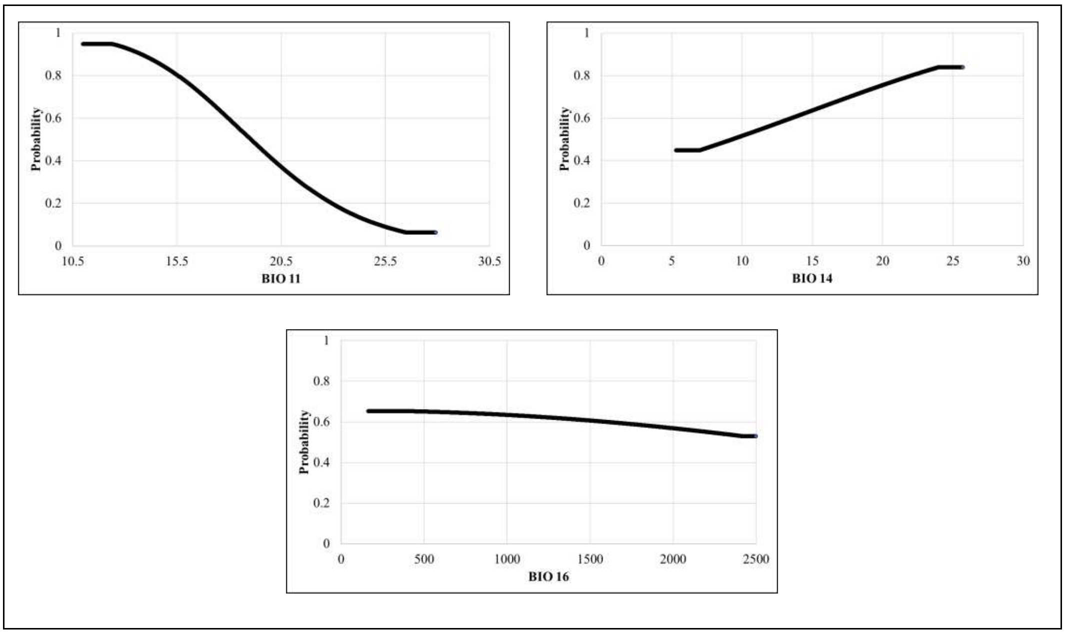


Figure 8. Response curves of the variables used for the model building of Nilgiri Laughingthrush

4.1.4 Palani Laughingthrush

For the PLT, eight models developed, and Model 7 found to be the most accurate and best-performing model. There were seven variables and Maxent features like L and Q with RM as 0.5 used to build the final model. Higher values of TSS (0.730) and AUC (0.905) indicate the greater accuracy of the model (Table 8).

Table 8. Different model suggestions and associated accuracy indices of the Palani Laughingthrush

Model	Variables	Features/RM	AIC	TSS	AUC
Model 1	BIO 2, BIO 3, BIO 11, BIO 14, BIO 16, BIO 18, BIO 19, aspect, slope, evi_avg	LQ/0.5	2150.49	0.724	0.89
Model 2	BIO 3, BIO 11, BIO 14, BIO 16, BIO 18, aspect, evi_avg	LQ/0.5	2154.31	0.722	0.89
Model 3	BIO 3, BIO 11, BIO 18, aspect	H/2	2156.59	0.731	0.91
Model 4	BIO 3, BIO 11, BIO 14, BIO 16, BIO 18, BIO 19, slope	LQ/0.5	2148.41	0.751	0.9
Model 5	BIO 3, BIO 11, BIO 14, BIO 16, BIO 18, BIO 19	LQ/0.5	2143.93	0.701	0.9
Model 6	BIO 3, BIO 11, BIO 16, BIO 18	LQ/0.5	2153.38	0.712	0.9
Model 7	BIO 3, BIO 11, BIO 14, BIO 19	LQ/0.5	2143.82	0.730	0.91
Model 8	BIO 3, BIO 11, BIO 14	LQ/0.5	2152.76	0.701	0.91

The BIO 11 considered the single most crucial variable, and 99% contributed to the model building, and it has the permutation importance of 99.4%. All other variables contributed a little to the model (Table 9). Jackknife analysis also indicates the importance of BIO 11, and it has a higher test gain (Figure 9). Furthermore, the probability of the species habitat suitability under BIO 11 becomes more elevated around 17.5°C (Figure 10).

Table 9. Variables included in the final model of Palani Laughingthrush and associated calculations

Variable	PC	PI	Mean	Max	Min	SD
BIO 3	0.6	0.3	5.9	6.6	5.2	0.4
BIO 11	99.0	99.4	22.0	31.1	12.9	5.3
BIO 14	0.4	0.2	13.0	28.6	-2.6	9.0
BIO 19	0.0	0.1	995.5	1981.3	9.7	570.0

PC: Percent Contribution; PI: Permutation Importance; Max: Maximum; Min: Minimum; SD: Standard Deviation

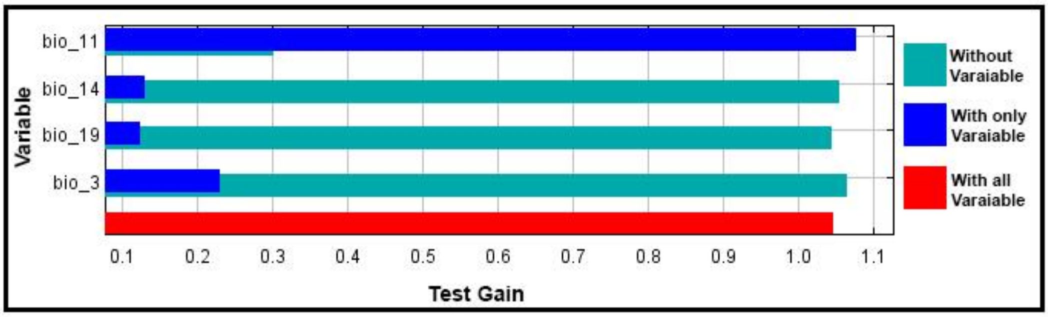


Figure 9. Jackknife test graphs showing the test gain of different variables used in the model building of Palani Laughingthrush

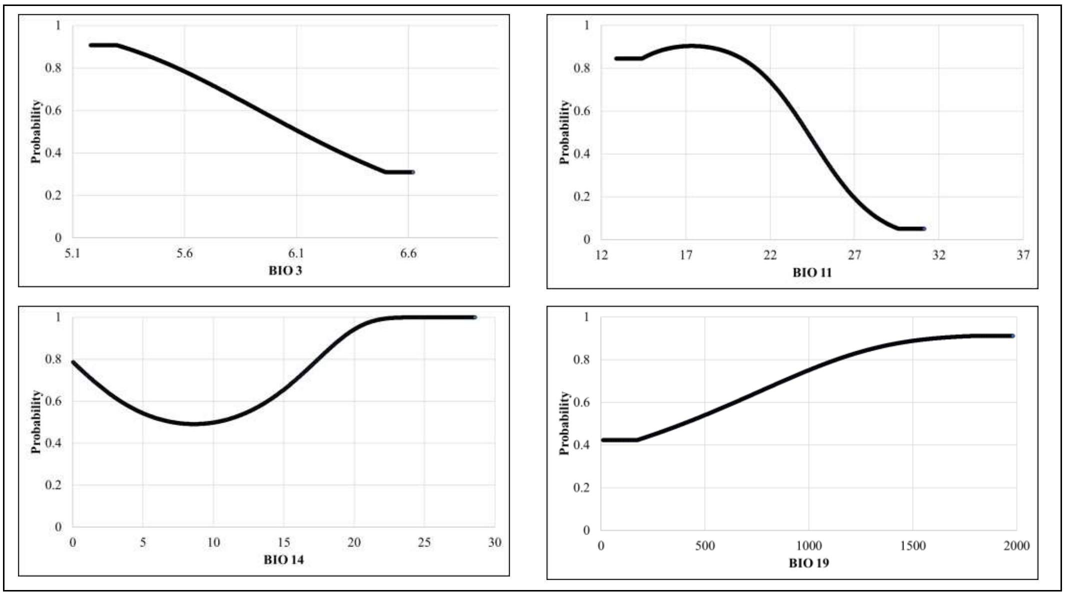


Figure 10. Response curves of the variables used for the model building of Palani Laughingthrush

4.1.5 Nilgiri Flycatcher

Six models built for the NIF, and Model 3 selected as the final model. Six environmental variables were defining the habitat suitability of the species. Maxent was running with the combination of L, Q and H and the RM used as 4. The TSS (0.606) and AUC (0.852) values indicate the high accuracy of the model (Table 10).

Table 10. Different model suggestions and associated accuracy indices of the Nilgiri Flycatcher

Model	Variables	Features/RM	AIC	TSS	AUC
Model 1	BIO 2, BIO 3, BIO 11, BIO 13, BIO 14, BIO 18, aspect, slope, evi_avg	LQHP/4	6062.40	0.602	0.83
Model 2	BIO 3, BIO 11, BIO 13, BIO 14, BIO 18, slope, evi_avg	LQHPT/1.5	6064.85	0.564	0.81
Model 3	BIO 3, BIO 11, BIO 14, BIO 18, slope, evi_avg	LQH/4	6052.20	0.606	0.85
Model 4	BIO 3, BIO 11, BIO 14, BIO 18, slope	LQHPT/2.5	6090.42	0.569	0.84
Model 5	BIO 3, BIO 11, BIO 14, BIO 18	H/2	6087.21	0.581	0.84
Model 6	BIO 3, BIO 11, BIO 18	H/1.5	6087.70	0.583	0.84

The BIO 11 alone can explain the habitat suitability of the NIF with 92.4% permutation importance and 95.2% of contribution to the model development (Table 11). The slope did not contribute to the model building, but it has some test gain in jackknife analysis. The BIO 11 has also a higher test gain in the jackknife analysis (Figure 11). The probability of the NIF suitability becomes high around 15°C of BIO 11, and further increase of the BIO 11 negatively affects habitat suitability (Figure 12).

Table 11. Variables included in the final model of Nilgiri Flycatcher and associated calculations

Variable	PC	PI	Mean	Max	Min	SD
BIO 3	0.0	0.0	4.9	5.4	4.4	0.3
BIO 11	95.2	92.4	19.4	28.0	10.8	5.0
BIO 14	0.2	0.0	24.0	51.6	-3.6	16.0
BIO 18	2.4	4.2	318.0	609.6	26.4	168.6
EVI_avg	2.2	3.4	2987.5	6165.7	-190.7	1837.7
Slope	0.0	0.0	89.4	90.1	88.7	0.4

PC: Percent Contribution; PI: Permutation Importance; Max: Maximum; Min: Minimum; SD: Standard Deviation

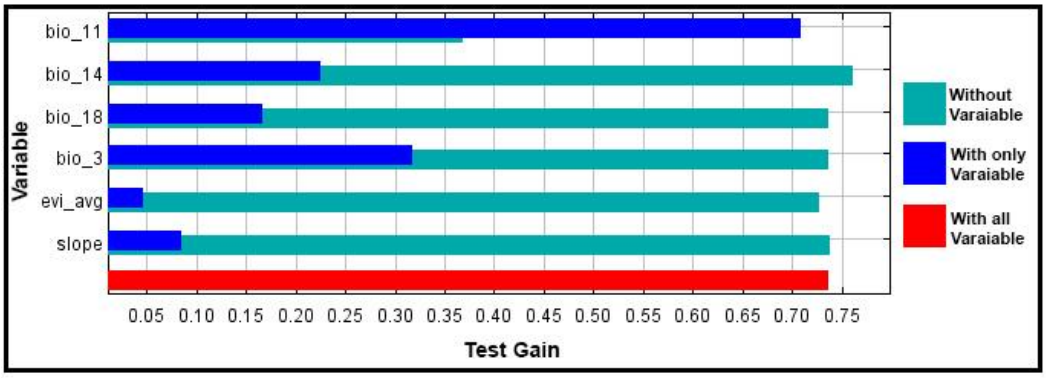


Figure 11. Jackknife test graphs showing the test gain of different variables used in the model building of Nilgiri Flycatcher

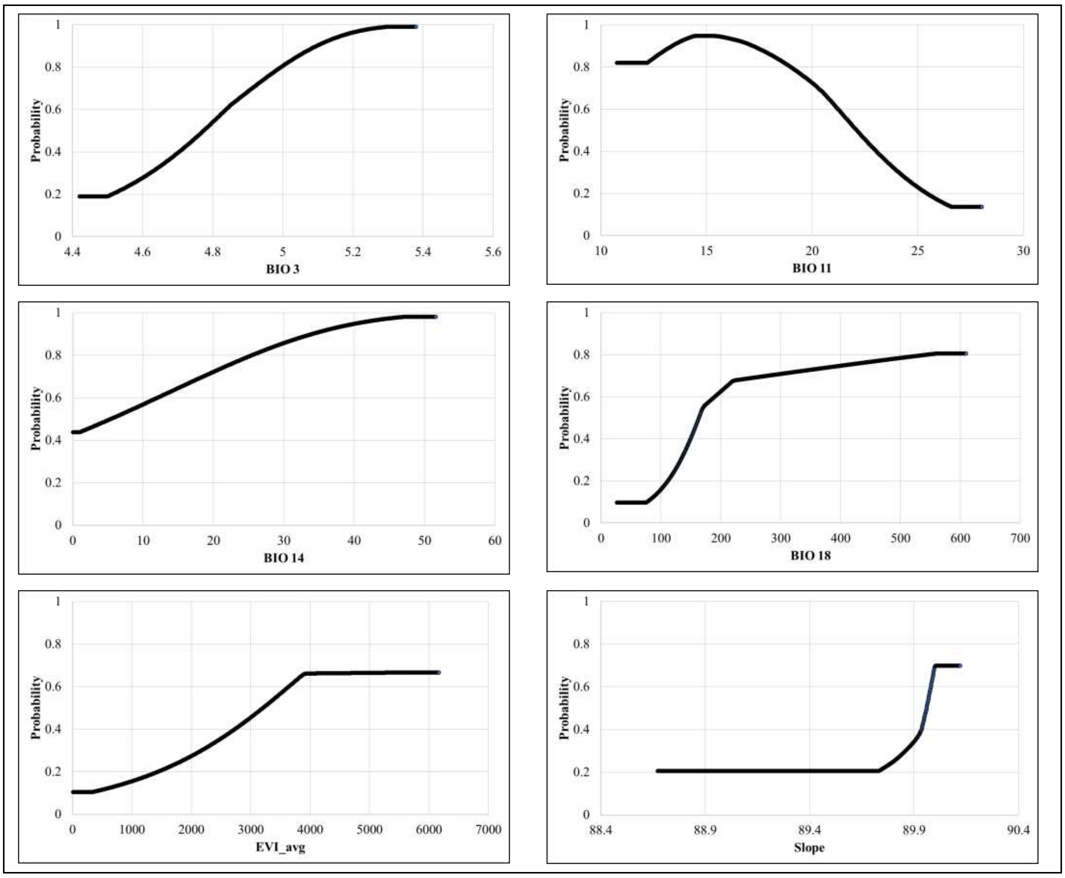


Figure 12. Response curves of the variables used for the model building of Nilgiri Flycatcher

4.1.6 Black-and-orange Flycatcher

Three models developed for the BOF and Model 3 found as the best performing model. The model developed using four variables, and Maxent ran with

L, Q and H features and RM as 2. Greater values of TSS (0.706) and AUC (0.913) indicate the higher accuracy of the model (Table 12).

Table 12. Different model suggestions and associated accuracy indices of the Black-and-orange Flycatcher

Model	Variables	Features/RM	AIC	TSS	AUC
Model 1	BIO 2, BIO 3, BIO 11, BIO 14, BIO 16, BIO 18, aspect, slope, evi_avg	H/4	3690.69	0.722	0.90
Model 2	BIO 3, BIO 11, BIO 14, BIO 16, BIO 18, slope	H/4	3694.02	0.713	0.90
Model 3	BIO 3, BIO 11, BIO 14, slope	LQH/2	3668.34	0.706	0.91

The BIO 11 could be considered the single most crucial variable with 99.3% contribution to the model building and 98.9% of permutation importance (Table 13). The jackknife analysis also shows the importance of BIO 11 with the higher test gain (Figure 13). Furthermore, the probability of species habitat suitability become higher around 16°C of BIO 11 (Figure 14).

Table 13. Variables included in the final model of Black-and-orange Flycatcher and associated calculations

Variable	PC	PI	Mean	Max	Min	SD
BIO 3	0.6	1.0	4.9	5.4	4.4	0.3
BIO 11	99.3	98.9	19.6	28.0	11.1	4.9
Slope	0.1	0.0	89.4	90.1	88.7	0.4

PC: Percent Contribution; PI: Permutation Importance; Max: Maximum; Min: Minimum; SD: Standard Deviation

Figure 13. Jackknife test graphs showing the test gain of different variables used in the model building of Black-and-orange Flycatcher

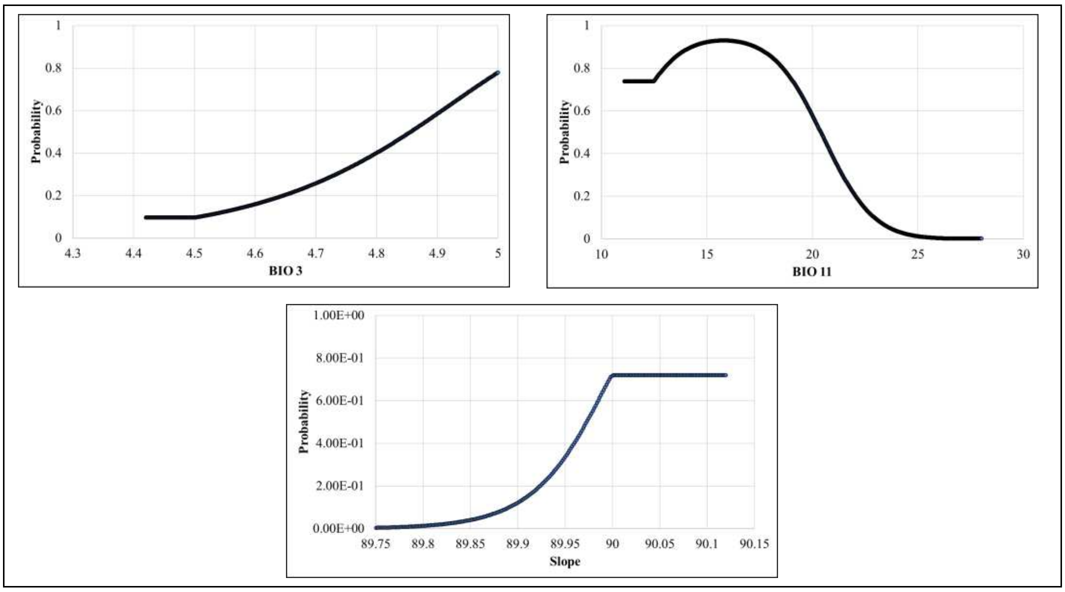


Figure 14. Response curves of the variables used for the model building of Black-and-orange Flycatcher

4.2 CURRENT HABITAT SUITABILITY ANALYSIS

4.2.1 Wayanad Laughingthrush

The best performing model of the WLT (AIC = 1987.42) predicted an area of 16584km^2 as suitable habitat across the background. The total suitable habitat covered 22% of the background area used in the Maxent modelling (Table 14). Out of the total suitable area, 26.50% fall under the protected area network. The model also predicted new suitable habitat, where previous records were not available, in the north of Kaveri River (Figure 15). In addition, new suitable habitats predicted in the following protected areas of Karnataka State; Kudremukh NP, Talakaveri WLS, Sharavathi Valley WLS and Mookambika WLS.

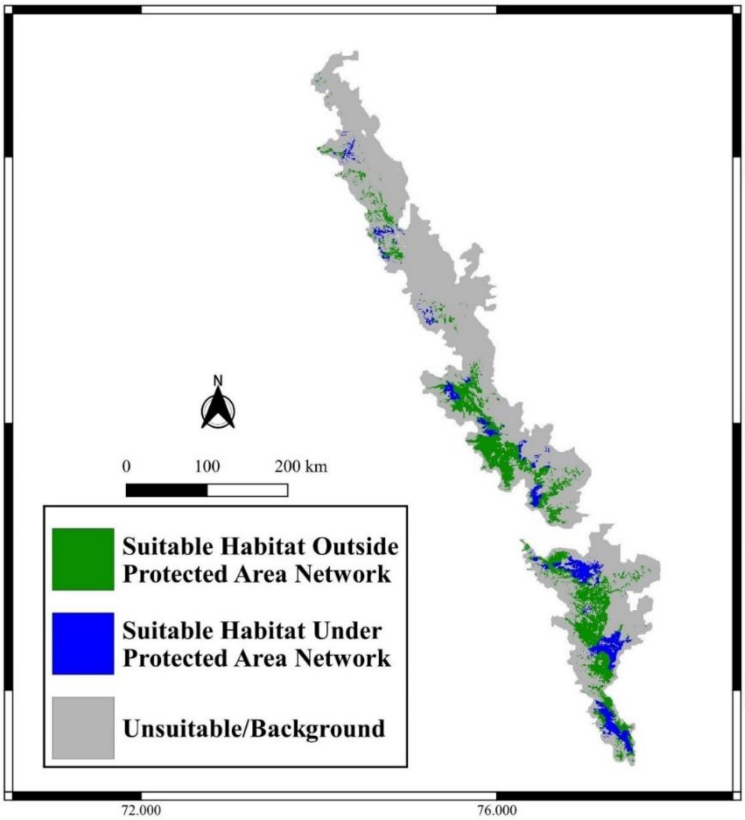


Figure 15. Predicted habitat suitability of Wayanad Laughingthrush with the indication of suitable habitat available in the protected area network

Table 14. Suitable habitat available for different species under current climate

Species	max SSS Threshold*	Suitable Habitat (km^2)	Unsuitable Habitat (km^2)
Wayanad Laughingthrush	0.594	16584	58751
Banasura Laughingthrush	0.735	47	10658
Nilgiri Laughingthrush	0.697	1641	4889
Palani Laughingthrush	0.705	3096	16877
Nilgiri Flycatcher	0.631	12707	51920
Black-and-orange Flycatcher	0.609	6532	46852

* Maximum test sensitivity plus specificity cloglog threshold

4.2.2 Banasura Laughingthrush

The robust model (AIC = 115.98) predicted an area of 47km^2 as the suitable habitat for the BLT. The suitable habitat covered only 0.4% of the background area (Table 14). Most importantly, the suitable habitat predicted for the BLT is not falling within any of the protected area networks. Core distribution of this species reported from Vavul Mala and Chembra Mala (west of Wayanad Wildlife Sanctuary) of Wayanad District. The model predicted some new possible habitat near Padinjarathara (11.6860°N 75.9086°E) of Wayanad District (Figure 16).

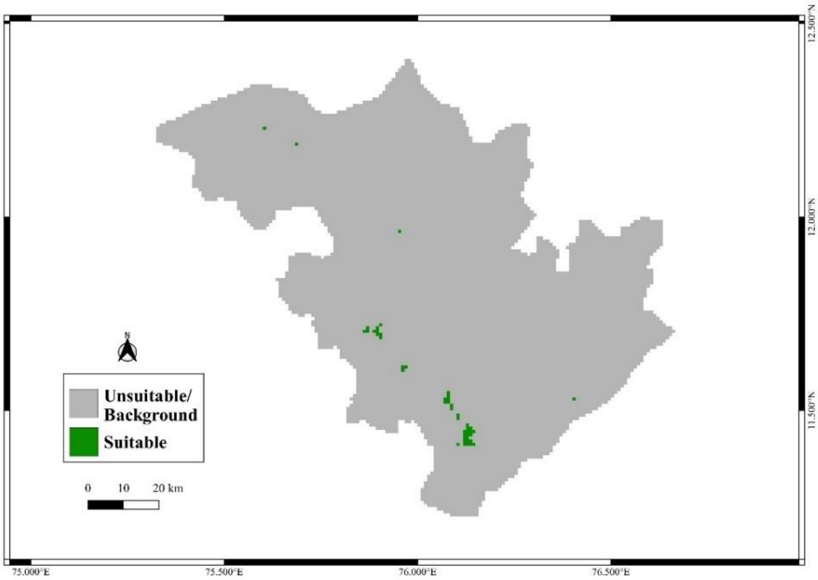


Figure 16. Predicted habitat suitability of Banasura Laughingthrush

4.2.3 Nilgiri Laughingthrush

For NLT, the final model (AIC = 680.82) given the suitable habitat of 630km^2, which covered 9.60% of the background area selected (Table 14). The species mainly distributed in the high altitudes of Nilgiri Hills. However, only 3.17% of the total suitable area for the NLT distributed under the protected area network in Kerala and Tamil Nadu states, where the species is known to occur (Figure 17).

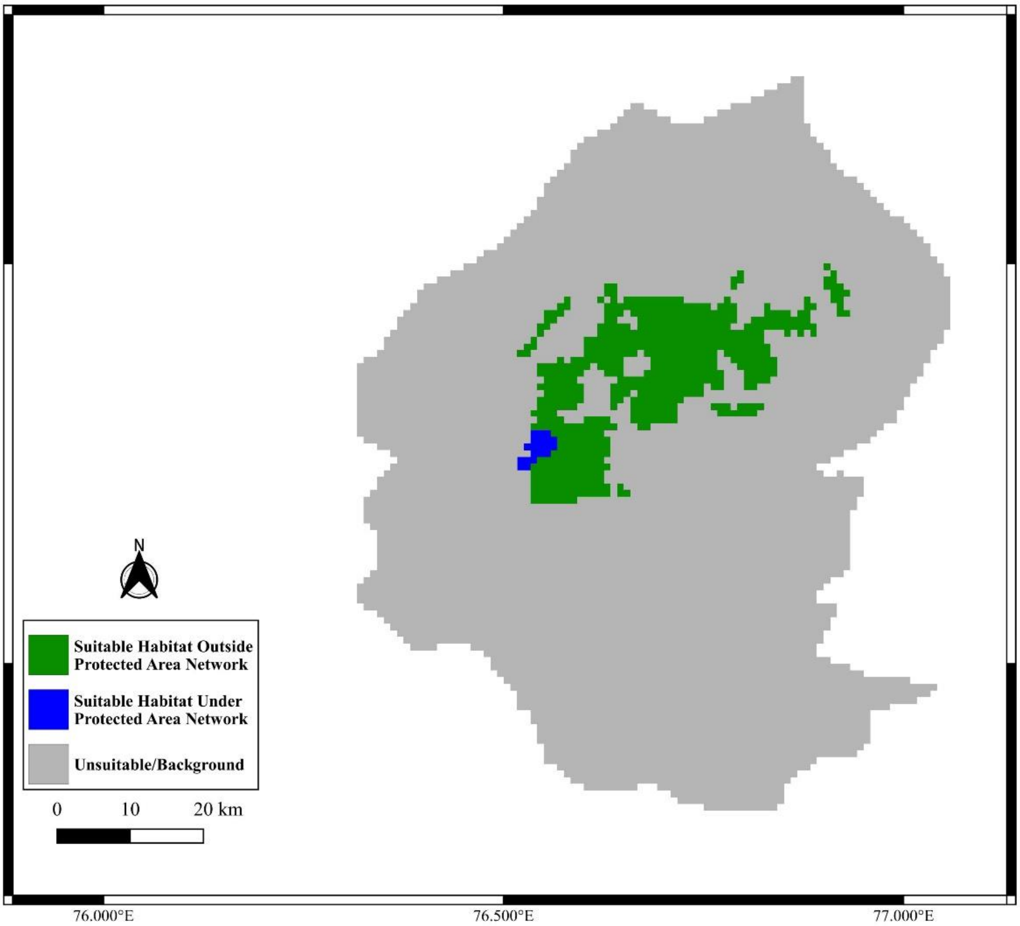


Figure 17. Predicted habitat suitability of Nilgiri Laughingthrush with the indication of suitable habitat available in the protected area network

4.2.4 Palani Laughingthrush

The best model of the PLT (AIC = 2143.82) predicted 3,096km^2 as suitable habitat. The suitable habitat covered 15.50% of the background area (Table 14). Out of the total suitable habitat, only 30.30% distributed under the protected area network. The model did not predict any unknown suitable location except for tiny patches near Vagamon and Kattappana of Kerala and Tanniparai of Tamil Nadu. The PLT primarily distributed in the Anamalai Hills and Pandalam Hills of the WG (Figure 18).

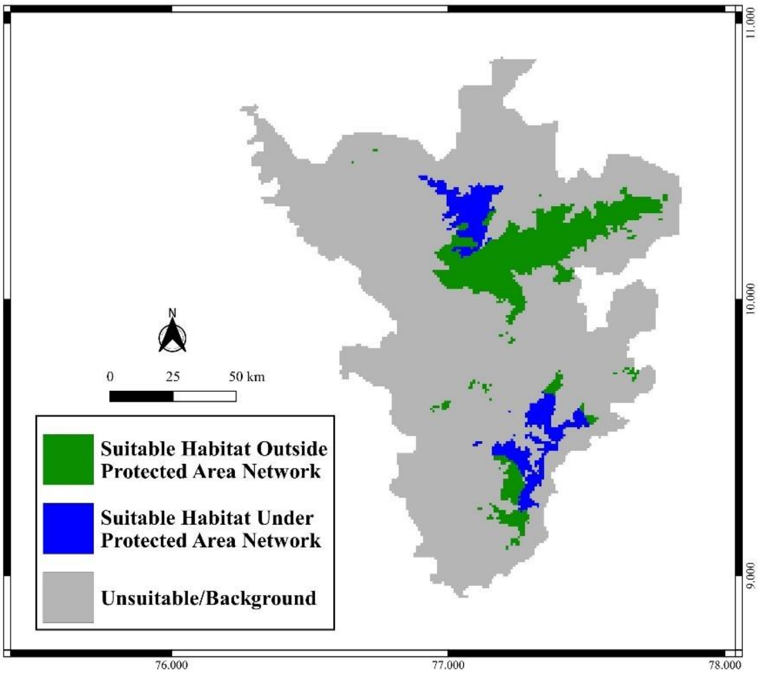


Figure 18. Predicted habitat suitability of Palani Laughingthrush with the indication of suitable habitat available in the protected area network

4.2.5 Nilgiri Flycatcher

For the NIF, the robust model (AIC = 6052.20) predicted an area of 12,707km^2 as its suitable habitat. Total suitable habitat for NIF spread over 19.70% of the background used in the modelling (Table 14). Within the total suitable area, only 24.10% falls under the protected area network. The model predicted some potentially suitable habitats in the parts of Kudremukh NP, Pushpagiri WLS, Talakaveri WLS, Cauvery WLS and Biligiri Rangaswamy Temple WLS in Karnataka State, from where the species has not been reported previously (Figure 19).

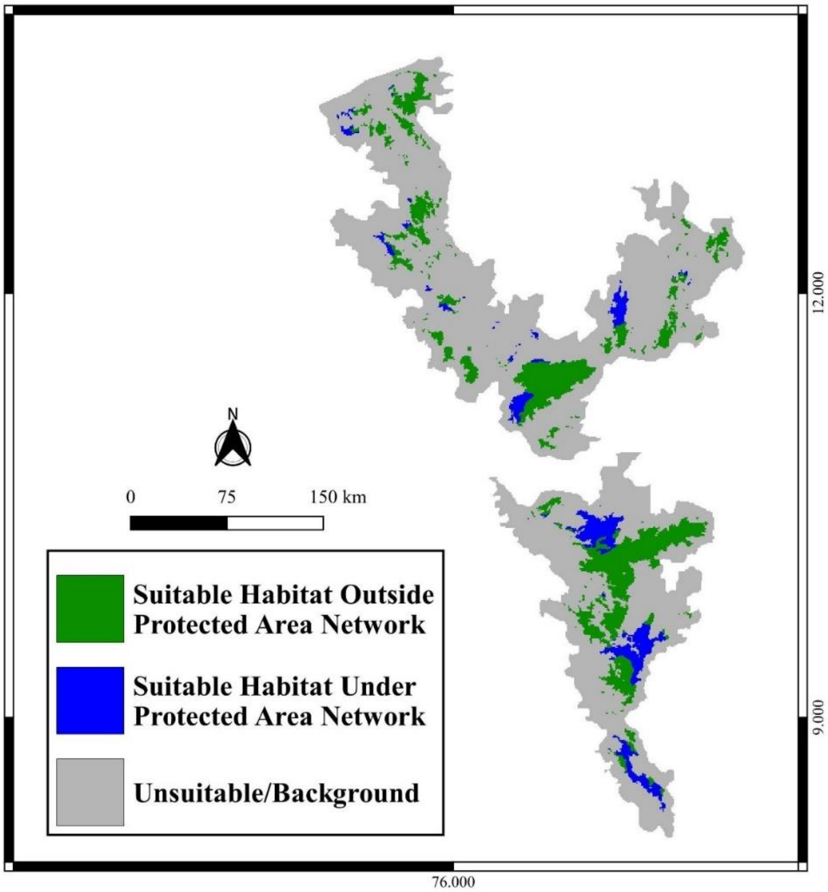


Figure 19. Predicted habitat suitability of Nilgiri Flycatcher with the indication of suitable habitat available in the protected area network

4.2.6 Black-and-orange Flycatcher

The final model of the BOF (AIC = 3668.34) given the total suitable habitat as 6,532 km^2, which covered 12.20% of the background area (Table 14). The model also predicted some new suitable habitats in Talakaveri WLS and Pushpagiri WLS in Karnataka. However, out of the total suitable habitat, only 26.50% distributed inside the protected area network (Figure 20).

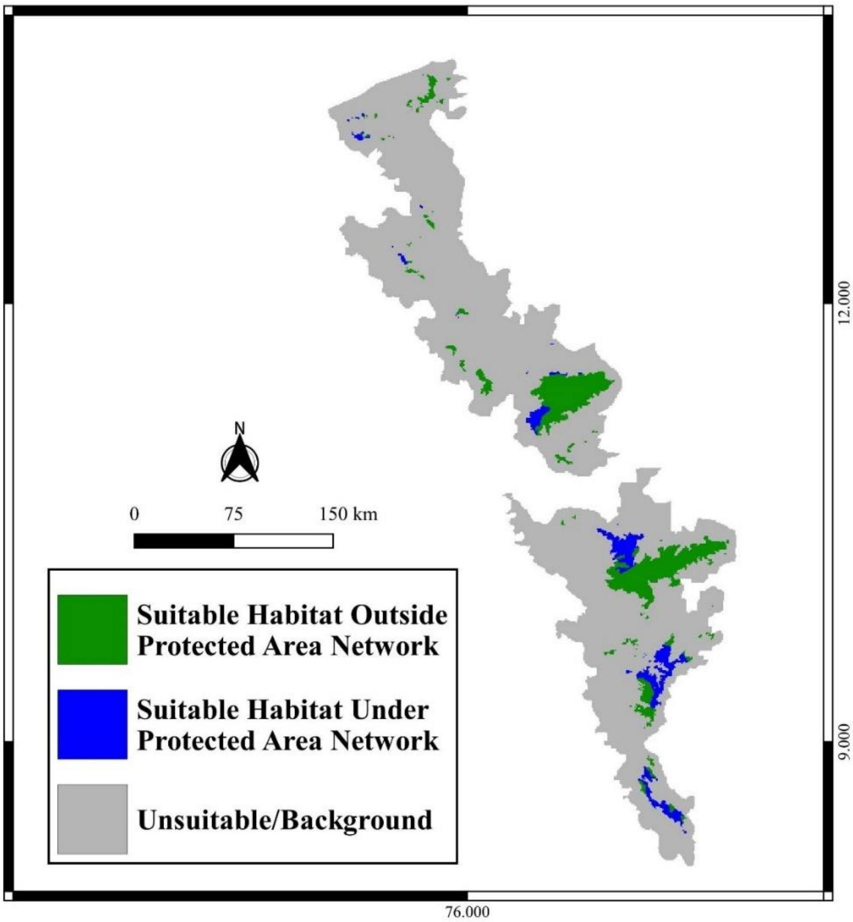


Figure 20. Predicted habitat suitability of Black-and-orange Flycatcher with the indication of suitable habitat available in the protected area network

4.3 FUTURE HABITAT SUITABILITY CHANGES

4.3.1 Wayanad Laughingthrush

The future habitat suitability change analysis of the WLT indicates the net loss of 48.80% suitable habitat compared to available suitable habitat under RCP 8.5 (2050s) (Table 15). The loss of suitability present in the entire distribution of the species. WLT found to lose the greatest of its habitat between the locations south of the Palakkad Gap and north of the Chaliyar River. The model, however, also predicted the habitat gain for WLT in some parts of the landscapes like Anamalai Hills (Munnar), Nilgiri Hills and north of Kaveri River (Figure 21).

Table 15. Habitat suitability changes from the currently suitable habitat of Wayanad Laughingthrush under various climate change scenarios

RCP Scenario	max SSS Threshold	No Change (km^2)	Loss (km^2)	Gain (km^2)	Suitable Habitat (km^2)	Net Gain (%)
4.5 (2050s)	0.597	67200	7123	846	8975	-41.2
6.0 (2050s)	0.598	67855	6460	854	9646	-36.8
8.5 (2050s)	0.591	66280	8164	725	7813	-48.8

No Change: no change in habitat suitability in the future scenario from current scenario; Loss: currently suitable habitat changed to unsuitable habitat in future; Gain: currently unsuitable habitat changed to suitable habitat in future; Net Gain = (Area of currently suitable habitat + Gain – Loss)

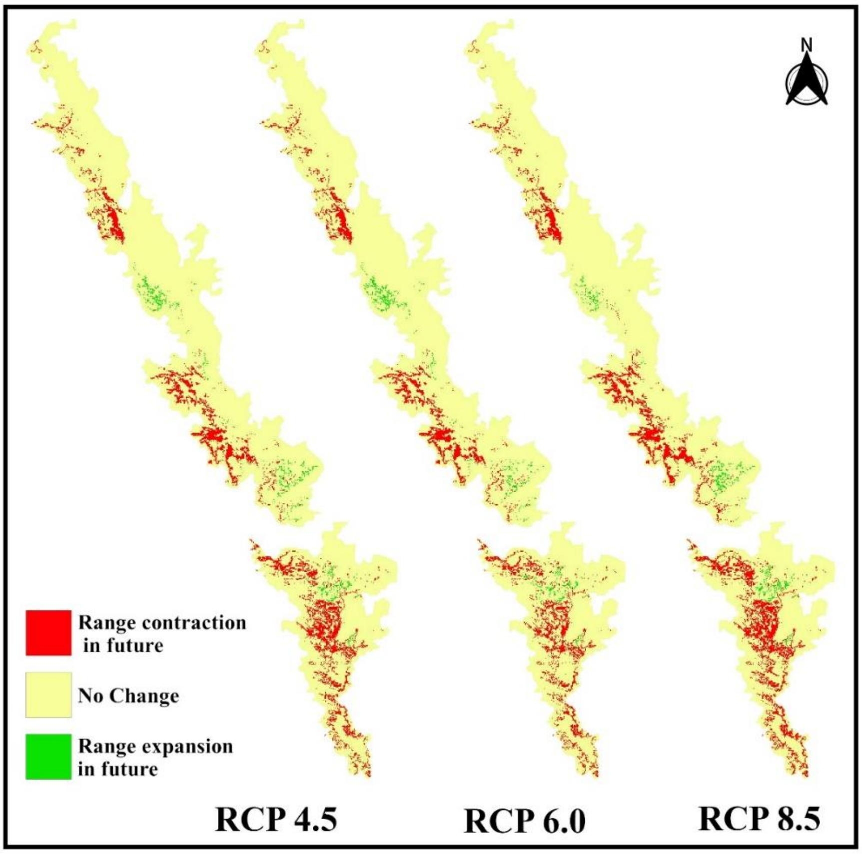


Figure 21. Future habitat suitability changes of Wayanad Laughingthrush under different climate change scenarios

4.3.2 Banasura Laughingthrush

The model predicted the loss of suitable habitat of 72.30% of currently available habitat of 47km^2 under RCP 4.5 and 8.5 (2050s) (Table 16). The habitat becomes unsuitable in most of the current distributional range of the BLT. The model did not give any gain of suitable habitat for the BLT under any of the climate change scenarios (Figure 22).

Table 16. Habitat suitability changes from the currently suitable habitat of Banasura Laughingthrush under various climate change scenarios

RCP Scenario	max SSS Threshold	No Change (km^2)	Loss (km^2)	Gain (km^2)	Suitable Habitat (km^2)	Net Gain (%)
4.5 (2050s)	0.707	10587	34	0	13	-72.3
6.0 (2050s)	0.711	10590	31	0	16	-66.0
8.5 (2050s)	0.706	10587	34	0	13	-72.3

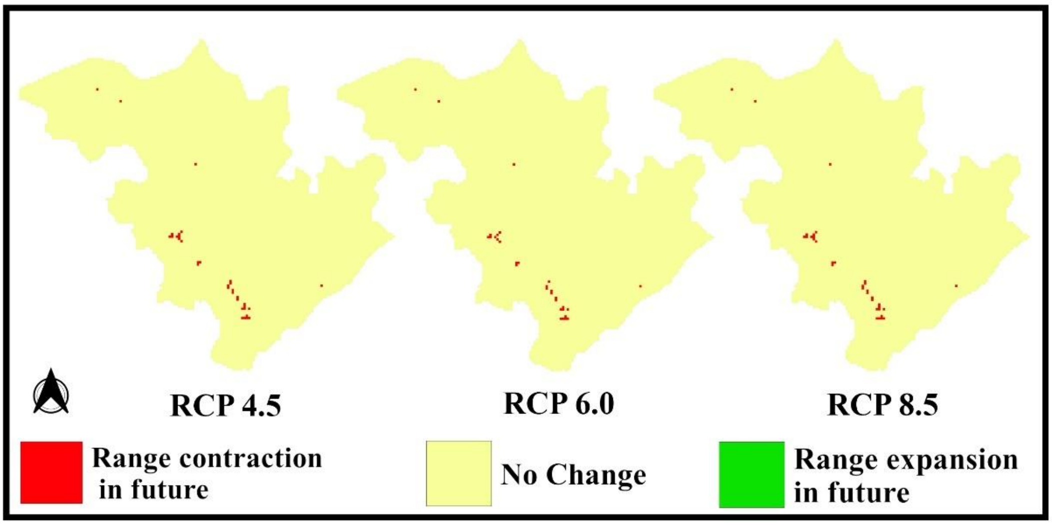


Figure 22. Future habitat suitability changes of Banasura Laughingthrush under different climate change scenarios

4.3.3 Nilgiri Laughingthrush

The Maxent model of the NLT predicted the gain of suitable habitat in RCP 4.5 and RCP 6.0, however a considerable loss in RCP 8.5. The species could be gaining 7.60% [RCP 6.0 (2050s)] to 40.60% [RCP 4.5 (2050s)] of an additional habitat compared to the currently available habitat (Table 17). However, the model predicted the loss to the tune of 51.70% of suitable habitat under RCP 8.5 (2050s). Thus, under the extreme climate change scenario, the NLT could be losing most of its existing habitats (Figure 23).

Table 17. Habitat suitability changes from the currently suitable habitat of Nilgiri Laughingthrush under various climate change scenarios

RCP Scenario	max SSS Threshold	No Change (km^2)	Loss (km^2)	Gain (km^2)	Suitable Habitat (km^2)	Net Gain (%)
4.5 (2050s)	0.781	6201	13	269	886	40.6
6.0 (2050s)	0.773	6347	44	92	678	7.6
8.5 (2050s)	0.773	6151	329	3	304	-51.7

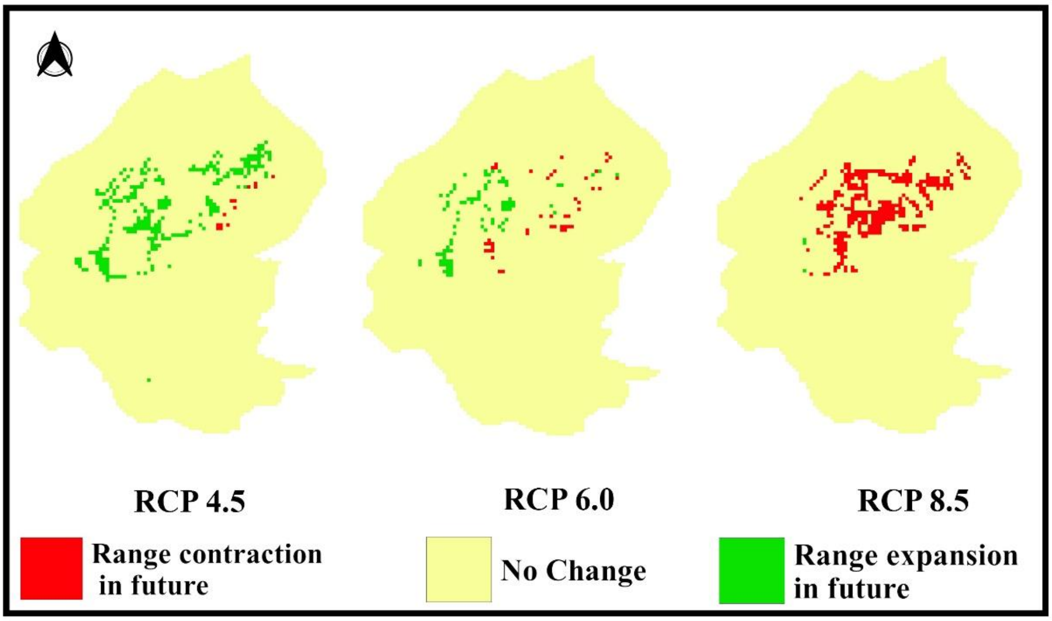


Figure 23. Future habitat suitability changes of Nilgiri Laughingthrush under different climate change scenarios

4.3.4 Palani Laughingthrush

The model associated with the PLT predicted 27.50% [RCP 4.5 (2050s)] loss of habitat suitability compared to current habitat availability (Table 18). High contraction of suitable habitat of the PLT could be happening in the hills associated with Periyar Tiger Reserve (Pandalam Hills). The habitat loss in the Anamalai Hills would be more towards to the fringes of the species distribution. However, 8.30% (RCP 6.0: 2050s) suitable habitat additionally predicted compared to the current habitat condition (Figure 24).

Table 18. Habitat suitability changes from the currently suitable habitat of Palani Laughingthrush under various climate change scenarios

RCP Scenario	max SSS Threshold	No Change (km^2)	Loss (km^2)	Gain (km^2)	Suitable Habitat (km^2)	Net Gain (%)
4.5 (2050s)	0.708	18938	872	22	2246	-27.50
6.0 (2050s)	0.579	19340	117	375	3354	8.30
8.5 (2050s)	0.636	19005	796	31	2331	-24.70

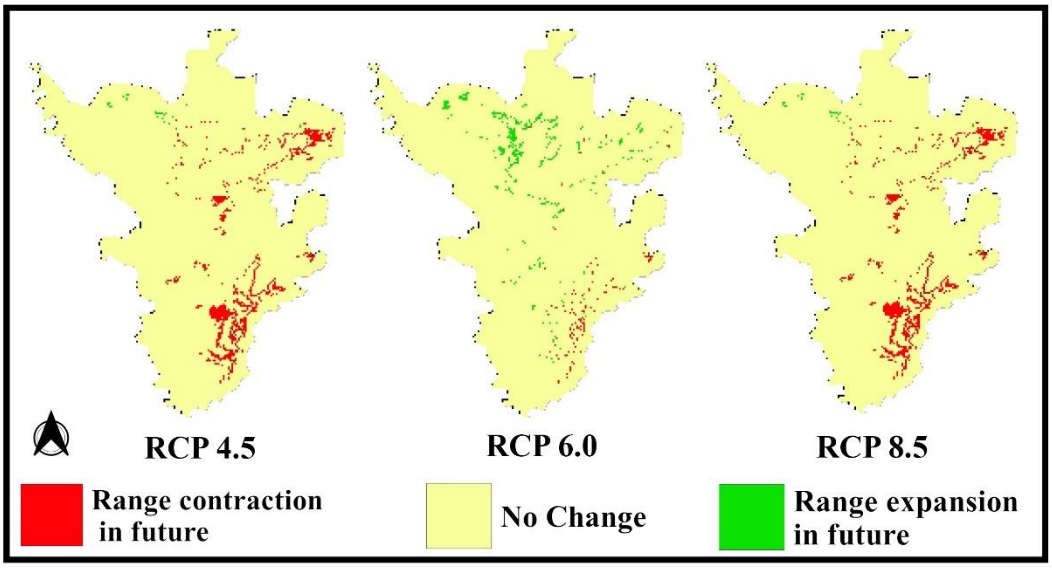


Figure 24. Future habitat suitability changes of Palani Laughingthrush under different climate change scenarios

4.3.5 Nilgiri Flycatcher

The NIF model predicted a 45.80% suitable habitat loss compared to currently available habitat under RCP 8.5 (2050s) (

Table 19). The species would be losing the suitable habitat more or less evenly throughout its distributional range. More contraction of the habitat would happen in Agasthyamalai Hills, Anamalai Hills, Biligirirangana Hills and north of the Kaveri River. The model, however, randomly predicted very few gains of suitable habitat for the NIF (Figure 25).

Table 19. Habitat suitability changes from the currently suitable habitat of Nilgiri Flycatcher under various climate change scenarios

RCP Scenario	max SSS Threshold	No Change (km^2)	Loss (km^2)	Gain (km^2)	Suitable Habitat (km^2)	Net Gain (%)
4.5 (2050s)	0.613	59512	4911	21	8733	-35.90
6.0 (2050s)	0.613	60038	4373	33	9283	-31.90
8.5 (2050s)	0.613	58180	6255	9	7377	-45.80

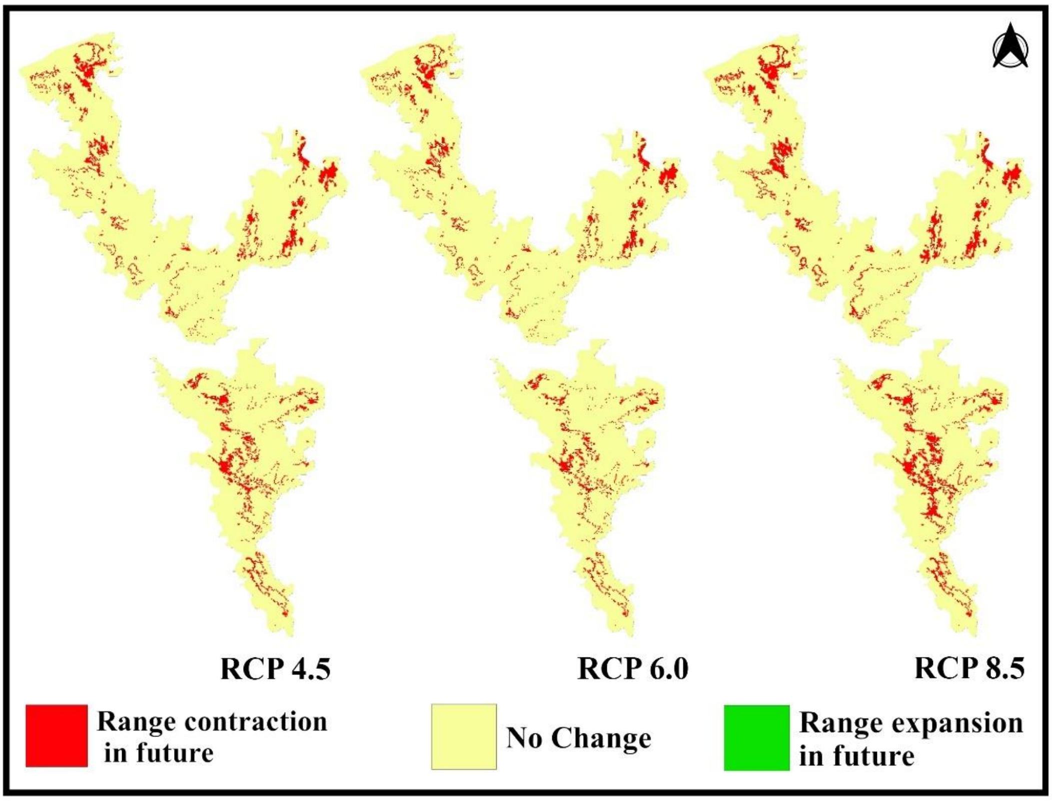


Figure 25. Future habitat suitability changes of Nilgiri Flycatcher under different climate change scenarios

4.3.6 Black-and-orange Flycatcher

The Maxent model for the species projected a 30.80% loss of suitable habitat compared to the currently suitable habitat (Table 20). Significant loss of suitable habitat would be happening in the Agasthyamalai and Anamalai Hills.

Interestingly, the range contraction mainly predicted from its distributional range south of the Palakkad Gap. However, an expansion of habitat indicated in the Nilgiri Hills (north of the Palakkad gap), especially in the fringe areas of the current distributional range of the BOF (Figure 26).

Table 20. Habitat suitability changes from the currently suitable habitat of Black-and-orange Flycatcher under various climate change scenarios

RCP Scenario	max SSS Threshold	No Change (km^2)	Loss (km^2)	Gain (km^2)	Suitable Habitat (km^2)	Net Gain (%)
4.5 (2050s)	0.603	51440	1465	128	5195	-20.50
6.0 (2050s)	0.606	51554	1336	143	5339	-18.30
8.5 (2050s)	0.606	50972	2037	24	4519	-30.80

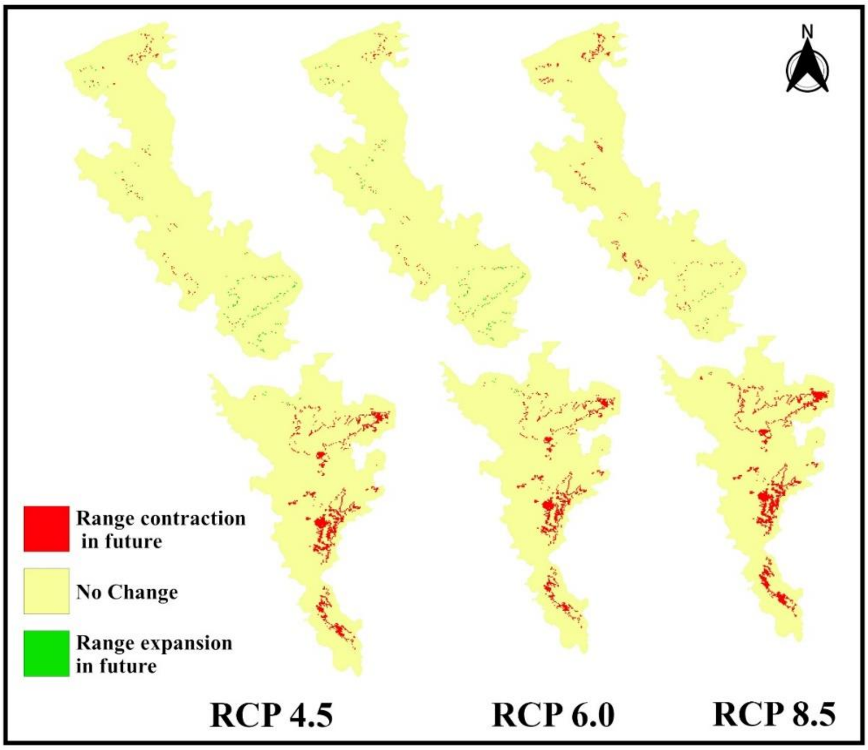


Figure 26. Future habitat suitability changes of Black-and-orange Flycatcher under different climate change scenarios

5 DISCUSSION

5.1 VARIABLE SELECTION FOR THE MODEL BUILDING

The variables selected for the model development should be related to species ecology and include a sufficient number of variables that explain all aspects of the habitat requirement of a species (Austin and Van Niel, 2011). Based on the availability, an adequate number of variables included in the current study. The elevation plays a crucial role in shaping the distribution of all selected species of birds for this study. But multicollinearity test showed a high correlation of elevation with several other bioclimatic variables. Also, the research mainly focussed on the climate suitability of the species than other static variable dependence in the distribution.

In this study, the BIO 11 found to be the common variable and high percentage of permutation importance in all six models. Furthermore, the same variable also has high permutation importance in the model of Nilgiri Pipit *Anthus nilghiriensis*, which is a sky island restricted species of the WG (Jose, 2020). The current study and previously mentioned studies show the importance of BIO 11 in the habitat farming of the restricted distributed montane birds of the WG. Several other modelling studies carried out on the sky island specialist mammals of the WG (Sony *et al.*, 2018; Raman *et al.*, 2020), but that models developed based on the other bioclimatic variables. So, different taxa or species require a different set of variables for the successful development of the SDMs.

5.2 HABITAT SUITABILITY PREDICTIONS UNDER CURRENT CLIMATE

5.2.1 Wayanad Laughingthrush

The WLT mainly distributed between the elevation band of 455m to 760m (Collar and Robson, 2020), and the model also suggested relatively the same habitat suitability. The WG's midlands and high elevation landscapes having evergreen and semi-evergreen forests, including cane-brakes, are available (Nair, 1991), that thought to be the best vegetation combination for the WLT. The model also suggested some new suitable habitats south of the Goa Gap and north of the Kaveri River. However, the presence of the Goa Gap limited the further dispersion chances of the species because of the unavailability of suitable vegetation types and climate beyond the boundary (Ramachandran *et al.*, 2017). Also, the eastern slopes of the WG in Karnataka and Tamil Nadu would be unfavourable to the WLT due to the presence of drier conditions than the wetter western slopes of the WG.

5.2.2 Banasura Laughingthrush

The BLT has highly restricted distribution in the part of Brahmagiri Hills (Praveen, 2020). The model predicted suitable habitats in Vavul Mala and Chembra Peak of Wayanad district of Kerala. The model also predicted some suitable isolated habitats, but those can neglect because of the population disconnection from the source population to the predicted habitat. Due to the low population density and specific habitat requirement for the BLT, like *shola* forest (Praveen, 2020), the further dispersion of the species outside such habitat is limited.

5.2.3 Nilgiri Laughingthrush

The NLT is a species that is another exclusive *shola* habitat dependant and frequent above 1600m elevation (Collar *et al.*, 2020a). The Maxent model also predicted the suitable habitat for the NLT as the montane forests of Nilgiri Hills. The high elevation montane forests of Nilgiri Hills surrounded by the low elevation habitats prevent further dispersion of this species (Ramachandran *et al.*, 2017).

5.2.4 Palani Laughingthrush

The model predicted two significant suitable landscapes for the PLT: Anamalai Hills and Pandalam Hills, in the background region. The high elevation hills are also available in the same landscapes. The PLT preferred the elevation band of 1200m to 2600m (Collar *et al.*, 2020b), which matches the model suggestion. The Palakkad Gap in the north of the extent of species and Shenkottah

Gap in the south prevent the further dispersion of the species. The drier and low altitude habitats surrounded by the montane forests of Anamalai Hills and Pandalam Hills are unsuitable for the PLT.

5.2.5 Nilgiri Flycatcher

The NIF continuously distributed to the south of the Chaliyar River and is patchily distributed in the Brahmagiri Hills (Clement, 2020b). The species is more frequent above 1200m elevation (Clement, 2020b), and the model also predicted a similar pattern. The species more habited in the *shola* forests of the WG (Sashikumar *et al.*, 2011; Clement, 2020b). The unavailability of such a habitat beyond the background's northern limit prevents the further dispersion of the species. Low elevated drier habitats in the eastern slopes in Tamil Nadu and Karnataka also block the expansion of the population of NIF.

5.2.6 Black-and-orange Flycatcher

According to the model, the BOF has suitable habitats in Nilgiri, Anamalai, Pandalam and Agasthyamalai Hills of the WG. The model also predicted some random and disconnected suitable habitats in the Brahmagiri Hills. There is an apparent disconnection between the primary suitable montane forests, unlike the case of NIF. The species can't disperse beyond the extends of the background because of the unavailability of suitable habitats like *shola* at the northern extent and drier habitats at the eastern slopes. The BOF prefers the habitat above 700m, though it is more frequent above 1600m (Khan, 1979; Clement, 2020a). The Maxent model for BOF also suggested a similar pattern.

5.3 CLIMATE CHANGE IMPACT AND SUITABILITY CHANGES

Based on the above discussion, it is evident that all the six species would be losing their suitable habitats under extreme climate change scenario. Climate change may be badly affecting the suitable habitat of several species and may lose their potential habitat. These species may be responding to the change in climatic conditions either by shifting their distributional range to their desired climates or may even become locally extinct (Parmesan, 2006; Bellard *et al.*, 2012). The elevational shift may be a possible solution to overcome climate warming (Stuhldreher and Fartmann, 2018). Still, the sky island specialists of the WG already exist in the highest elevation regions. Such altitudinal shift in the distribution range of a species leads to competition for resources and occupation.

5.3.1 Laughingthrushes of the Western Ghats

The WLT would lose about 36.80% to 48.80% of suitable habitat under different climate change scenarios. The majority of the habitat loss predicted to the south of the Kaveri River, which is the current favourable habitat of the species. It is evident that a large extent of the suitable habitat of the WLT, thorny cane-brakes in the evergreen forests (Collar and Robson, 2020), would change into unsuitable habitat even though some studies predicted the expansion of evergreen forests in the southern WG (Ravindranath and Sukumar, 1998). However, there should be a need for vegetation type change models according to the recent climate change models to explain the habitat suitability change of the WLT. The WLT prefers mid-elevation to high-elevation habitats. So, the WLT could be moving to a further higher elevation if the climate is getting warmer. The Maxent model of the species also predicted such gain of suitable habitat in the high-altitude regions of Anamalai, Nilgiri and Brahmagiri Hills.

All three laughingthrushes under the *Montecincla* genus considered a single species until the recent genetic studies elevated them to three distinct species (Robin *et al.*, 2017). Due to the close relationship between these species, they occupied the same habitat type in different landscapes. These laughingthrushes prefer *shola* habitat in the sky islands of the WG (Collar *et al.*, 2020a, 2020b; Praveen, 2020). All laughingthrushes would lose suitable habitat under different climate change scenarios. The BLT would lose more than 70% of the suitable habitat, leading to the extinction of the species. However, the PLT would lose 24.70% to 27.50% of suitable habitat, however the gain under the RCP 6.0 scenario.

Interestingly, the NLT would gain habitat under two moderate climate change scenarios (RCP 4.5 and RCP 6.0) but lose more than 50% of suitable habitat in verse climate change scenario (RCP 8.5). Expansion of evergreen forest due to the increasing carbon emission and increasing precipitation (Sukumar *et al.*, 1995; Gopalakrishnan *et al.*, 2011) is the best possible explanation for gaining a suitable habitat for both NLT and PLT under moderate climate change scenario. However, under RCP 8.5, all these laughingthrushes would be lost suitable habitat. The ongoing deterioration of *shola* forests (Arasumani *et al.*, 2018, 2019) and the predicted decline of the *shola*-grassland ecosystem (Sukumar *et al.*, 1995) could be the reason for the contraction of suitable habitats for the sky island restricted species, such as the laughingthrushes.

5.3.2 Flycatchers of the Western Ghats

The NIF would affect more severely in losing suitable habitats (35.90% to 45.85%) than the BOF (20.47% to 30.82%). Loss of suitable habitats for the NIF seen in the entire range of the species. But in the case of the BOF, loss of suitable habitats occurs in the Anamalai, Pandalam and Agasthyamalai Hills compared to other regions. These two species also highly preferred *shola* forest, and climate change may deteriorate the montane ecosystems of the WG (Sukumar *et al.*, 1995).

5.4 SUITABLE HABITAT UNDER PROTECTED AREA NETWORK

One of the significant findings of the current study is that the present protected area network of the WG is inadequate in according protections to the species under discussion. The PLT is the one species which has been better protected within the PA network in the WG, with 30.30% of its suitable habitat under the PA network. However, it is a matter of major concern to note that none of the suitable habitats for the BLT falls within any of the PAs and urgent steps need to be taken to accord the greatest protection to this species. Only 3.17% of the suitable habitat of the NLT falls under the protected area network, however for the other three species, such as WLT, NIF and BOF, around 25% of the suitable habitats comes under the protected area network. Most of the high-altitude habitats that fall within the protected areas situated in Agasthyamalai, Pandalam and Anamalai Hills and remaining landscapes were poorly protected. The montane habitat like *shola* forests is under various threat from anthropogenic activities and climate change (Sukumar *et al.*, 1995). The studies showing that the rate of deterioration of *shola* habitat is very high in the forests outside the protected area network and loss of such habitat is slow in the existing protected areas (Arasumani *et al.*, 2018, 2019). If the habitats become disconnected due to forest deterioration, then the species populations become isolated. Long-term isolation of the populations would lead to the local extinction of the species (Wilcox and Murphy, 1985).

5.5 LIMITATIONS OF THE STUDY

The layers like bioclimatic variables, digital elevation model and enhanced vegetation index were used for developing the models. However, the species habitat could be associated with more variables (Araújo and Guisan, 2006) like insect population availability, types of vegetation, fruit tree distribution and so on. But most of such layers are not available in the required format to perform the SDMs. In this study maximum variables, that frame the habitat of selected birds, were incorporated. The species-specific microclimatic studies and habitat-specific studies would be needed to develop accurate models. The quality of the climate models is also questionable because of the limited number of weather stations in the study area. The high-resolution climate models in different families were selected to overcome this problem.

6 SUMMARY

Climate change is affecting the distribution and phenology of all organisms including birds. The montane habitat is more vulnerable to climate change and organisms restricted in such sky islands can be used as the bioindicators of climate change. Species distribution modelling thought to be the best tool to understand the climate change response by the organisms. Among different types of species distribution modelling technique, Maximum entropy modelling gain popularity due to the performance, accuracy and easiness to carry out. The current study aims to determine the environmental and/or climatic variables that influence the distribution of selected endemic birds of the Western Ghats. The study also aims to analyse the suitable habitats of the selected endemic birds of the Western Ghats. It is also proposed to predict the future changes in the habitat suitability of selected endemic birds of the Western Ghats under different climate change scenarios such as RCP 4.5, RCP 6.0 and RCP 8.5 for the period of 2050s (2041-2060) by using the Maxent algorithm.

The Maxent models can be developed by using presence-only occurrence data and environmental variables. The occurrence data can be retrieved from the eBird database and eBird maintain the data quality by the rigorous review process. Bioclimatic variables 1 to 19, digital elevation model (elevation, slope and aspect) and 10-year averaged enhanced vegetation index were used to develop the Maxent models. Pearson's multicollinearity test was helped to eliminate highly correlated ($|R|>0.75$) variables. The ENM evaluation tool was used to determines the Maxent features, number of background points and regularization multiplier. Future predictions were done by averaging three different earth system models under Coupled Model Intercomparison Project 5 to reduce model-to-model bias. There were six species of birds, such as Wayanad Laughingthrush (WLT) *Ianthocincla delesserti*, Banasura Laughingthrush (BLT) *Montecincla jerdoni*, Nilgiri Laughingthrush (NLT) *M. cachinnans*, Palani Laughingthrush (PLT) *M. fairbanki*, Nilgiri Flycatcher (NIF) *Eumyias albicaudatus* and Black-and-orange Flycatcher (BOF) *Ficedula nigrorufa*, were selected for the study.

The highlights of the results summarised here:

- Mean Temperature of Coldest Quarter (BIO 11) found to be the highly important environmental variable in all models of the selected species of birds
- An area of 16,584 km^2 predicted as suitable habitat for the WLT and it covered 22% of the background
- For the BLT, the model predicted 47 km^2 as suitable habitat and that only covered 0.40% of the background
- The suitable habitat of NLT found to be 630 km^2 and it covered 9.60% of the background
- The PLT model predicted 3,096 km^2 as suitable habitat and it comes 15.5% of the background
- The model predicted 12,707 km^2 as suitable habitat for NIF and it covered 19.70% of the background
- An area of 6,532 km^2 predicted as suitable habitat for the BOF, which covered 12.20% of the background
- 26.53%, 24.07% and 26.50% of suitable habitat of the WLT, NIF and BOF respectively distributed within the protected area network
- 3.17% and 30.30% of suitable habitat of NLT and PLT respectively fall under the protected area network and however none of the suitable habitats of the BLT coming under the protected area network
- Under future climate change scenarios, the WLT would be losing 36.80% to 41.20% of the current suitable habitat
- The BLT would be losing 66.00% to 72.30% of current suitable habitat under future climate change scenarios
- The NLT would be gaining 7.60% to 40.60% of additional habitat under moderate climate change scenarios but it would lose the habitat to the tune of 51.70% under the extreme scenario
- 24.70% to 27.50% of suitable habitat would be lost under RCP 8.5 and RCP 4.5 respectively for the PLT, however, it will gain 8.30% of habitat under RCP 6.0
- The NIF would be losing 31.90% to 45.80% of habitat under various climate change scenarios

- 18.30% to 30.80% of suitable habitat would be lost for BOF under various climate change scenarios
- Realignment of the protected area network in the WG is recommended to ensure the long-term conservation of the six selected species of birds of this study
- Greenhouse gas emission reduction and restoration of the degraded habitats are recommended as some possible solutions to mitigate and reduce the impact of climate change.

Future Recommendations:

- Conducting periodical bird surveys in Western Ghats for understanding the most accurate distribution of the species and changes in population dynamics
- Developing the SDMs of other endemic birds of the Western Ghats
- Standardise the most accurate earth system models for the Western Ghats
- Use shared socioeconomic pathway simulations for further improvement of the predictions

7 REFERENCES

Acharya, B.K., Sanders, N.J., Vijayan, L., and Chettri, B. 2011. Elevational Gradients in Bird Diversity in the Eastern Himalaya: An Evaluation of Distribution Patterns and Their Underlying Mechanisms, *PLoS One*. (Edited by D. Nogues-Bravo), 6(12): e29097. DOI: 10.1371/journal.pone.0029097.

Aiello-Lammens, M.E., Boria, R.A., Radosavljevic, A., Vilela, B., and Anderson, R.P. 2015. spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models, *Ecography (Cop.)*. Blackwell Publishing Ltd, 38(5): 541–545. DOI: 10.1111/ecog.01132.

Allouche, O., Tsoar, A., and Kadmon, R. 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS), *J. Appl. Ecol.*, 43(6): 1223–1232. DOI: 10.1111/j.1365-2664.2006.01214.x.

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. DOI: 10.1016/S0304-3800(02)00349-6.

Anderson, R.P. and Martinez-Meyer, E. 2004. Modeling species' geographic distributions for preliminary conservation assessments: an implementation with the spiny pocket mice (Heteromys) of Ecuador, *Biol. Conserv.*, 116(2): 167–179. DOI: 10.1016/S0006-3207(03)00187-3.

Anderson, R.P. and Raza, A. 2010. The effect of the extent of the study region on GIS models of species geographic distributions and estimates of niche evolution: preliminary tests with montane rodents (genus Nephelomys) in Venezuela, *J. Biogeogr.*, 37(7): 1378–1393. DOI: 10.1111/j.1365-2699.2010.02290.x.

Aragón, P., Lobo, J.M., Olalla-Tárraga, M.Á., and Rodríguez, M.Á. 2010. The contribution of contemporary climate to ectothermic and endothermic vertebrate distributions in a glacial refuge, *Glob. Ecol. Biogeogr.*, 19(1): 40–

49. DOI: 10.1111/j.1466-8238.2009.00488.x.

Arasumani, M., Khan, D., Das, A., Lockwood, I., Stewart, R., Kiran, R.A., Muthukumar, M., Bunyan, M., and Robin, V. V. 2018. Not seeing the grass for the trees: Timber plantations and agriculture shrink tropical montane grassland by two-thirds over four decades in the Palani Hills, a Western Ghats Sky Island, *PLoS One*, 13(1): e0190003. DOI: 10.1371/journal.pone.0190003.

Arasumani, M., Khan, D., Vishnudas, C.K., Muthukumar, M., Bunyan, M., and Robin, V. V 2019. Invasion compounds an ecosystem-wide loss to afforestation in the tropical grasslands of the Shola Sky Islands, *Biol. Conserv.*, 230: 141–150. DOI: 10.1016/j.biocon.2018.12.019.

Araújo, M.B. and Guisan, A. 2006. Five (or so) challenges for species distribution modelling, *J. Biogeogr.*, 33(10): 1677–1688. DOI: 10.1111/j.1365-2699.2006.01584.x.

Ash, A. and Shwartz, M. 1999. R2: a useful measure of model performance when predicting a dichotomous outcome, *Stat. Med.*, 18(4): 375–384. DOI: 10.1002/(SICI)1097-0258(19990228)18:4<375::AID-SIM20>3.0.CO;2-J.

Austin, M.. 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling, *Ecol. Modell.*, 157(2–3): 101–118. DOI: 10.1016/S0304-3800(02)00205-3.

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

Austin, M.P., Nicholls, A.O., and Margules, C.R. 1990. Measurement of the Realized Qualitative Niche: Environmental Niches of Five Eucalyptus Species, *Ecol. Monogr.*, 60(2): 161–177. DOI: 10.2307/1943043.

Austin, M.P. and Van Niel, K.P. 2011. Improving species distribution models for climate change studies: variable selection and scale, *J. Biogeogr.*, 38(1): 1–8. DOI: 10.1111/j.1365-2699.2010.02416.x.

Baldwin, R. 2009. Use of Maximum Entropy Modeling in Wildlife Research, *Entropy*, 11(4): 854–866. DOI: 10.3390/e11040854.

Baldwin, R.A. and Bender, L.C. 2008. Den-Site Characteristics of Black Bears in Rocky Mountain National Park, Colorado, *J. Wildl. Manage.*, 72(8): 1717–1724. DOI: 10.2193/2007-393.

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. DOI: 10.1073/pnas.0803506105.

Becker, P.H. 2003. Biomonitoring with birds, In: *Trace Met. other Contam. Environ.* Elsevier, pp. 677–736. DOI: 10.1016/S0927-5215(03)80149-2.

Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W., and Courchamp, F. 2012. Impacts of climate change on the future of biodiversity, *Ecol. Lett.*, 15(4): 365–377. DOI: 10.1111/j.1461-0248.2011.01736.x.

Biggerstaff, B.J. 2000. Comparing diagnostic tests: a simple graphic using likelihood ratios, *Stat. Med.*, 19(5): 649–663. DOI: 10.1002/(SICI)1097-0258(20000315)19:5<649::AID-SIM371>3.0.CO;2-H.

Billlerman, S., Keeney, B., Rodewald, P., and Schulenberg, T. 2020. *Birds of the World*, *Cornell Lab. Ornithol. Ithaca, NY, USA*. Available: https://birdsoftheworld.org/bow/home [4 April 2021].

Böhning, D., Böhning, W., and Holling, H. 2008. Revisiting youden's index as a useful measure of the misclassification error in meta-analysis of diagnostic studies, *Stat. Methods Med. Res.*, 17(6): 543–554. DOI: 10.1177/0962280207081867.

Bojorquez-Tapia, L.A., Azuara, I., Ezcurra, E., and Flores-Villela, O. 1995. Identifying Conservation Priorities in Mexico Through Geographic Information Systems and Modeling, *Ecol. Appl.*, 5(1): 215–231. DOI: 10.2307/1942065.

Briggs, W.M. and Zaretzki, R. 2008. The Skill Plot: A Graphical Technique for

Evaluating Continuous Diagnostic Tests, *Biometrics*, 64(1): 250–256. DOI: 10.1111/j.1541-0420.2007.00781_1.x.

Brown, J.L. 2014. SDMtoolbox: a python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses, *Methods Ecol. Evol.* (Edited by B. Anderson), 5(7): 694–700. DOI: 10.1111/2041-210X.12200.

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: Verner, J. A., Morrison, M. L., and Ralph, C. J. (eds.), *Wildl. 2000 Model. Habitat Relationships Terr. Vertebr.* Madison, WI, USA: University of Wisconsin Press, pp. 171–175.

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

CEPF 2021. *Critical Ecosystem Partnership Fund: Western Ghats and Sri Lanka*. Arlington, Virginia, United States. Available: https://www.cepf.net/our-work/biodiversity-hotspots/western-ghats-and-sri-lanka [1 April 2021].

Chamberlain, D., Brambilla, M., Caprio, E., Pedrini, P., and Rolando, A. 2016. Alpine bird distributions along elevation gradients: the consistency of climate and habitat effects across geographic regions, *Oecologia*, 181(4): 1139–1150. DOI: 10.1007/s00442-016-3637-y.

Chen, I.-C., Hill, J.K., Ohlemuller, R., Roy, D.B., and Thomas, C.D. 2011. Rapid Range Shifts of Species Associated with High Levels of Climate Warming, *Science (80-.).*, 333(6045): 1024–1026. DOI: 10.1126/science.1206432.

Clement, P. 2020a. Black-and-orange Flycatcher (Ficedula nigrorufa), In: del Hoyo, J. et al. (eds.), *Birds of the World*. Ithaca, NY, USA: Cornell Lab of Ornithology. DOI: 10.2173/bow.barfly1.01.

Clement, P. 2020b. Nilgiri Flycatcher (Eumyias albicaudatus), In: del Hoyo, J. et al. (eds.), *Birds of the World*. Ithaca, NY, USA: Cornell Lab of Ornithology. DOI: 10.2173/bow.nilfly2.01.

Cohen, J. 1960. A Coefficient of Agreement for Nominal Scales, *Educ. Psychol. Meas.*, 20(1): 37–46. DOI: 10.1177/001316446002000104.

Collar, N. and Robson, C. 2020. Wayanad Laughingthrush (Ianthocincla delesserti), In: del Hoyo, J. et al. (eds.), *Birds of the World*. Ithaca, NY, USA: Cornell Lab of Ornithology. DOI: 10.2173/bow.wynlau1.01.

Collar, N., Robson, C., and Christie, D. 2020a. Nilgiri Laughingthrush (Montecincla cachinnans), In: Billerman, S. M., Keeney, B. K., and Rodewald, P. G. (eds.), *Birds of the World*. Ithaca, NY, USA: Cornell Lab of Ornithology. DOI: 10.2173/bow.bkclau2.01.1.

Collar, N., Robson, C., and Christie, D. 2020b. Palani Laughingthrush (Montecincla fairbanki), In: del Hoyo, J. et al. (eds.), *Birds of the World*. Ithaca, NY, USA: Cornell Lab of Ornithology. DOI: 10.2173/bow.kerlau2.01.

Coxen, C.L., Frey, J.K., Carleton, S.A., and Collins, D.P. 2017. Species distribution models for a migratory bird based on citizen science and satellite tracking data, *Glob. Ecol. Conserv.* Elsevier Ltd, 11: 298–311. DOI: 10.1016/j.gecco.2017.08.001.

Crick, H.Q.P. 2004. Impact of climate chnage on birds, *Ibis (Lond. 1859).*, 146(1): 48–56. DOI: doi: 10.1111/j.1474-919X.2004.00327.x.

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. DOI: 10.1016/j.biocon.2008.07.010.

eBird 2021. *eBird: An online database of bird distribution and abundance*, *eBird, Cornell Lab Ornithol. Ithaca, New York*. Available: http://www.ebird.org [4 April 2021].

Elith, J., H. Graham, C., P. Anderson, R., Dudík, M., Ferrier, S., Guisan, A., J. Hijmans, R., Huettmann, F., R. Leathwick, J., Lehmann, A., Li, J., G. Lohmann, L., A. Loiselle, B., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., McC. M. Overton, J., Townsend Peterson, A., J. Phillips, S., Richardson, K., Scachetti-Pereira, R., E. Schapire, R., Soberón, J., Williams, S., S. Wisz, M., and E. Zimmermann, N. 2006. Novel methods improve prediction of species' distributions from occurrence data, *Ecography (Cop.)*., 29(2): 129–151. DOI: 10.1111/j.2006.0906-7590.04596.x.

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. DOI: 10.1111/j.1472-4642.2010.00725.x.

Elith, J. and Leathwick, J.R. 2009. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time, *Annu. Rev. Ecol. Evol. Syst.*, 40(1): 677–697. DOI: 10.1146/annurev.ecolsys.110308.120159.

Engler, R., Guisan, A., and Rechsteiner, L. 2004. An improved approach for predicting the distribution of rare and endangered species from occurrence and pseudo-absence data, *J. Appl. Ecol.*, 41(2): 263–274. DOI: 10.1111/j.0021-8901.2004.00881.x.

ENVIS Centre on Wildlife and Protected Areas 2020. *Maps of protected areas in India*, *Minist. Environ. For. Clim. Chang.* Government of India. Available: http://www.wiienvis.nic.in/Database/Maps_PAs_1267.aspx [1 April 2021].

Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., and Taylor, K.E. 2016. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geosci. Model Dev.*, 9(5): 1937–1958. DOI: 10.5194/gmd-9-1937-2016.

Ferrier, S., Watson, G., Pearce, J., and Drielsma, M. 2002. Extended statistical approaches to modelling spatial pattern in biodiversity in northeast New South Wales. I. Species-level modelling, *Biodivers. Conserv.*, 11(12): 2275–2307. DOI: 10.1023/A:1021302930424.

Ferrier, S. 2002. Mapping Spatial Pattern in Biodiversity for Regional Conservation Planning: Where to from Here?, *Syst. Biol.* (Edited by V. Funk), 51(2): 331–363. DOI: 10.1080/10635150252899806.

Fick, S.E. and Hijmans, R.J. 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas, *Int. J. Climatol.*, 37(12): 4302–4315. DOI: 10.1002/joc.5086.

Fielding, A.H. and John, F.B. 1997. A Review of Methods for the Assessment of Prediction Errors in Conservation Presence/Absence Models, *Environ. Conserv.*, 24(1): 38–49. Available: www.jstor.org/stable/44519240.

Friedman, J., Hastie, T., and Tibshirani, R. 2000. Additive logistic regression: a statistical view of boosting (With discussion and a rejoinder by the authors), *Ann. Stat.*, 28(2). DOI: 10.1214/aos/1016218223.

Funk, V.A. and Richardson, K.S. 2002. Systematic data in biodiversity studies: use it or lose it, *Syst. Biol.* (Edited by A.K. Sakai), 51(2): 303–316. DOI: 10.1080/10635150252899789.

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: *Large Scale Ecol. Conserv. Biol.* Oxford: Blackwell, pp. 153–177.

Giriraj, A., Irfan-Ullah, M., Ramesh, B.R., Karunakaran, P. V, Jentsch, A., and Murthy, M.S.R. 2008. Mapping the potential distribution of Rhododendron arboreum Sm. ssp. nilagiricum (Zenker) Tagg (Ericaceae), an endemic plant using ecological niche modelling, *Curr. Sci.*, 94(12): 1605–1612.

Glas, A.S., Lijmer, J.G., Prins, M.H., Bonsel, G.J., and Bossuyt, P.M.M. 2003. The diagnostic odds ratio: a single indicator of test performance, *J. Clin. Epidemiol.*, 56(11): 1129–1135. DOI: 10.1016/S0895-4356(03)00177-X.

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

Graham, C., Ferrier, S., Huettman, F., Moritz, C., and Peterson, A. 2004. New developments in museum-based informatics and applications in biodiversity analysis, *Trends Ecol. Evol.*, 19(9): 497–503. DOI: 10.1016/j.tree.2004.07.006.

Graham, C.H., Moritz, C., and Williams, S.E. 2006. Habitat history improves prediction of biodiversity in rainforest fauna, *Proc. Natl. Acad. Sci.*, 103(3): 632–636. DOI: 10.1073/pnas.0505754103.

Gregory, R.D., Willis, S.G., Jiguet, F., Voříšek, P., Klvaňová, A., van Strien, A., Huntley, B., Collingham, Y.C., Couvet, D., and Green, R.E. 2009. An Indicator of the Impact of Climatic Change on European Bird Populations, *PLoS One*. (Edited by P.M. Bennett), 4(3): e4678. DOI: 10.1371/journal.pone.0004678.

Guisan, A., Theurillat, J.-P., and Kienast, F. 1998. Predicting the potential distribution of plant species in an alpine environment, *J. Veg. Sci.*, 9(1): 65–74. DOI: 10.2307/3237224.

Guisan, A. and Thuiller, W. 2005. Predicting species distribution: Offering more than simple habitat models, *Ecol. Lett.*, 8(9): 993–1009. DOI: 10.1111/j.1461-0248.2005.00792.x.

Guisan, A. and Zimmermann, N.E. 2000. Predictive habitat distribution models in ecology, *Ecol. Modell.*, 135(2–3): 147–186. DOI: 10.1016/S0304-3800(00)00354-9.

Hand, D.J. 2001. Measuring Diagnostic Accuracy of Statistical Prediction Rules, *Stat. Neerl.*, 55(1): 3–16. DOI: 10.1111/1467-9574.00153.

Harris, J.B.C., Sekercioglu, C.H., Sodhi, N.S., Fordham, D.A., Paton, D.C., and Brook, B.W. 2011. The tropical frontier in avian climate impact research, *Ibis (Lond. 1859).*, 153(4): 877–882. DOI: 10.1111/j.1474-919X.2011.01166.x.

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., Porter, E.E., and Turner, J.R.G. 2003. Energy, water, and broad-scale geographic patterns of species richness, *Ecology*, 84(12): 3105–3117. DOI: 10.1890/03-8006.

Heikkinen, R.K., Thuiller, W., Luoto, M., Araujo, M.B., Virkkala, R., and Sykes, M.T. 2006. Methods and uncertainties in bioclimatic envelope modelling under climate change, *Prog. Phys. Geogr.*, 30(6): 751–777. Available: //000243236600004.

Hernandez, P.A., Graham, C.H., Master, L.L., and Albert, D.L. 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods, *Ecography (Cop.).*, 29(5): 773–785. DOI: 10.1111/j.0906-7590.2006.04700.x.

Hijmans, R.J., Garrett, K.A., Huamán, Z., Zhang, D.P., Schreuder, M., and Bonierbale, M. 2000. Assessing the Geographic Representativeness of Genebank Collections: the Case of Bolivian Wild Potatoes, *Conserv. Biol.*, 14(6): 1755–1765. DOI: 10.1111/j.1523-1739.2000.98543.x.

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. DOI: 10.1002/joc.1276.

Hirzel, A. and Guisan, A. 2002. Which is the optimal sampling strategy for habitat suitability modelling, *Ecol. Modell.*, 157(2–3): 331–341. DOI: 10.1016/S0304-3800(02)00203-X.

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

Holt, R.D. 1990. The microevolutionary consequences of climate change, *Trends Ecol. Evol.*, 5(9): 311–315. DOI: 10.1016/0169-5347(90)90088-U.

Huettmann, F. 2005. Databases and science-based management in the context of wildlife and habitat: toward a certified ISO standard for objective decision-making for the global community by using the internet, *J. Wildl. Manage.*, 69(2): 466–472.

Huntley, B., Collingham, Y.C., Green, R.E., Hilton, G.M., Rahbek, C., and Willis, S.G. 2006. Potential impacts of climatic change upon geographical distributions of birds, *Ibis (Lond. 1859).*, 148: 8–28. DOI: 10.1111/j.1474-919X.2006.00523.x.

IPBES 2019. *IPBES Global Assessment Summary for Policymakers*. (Edited by S. Díaz et al.). IPBES secretariat, Bonn, Germany. Available:

https://ipbes.net/system/tdf/ipbes_global_assessment_report_summary_for_policymakers.pdf?file=1&type=node&id=35329.

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*, *Ipcc*.

IPCC 2018. *Global Warming of 1.5°C: An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to eradicate poverty*. Available: https://www.ipcc.ch/site/assets/uploads/sites/2/2019/05/SR15_SPM_version_report_LR.pdf.

IPCC 2019. *Summary for Policymakers. Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R. Shukla, J. Skea, E. Calvo*.

Isaac, N.J.B., van Strien, A.J., August, T.A., de Zeeuw, M.P., and Roy, D.B. 2014. Statistics for citizen science: Extracting signals of change from noisy ecological data, *Methods Ecol. Evol.*, 5(10): 1052–1060. DOI: 10.1111/2041-210X.12254.

IUCN 2021. *The IUCN Red List of Threatened Species. Version 2021-1*. Available: https://www.iucnredlist.org [1 April 2021].

Jha, A. and Vasudevan, K. 2019. Environmental niche forecasts of globally threatened yellow-throated bulbul, Pycnonotus xantholaemus for conservation prospects in the Deccan peninsula, India, *bioRxiv*. DOI: 10.1101/633214.

Jones, M.C., Dye, S.R., Fernandes, J.A., Frölicher, T.L., Pinnegar, J.K., Warren, R., and Cheung, W.W.L. 2013. Predicting the Impact of Climate Change on Threatened Species in UK Waters, *PLoS One*. (Edited by J.G. Hiddink), 8(1): e54216. DOI: 10.1371/journal.pone.0054216.

Jose, S. V 2020. Predicting the habitat suitability of an endemic species, Anthus nilghiriensis (Nilgiri Pipit) in the Western Ghats, In: Kumar A, B. (ed.), *Proc. Int. Biodivers. Congr.* Centre for Innovation in Science and Social Action, pp. 209–214.

Jose, V.S. and Nameer, P.O. 2020. The expanding distribution of the Indian Peafowl (Pavo cristatus) as an indicator of changing climate in Kerala, southern India: A modelling study using MaxEnt, *Ecol. Indic.* DOI: 10.1016/j.ecolind.2019.105930.

Kadmon, R., Farber, O., and Danin, A. 2004. Effect of roadside bias on the accuracy of predictive maps produced by bioclimatic models, *Ecol. Appl.*, 14(2): 401–413. DOI: 10.1890/02-5364.

Kamp, J., Oppel, S., Heldbjerg, H., Nyegaard, T., and Donald, P.F. 2016. Unstructured citizen science data fail to detect long-term population declines of common birds in Denmark, *Divers. Distrib.*, 22(10): 1024–1035. DOI: 10.1111/ddi.12463.

Karger, D.N., Conrad, O., Böhner, J., Kawohl, T., Kreft, H., Soria-Auza, R.W., Zimmermann, N.E., Linder, H.P., and Kessler, M. 2017. Climatologies at high resolution for the earth's land surface areas, *Sci. Data*. The Author(s), 4: 1–20. DOI: 10.1038/sdata.2017.122.

Khan, M.A.R. 1979. Ecology of The Black- and orange Flycatcher Muscicapa nigrorufa (Jerdon) In southern India, *J. Bombay Nat. Hist. Soc.*, 75(3): 773–791.

Kim, J.-Y., Lee, S., Shin, M.-S., Lee, C.-H., Seo, C., and Eo, S.H. 2018. Altitudinal patterns in breeding bird species richness and density in relation to climate, habitat heterogeneity, and migration influence in a temperate montane forest (South Korea), *PeerJ*, 6: e4857. DOI: 10.7717/peerj.4857.

Kobler, A. and Adamic, M. 2000. Identifying brown bear habitat by a combined GIS and machine learning method, *Ecol. Modell.*, 135(2–3): 291–300. DOI: 10.1016/S0304-3800(00)00384-7.

Kraemer, H.C. 2006. Correlation coefficients in medical research: from product moment correlation to the odds ratio, *Stat. Methods Med. Res.*, 15(6): 525–545. DOI: 10.1177/0962280206070650.

Leathwick, J., Elith, J., Francis, M., 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. DOI: 10.3354/meps321267.

Leathwick, J.R., Rowe, D., Richardson, J., Elith, J., and Hastie, T. 2005. Using multivariate adaptive regression splines to predict the distributions of New Zealand's freshwater diadromous fish, *Freshw. Biol.*, 50(12): 2034–2052. DOI: 10.1111/j.1365-2427.2005.01448.x.

Lee, P.-F., Ding, T.-S., Hsu, F.-H., and Geng, S. 2004. Breeding bird species richness in Taiwan: distribution on gradients of elevation, primary productivity and urbanization, *J. Biogeogr.*, 31(2): 307–314. DOI: 10.1046/j.0305-0270.2003.00988.x.

Lee, W.-C. and Hsiao, C.K. 1996. Alternative Summary Indices for the Receiver Operating Characteristic Curve, *Epidemiology*, 7(6): 605–611.

Liu, C., Berry, P.M., Dawson, T.P., and Pearson, R.G. 2005. Selecting thresholds of occurrence in the prediction of species distributions, *Ecography (Cop.).*, 28(3): 385–393. DOI: 10.1111/j.0906-7590.2005.03957.x.

Liu, C., White, M., and Newell, G. 2013. Selecting thresholds for the prediction of species occurrence with presence-only data, *J. Biogeogr.*, 40(4): 778–789. DOI: 10.1111/jbi.12058.

Lobo, J.M., Jiménez-Valverde, A., and Real, R. 2008. AUC: a misleading measure of the performance of predictive distribution models, *Glob. Ecol. Biogeogr.*, 17(2): 145–151. DOI: 10.1111/j.1466-8238.2007.00358.x.

Lomolino, M. V. 2001. Elevation gradients of species-density: historical and prospective views, *Glob. Ecol. Biogeogr.*, 10(1): 3–13. DOI: 10.1046/j.1466-822x.2001.00229.x.

Lowe, D.G. 1995. Similarity Metric Learning for a Variable-Kernel Classifier, *Neural Comput.*, 7(1): 72–85. DOI: 10.1162/neco.1995.7.1.72.

Mace, G.M. and Baillie, J.E.M. 2007. The 2010 biodiversity indicators: challenges for science and policy, *Conserv. Biol.*, 21(6): 1406–1413. DOI: 10.1111/j.1523-1739.2007.00830.x.

Malcolm, J.R., Liu, C., Neilson, R.P., Hansen, L., and Hannah, L. 2006. Global warming and extinctions of endemic species from biodiversity hotspots, *Conserv. Biol.*, 20(2): 538–548. DOI: 10.1111/j.1523-1739.2006.00364.x.

Manel, S., Williams, H.C., and Ormerod, S.J. 2001. Evaluating presence-absence models in ecology: the need to account for prevalence, *J. Appl. Ecol.*, 38(5): 921–931. DOI: 10.1046/j.1365-2664.2001.00647.x.

McCain, C.M. 2009. Global analysis of bird elevational diversity, *Glob. Ecol. Biogeogr.*, 18(3): 346–360. DOI: 10.1111/j.1466-8238.2008.00443.x.

McClish, D.K. 1989. Analyzing a Portion of the ROC Curve, *Med. Decis. Mak.*, 9(3): 190–195. DOI: 10.1177/0272989X8900900307.

McCormack, J.E., Huang, H., and Knowles, L.L. 2009. Sky Islands, *Encycl. Islands*, 4: 841–843.

McKechnie, A.E. 2008. Phenotypic flexibility in basal metabolic rate and the changing view of avian physiological diversity: a review, *J. Comp. Physiol. B*, 178(3): 235–247. DOI: 10.1007/s00360-007-0218-8.

McNab, B.K. 2009. Ecological factors affect the level and scaling of avian BMR, *Comp. Biochem. Physiol. Part A Mol. Integr. Physiol.*, 152(1): 22–45. DOI: 10.1016/j.cbpa.2008.08.021.

McSweeney, C.F., Jones, R.G., Lee, R.W., and Rowell, D.P. 2015. Selecting CMIP5 GCMs for downscaling over multiple regions, *Clim. Dyn.*, 44(11–12): 3237–3260. DOI: 10.1007/s00382-014-2418-8.

Meehl, G.A., Boer, G.J., Covey, C., Latif, M., and Stouffer, R.J. 2000. The Coupled Model Intercomparison Project (CMIP), *Bull. Am. Meteorol. Soc.* DOI:

10.1175/1520-0477(2000)081<0313:tcmipc>2.3.co;2.

Melillo, J., Prentice, I., Farquhar, G., Schulze, E., and Sala, O. 1995. Terrestrial biotic responses to environmental change and feedbacks to climate, In: Houghton, J. et al. (eds.), *Clim. Chang. 1995 Sci. Clim. Chang.* Intergovernmental Panel on Climate Change, Cambridge University Press, pp. 445–471.

Merow, C., Smith, M.J., and Silander, J.A. 2013. A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter, *Ecography (Cop.)*., 36(10): 1058–1069. DOI: 10.1111/j.1600-0587.2013.07872.x.

Muscarella, R., Galante, P.J., Soley-Guardia, M., Boria, R.A., Kass, J.M., Uriarte, M., and Anderson, R.P. 2014. ENMeval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models, *Methods Ecol. Evol.* (Edited by J. McPherson), 5(11): 1198–1205. DOI: 10.1111/2041-210X.12261.

Myers, N., Mittermeier, R.A., Mittermeier, C.G., Da Fonseca, G.A.B., and Kent, J. 2000. Biodiversity hotspots for conservation priorities, *Nature*, 403(6772): 853–858. DOI: 10.1038/35002501.

Nair, S.C. 1991. *The southern western Ghats : a biodiversity conservation plan*. New Delhi: Indian National Trust for Art and Cultural Heritage.

Mac Nally, R. 2000. Regression and model-building in conservation biology, biogeography and ecology: The distinction between – and reconciliation of – 'predictive' and 'explanatory' models, *Biodivers. Conserv.*, 9(5): 655–671. DOI: 10.1023/A:1008985925162.

Navarro, S.A.G. 1992. Altitudinal Distribution of Birds in the Sierra Madre Del Sur, Guerrero, Mexico, *Condor*, 94(1): 29–39. DOI: 10.2307/1368793.

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

Nogués-Bravo, D., Araújo, M.B., Errea, M.P., and Martínez-Rica, J.P. 2007. Exposure of global mountain systems to climate warming during the 21st Century, *Glob. Environ. Chang.*, 17(3–4): 420–428. DOI: 10.1016/j.gloenvcha.2006.11.007.

Pacifici, K., Reich, B.J., Miller, D.A.W., Gardner, B., Stauffer, G., Singh, S., McKerrow, A., and Collazo, J.A. 2017. Integrating multiple data sources in species distribution modeling: a framework for data fusion*, *Ecology*, 98(3): 840–850. DOI: 10.1002/ecy.1710.

Parmesan, C. 2006. Ecological and Evolutionary Responses to Recent Climate Change, *Annu. Rev. Ecol. Evol. Syst.*, 37(1): 637–669. DOI: 10.1146/annurev.ecolsys.37.091305.110100.

Pautasso, M. 2012. Observed impacts of climate change on terrestrial birds in Europe: an overview, *Ital. J. Zool.*, 79(2): 296–314. DOI: 10.1080/11250003.2011.627381.

Pearce, J. and Ferrier, S. 2000. Evaluating the predictive performance of habitat models developed using logistic regression, *Ecol. Modell.*, 133(3): 225–245. DOI: 10.1016/S0304-3800(00)00322-7.

Pearson, R.G., Raxworthy, C.J., Nakamura, M., and Townsend Peterson, A. 2007. Predicting species distributions from small numbers of occurrence records: A test case using cryptic geckos in Madagascar, *J. Biogeogr.* DOI: 10.1111/j.1365-2699.2006.01594.x.

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. DOI: 10.1046/j.1466-822X.2003.00042.x.

Peterson, A.T., Sánchez-Cordero, V., Soberón, J., Bartley, J., Buddemeier, R.W., and Navarro-Sigüenza, A.G. 2001. Effects of global climate change on geographic distributions of Mexican Cracidae, *Ecol. Modell.*, 144(1): 21–30. DOI: 10.1016/S0304-3800(01)00345-3.

Peterson, A.T. 2003. Projected climate change effects on Rocky Mountain and

Great Plains birds: Generalities of biodiversity consequences, *Glob. Chang. Biol.*, 9(5): 647–655. DOI: 10.1046/j.1365-2486.2003.00616.x.

Peterson, A.T. and Cohoon, K.P. 1999. Sensitivity of distributional prediction algorithms to geographic data completeness, *Ecol. Modell.*, 117(1): 159–164. DOI: 10.1016/S0304-3800(99)00023-X.

Peterson, A.T., Navarro-Sigüenza, A.G., and Benítez-Díaz, H. 1998. The need for continued scientific collecting; a geographic analysis of Mexican bird specimens, *Ibis (Lond. 1859).*, 140(2): 288–294. DOI: 10.1111/j.1474-919X.1998.tb04391.x.

Peterson, A.T., Papeş, M., and Soberón, J. 2008. Rethinking receiver operating characteristic analysis applications in ecological niche modeling, *Ecol. Modell.*, 213(1): 63–72. DOI: 10.1016/j.ecolmodel.2007.11.008.

Peterson, A.T. and Robins, C.R. 2003. Using Ecological-Niche Modeling to Predict Barred Owl Invasions with Implications for Spotted Owl Conservation, *Conserv. Biol.*, 17(4): 1161–1165. DOI: 10.1046/j.1523-1739.2003.02206.x.

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. DOI: 10.1016/S0020-7519(03)00094-8.

Peterson, A.T., Stockwell, D.R., and Kluza, D.A. 2002. Distributional prediction based on ecological niche modeling of primary occurrence data, In: Scott, J. M. et al. (eds.), *Predict. species Occur. issues scale accuracy*. Island Press, pp. 617–623.

Phillips, S.J., Anderson, R.P., Dudík, M., Schapire, R.E., and Blair, M.E. 2017. Opening the black box: an open-source release of Maxent, *Ecography (Cop.).*, 40(7): 887–893. DOI: 10.1111/ecog.03049.

Phillips, S.J., Anderson, R.P., and Schapire, R.E. 2006. Maximum entropy modeling of species geographic distributions, *Ecol. Modell.*, 190(3–4): 231–259. DOI: 10.1016/j.ecolmodel.2005.03.026.

Phillips, S.J., Dudík, M., and Schapire, R.E. 2004. A maximum entropy approach to species distribution modeling, In: *Twenty-first Int. Conf. Mach. Learn. - ICML '04*. New York, New York, USA: ACM Press, p. 83. DOI: 10.1145/1015330.1015412.

Pramanik, M., Paudel, U., Mondal, B., Chakraborti, S., and 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. DOI: 10.1016/j.crm.2017.11.002.

Praveen, J. 2020. Banasura Laughingthrush (Montecincla jerdoni), In: del Hoyo, J. et al. (eds.), *Birds of the World*. Ithaca, NY, USA: Cornell Lab of Ornithology. Available: https://birdsoftheworld.org/bow/species/bkclau1/cur/introduction [1 April 2021].

Priti, H., Aravind, N.A., Uma Shaanker, R., 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. DOI: 10.1016/j.ecoleng.2016.01.006.

R Core Team 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Radosavljevic, A. and Anderson, R.P. 2014. Making better M <scp>axent</scp> models of species distributions: complexity, overfitting and evaluation, *J. Biogeogr.* (Edited by M. Araújo), 41(4): 629–643. DOI: 10.1111/jbi.12227.

Ramachandran, V., Robin, V. V., Tamma, K., and Ramakrishnan, U. 2017. Climatic and geographic barriers drive distributional patterns of bird phenotypes within peninsular India, *J. Avian Biol.*, 48(5): 620–630. DOI: 10.1111/jav.01278.

Raman, S., Shameer, T.T., Sanil, R., Usha, P., and Kumar, S. 2020. Protrusive influence of climate change on the ecological niche of endemic brown mongoose (Herpestes fuscus fuscus): a MaxEnt approach from Western

Ghats, India, *Model. Earth Syst. Environ.* DOI: 10.1007/s40808-020-00790-1.

Ramesh, V., Gopalakrishna, T., Barve, S., and Melnick, D.J. 2017. IUCN greatly underestimates threat levels of endemic birds in the Western Ghats, *Biol. Conserv.*, 210: 205–221. DOI: 10.1016/j.biocon.2017.03.019.

Ravindranath, N.H. and Sukumar, R. 1998. Climate Change and Tropical Forests in India, In: *Potential Impacts Clim. Chang. Trop. For. Ecosyst.* Dordrecht: Springer Netherlands, pp. 423–441. DOI: 10.1007/978-94-017-2730-3_21.

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. DOI: 10.1890/03-5374.

Ricketts, T.H., Dinerstein, E., Boucher, T., Brooks, T.M., Butchart, S.H.M., Hoffmann, M., Lamoreux, J.F., Morrison, J., Parr, M., Pilgrim, J.D., Rodrigues, A.S.L., Sechrest, W., Wallace, G.E., Berlin, K., Bielby, J., Burgess, N.D., Church, D.R., Cox, N., Knox, D., Loucks, C., Luck, G.W., Master, L.L., Moore, R., Naidoo, R., Ridgely, R., Schatz, G.E., Shire, G., Strand, H., Wettengel, W., and Wikramanayake, E. 2005. Pinpointing and preventing imminent extinctions, *Proc. Natl. Acad. Sci.*, 102(51): 18497–18501. DOI: 10.1073/pnas.0509060102.

Ricklefs, R.E. 2004. A comprehensive framework for global patterns in biodiversity, *Ecol. Lett.*, 7(1): 1–15. DOI: 10.1046/j.1461-0248.2003.00554.x.

Robin, V. V., Vishnudas, C.K., Gupta, P., Rheindt, F.E., Hooper, D.M., Ramakrishnan, U., and Reddy, S. 2017. Two new genera of songbirds represent endemic radiations from the Shola Sky Islands of the Western Ghats, India, *BMC Evol. Biol.* DOI: 10.1186/s12862-017-0882-6.

Robin, V. V. and Nandini, R. 2012. Shola habitats on sky islands: Status of research: On montane forests and grasslands in southern India, *Curr. Sci.*, 103(21):

1427–1437.

Robin, V. V., Sinha, A., and Ramakrishnan, U. 2010. Ancient Geographical Gaps and Paleo-Climate Shape the Phylogeography of an Endemic Bird in the Sky Islands of Southern India, *PLoS One*. (Edited by S. Gadagkar), 5(10): e13321. DOI: 10.1371/journal.pone.0013321.

Robinson, O.J., Ruiz-Gutierrez, V., Fink, D., Meese, R.J., Holyoak, M., and Cooch, E.G. 2018. Using citizen science data in integrated population models to inform conservation, *Biol. Conserv.*, 227: 361–368. DOI: 10.1016/j.biocon.2018.10.002.

Rogora, M., Frate, L., Carranza, M.L., Freppaz, M., Stanisci, A., Bertani, I., Bottarin, R., Brambilla, A., Canullo, R., Carbognani, M., Cerrato, C., Chelli, S., Cremonese, E., Cutini, M., Di Musciano, M., Erschbamer, B., Godone, D., Iocchi, M., Isabellon, M., Magnani, A., Mazzola, L., Morra di Cella, U., Pauli, H., Petey, M., Petriccione, B., Porro, F., Psenner, R., Rossetti, G., Scotti, A., Sommaruga, R., Tappeiner, U., Theurillat, J.-P., Tomaselli, M., Viglietti, D., Viterbi, R., Vittoz, P., Winkler, M., and Matteucci, G. 2018. Assessment of climate change effects on mountain ecosystems through a cross-site analysis in the Alps and Apennines, *Sci. Total Environ.* Elsevier B.V., 624: 1429–1442. DOI: 10.1016/j.scitotenv.2017.12.155.

Root, T. 1988. Energy constraints on avian distributions and abundances, *Ecology*, 69(2): 330–339. DOI: 10.2307/1940431.

Root, T. 2006. Environmental Factors Associated with Avian Distributional Boundaries, *J. Biogeogr.*, 15(3): 489. DOI: 10.2307/2845278.

Root, T.L. and Schneider, S.H. 1993. Can Large-Scale Climatic Models Be Linked with Multiscale Ecological Studies?, *Conserv. Biol.*, 7(2): 256–270. DOI: 10.1046/j.1523-1739.1993.07020256.x.

Rushton, S.P., Ormerod, S.J., and Kerby, G. 2004. New paradigms for modelling species distributions?, *J. Appl. Ecol.*, 41(2): 193–200. DOI: 10.1111/j.0021-8901.2004.00903.x.

Saatchi, S., Buermann, W., ter Steege, H., Mori, S., and Smith, T.B. 2008. Modeling distribution of Amazonian tree species and diversity using remote sensing measurements, *Remote Sens. Environ.*, 112(5): 2000–2017. DOI: 10.1016/j.rse.2008.01.008.

Sanderson, B.M., Knutti, R., and Caldwell, P. 2015. A Representative Democracy to Reduce Interdependency in a Multimodel Ensemble, *J. Clim.*, 28(13): 5171–5194. DOI: 10.1175/JCLI-D-14-00362.1.

Sashikumar, C., Praveen, J., Palot, M., and Nameer, P. 2011. *Birds of Kerala: status and distribution*. Kottayam, Kerala: DC Books.

Sexton, J.P., McIntyre, P.J., Angert, A.L., and Rice, K.J. 2009. Evolution and Ecology of Species Range Limits, *Annu. Rev. Ecol. Evol. Syst.*, 40(1): 415–436. DOI: 10.1146/annurev.ecolsys.110308.120317.

Soberon, J. and Peterson, A.T. 2005. Interpretation of Models of Fundamental Ecological Niches and Species' Distributional Areas, *Biodivers. Informatics*, 2: 1–10. DOI: 10.17161/bi.v2i0.4.

Sohl, T.L. 2014. The Relative Impacts of Climate and Land-Use Change on Conterminous United States Bird Species from 2001 to 2075, *PLoS One*. (Edited by S.S. Romanach), 9(11): e112251. DOI: 10.1371/journal.pone.0112251.

SoIB 2018. *State of India's Birds 2020: Range, trends and conservation status.* The SoIB Partnership.

Sony, R.K., Sen, S., Kumar, S., Sen, M., and Jayahari, K.M. 2018. Niche models inform the effects of climate change on the endangered Nilgiri Tahr (Nilgiritragus hylocrius) populations in the southern Western Ghats, India, *Ecol. Eng.* DOI: 10.1016/j.ecoleng.2018.06.017.

LA Sorte, F.A. and Frank, R.T. 2007. Poleward shifts in winter ranges of north American birds, *Ecology*, 88(7): 1803–1812. DOI: 10.1890/06-1072.1.

La Sorte, F.A. and Jetz, W. 2010. Avian distributions under climate change:

towards improved projections, *J. Exp. Biol.*, 213(6): 862–869. DOI: 10.1242/jeb.038356.

Stephenson, D.B. 2000. Use of the ‘Odds Ratio’ for Diagnosing Forecast Skill, *Weather Forecast.*, 15(2): 221–232. DOI: 10.1175/1520-0434(2000)015<0221:UOTORF>2.0.CO;2.

Stockwell, D. 1999. The GARP modelling system: problems and solutions to automated spatial prediction, *Int. J. Geogr. Inf. Sci.*, 13(2): 143–158. DOI: 10.1080/136588199241391.

Stockwell, D.R.. and Peterson, A.T. 2002. Effects of sample size on accuracy of species distribution models, *Ecol. Modell.*, 148(1): 1–13. DOI: 10.1016/S0304-3800(01)00388-X.

Stockwell, D.R. and Noble, I.R. 1992. Induction of sets of rules from animal distribution data: a robust and informative method of data analysis, *Math. Comput. Simul.*, 33(5–6): 385–390.

Strimas-Mackey, M., Hochachka, W.M., Ruiz-Gutierrez, V., Robinson, O.J., Miller, E.T., Auer, T., Kelling, S., Fink, D., and Johnston, A. 2020. *Best Practices for Using eBird Data*. Cornell Lab of Ornithology, Ithaca, New York. Available: https://cornelllabofornithology.github.io/ebird-best-practices/index.html [22 March 2021].

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

Suárez-Seoane, S., García de la Morena, E.L., Morales Prieto, M.B., 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(1–2): 17–29. DOI: 10.1016/j.ecolmodel.2008.07.035.

Sukumar, R., Suresh, H.S., and Ramesh, R. 1995. Climate Change and Its Impact on Tropical Montane Ecosystems in Southern India, *J. Biogeogr.*, 22: 533–

536.

Sullivan, B.L., Wood, C.L., Iliff, M.J., Bonney, R.E., Fink, D., and Kelling, S. 2009. eBird: A citizen-based bird observation network in the biological sciences, *Biol. Conserv.* Elsevier Ltd, 142(10): 2282–2292. DOI: 10.1016/j.biocon.2009.05.006.

Sullivan, B.L., Phillips, T., Dayer, A.A., Wood, C.L., Farnsworth, A., Iliff, M.J., Davies, I.J., Wiggins, A., Fink, D., Hochachka, W.M., Rodewald, A.D., Rosenberg, K. V., Bonney, R., and Kelling, S. 2017. Using open access observational data for conservation action: A case study for birds, *Biol. Conserv.*, 208: 5–14. DOI: 10.1016/j.biocon.2016.04.031.

Synes, N.W. and Osborne, P.E. 2011. Choice of predictor variables as a source of uncertainty in continental-scale species distribution modelling under climate change, *Glob. Ecol. Biogeogr.*, 20(6): 904–914. DOI: 10.1111/j.1466-8238.2010.00635.x.

Thomas, C.D., Cameron, A., Green, R.E., Bakkenes, M., Beaumont, L.J., Collingham, Y.C., Erasmus, B.F.N., Ferreira De Siqueira, M., Grainger, A., Hannah, L., Hughes, L., Huntley, B., Van Jaarsveld, A.S., Midgley, G.F., Miles, L., Ortega-Huerta, M.A., Peterson, A.T., Phillips, O.L., and Williams, S.E. 2004. Extinction risk from climate change, *Nature*, 427: 145–148. DOI: 10.1038/nature02121.

Thomas, C.D. 2010. Climate, climate change and range boundaries, *Divers. Distrib.*, 16(3): 488–495. DOI: 10.1111/j.1472-4642.2010.00642.x.

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. DOI: 10.1111/j.1472-4642.2008.00535.x.

Thuiller, W. 2007. Climate change and the ecologist, *Nature*, 448(7153): 550–552. DOI: 10.1038/448550a.

Trautmann, S. 2018. Climate Change Impacts on Bird Species, In: *Bird Species*.

Cham: Springer, pp. 217–234. DOI: 10.1007/978-3-319-91689-7_12.

UNESCO 2012. *Nilgiri Biosphere Reserve, India*. Available: https://en.unesco.org/biosphere/aspac/nilgiri (accessed on 29 March 2021). Available: https://en.unesco.org/biosphere/aspac/nilgiri [27 March 2021].

UNESCO 2016. *Agasthyamala Biosphere Reserve, India*. Available: https://en.unesco.org/biosphere/aspac/agasthyamala (accessed on 29 March 2021). Available: https://en.unesco.org/biosphere/aspac/agasthyamala [27 March 2021].

UNESCO World Heritage Committee 2017. *Decisions Adopted During the 41st Session of the World Heritage Committee,*. Krakow, Poland. Available: https://whc.unesco.org/archive/2017/whc17-41com-18-en.pdf.

Virkkala, R., Marmion, M., Heikkinen, R.K., Thuiller, W., and Luoto, M. 2010. Predicting range shifts of northern bird species: Influence of modelling technique and topography, *Acta Oecologica*, 36(3): 269–281. DOI: 10.1016/j.actao.2010.01.006.

Walsberg, G.E. 1993. Thermal Consequences of Diurnal Microhabitat Selection in a Small Bird, *Ornis Scand.*, 24(3): 174. DOI: 10.2307/3676733.

Walther, G.-R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T.J.C., Fromentin, J.-M., Hoegh-Guldberg, O., and Bairlein, F. 2002. Ecological responses to recent climate change., *Nature*, 416(6879): 389–95. DOI: 10.1038/416389a.

Walther, G.-R. 2010. Community and ecosystem responses to recent climate change, *Philos. Trans. R. Soc. B Biol. Sci.*, 365(1549): 2019–2024. DOI: 10.1098/rstb.2010.0021.

Weimerskirch, H., Inchausti, P., Guinet, C., and Barbraud, C. 2003. Trends in bird and seal populations as indicators of a system shift in the Southern Ocean, *Antarct. Sci.*, 15(2): 249–256. DOI: 10.1017/S0954102003001202.

Wiens, J.J. 2011. The niche, biogeography and species interactions, *Philos. Trans.*

R. Soc. B Biol. Sci., 366(1576): 2336–2350. DOI: 10.1098/rstb.2011.0059.

Wilcox, B.A. and Murphy, D.D. 1985. Conservation strategy: the effects of fragmentation on extinction., *Am. Nat.*, 125(6): 879–887. DOI: 10.1086/284386.

Williams, P.H., Margules, C.R., and Hilbert, D.W. 2002. Data requirements and data sources for biodiversity priority area selection, *J. Biosci.*, 27(4 SUPPL. 2): 327–338. DOI: 10.1007/BF02704963.

Wilson, J.G. 1994. The Role of Bioindicators in Estuarine Management, *Estuaries*, 17(1): 94. DOI: 10.2307/1352337.

Wordley, C.F.R., Sankaran, M., Mudappa, D., and Altringham, J.D. 2015. Landscape scale habitat suitability modelling of bats in the Western Ghats of India: Bats like something in their tea, *Biol. Conserv.* Elsevier B.V., 191: 529–536. DOI: 10.1016/j.biocon.2015.08.005.

Yee, T.W. and Mitchell, N.D. 1991. Generalized additive models in plant ecology, *J. Veg. Sci.*, 2(5): 587–602. DOI: 10.2307/3236170.

Youden, W.J. 1950. Index for rating diagnostic tests, *Cancer*, 3(1): 32–35. DOI: 10.1002/1097-0142(1950)3:1<32::AID-CNCR2820030106>3.0.CO;2-3.

Zurell, D., Franklin, J., König, C., Bouchet, P.J., Dormann, C.F., Elith, J., Fandos, G., Feng, X., Guillera-Arroita, G., Guisan, A., Lahoz-Monfort, J.J., Leitão, P.J., Park, D.S., Peterson, A.T., Rapacciuolo, G., Schmatz, D.R., Schröder, B., Serra-Diaz, J.M., Thuiller, W., Yates, K.L., Zimmermann, N.E., and Merow, C. 2020. A standard protocol for reporting species distribution models, *Ecography (Cop.)*, 43(9): 1261–1277. DOI: 10.1111/ecog.04960.

MODELLING CLIMATE CHANGE IMPACT ON THE HIGH-ALTITUDE BIRDS OF WESTERN GHATS, INDIA

by

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ABSTRACT

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8 ABSTRACT

The montane ecosystems are highly susceptible to anthropogenic climate change. The habitat specialist species restricted in such ecosystems could be used as bioindicators as they are sensitive to climate change. In this study, species distribution modelling of six endemic birds residing in the montane ecosystems of the Western Ghats, were analysed to understand the patterns of species distribution in the changing climate scenarios. The maximum entropy (MaxEnt) algorithm was selected as the modelling tool for the study. The ENM Evaluate tool was used to determines the MaxEnt model settings, and the best-performing model was selected based on the Akaike Information Criterion (AIC) value. The six birds assessed in this study were Wayanad Laughingthrush, Banasura Laughingthrush , Nilgiri Laughingthrush, Palani Laughingthrush, Nilgiri Flycatcher and Black-and-orange Flycatcher, all of which are restricted distributed and threatened bird species. Different variables were used to develop the models for each of these species. However, the mean temperature of the coldest quarter (BIO 11) was found to be the most influencing variable in all models.

The current suitable habitats available for the different species were 47km^2 for Banasura Laughingthrush, 630km^2 for Nilgiri Laughingthrush, 3,096km^2 for Palani Laughingthrush, 6,532km^2 for Black-and-orange Flycatcher, 12,707km^2 for Nilgiri Flycatcher and 16,584km^2 for Wayanad Laughingthrush. The models also predicted the loss of suitable habitat under various climate change scenarios. The habitat loss due to the climate change was the greatest for the Banasura Laughingthrush, which could be losing the habitat to the tune of 66%-72.3%, while the habitat loss will be to the tune of 51.7% in the case of Nilgiri Laughingthrush. In the case of other species the habitat loss will be Wayanad Laughingthrush (36.8%-41.2%), Nilgiri Flycatcher (31.9%-45.8%), Black-and-orange Flycatcher (18.3%- 30.8%) and Palani Laughingthrush (24.7%-27.5%).

The whole population of the Banasura Laughingthrush is not protected under any of the protected areas in Western Ghats, while only 3.17% of the suitable habitat of the Nilgiri Laughingthrush falls under the protected area network. In the case of

other species under study also only 20 to 30% of the suitable habitats falls under the PA network. Realignment of the protected area network of the Western Ghats by including the distributional range of the above species of birds may ensure the long-term conservation of these species.

9 APPENDIX

Appendix I. Details of the occurrence data used for developing the models of the selected birds

Species	Longitude	Latitude	Date	State	Unique ID
WLT	76.75	11.31	19-12-1974	Tamil Nadu	315|WLT19121974
WLT	76.37	11.67	13-01-1979	Kerala	735|WLT13011979
WLT	77.18	9.58	28-12-1991	Kerala	769|WLT28121991
WLT	76.84	10.47	02-04-2000	Tamil Nadu	685|WLT02042000
WLT	76.89	10.42	19-05-2000	Tamil Nadu	942|WLT19052000
WLT	74.34	15.39	18-02-2001	Karnataka	774|WLT18022001
WLT	76.94	10.25	14-01-2002	Tamil Nadu	617|WLT14012002
WLT	76.90	10.35	27-02-2005	Tamil Nadu	213|WLT27022005
WLT	76.70	10.54	21-02-2006	Kerala	035|WLT21022006
WLT	76.62	10.25	26-05-2006	Kerala	160|WLT26052006
WLT	76.80	10.52	24-12-2006	Kerala	173|WLT24122006
WLT	76.81	10.36	24-12-2006	Kerala	464|WLT24122006
WLT	76.62	10.96	12-02-2007	Kerala	990|WLT12022007
WLT	77.09	9.51	02-02-2008	Kerala	064|WLT02022008
WLT	77.34	9.57	03-02-2008	Kerala	088|WLT03022008
WLT	76.83	10.28	24-02-2008	Kerala	463|WLT24022008
WLT	76.38	11.44	27-12-2008	Kerala	249|WLT27122008
WLT	76.77	10.38	19-11-2009	Kerala	736|WLT19112009

Species	Longitude	Latitude	Date	State	Unique ID
WLT	77.20	9.10	01-01-2010	Kerala	528|WLT01012010
WLT	76.16	11.47	10-12-2010	Kerala	266|WLT10122010
WLT	75.87	11.93	07-01-2011	Kerala	281|WLT07012011
WLT	75.89	11.55	12-03-2011	Kerala	317|WLT12032011
WLT	76.67	10.96	31-03-2011	Kerala	325|WLT31032011
WLT	76.42	11.18	07-04-2011	Kerala	329|WLT07042011
WLT	76.42	11.11	08-04-2011	Kerala	330|WLT08042011
WLT	76.77	10.12	29-01-2012	Kerala	522|WLT29012012
WLT	76.94	9.73	03-02-2013	Kerala	874|WLT03022013
WLT	76.74	11.40	21-12-2013	Tamil Nadu	481|WLT21122013
WLT	76.44	10.45	30-11-2014	Kerala	281|WLT30112014
WLT	77.40	8.57	18-02-2015	Tamil Nadu	821|WLT18022015
WLT	76.99	10.38	08-03-2015	Tamil Nadu	282|WLT08032015
WLT	75.90	11.72	13-04-2015	Kerala	750|WLT13042015
WLT	77.26	10.13	19-04-2015	Kerala	397|WLT19042015
WLT	75.96	11.88	15-05-2015	Kerala	281|WLT15052015
WLT	77.46	8.46	13-06-2015	Tamil Nadu	059|WLT13062015
WLT	76.63	10.31	08-08-2015	Kerala	279|WLT08082015

Species	Longitude	Latitude	Date	State	Unique ID
WLT	76.72	10.30	05-09-2015	Kerala	286|WLT05092015
WLT	76.59	10.42	13-09-2015	Kerala	177|WLT13092015
WLT	76.79	10.30	18-09-2015	Kerala	786|WLT18092015
WLT	76.95	10.33	28-10-2015	Tamil Nadu	089|WLT28102015
WLT	76.87	11.41	15-11-2016	Tamil Nadu	569|WLT15112016
WLT	74.21	14.98	19-11-2016	Goa	810|WLT19112016
WLT	77.26	10.03	30-11-2016	Kerala	685|WLT30112016
WLT	76.67	10.46	15-01-2017	Kerala	075|WLT15012017
WLT	76.10	11.36	16-01-2017	Kerala	625|WLT16012017
WLT	75.96	12.14	22-01-2017	Karnataka	534|WLT22012017
WLT	76.13	11.32	01-02-2017	Kerala	767|WLT01022017
WLT	76.48	10.48	04-03-2017	Kerala	241|WLT04032017
WLT	76.57	10.46	19-08-2017	Kerala	099|WLT19082017
WLT	74.25	15.04	27-10-2017	Goa	154|WLT27102017
WLT	76.10	11.53	26-01-2018	Kerala	482|WLT26012018
WLT	75.96	11.59	11-02-2018	Kerala	738|WLT11022018
WLT	75.95	11.54	11-03-2018	Kerala	942|WLT11032018
WLT	75.84	11.71	11-03-2018	Kerala	884|WLT11032018
WLT	74.25	15.12	30-04-2018	Goa	531|WLT30042018
WLT	77.34	9.64	11-05-2018	Tamil Nadu	948|WLT11052018
WLT	77.14	9.46	12-05-2018	Kerala	870|WLT12052018

Species	Longitude	Latitude	Date	State	Unique ID
WLT	76.74	10.93	28-11-2018	Tamil Nadu	163|WLT28112018
WLT	77.36	8.54	04-12-2018	Tamil Nadu	603|WLT04122018
WLT	75.69	12.44	06-12-2018	Karnataka	829|WLT06122018
WLT	75.96	12.00	09-12-2018	Karnataka	012|WLT09122018
WLT	75.66	12.22	15-01-2019	Karnataka	867|WLT15012019
WLT	77.21	8.83	20-01-2019	Kerala	685|WLT20012019
WLT	77.21	9.33	24-01-2019	Kerala	638|WLT24012019
WLT	77.32	9.52	25-01-2019	Kerala	027|WLT25012019
WLT	77.21	9.39	25-01-2019	Kerala	681|WLT25012019
WLT	77.29	9.29	25-01-2019	Tamil Nadu	134|WLT25012019
WLT	77.39	9.48	25-01-2019	Tamil Nadu	631|WLT25012019
WLT	77.24	9.49	26-01-2019	Kerala	540|WLT26012019
WLT	77.19	9.48	26-01-2019	Kerala	174|WLT26012019
WLT	77.33	9.44	26-01-2019	Kerala	032|WLT26012019
WLT	77.32	9.39	27-01-2019	Kerala	166|WLT27012019
WLT	77.18	9.42	27-01-2019	Kerala	464|WLT27012019
WLT	77.26	9.45	28-01-2019	Kerala	113|WLT28012019
WLT	75.10	13.51	06-02-2019	Karnataka	253|WLT06022019
WLT	77.03	10.18	22-02-2019	Kerala	738|WLT22022019
WLT	77.11	10.20	23-02-2019	Kerala	384|WLT23022019
WLT	76.41	11.22	02-03-2019	Kerala	951|WLT02032019

Species	Longitude	Latitude	Date	State	Unique ID
WLT	76.45	11.31	02-03-2019	Kerala	429|WLT02032019
WLT	76.96	10.08	17-03-2019	Kerala	867|WLT17032019
WLT	76.80	11.33	24-03-2019	Tamil Nadu	097|WLT24032019
WLT	76.66	10.53	30-05-2019	Kerala	487|WLT30052019
WLT	77.22	9.80	30-06-2019	Kerala	592|WLT30062019
WLT	76.98	10.43	08-07-2019	Tamil Nadu	303|WLT08072019
WLT	77.08	10.11	03-08-2019	Kerala	912|WLT03082019
WLT	75.94	11.85	10-01-2020	Kerala	507|WLT10012020
WLT	77.07	10.06	12-01-2020	Kerala	887|WLT12012020
WLT	77.11	8.77	17-01-2020	Kerala	872|WLT17012020
WLT	76.65	11.02	19-01-2020	Kerala	661|WLT19012020
WLT	76.53	10.39	09-02-2020	Kerala	589|WLT09022020
WLT	77.14	9.33	08-03-2020	Kerala	118|WLT08032020
WLT	77.20	8.70	11-03-2020	Tamil Nadu	505|WLT11032020
WLT	76.98	9.28	15-03-2020	Kerala	704|WLT15032020
WLT	77.19	8.76	24-08-2020	Tamil Nadu	465|WLT24082020
WLT	74.24	15.38	28-10-2020	Goa	759|WLT28102020
BLT	75.87	11.95	09-03-2012	Kerala	225|BLT09032012
BLT	76.13	11.43	11-03-2018	Kerala	666|BLT11032018
BLT	76.12	11.43	11-03-2018	Kerala	257|BLT11032018
BLT	76.13	11.45	10-03-2018	Kerala	553|BLT10032018

Species	Longitude	Latitude	Date	State	Unique ID
BLT	76.12	11.43	11-03-2018	Kerala	223|BLT11032018
BLT	76.13	11.47	20-12-2008	Kerala	327|BLT20122008
BLT	76.08	11.56	07-12-2010	Kerala	264|BLT07122010
BLT	76.13	11.47	15-01-2012	Kerala	604|BLT15012012
BLT	76.08	11.54	11-01-2019	Kerala	418|BLT11012019
BLT	76.08	11.54	11-01-2019	Kerala	448|BLT11012019
NLT	76.64	10.95	12-02-2007	Kerala	032|NLT12022007
NLT	76.63	10.96	14-01-2017	Kerala	915|NLT14012017
NLT	76.47	11.11	19-07-2019	Kerala	323|NLT19072019
NLT	76.64	11.57	18-11-2012	Tamil Nadu	354|NLT18112012
NLT	76.68	11.46	01-02-2013	Tamil Nadu	868|NLT01022013
NLT	76.60	11.40	19-10-2014	Tamil Nadu	975|NLT19102014
NLT	76.89	11.44	30-12-2014	Tamil Nadu	285|NLT30122014
NLT	76.80	11.49	12-06-2015	Tamil Nadu	183|NLT12062015
NLT	76.65	11.47	05-03-2016	Tamil Nadu	558|NLT05032016
NLT	76.62	11.47	04-03-2016	Tamil Nadu	177|NLT04032016
NLT	76.85	11.40	24-05-2016	Tamil Nadu	455|NLT24052016
NLT	76.76	11.37	17-07-2016	Tamil Nadu	690|NLT17072016
NLT	76.98	11.42	05-07-2016	Tamil Nadu	570|NLT05072016
NLT	76.60	11.32	11-09-2016	Tamil Nadu	491|NLT11092016
NLT	76.87	11.41	15-11-2016	Tamil Nadu	569|NLT15112016

Species	Longitude	Latitude	Date	State	Unique ID
NLT	76.74	11.40	14-01-2017	Tamil Nadu	180|NLT14012017
NLT	76.67	11.39	31-01-2017	Tamil Nadu	386|NLT31012017
NLT	76.90	11.51	12-02-2017	Tamil Nadu	510|NLT12022017
NLT	76.71	11.41	31-05-2017	Tamil Nadu	549|NLT31052017
NLT	76.60	11.34	18-08-2017	Tamil Nadu	982|NLT18082017
NLT	76.81	11.35	20-10-2017	Tamil Nadu	766|NLT20102017
NLT	76.70	11.32	17-11-2017	Tamil Nadu	949|NLT17112017
NLT	76.84	11.38	26-01-2017	Tamil Nadu	907|NLT26012017
NLT	76.80	11.47	04-02-2018	Tamil Nadu	429|NLT04022018
NLT	76.64	11.35	02-03-2018	Tamil Nadu	403|NLT02032018
NLT	76.76	11.31	02-09-2018	Tamil Nadu	705|NLT02092018
NLT	76.77	11.41	09-07-2018	Tamil Nadu	321|NLT09072018
NLT	76.91	11.48	09-08-2018	Tamil Nadu	749|NLT09082018
NLT	76.62	11.22	07-08-2018	Tamil Nadu	224|NLT07082018
NLT	76.65	11.28	25-11-2018	Tamil Nadu	757|NLT25112018
NLT	76.65	11.44	09-12-2018	Tamil Nadu	269|NLT09122018
NLT	76.69	11.42	09-12-2018	Tamil Nadu	693|NLT09122018
NLT	76.91	11.36	02-12-2018	Tamil Nadu	327|NLT02122018
NLT	76.81	11.38	02-02-2019	Tamil Nadu	932|NLT02022019
NLT	76.80	11.33	24-03-2019	Tamil Nadu	097|NLT24032019
NLT	76.72	11.44	04-03-2019	Tamil Nadu	213|NLT04032019

Species	Longitude	Latitude	Date	State	Unique ID
NLT	76.51	11.48	14-04-2019	Tamil Nadu	613|NLT14042019
NLT	76.70	11.38	04-07-2019	Tamil Nadu	607|NLT04072019
NLT	76.89	11.41	17-08-2019	Tamil Nadu	501|NLT17082019
NLT	76.61	11.30	11-09-2019	Tamil Nadu	817|NLT11092019
NLT	76.72	11.39	21-09-2019	Tamil Nadu	399|NLT21092019
NLT	76.64	11.27	09-11-2019	Tamil Nadu	398|NLT09112019
NLT	76.79	11.35	20-12-2019	Tamil Nadu	841|NLT20122019
NLT	76.87	11.44	13-12-2019	Tamil Nadu	114|NLT13122019
NLT	76.53	11.22	18-01-2020	Tamil Nadu	756|NLT18012020
NLT	76.73	11.42	18-01-2020	Tamil Nadu	899|NLT18012020
NLT	76.64	11.31	20-02-2020	Tamil Nadu	412|NLT20022020
NLT	76.59	11.22	16-10-2017	Tamil Nadu	364|NLT16102017
NLT	76.63	11.25	27-02-2020	Tamil Nadu	480|NLT27022020
NLT	76.65	11.32	21-02-2020	Tamil Nadu	391|NLT21022020
NLT	76.54	11.48	24-03-2020	Tamil Nadu	459|NLT24032020
NLT	76.61	11.26	06-03-2020	Tamil Nadu	661|NLT06032020
NLT	76.80	11.40	14-09-2020	Tamil Nadu	030|NLT14092020
NLT	76.56	11.29	10-11-2020	Tamil Nadu	303|NLT10112020
NLT	76.89	11.48	09-11-2020	Tamil Nadu	432|NLT09112020
NLT	76.58	11.30	28-11-2020	Tamil Nadu	086|NLT28112020
PLT	77.04	10.18	24-02-2019	Kerala	167|PLT24022019

Species	Longitude	Latitude	Date	State	Unique ID
PLT	77.06	10.18	23-02-2019	Kerala	302|PLT23022019
PLT	77.02	10.22	23-02-2019	Kerala	446|PLT23022019
PLT	77.06	10.14	20-02-2000	Kerala	135|PLT20022000
PLT	77.05	10.07	11-02-2006	Kerala	848|PLT11022006
PLT	77.30	9.59	03-02-2008	Kerala	054|PLT03022008
PLT	77.19	10.10	31-01-2009	Kerala	781|PLT31012009
PLT	77.25	10.00	24-01-2009	Kerala	775|PLT24012009
PLT	77.19	10.18	17-01-2009	Kerala	771|PLT17012009
PLT	77.00	10.16	30-01-2009	Kerala	780|PLT30012009
PLT	77.19	10.20	08-01-2009	Kerala	766|PLT08012009
PLT	77.06	10.09	30-01-2009	Kerala	934|PLT30012009
PLT	77.08	10.23	09-12-2012	Kerala	027|PLT09122012
PLT	77.09	10.29	08-12-2012	Kerala	194|PLT08122012
PLT	77.25	10.13	08-12-2012	Kerala	203|PLT08122012
PLT	77.15	10.33	08-12-2012	Kerala	823|PLT08122012
PLT	77.10	10.17	07-12-2012	Kerala	630|PLT07122012
PLT	77.15	9.94	26-04-2015	Kerala	579|PLT26042015
PLT	77.08	10.08	09-05-2015	Kerala	171|PLT09052015
PLT	77.01	10.20	06-05-2015	Kerala	788|PLT06052015
PLT	77.12	10.06	02-10-2015	Kerala	025|PLT02102015
PLT	77.20	10.31	22-10-2015	Kerala	357|PLT22102015

Species	Longitude	Latitude	Date	State	Unique ID
PLT	77.14	10.04	05-12-2015	Kerala	667|PLT05122015
PLT	77.26	10.15	17-02-2016	Kerala	285|PLT17022016
PLT	77.19	10.23	12-09-2016	Kerala	235|PLT12092016
PLT	77.11	9.78	16-09-2016	Kerala	224|PLT16092016
PLT	77.24	10.17	29-10-2016	Kerala	304|PLT29102016
PLT	77.08	10.15	26-12-2016	Kerala	603|PLT26122016
PLT	77.12	10.18	23-01-2017	Kerala	423|PLT23012017
PLT	77.18	10.19	28-04-2017	Kerala	363|PLT28042017
PLT	77.31	9.57	28-10-2017	Kerala	311|PLT28102017
PLT	77.23	10.14	15-10-2017	Kerala	489|PLT15102017
PLT	77.15	10.12	10-10-2017	Kerala	046|PLT10102017
PLT	77.21	10.13	14-10-2017	Kerala	520|PLT14102017
PLT	77.09	10.03	15-12-2017	Kerala	344|PLT15122017
PLT	77.13	10.11	16-01-2018	Kerala	908|PLT16012018
PLT	77.01	10.06	16-03-2018	Kerala	721|PLT16032018
PLT	77.04	10.06	16-03-2018	Kerala	568|PLT16032018
PLT	77.10	10.14	02-03-2018	Kerala	846|PLT02032018
PLT	77.24	10.20	12-04-2018	Kerala	079|PLT12042018
PLT	77.27	10.20	16-04-2018	Kerala	101|PLT16042018
PLT	77.26	10.17	15-04-2018	Kerala	943|PLT15042018
PLT	77.23	9.97	17-04-2018	Kerala	317|PLT17042018

Species	Longitude	Latitude	Date	State	Unique ID
PLT	76.99	10.03	23-11-2018	Kerala	950|PLT23112018
PLT	77.26	9.41	26-01-2019	Kerala	269|PLT26012019
PLT	77.10	10.09	19-01-2019	Kerala	328|PLT19012019
PLT	77.39	9.50	26-01-2019	Kerala	089|PLT26012019
PLT	77.34	9.58	27-01-2019	Kerala	401|PLT27012019
PLT	77.13	10.16	20-01-2019	Kerala	470|PLT20012019
PLT	77.38	9.49	25-01-2019	Kerala	047|PLT25012019
PLT	77.04	10.23	22-02-2019	Kerala	036|PLT22022019
PLT	77.21	10.06	02-02-2019	Kerala	831|PLT02022019
PLT	77.09	10.18	21-02-2019	Kerala	254|PLT21022019
PLT	77.02	10.17	21-02-2019	Kerala	143|PLT21022019
PLT	77.07	10.27	22-02-2019	Kerala	207|PLT22022019
PLT	77.11	10.28	24-02-2019	Kerala	166|PLT24022019
PLT	77.12	10.04	03-02-2019	Kerala	218|PLT03022019
PLT	77.07	10.21	23-02-2019	Kerala	270|PLT23022019
PLT	77.22	10.21	24-02-2019	Kerala	595|PLT24022019
PLT	77.23	10.22	23-02-2019	Kerala	523|PLT23022019
PLT	77.24	10.24	23-02-2019	Kerala	866|PLT23022019
PLT	77.17	10.12	10-03-2019	Kerala	494|PLT10032019
PLT	77.01	10.09	16-03-2019	Kerala	378|PLT16032019
PLT	77.13	10.09	10-03-2019	Kerala	541|PLT10032019

Species	Longitude	Latitude	Date	State	Unique ID
PLT	76.99	10.09	16-03-2019	Kerala	520|PLT16032019
PLT	76.97	10.15	15-03-2019	Kerala	458|PLT15032019
PLT	76.99	10.07	15-03-2019	Kerala	578|PLT15032019
PLT	77.10	10.23	15-03-2019	Kerala	539|PLT15032019
PLT	76.99	10.11	15-03-2019	Kerala	873|PLT15032019
PLT	76.91	10.09	16-03-2019	Kerala	853|PLT16032019
PLT	76.96	10.08	17-03-2019	Kerala	570|PLT17032019
PLT	77.16	10.04	12-04-2019	Kerala	656|PLT12042019
PLT	77.07	10.06	23-04-2019	Kerala	841|PLT23042019
PLT	77.18	10.25	13-04-2019	Kerala	914|PLT13042019
PLT	77.10	10.07	04-08-2019	Kerala	620|PLT04082019
PLT	77.20	10.15	03-08-2019	Kerala	787|PLT03082019
PLT	77.08	10.11	03-08-2019	Kerala	502|PLT03082019
PLT	77.12	10.00	26-01-2020	Kerala	543|PLT26012020
PLT	77.06	10.12	06-02-2020	Kerala	301|PLT06022020
PLT	77.17	10.08	08-09-2020	Kerala	878|PLT08092020
PLT	77.04	10.14	27-01-2021	Kerala	511|PLT27012021
PLT	77.04	10.00	17-01-2021	Kerala	492|PLT17012021
PLT	76.87	9.49	10-11-2014	Kerala	283|PLT10112014
PLT	77.23	9.19	01-01-2010	Kerala	246|PLT01012010
PLT	77.23	9.34	25-01-2019	Kerala	149|PLT25012019

Species	Longitude	Latitude	Date	State	Unique ID
PLT	77.01	10.35	26-01-2000	Tamil Nadu	887|PLT26012000
PLT	77.02	10.33	19-01-2005	Tamil Nadu	943|PLT19012005
PLT	76.98	10.39	17-06-2015	Tamil Nadu	195|PLT17062015
PLT	77.00	10.38	05-10-2016	Tamil Nadu	113|PLT05102016
PLT	77.00	10.27	15-01-2017	Tamil Nadu	208|PLT15012017
PLT	76.99	10.40	07-02-2017	Tamil Nadu	463|PLT07022017
PLT	77.07	10.32	16-03-2018	Tamil Nadu	065|PLT16032018
PLT	77.00	10.31	17-03-2018	Tamil Nadu	855|PLT17032018
PLT	77.00	10.33	30-07-2018	Tamil Nadu	840|PLT30072018
PLT	77.04	10.33	26-01-2019	Tamil Nadu	729|PLT26012019
PLT	76.95	10.41	10-03-2019	Tamil Nadu	193|PLT10032019
PLT	77.51	10.36	09-01-2011	Tamil Nadu	312|PLT09012011
PLT	77.57	10.31	03-08-2014	Tamil Nadu	030|PLT03082014
PLT	77.44	10.21	15-06-2014	Tamil Nadu	638|PLT15062014
PLT	77.38	10.24	15-06-2014	Tamil Nadu	111|PLT15062014
PLT	77.42	10.24	15-06-2014	Tamil Nadu	803|PLT15062014
PLT	77.53	10.24	12-10-2016	Tamil Nadu	635|PLT12102016
PLT	77.48	10.24	28-05-2011	Tamil Nadu	103|PLT28052011
PLT	77.52	10.30	23-06-2017	Tamil Nadu	504|PLT23062017
PLT	77.50	10.23	23-01-2018	Tamil Nadu	050|PLT23012018
PLT	77.49	10.22	11-04-2018	Tamil Nadu	147|PLT11042018

Species	Longitude	Latitude	Date	State	Unique ID
PLT	77.55	10.29	29-05-2018	Tamil Nadu	451|PLT29052018
PLT	77.41	10.26	30-03-2019	Tamil Nadu	250|PLT30032019
PLT	77.43	10.20	06-03-2019	Tamil Nadu	544|PLT06032019
PLT	77.45	10.23	21-05-2019	Tamil Nadu	056|PLT21052019
PLT	77.50	10.25	18-05-2019	Tamil Nadu	541|PLT18052019
PLT	77.46	10.25	19-06-2019	Tamil Nadu	537|PLT19062019
PLT	77.60	10.33	23-07-2019	Tamil Nadu	232|PLT23072019
PLT	77.55	10.27	09-07-2019	Tamil Nadu	479|PLT09072019
PLT	77.31	10.21	03-01-2020	Tamil Nadu	091|PLT03012020
PLT	77.36	10.29	28-11-2020	Tamil Nadu	238|PLT28112020
PLT	77.48	10.27	29-11-2020	Tamil Nadu	348|PLT29112020
PLT	77.34	10.19	17-12-2020	Tamil Nadu	163|PLT17122020
PLT	77.64	10.22	23-01-2021	Tamil Nadu	846|PLT23012021
PLT	77.40	10.29	16-01-2021	Tamil Nadu	712|PLT16012021
PLT	77.22	10.08	16-09-2017	Tamil Nadu	494|PLT16092017
PLT	77.36	9.60	28-12-2017	Tamil Nadu	405|PLT28122017
PLT	77.32	9.60	13-05-2018	Tamil Nadu	616|PLT13052018
PLT	77.38	9.53	25-01-2019	Tamil Nadu	340|PLT25012019
PLT	77.09	10.31	13-05-2019	Tamil Nadu	716|PLT13052019
PLT	77.37	9.54	26-01-2019	Tamil Nadu	776|PLT26012019
PLT	77.30	9.31	27-01-2019	Tamil Nadu	198|PLT27012019

Species	Longitude	Latitude	Date	State	Unique ID
PLT	77.27	10.13	23-02-2019	Tamil Nadu	232|PLT23022019
PLT	77.29	10.21	24-02-2019	Tamil Nadu	446|PLT24022019
PLT	77.26	10.23	08-03-2020	Tamil Nadu	496|PLT08032020
NIF	77.17	11.90	06-11-2018	Karnataka	583|NIF06112018
NIF	77.18	11.87	07-11-2018	Karnataka	810|NIF07112018
NIF	75.30	13.15	19-05-2012	Karnataka	112|NIF19052012
NIF	75.75	13.52	24-12-2012	Karnataka	873|NIF24122012
NIF	75.77	13.31	09-04-2013	Karnataka	359|NIF09042013
NIF	75.73	13.45	26-09-2016	Karnataka	229|NIF26092016
NIF	75.73	13.41	26-09-2016	Karnataka	711|NIF26092016
NIF	75.97	11.95	15-05-2008	Karnataka	877|NIF15052008
NIF	75.66	12.22	15-01-2019	Karnataka	867|NIF15012019
NIF	75.92	11.95	10-09-2016	Karnataka	493|NIF10092016
NIF	76.56	10.20	11-10-2015	Kerala	261|NIF11102015
NIF	76.69	10.13	01-01-2018	Kerala	769|NIF01012018
NIF	77.03	10.20	22-02-2019	Kerala	861|NIF22022019
NIF	77.02	10.22	23-02-2019	Kerala	446|NIF23022019
NIF	77.00	9.97	30-12-1978	Kerala	708|NIF30121978
NIF	77.34	9.57	03-02-2008	Kerala	088|NIF03022008
NIF	77.38	9.50	13-05-2018	Kerala	626|NIF13052018
NIF	77.09	9.51	02-02-2008	Kerala	064|NIF02022008

Species	Longitude	Latitude	Date	State	Unique ID
NIF	77.19	10.18	17-01-2009	Kerala	771|NIF17012009
NIF	77.09	10.13	18-01-2009	Kerala	692|NIF18012009
NIF	77.13	10.29	04-01-2009	Kerala	690|NIF04012009
NIF	77.06	10.09	30-01-2009	Kerala	934|NIF30012009
NIF	77.16	10.27	12-01-2009	Kerala	769|NIF12012009
NIF	77.23	10.06	28-01-2009	Kerala	778|NIF28012009
NIF	77.03	10.12	07-04-2010	Kerala	513|NIF07042010
NIF	77.24	9.99	08-12-2012	Kerala	922|NIF08122012
NIF	77.08	10.23	09-12-2012	Kerala	027|NIF09122012
NIF	77.04	10.23	08-12-2012	Kerala	253|NIF08122012
NIF	77.08	10.15	29-01-2013	Kerala	963|NIF29012013
NIF	76.99	9.81	03-02-2013	Kerala	868|NIF03022013
NIF	76.97	9.79	02-02-2013	Kerala	242|NIF02022013
NIF	76.98	9.76	02-02-2013	Kerala	831|NIF02022013
NIF	77.26	10.15	07-11-2014	Kerala	403|NIF07112014
NIF	76.99	10.06	19-04-2015	Kerala	616|NIF19042015
NIF	77.01	10.20	06-05-2015	Kerala	788|NIF06052015
NIF	76.75	10.13	28-12-2015	Kerala	088|NIF28122015
NIF	77.14	10.04	06-05-2016	Kerala	166|NIF06052016
NIF	77.15	10.12	08-08-2016	Kerala	118|NIF08082016
NIF	77.24	10.17	29-10-2016	Kerala	304|NIF29102016

Species	Longitude	Latitude	Date	State	Unique ID
NIF	77.06	10.12	24-10-2016	Kerala	973|NIF24102016
NIF	77.20	10.31	22-10-2015	Kerala	357|NIF22102015
NIF	77.16	9.59	20-11-2016	Kerala	224|NIF20112016
NIF	77.04	10.00	27-12-2016	Kerala	651|NIF27122016
NIF	77.12	10.18	23-01-2017	Kerala	423|NIF23012017
NIF	76.99	9.58	29-01-2017	Kerala	591|NIF29012017
NIF	77.18	10.19	28-04-2017	Kerala	363|NIF28042017
NIF	77.22	10.35	19-04-2017	Kerala	440|NIF19042017
NIF	76.99	10.04	20-06-2017	Kerala	242|NIF20062017
NIF	76.87	9.73	18-08-2017	Kerala	685|NIF18082017
NIF	76.89	9.91	05-08-2017	Kerala	619|NIF05082017
NIF	77.07	10.08	18-04-2014	Kerala	770|NIF18042014
NIF	76.92	9.82	25-11-2017	Kerala	515|NIF25112017
NIF	76.93	9.74	03-11-2017	Kerala	779|NIF03112017
NIF	77.05	10.07	20-12-2017	Kerala	537|NIF20122017
NIF	77.09	10.03	15-12-2017	Kerala	344|NIF15122017
NIF	77.16	10.04	23-12-2017	Kerala	238|NIF23122017
NIF	76.94	10.05	20-12-2017	Kerala	530|NIF20122017
NIF	77.13	10.11	16-01-2018	Kerala	908|NIF16012018
NIF	77.14	9.65	04-02-2018	Kerala	594|NIF04022018
NIF	77.07	10.06	26-03-2018	Kerala	998|NIF26032018

Species	Longitude	Latitude	Date	State	Unique ID
NIF	77.04	10.06	16-03-2018	Kerala	568|NIF16032018
NIF	77.10	10.09	23-03-2018	Kerala	608|NIF23032018
NIF	77.09	10.27	03-04-2018	Kerala	342|NIF03042018
NIF	77.26	10.20	21-04-2018	Kerala	745|NIF21042018
NIF	77.21	10.24	05-04-2018	Kerala	303|NIF05042018
NIF	77.26	9.52	12-05-2018	Kerala	275|NIF12052018
NIF	77.11	9.53	12-05-2018	Kerala	189|NIF12052018
NIF	77.28	9.48	13-05-2018	Kerala	168|NIF13052018
NIF	77.07	10.19	17-08-2015	Kerala	940|NIF17082015
NIF	77.06	10.01	06-11-2018	Kerala	066|NIF06112018
NIF	77.20	10.20	20-12-2018	Kerala	165|NIF20122018
NIF	77.02	10.06	20-01-2019	Kerala	122|NIF20012019
NIF	77.19	10.22	14-01-2019	Kerala	329|NIF14012019
NIF	77.34	9.55	26-01-2019	Kerala	518|NIF26012019
NIF	77.20	10.15	19-01-2019	Kerala	336|NIF19012019
NIF	77.26	9.41	26-01-2019	Kerala	269|NIF26012019
NIF	77.18	10.04	03-02-2019	Kerala	639|NIF03022019
NIF	77.11	10.28	24-02-2019	Kerala	171|NIF24022019
NIF	77.26	10.17	23-02-2019	Kerala	635|NIF23022019
NIF	77.02	10.17	23-02-2019	Kerala	212|NIF23022019
NIF	77.00	10.16	22-02-2019	Kerala	526|NIF22022019

Species	Longitude	Latitude	Date	State	Unique ID
NIF	77.09	10.18	21-02-2019	Kerala	373|NIF21022019
NIF	77.24	10.24	23-02-2019	Kerala	866|NIF23022019
NIF	77.22	10.20	23-02-2019	Kerala	246|NIF23022019
NIF	77.09	10.20	21-02-2019	Kerala	712|NIF21022019
NIF	77.22	10.22	24-02-2019	Kerala	431|NIF24022019
NIF	77.12	10.20	22-02-2019	Kerala	523|NIF22022019
NIF	77.01	10.08	12-12-2009	Kerala	682|NIF12122009
NIF	77.17	10.12	10-03-2019	Kerala	494|NIF10032019
NIF	76.99	10.09	16-03-2019	Kerala	520|NIF16032019
NIF	77.09	10.11	10-03-2019	Kerala	510|NIF10032019
NIF	76.97	10.09	17-03-2019	Kerala	623|NIF17032019
NIF	77.13	10.09	10-03-2019	Kerala	541|NIF10032019
NIF	76.97	10.07	07-05-2019	Kerala	080|NIF07052019
NIF	76.90	9.70	14-09-2019	Kerala	493|NIF14092019
NIF	77.03	10.04	27-10-2019	Kerala	577|NIF27102019
NIF	77.12	10.04	18-01-2020	Kerala	963|NIF18012020
NIF	77.10	10.22	08-12-2012	Kerala	208|NIF08122012
NIF	77.06	10.14	26-02-2020	Kerala	470|NIF26022020
NIF	77.27	10.21	08-03-2020	Kerala	030|NIF08032020
NIF	77.03	10.14	17-10-2020	Kerala	007|NIF17102020
NIF	77.22	9.96	23-12-2020	Kerala	200|NIF23122020

Species	Longitude	Latitude	Date	State	Unique ID
NIF	76.95	10.09	19-12-2020	Kerala	771|NIF19122020
NIF	77.10	10.06	28-01-2021	Kerala	703|NIF28012021
NIF	77.06	10.04	24-01-2021	Kerala	007|NIF24012021
NIF	75.87	11.95	09-03-2012	Kerala	225|NIF09032012
NIF	76.87	9.49	10-11-2014	Kerala	283|NIF10112014
NIF	76.81	9.77	15-04-2017	Kerala	556|NIF15042017
NIF	76.13	11.43	11-03-2018	Kerala	683|NIF11032018
NIF	75.88	11.70	11-03-2018	Kerala	384|NIF11032018
NIF	76.42	11.09	25-12-1990	Kerala	331|NIF25121990
NIF	76.70	10.54	21-02-2006	Kerala	035|NIF21022006
NIF	76.64	10.95	12-02-2007	Kerala	032|NIF12022007
NIF	76.44	11.20	06-04-2011	Kerala	328|NIF06042011
NIF	76.43	11.11	08-02-2014	Kerala	997|NIF08022014
NIF	76.70	11.06	22-02-2015	Kerala	047|NIF22022015
NIF	76.45	11.09	08-12-2015	Kerala	065|NIF08122015
NIF	76.44	11.15	06-05-2016	Kerala	619|NIF06052016
NIF	76.69	10.52	13-01-2019	Kerala	142|NIF13012019
NIF	76.80	10.49	04-08-2019	Kerala	546|NIF04082019
NIF	76.67	10.47	09-01-2021	Kerala	732|NIF09012021
NIF	77.17	9.44	27-12-2016	Kerala	769|NIF27122016
NIF	77.07	9.42	13-05-2018	Kerala	457|NIF13052018

Species	Longitude	Latitude	Date	State	Unique ID
NIF	77.23	9.34	25-01-2019	Kerala	149|NIF25012019
NIF	77.18	9.43	26-01-2019	Kerala	010|NIF26012019
NIF	77.18	9.35	26-01-2019	Kerala	937|NIF26012019
NIF	76.42	10.50	04-03-2017	Kerala	954|NIF04032017
NIF	77.19	8.68	26-08-2015	Kerala	639|NIF26082015
NIF	75.81	11.85	17-12-2010	Kerala	272|NIF17122010
NIF	75.94	11.94	12-01-2011	Kerala	284|NIF12012011
NIF	76.13	11.47	15-01-2012	Kerala	604|NIF15012012
NIF	76.09	11.85	11-04-2015	Kerala	462|NIF11042015
NIF	76.05	11.52	22-01-2016	Kerala	730|NIF22012016
NIF	76.07	11.66	15-02-2016	Kerala	122|NIF15022016
NIF	76.16	11.55	17-07-2016	Kerala	035|NIF17072016
NIF	76.21	11.75	10-09-2016	Kerala	701|NIF10092016
NIF	76.10	11.53	10-02-2018	Kerala	719|NIF10022018
NIF	76.14	11.51	10-02-2018	Kerala	186|NIF10022018
NIF	76.10	11.59	09-03-2018	Kerala	119|NIF09032018
NIF	76.10	11.49	03-10-2018	Kerala	493|NIF03102018
NIF	76.11	11.51	03-10-2018	Kerala	520|NIF03102018
NIF	76.08	11.54	11-01-2019	Kerala	448|NIF11012019
NIF	75.91	11.71	22-02-2020	Kerala	681|NIF22022020
NIF	76.05	11.54	27-10-2020	Kerala	197|NIF27102020

Species	Longitude	Latitude	Date	State	Unique ID
NIF	77.24	10.12	14-10-2017	Kerala	556|NIF14102017
NIF	77.01	10.35	26-01-2000	Tamil Nadu	887|NIF26012000
NIF	76.91	10.31	24-01-2000	Tamil Nadu	505|NIF24012000
NIF	76.90	10.34	18-01-2002	Tamil Nadu	596|NIF18012002
NIF	76.93	10.32	08-01-2004	Tamil Nadu	408|NIF08012004
NIF	76.72	10.94	15-04-2014	Tamil Nadu	042|NIF15042014
NIF	76.94	10.35	30-05-2015	Tamil Nadu	722|NIF30052015
NIF	76.98	10.45	13-09-2015	Tamil Nadu	186|NIF13092015
NIF	76.95	10.33	28-10-2015	Tamil Nadu	089|NIF28102015
NIF	76.97	10.34	22-01-2016	Tamil Nadu	946|NIF22012016
NIF	77.02	10.33	12-03-2016	Tamil Nadu	518|NIF12032016
NIF	76.98	10.36	03-01-2017	Tamil Nadu	624|NIF03012017
NIF	76.99	10.39	03-03-2017	Tamil Nadu	456|NIF03032017
NIF	76.94	11.35	14-05-2017	Tamil Nadu	251|NIF14052017
NIF	76.88	10.30	06-11-2017	Tamil Nadu	864|NIF06112017
NIF	76.95	10.41	26-01-2018	Tamil Nadu	642|NIF26012018
NIF	76.97	10.27	09-02-2018	Tamil Nadu	735|NIF09022018
NIF	76.86	11.34	08-03-2018	Tamil Nadu	593|NIF08032018
NIF	77.07	10.32	16-03-2018	Tamil Nadu	065|NIF16032018
NIF	76.96	10.40	13-03-2019	Tamil Nadu	226|NIF13032019
NIF	77.03	10.30	06-10-2018	Tamil Nadu	779|NIF06102018

Species	Longitude	Latitude	Date	State	Unique ID
NIF	77.00	10.33	30-09-2018	Tamil Nadu	910|NIF30092018
NIF	76.98	10.27	24-09-2018	Tamil Nadu	464|NIF24092018
NIF	77.04	10.39	09-01-2019	Tamil Nadu	883|NIF09012019
NIF	77.04	10.33	26-01-2019	Tamil Nadu	063|NIF26012019
NIF	77.02	10.37	09-01-2019	Tamil Nadu	138|NIF09012019
NIF	76.90	11.33	18-02-2019	Tamil Nadu	378|NIF18022019
NIF	77.01	10.28	19-07-2019	Tamil Nadu	409|NIF19072019
NIF	76.99	10.29	28-03-2020	Tamil Nadu	948|NIF28032020
NIF	76.99	10.37	05-01-2020	Tamil Nadu	554|NIF05012020
NIF	76.73	10.97	12-12-2020	Tamil Nadu	006|NIF12122020
NIF	77.50	10.25	03-05-2015	Tamil Nadu	700|NIF03052015
NIF	77.54	10.24	15-07-2015	Tamil Nadu	570|NIF15072015
NIF	77.45	10.27	13-05-2017	Tamil Nadu	643|NIF13052017
NIF	77.55	10.21	12-05-2017	Tamil Nadu	644|NIF12052017
NIF	77.36	10.23	06-08-2017	Tamil Nadu	794|NIF06082017
NIF	77.50	10.23	23-01-2018	Tamil Nadu	050|NIF23012018
NIF	77.49	10.22	11-04-2018	Tamil Nadu	147|NIF11042018
NIF	77.54	10.31	29-05-2018	Tamil Nadu	437|NIF29052018
NIF	77.48	10.28	28-07-2017	Tamil Nadu	454|NIF28072017
NIF	77.57	10.31	03-08-2014	Tamil Nadu	030|NIF03082014
NIF	77.37	10.27	14-09-2018	Tamil Nadu	355|NIF14092018
NIF	77.50	10.20	29-12-2018	Tamil Nadu	493|NIF29122018
NIF	77.58	10.35	08-01-2019	Tamil Nadu	527|NIF08012019
NIF	77.63	10.25	07-01-2019	Tamil Nadu	935|NIF07012019
NIF	77.48	10.24	02-04-2019	Tamil Nadu	766|NIF02042019
NIF	77.40	10.19	09-05-2019	Tamil Nadu	863|NIF09052019
NIF	77.37	10.30	01-06-2019	Tamil Nadu	613|NIF01062019
NIF	77.46	10.22	05-06-2019	Tamil Nadu	748|NIF05062019
NIF	77.60	10.33	23-07-2019	Tamil Nadu	232|NIF23072019
NIF	77.65	10.29	12-06-2018	Tamil Nadu	074|NIF12062018
NIF	77.54	10.29	11-07-2019	Tamil Nadu	750|NIF11072019
NIF	77.39	10.25	05-07-2019	Tamil Nadu	178|NIF05072019
NIF	77.61	10.27	14-10-2019	Tamil Nadu	389|NIF14102019
NIF	77.73	10.30	21-05-2010	Tamil Nadu	060|NIF21052010
NIF	77.42	10.25	16-01-2021	Tamil Nadu	564|NIF16012021
NIF	77.53	10.27	23-01-2021	Tamil Nadu	775|NIF23012021
NIF	77.51	10.29	30-01-2021	Tamil Nadu	962|NIF30012021
NIF	77.36	8.51	28-04-2009	Tamil Nadu	729|NIF28042009
NIF	76.71	11.42	07-03-2011	Tamil Nadu	286|NIF07032011
NIF	76.86	11.37	09-03-2011	Tamil Nadu	447|NIF09032011
NIF	76.69	11.40	02-02-2012	Tamil Nadu	107|NIF02022012
NIF	76.68	11.28	07-04-2012	Tamil Nadu	361|NIF07042012

Species	Longitude	Latitude	Date	State	Unique ID
NIF	76.89	11.44	30-12-2014	Tamil Nadu	285|NIF30122014
NIF	76.64	11.27	20-02-2015	Tamil Nadu	522|NIF20022015
NIF	76.73	11.42	23-02-2015	Tamil Nadu	648|NIF23022015
NIF	76.56	11.29	04-02-2015	Tamil Nadu	297|NIF04022015
NIF	76.80	11.49	12-06-2015	Tamil Nadu	183|NIF12062015
NIF	76.83	11.38	25-10-2015	Tamil Nadu	972|NIF25102015
NIF	76.90	11.37	12-12-2015	Tamil Nadu	950|NIF12122015
NIF	76.73	11.26	14-02-2016	Tamil Nadu	609|NIF14022016
NIF	76.64	11.47	05-03-2016	Tamil Nadu	759|NIF05032016
NIF	76.63	11.49	05-03-2016	Tamil Nadu	721|NIF05032016
NIF	76.66	11.48	05-03-2016	Tamil Nadu	607|NIF05032016
NIF	76.59	11.40	11-06-2016	Tamil Nadu	755|NIF11062016
NIF	76.81	11.41	14-03-2016	Tamil Nadu	216|NIF14032016
NIF	76.98	11.42	05-07-2016	Tamil Nadu	570|NIF05072016
NIF	76.86	11.43	03-04-2016	Tamil Nadu	508|NIF03042016
NIF	76.79	11.35	09-10-2016	Tamil Nadu	164|NIF09102016
NIF	76.60	11.34	29-01-2017	Tamil Nadu	908|NIF29012017
NIF	76.89	11.39	04-02-2017	Tamil Nadu	874|NIF04022017
NIF	76.86	11.39	19-10-2017	Tamil Nadu	355|NIF19102017
NIF	76.93	11.36	04-02-2017	Tamil Nadu	791|NIF04022017
NIF	76.65	11.37	24-02-2017	Tamil Nadu	085|NIF24022017

Species	Longitude	Latitude	Date	State	Unique ID
NIF	76.59	11.32	25-02-2017	Tamil Nadu	324|NIF25022017
NIF	76.67	11.39	16-04-2017	Tamil Nadu	326|NIF16042017
NIF	76.79	11.37	13-05-2017	Tamil Nadu	596|NIF13052017
NIF	76.90	11.46	13-05-2017	Tamil Nadu	038|NIF13052017
NIF	76.77	11.36	03-06-2017	Tamil Nadu	460|NIF03062017
NIF	76.56	11.58	30-07-2017	Tamil Nadu	938|NIF30072017
NIF	76.59	11.22	16-10-2017	Tamil Nadu	364|NIF16102017
NIF	76.79	11.33	25-11-2017	Tamil Nadu	222|NIF25112017
NIF	76.55	11.47	31-01-2018	Tamil Nadu	355|NIF31012018
NIF	76.36	11.52	01-01-2018	Tamil Nadu	103|NIF01012018
NIF	76.74	11.38	25-03-2018	Tamil Nadu	081|NIF25032018
NIF	76.61	11.21	19-04-2018	Tamil Nadu	376|NIF19042018
NIF	76.35	11.51	02-04-2018	Tamil Nadu	774|NIF02042018
NIF	76.33	11.49	29-04-2018	Tamil Nadu	406|NIF29042018
NIF	76.76	11.31	02-09-2018	Tamil Nadu	705|NIF02092018
NIF	76.66	11.25	28-06-2018	Tamil Nadu	671|NIF28062018
NIF	76.77	11.41	09-07-2018	Tamil Nadu	321|NIF09072018
NIF	76.91	11.51	22-07-2018	Tamil Nadu	039|NIF22072018
NIF	76.74	11.31	26-08-2018	Tamil Nadu	905|NIF26082018
NIF	76.91	11.48	17-05-2018	Tamil Nadu	100|NIF17052018
NIF	76.62	11.33	11-08-2018	Tamil Nadu	106|NIF11082018

Species	Longitude	Latitude	Date	State	Unique ID
NIF	76.65	11.44	09-12-2018	Tamil Nadu	269|NIF09122018
NIF	76.72	11.39	26-01-2019	Tamil Nadu	299|NIF26012019
NIF	76.69	11.42	14-01-2019	Tamil Nadu	150|NIF14012019
NIF	76.81	11.38	02-02-2019	Tamil Nadu	932|NIF02022019
NIF	76.86	11.41	17-03-2019	Tamil Nadu	290|NIF17032019
NIF	76.83	11.35	14-04-2015	Tamil Nadu	377|NIF14042015
NIF	76.64	11.35	08-04-2019	Tamil Nadu	020|NIF08042019
NIF	76.51	11.48	14-04-2019	Tamil Nadu	613|NIF14042019
NIF	76.67	11.45	01-05-2019	Tamil Nadu	406|NIF01052019
NIF	76.75	11.34	01-05-2019	Tamil Nadu	580|NIF01052019
NIF	76.64	11.57	16-06-2019	Tamil Nadu	888|NIF16062019
NIF	76.84	11.40	06-06-2019	Tamil Nadu	183|NIF06062019
NIF	76.68	11.47	23-02-2020	Tamil Nadu	972|NIF23022020
NIF	76.75	11.41	11-09-2019	Tamil Nadu	778|NIF11092019
NIF	76.81	11.32	27-12-2018	Tamil Nadu	277|NIF27122018
NIF	76.61	11.30	11-09-2019	Tamil Nadu	817|NIF11092019
NIF	76.62	11.24	09-11-2019	Tamil Nadu	122|NIF09112019
NIF	76.50	11.51	24-11-2019	Tamil Nadu	242|NIF24112019
NIF	76.90	11.40	26-12-2019	Tamil Nadu	480|NIF26122019
NIF	76.53	11.49	17-01-2020	Tamil Nadu	720|NIF17012020
NIF	76.88	11.42	16-02-2020	Tamil Nadu	482|NIF16022020

Species	Longitude	Latitude	Date	State	Unique ID
NIF	76.64	11.31	20-02-2020	Tamil Nadu	412|NIF20022020
NIF	76.65	11.32	21-02-2020	Tamil Nadu	391|NIF21022020
NIF	76.61	11.49	14-02-2020	Tamil Nadu	424|NIF14022020
NIF	76.62	11.46	12-02-2020	Tamil Nadu	605|NIF12022020
NIF	76.73	11.28	13-03-2020	Tamil Nadu	665|NIF13032020
NIF	76.54	11.48	24-03-2020	Tamil Nadu	459|NIF24032020
NIF	76.61	11.26	04-03-2020	Tamil Nadu	562|NIF04032020
NIF	76.58	11.29	11-11-2020	Tamil Nadu	483|NIF11112020
NIF	76.81	11.35	07-11-2020	Tamil Nadu	286|NIF07112020
NIF	76.64	11.54	28-01-2021	Tamil Nadu	826|NIF28012021
NIF	76.61	11.51	27-01-2021	Tamil Nadu	835|NIF27012021
NIF	76.56	11.20	20-01-2021	Tamil Nadu	723|NIF20012021
NIF	77.40	9.71	16-11-2014	Tamil Nadu	777|NIF16112014
NIF	77.34	9.64	11-05-2018	Tamil Nadu	948|NIF11052018
NIF	77.36	9.60	28-12-2017	Tamil Nadu	405|NIF28122017
NIF	77.38	9.53	25-01-2019	Tamil Nadu	340|NIF25012019
NIF	77.27	10.02	06-12-2020	Tamil Nadu	067|NIF06122020
NIF	77.48	8.47	27-04-2009	Tamil Nadu	683|NIF27042009
NIF	77.31	8.69	20-02-2015	Tamil Nadu	712|NIF20022015
NIF	77.39	8.55	03-12-2018	Tamil Nadu	052|NIF03122018
NIF	77.35	8.54	04-12-2018	Tamil Nadu	166|NIF04122018

Species	Longitude	Latitude	Date	State	Unique ID
NIF	77.26	8.59	09-03-2020	Tamil Nadu	373|NIF09032020
NIF	77.14	10.43	05-05-2005	Tamil Nadu	424|NIF05052005
NIF	77.16	10.46	17-12-2017	Tamil Nadu	722|NIF17122017
NIF	77.09	10.43	19-12-2017	Tamil Nadu	290|NIF19122017
NIF	77.26	10.43	15-02-2020	Tamil Nadu	773|NIF15022020
NIF	77.31	9.59	12-05-2018	Tamil Nadu	605|NIF12052018
NIF	77.29	10.21	24-02-2019	Tamil Nadu	446|NIF24022019
NIF	76.84	10.33	03-08-2019	Tamil Nadu	819|NIF03082019
NIF	77.26	10.23	08-03-2020	Tamil Nadu	496|NIF08032020
BOF	75.75	13.52	24-12-2012	Karnataka	873|BOF24122012
BOF	75.75	13.55	26-09-2016	Karnataka	260|BOF26092016
BOF	75.28	13.14	29-12-2016	Karnataka	679|BOF29122016
BOF	75.66	12.22	15-01-2019	Karnataka	867|BOF15012019
BOF	77.03	10.20	22-02-2019	Kerala	861|BOF22022019
BOF	77.07	10.18	18-07-2020	Kerala	943|BOF18072020
BOF	77.07	10.15	16-01-2009	Kerala	770|BOF16012009
BOF	77.08	10.04	19-01-2009	Kerala	772|BOF19012009
BOF	77.19	10.18	17-01-2009	Kerala	771|BOF17012009
BOF	77.00	10.16	30-01-2009	Kerala	780|BOF30012009
BOF	77.35	9.58	06-03-2009	Kerala	799|BOF06032009
BOF	77.01	10.08	12-12-2009	Kerala	682|BOF12122009

Species	Longitude	Latitude	Date	State	Unique ID
BOF	77.06	10.09	09-11-2011	Kerala	429|BOF09112011
BOF	77.08	10.23	09-12-2012	Kerala	027|BOF09122012
BOF	77.24	9.99	08-12-2012	Kerala	922|BOF08122012
BOF	77.09	10.29	08-12-2012	Kerala	194|BOF08122012
BOF	77.15	10.33	08-12-2012	Kerala	823|BOF08122012
BOF	77.04	10.15	11-10-2014	Kerala	726|BOF11102014
BOF	77.26	10.15	07-11-2014	Kerala	403|BOF07112014
BOF	77.08	10.08	09-05-2015	Kerala	171|BOF09052015
BOF	77.05	10.13	30-08-2015	Kerala	663|BOF30082015
BOF	77.19	10.23	12-09-2016	Kerala	235|BOF12092016
BOF	77.04	10.05	25-12-2016	Kerala	064|BOF25122016
BOF	77.31	9.59	02-12-2016	Kerala	045|BOF02122016
BOF	77.19	10.20	26-01-2017	Kerala	644|BOF26012017
BOF	77.09	10.15	25-04-2017	Kerala	195|BOF25042017
BOF	77.18	10.19	28-04-2017	Kerala	363|BOF28042017
BOF	77.17	10.29	25-06-2017	Kerala	014|BOF25062017
BOF	77.21	10.13	14-10-2017	Kerala	520|BOF14102017
BOF	77.16	10.04	23-12-2017	Kerala	238|BOF23122017
BOF	77.07	10.06	25-01-2018	Kerala	094|BOF25012018
BOF	77.09	10.09	17-03-2018	Kerala	839|BOF17032018
BOF	77.26	10.20	21-04-2018	Kerala	745|BOF21042018

Species	Longitude	Latitude	Date	State	Unique ID
BOF	77.24	10.20	12-04-2018	Kerala	079|BOF12042018
BOF	77.06	10.11	28-04-2018	Kerala	822|BOF28042018
BOF	77.38	9.50	13-05-2018	Kerala	626|BOF13052018
BOF	77.26	10.13	03-09-2018	Kerala	087|BOF03092018
BOF	76.99	10.03	23-11-2018	Kerala	950|BOF23112018
BOF	77.14	10.04	12-12-2018	Kerala	635|BOF12122018
BOF	77.25	9.31	26-01-2019	Kerala	623|BOF26012019
BOF	77.13	10.16	20-01-2019	Kerala	470|BOF20012019
BOF	77.02	10.06	20-01-2019	Kerala	122|BOF20012019
BOF	77.18	9.50	26-01-2019	Kerala	877|BOF26012019
BOF	77.28	9.32	27-01-2019	Kerala	768|BOF27012019
BOF	77.18	9.58	26-01-2019	Kerala	146|BOF26012019
BOF	77.34	9.55	26-01-2019	Kerala	534|BOF26012019
BOF	77.22	10.21	24-02-2019	Kerala	595|BOF24022019
BOF	77.26	10.17	23-02-2019	Kerala	635|BOF23022019
BOF	77.02	10.17	23-02-2019	Kerala	212|BOF23022019
BOF	77.12	10.22	23-02-2019	Kerala	569|BOF23022019
BOF	77.04	10.23	22-02-2019	Kerala	036|BOF22022019
BOF	76.98	10.16	15-03-2019	Kerala	447|BOF15032019
BOF	76.99	10.11	15-03-2019	Kerala	873|BOF15032019
BOF	76.97	10.09	17-03-2019	Kerala	368|BOF17032019

Species	Longitude	Latitude	Date	State	Unique ID
BOF	77.09	10.11	10-03-2019	Kerala	510|BOF10032019
BOF	77.17	10.12	10-03-2019	Kerala	494|BOF10032019
BOF	76.99	10.07	15-03-2019	Kerala	578|BOF15032019
BOF	77.13	10.09	10-03-2019	Kerala	541|BOF10032019
BOF	77.15	10.12	17-05-2019	Kerala	333|BOF17052019
BOF	77.11	10.18	17-07-2019	Kerala	847|BOF17072019
BOF	77.19	10.16	03-08-2019	Kerala	295|BOF03082019
BOF	77.10	10.13	04-08-2019	Kerala	228|BOF04082019
BOF	77.03	9.72	24-01-2020	Kerala	284|BOF24012020
BOF	77.11	10.10	30-01-2020	Kerala	684|BOF30012020
BOF	77.12	10.04	19-07-2020	Kerala	564|BOF19072020
BOF	77.10	10.06	29-01-2021	Kerala	771|BOF29012021
BOF	77.22	8.82	07-09-2019	Kerala	589|BOF07092019
BOF	75.87	11.95	09-03-2012	Kerala	225|BOF09032012
BOF	76.12	11.43	11-03-2018	Kerala	223|BOF11032018
BOF	76.13	11.45	10-03-2018	Kerala	569|BOF10032018
BOF	76.64	10.95	12-02-2007	Kerala	032|BOF12022007
BOF	76.62	10.96	12-02-2007	Kerala	990|BOF12022007
BOF	76.42	11.18	07-04-2011	Kerala	329|BOF07042011
BOF	76.44	11.20	06-04-2011	Kerala	328|BOF06042011
BOF	76.45	11.09	08-12-2015	Kerala	065|BOF08122015

Species	Longitude	Latitude	Date	State	Unique ID
BOF	76.52	11.14	19-08-2017	Kerala	645|BOF19082017
BOF	76.66	10.47	19-08-2017	Kerala	495|BOF19082017
BOF	77.18	9.43	12-05-2018	Kerala	832|BOF12052018
BOF	77.23	9.34	25-01-2019	Kerala	149|BOF25012019
BOF	77.21	9.37	25-01-2019	Kerala	829|BOF25012019
BOF	77.18	9.39	25-01-2019	Kerala	983|BOF25012019
BOF	77.17	9.35	26-01-2019	Kerala	061|BOF26012019
BOF	77.23	8.63	25-12-2010	Kerala	294|BOF25122010
BOF	77.19	8.68	26-08-2015	Kerala	639|BOF26082015
BOF	77.18	8.66	09-03-2019	Kerala	391|BOF09032019
BOF	76.13	11.47	20-12-2008	Kerala	327|BOF20122008
BOF	76.14	11.51	10-02-2018	Kerala	186|BOF10022018
BOF	76.10	11.49	03-10-2018	Kerala	493|BOF03102018
BOF	76.99	10.44	23-01-1993	Tamil Nadu	025|BOF23011993
BOF	76.93	10.35	15-01-2000	Tamil Nadu	938|BOF15012000
BOF	77.01	10.35	26-01-2000	Tamil Nadu	887|BOF26012000
BOF	76.94	10.25	14-01-2002	Tamil Nadu	617|BOF14012002
BOF	76.97	10.34	15-01-2004	Tamil Nadu	440|BOF15012004
BOF	76.93	10.32	08-01-2004	Tamil Nadu	408|BOF08012004
BOF	77.02	10.33	12-03-2016	Tamil Nadu	518|BOF12032016
BOF	76.99	10.39	13-11-2016	Tamil Nadu	930|BOF13112016

Species	Longitude	Latitude	Date	State	Unique ID
BOF	76.95	10.41	26-01-2018	Tamil Nadu	642|BOF26012018
BOF	76.99	10.37	03-03-2018	Tamil Nadu	373|BOF03032018
BOF	76.98	10.37	24-10-2018	Tamil Nadu	987|BOF24102018
BOF	77.03	10.30	06-10-2018	Tamil Nadu	779|BOF06102018
BOF	76.97	10.40	07-12-2018	Tamil Nadu	806|BOF07122018
BOF	77.04	10.33	26-01-2019	Tamil Nadu	404|BOF26012019
BOF	77.01	10.43	10-01-2019	Tamil Nadu	558|BOF10012019
BOF	77.06	10.33	24-01-2019	Tamil Nadu	138|BOF24012019
BOF	76.99	10.29	28-03-2020	Tamil Nadu	948|BOF28032020
BOF	77.48	10.24	28-05-2011	Tamil Nadu	103|BOF28052011
BOF	77.57	10.31	03-08-2014	Tamil Nadu	030|BOF03082014
BOF	77.41	10.25	05-10-2014	Tamil Nadu	560|BOF05102014
BOF	77.53	10.24	31-12-2016	Tamil Nadu	120|BOF31122016
BOF	77.55	10.21	12-05-2017	Tamil Nadu	644|BOF12052017
BOF	77.45	10.27	13-05-2017	Tamil Nadu	643|BOF13052017
BOF	77.36	10.23	06-08-2017	Tamil Nadu	794|BOF06082017
BOF	77.49	10.22	11-04-2018	Tamil Nadu	147|BOF11042018
BOF	77.55	10.29	29-05-2018	Tamil Nadu	451|BOF29052018
BOF	77.50	10.23	19-05-2018	Tamil Nadu	153|BOF19052018
BOF	77.65	10.29	12-06-2018	Tamil Nadu	074|BOF12062018
BOF	77.42	10.22	04-07-2018	Tamil Nadu	358|BOF04072018

Species	Longitude	Latitude	Date	State	Unique ID
BOF	77.39	10.19	28-11-2018	Tamil Nadu	297|BOF28112018
BOF	77.43	10.20	06-03-2019	Tamil Nadu	544|BOF06032019
BOF	77.45	10.23	21-05-2019	Tamil Nadu	056|BOF21052019
BOF	77.37	10.30	01-06-2019	Tamil Nadu	613|BOF01062019
BOF	77.55	10.27	09-07-2019	Tamil Nadu	479|BOF09072019
BOF	77.39	10.25	05-07-2019	Tamil Nadu	178|BOF05072019
BOF	77.60	10.33	23-07-2019	Tamil Nadu	232|BOF23072019
BOF	77.32	10.20	04-01-2020	Tamil Nadu	525|BOF04012020
BOF	77.34	10.19	17-12-2020	Tamil Nadu	163|BOF17122020
BOF	77.40	10.29	16-01-2021	Tamil Nadu	712|BOF16012021
BOF	76.75	11.31	19-12-1974	Tamil Nadu	315|BOF19121974
BOF	76.68	11.28	07-04-2012	Tamil Nadu	361|BOF07042012
BOF	76.67	11.43	22-01-2014	Tamil Nadu	584|BOF22012014
BOF	76.55	11.27	22-01-2015	Tamil Nadu	839|BOF22012015
BOF	76.57	11.31	03-01-2015	Tamil Nadu	015|BOF03012015
BOF	76.83	11.35	14-04-2015	Tamil Nadu	377|BOF14042015
BOF	76.74	11.40	27-06-2015	Tamil Nadu	175|BOF27062015
BOF	76.83	11.38	25-10-2015	Tamil Nadu	972|BOF25102015
BOF	76.59	11.30	17-04-2004	Tamil Nadu	312|BOF17042004
BOF	76.59	11.39	02-03-2016	Tamil Nadu	973|BOF02032016
BOF	76.64	11.45	05-03-2016	Tamil Nadu	430|BOF05032016

Species	Longitude	Latitude	Date	State	Unique ID
BOF	76.67	11.38	07-06-2016	Tamil Nadu	020|BOF07062016
BOF	76.98	11.42	05-07-2016	Tamil Nadu	570|BOF05072016
BOF	76.60	11.32	11-09-2016	Tamil Nadu	491|BOF11092016
BOF	76.53	11.53	26-03-2017	Tamil Nadu	338|BOF26032017
BOF	76.58	11.48	03-03-2017	Tamil Nadu	852|BOF03032017
BOF	76.56	11.58	30-07-2017	Tamil Nadu	938|BOF30072017
BOF	76.70	11.59	13-08-2017	Tamil Nadu	178|BOF13082017
BOF	76.79	11.34	11-10-2017	Tamil Nadu	862|BOF11102017
BOF	76.77	11.36	22-10-2017	Tamil Nadu	306|BOF22102017
BOF	76.86	11.39	19-10-2017	Tamil Nadu	355|BOF19102017
BOF	76.79	11.31	08-10-2017	Tamil Nadu	880|BOF08102017
BOF	76.59	11.22	16-10-2017	Tamil Nadu	364|BOF16102017
BOF	76.62	11.33	17-02-2018	Tamil Nadu	025|BOF17022018
BOF	76.68	11.40	06-02-2018	Tamil Nadu	577|BOF06022018
BOF	76.87	11.42	19-04-2018	Tamil Nadu	852|BOF19042018
BOF	76.75	11.41	08-04-2018	Tamil Nadu	993|BOF08042018
BOF	76.75	11.38	26-04-2018	Tamil Nadu	937|BOF26042018
BOF	76.81	11.41	12-08-2018	Tamil Nadu	766|BOF12082018
BOF	76.92	11.36	10-09-2018	Tamil Nadu	260|BOF10092018
BOF	76.76	11.31	02-09-2018	Tamil Nadu	705|BOF02092018
BOF	76.62	11.45	27-12-2018	Tamil Nadu	295|BOF27122018

Species	Longitude	Latitude	Date	State	Unique ID
BOF	76.63	11.43	09-12-2018	Tamil Nadu	259|BOF09122018
BOF	76.92	11.53	19-12-2018	Tamil Nadu	143|BOF19122018
BOF	76.81	11.32	27-12-2018	Tamil Nadu	277|BOF27122018
BOF	76.80	11.37	16-02-2019	Tamil Nadu	131|BOF16022019
BOF	76.71	11.42	25-03-2019	Tamil Nadu	770|BOF25032019
BOF	76.69	11.42	17-04-2019	Tamil Nadu	631|BOF17042019
BOF	76.71	11.39	03-06-2019	Tamil Nadu	375|BOF03062019
BOF	76.64	11.35	10-09-2019	Tamil Nadu	724|BOF10092019
BOF	76.91	11.48	23-10-2019	Tamil Nadu	022|BOF23102019
BOF	76.64	11.27	09-11-2019	Tamil Nadu	398|BOF09112019
BOF	76.87	11.44	15-01-2020	Tamil Nadu	959|BOF15012020
BOF	76.84	11.40	04-01-2020	Tamil Nadu	762|BOF04012020
BOF	76.92	11.46	15-01-2020	Tamil Nadu	552|BOF15012020
BOF	76.65	11.32	21-02-2020	Tamil Nadu	391|BOF21022020
BOF	76.64	11.31	20-02-2020	Tamil Nadu	412|BOF20022020
BOF	76.68	11.47	23-02-2020	Tamil Nadu	972|BOF23022020
BOF	76.61	11.26	04-03-2020	Tamil Nadu	562|BOF04032020
BOF	76.73	11.28	13-03-2020	Tamil Nadu	665|BOF13032020
BOF	76.81	11.35	07-11-2020	Tamil Nadu	286|BOF07112020
BOF	76.89	11.48	09-11-2020	Tamil Nadu	432|BOF09112020
BOF	76.56	11.20	20-01-2021	Tamil Nadu	723|BOF20012021

Species	Longitude	Latitude	Date	State	Unique ID
BOF	76.62	11.23	19-01-2021	Tamil Nadu	083|BOF19012021
BOF	76.63	11.21	19-01-2021	Tamil Nadu	076|BOF19012021
BOF	77.34	9.64	11-05-2018	Tamil Nadu	948|BOF11052018
BOF	77.38	8.54	19-03-2016	Tamil Nadu	168|BOF19032016
BOF	77.36	8.55	05-07-2018	Tamil Nadu	109|BOF05072018
BOF	77.29	9.29	24-01-2019	Tamil Nadu	928|BOF24012019
BOF	77.20	8.70	11-03-2020	Tamil Nadu	505|BOF11032020
BOF	77.18	8.74	24-08-2020	Tamil Nadu	282|BOF24082020
BOF	77.09	10.32	25-01-2019	Tamil Nadu	436|BOF25012019
BOF	77.32	9.57	25-01-2019	Tamil Nadu	091|BOF25012019
BOF	77.37	9.54	26-01-2019	Tamil Nadu	776|BOF26012019
BOF	77.26	10.23	24-02-2019	Tamil Nadu	290|BOF24022019
BOF	77.29	10.21	24-02-2019	Tamil Nadu	446|BOF24022019
BOF	77.26	9.95	24-12-2020	Tamil Nadu	234|BOF24122020

Appendix II. Description of environmental variables used to develop the Maxent models of selected birds

Variable	Description	Definition	Unit	Formula
BIO 1	Annual Mean Temperature	The annual mean temperature	Degrees Celsius	$\frac{\sum_{i=1}^{i=12} Tavg_i}{12}$
BIO 2	Mean Diurnal Range	The mean of the monthly temperature ranges	Degrees Celsius	$\frac{\sum_{i=1}^{i=12} Tmax_i - Tmin_i}{12}$
BIO 3	Isothermality	It quantifies how large the day-to-night temperatures oscillate relative to the summer-to-winter (annual) oscillations	Degrees Celsius	$\frac{BIO\ 2}{BIO\ 7} \times 100$
BIO 4	Temperature Seasonality	The amount of temperature variation over a given year (or averaged years) based on the standard deviation (variation) of monthly temperature averages	Degrees Celsius	$SD\{Tavg_1, \ldots., Tavg_{12}\}$
BIO 5	Max Temperature of Warmest Month	The maximum monthly temperature occurrence over a given year (time-series) or averaged span of years (normal)	Degrees Celsius	$max\{Tavg_1, \ldots., Tavg_{12}\}$
BIO 6	Min Temperature of Coldest Month	The minimum monthly temperature occurrence over a given year (time-series) or averaged span of years (normal)	Degrees Celsius	$min\{Tavg_1, \ldots., Tavg_{12}\}$
BIO 7	Temperature Annual Range	A measure of temperature variation over a given period	Degrees Celsius	$BIO\ 5\ - BIO\ 6$
BIO 8	Mean Temperature of Wettest Quarter	This quarterly index approximates mean temperatures that prevail during the wettest season	Degrees Celsius	$\frac{\sum_{i=1}^{i=3} Tavg_i}{3} \begin{cases} Where\ monthly \\ temperature \\ averages\ are\ based \\ on\ the\ three\ selected \\ months\ of\ Q_{PPTmax} \end{cases}$

				$Q_{PPT_{max}} = \max\left[\left[\begin{matrix}\sum_{i=1}^{i=3} PPT_i, \\ \sum_{i=2}^{i=4} PPT_i, \\ \dots\dots\dots, \\ \sum_{i=11}^{i=1} PPT_i, \\ \sum_{i=12}^{i=2} PPT_i,\end{matrix}\right]\right] \begin{cases} Where\ precipitation \\ is\ evaluated\ for \\ 12\ consicutive \\ sets\ of\ 3\ months. \\ The\ last\ two\ sets \\ span\ two\ years \\ for\ time-series \\ data \end{cases}$
BIO 9	Mean Temperature of Driest Quarter	This quarterly index approximates mean temperatures that prevail during the driest quarter	Degrees Celsius	$\frac{\sum_{i=1}^{i=3} Tavg_i}{3} \begin{cases} Where\ monthly \\ temperature \\ averages\ are\ based \\ on\ the\ three\ selected \\ months\ of\ Q_{PPTmin} \end{cases}$ $Q_{PPT_{min}} = \min\left[\left[\begin{matrix}\sum_{i=1}^{i=3} PPT_i, \\ \sum_{i=2}^{i=4} PPT_i, \\ \dots\dots\dots, \\ \sum_{i=11}^{i=1} PPT_i, \\ \sum_{i=12}^{i=2} PPT_i,\end{matrix}\right]\right] \begin{cases} Where\ precipitation \\ is\ evaluated\ for \\ 12\ consicutive \\ sets\ of\ 3\ months. \\ The\ last\ two\ sets \\ span\ two\ years \\ for\ time-series \\ data \end{cases}$
BIO 10	Mean Temperature of Warmest Quarter	This quarterly index approximates mean temperatures that prevail during the warmest quarter	Degrees Celsius	$\frac{\sum_{i=1}^{i=3} Tavg_i}{3} \begin{cases} Where\ monthly \\ temperature \\ averages\ are\ based \\ on\ the\ three\ selected \\ months\ of\ Q_{Tmax} \end{cases}$

				$Q_{T_{max}} = \max \left[\left\| \begin{array}{c} \sum_{i=1}^{i=3} Tavg_i, \\ \sum_{i=2}^{i=4} Tavg_i, \\ \ldots\ldots\ldots.., \\ \sum_{i=11}^{i=1} Tavg_i, \\ \sum_{i=12}^{i=2} Tavg_i, \end{array} \right\| \right] \left\{ \begin{array}{c} Where\ temperatures \\ are\ evaluated\ for \\ 12\ consicutive \\ sets\ of\ 3\ months. \\ The\ last\ two\ sets \\ span\ two\ years \\ for\ time-series \\ data \end{array} \right.$
BIO 11	Mean Temperature of Coldest Quarter	This quarterly index approximates mean temperatures that prevail during the coldest quarter	Degrees Celsius	$\frac{\sum_{i=1}^{i=3} Tavg_i}{3} \left\{ \begin{array}{c} Where\ monthly \\ temperature \\ averages\ are\ based \\ on\ the\ three\ selected \\ months\ of\ Q_{Tmin} \end{array} \right.$ $Q_{T_{min}} = \min \left[\left\| \begin{array}{c} \sum_{i=1}^{i=3} Tavg_i, \\ \sum_{i=2}^{i=4} Tavg_i, \\ \ldots\ldots\ldots.., \\ \sum_{i=11}^{i=1} Tavg_i, \\ \sum_{i=12}^{i=2} Tavg_i, \end{array} \right\| \right] \left\{ \begin{array}{c} Where\ temperatures \\ are\ evaluated\ for \\ 12\ consicutive \\ sets\ of\ 3\ months. \\ The\ last\ two\ sets \\ span\ two\ years \\ for\ time-series \\ data \end{array} \right.$
BIO 12	Annual Precipitation	This is the sum of all total monthly precipitation values	kg m^{-2}	$\sum_{i=1}^{i=12} PPT_i$

BIO 13	Precipitation of Wettest Month	This index identifies the total precipitation that prevails during the wettest month	kg m^{-2}	max $([PPT_i, \ldots\ldots, PPT_{12}])$
BIO 14	Precipitation of Driest Month	This index identifies the total precipitation that prevails during the driest month	kg m^{-2}	min $([PPT_i, \ldots\ldots, PPT_{12}])$
BIO 15	Precipitation Seasonality	This is a measure of the variation in monthly precipitation totals over the course of the year. This index is the ratio of the standard deviation of the monthly total precipitation to the mean monthly total precipitation	kg m^{-2}	$\frac{SD\{PPT_1, \ldots, PPT_{12}\}}{1+\left({BIO\ 12}/{12}\right)} \times 100$
BIO 16	Precipitation of Wettest Quarter	This quarterly index approximates total precipitation that prevails during the wettest quarter	kg m^{-2}	max $\left[\left[\begin{array}{l}\sum_{i=1}^{i=3} PPT_i, \\ \sum_{i=2}^{i=4} PPT_i, \\ \ldots\ldots\ldots, \\ \sum_{i=11}^{i=1} PPT_i, \\ \sum_{i=12}^{i=2} PPT_i,\end{array}\right]\right] \left\{\begin{array}{c}\text{Where precipitation} \\ \text{is evaluated for 12} \\ \text{consecutive sets} \\ \text{of 3 months.} \\ \text{The last two} \\ \text{sets span} \\ \text{two years for} \\ \text{time} - \text{series data}\end{array}\right.$
BIO 17	Precipitation of Driest Quarter	This quarterly index approximates total precipitation that prevails during the driest quarter	kg m^{-2}	min $\left[\left[\begin{array}{l}\sum_{i=1}^{i=3} PPT_i, \\ \sum_{i=2}^{i=4} PPT_i, \\ \ldots\ldots\ldots, \\ \sum_{i=11}^{i=1} PPT_i, \\ \sum_{i=12}^{i=2} PPT_i,\end{array}\right]\right] \left\{\begin{array}{c}\text{Where precipitation} \\ \text{is evaluated for 12} \\ \text{consecutive sets} \\ \text{of 3 months.} \\ \text{The last two} \\ \text{sets span} \\ \text{two years for} \\ \text{time} - \text{series data}\end{array}\right.$

BIO 18	Precipitation of Warmest Quarter	This quarterly index approximates total precipitation that prevails during the warmest quarter	kg m^{-2}	$\sum_{i=1}^{i=3} PPT_i \left\{ \begin{array}{c} Where\ monthly \\ precipitation\ values \\ are\ based\ on\ the \\ three\ selected\ months \\ of\ Q_{Tmax} \end{array} \right.$
BIO 19	Precipitation of Coldest Quarter	This quarterly index approximates total precipitation that prevails during the coldest quarter	kg m^{-2}	$\sum_{i=1}^{i=3} PPT_i \left\{ \begin{array}{c} Where\ monthly \\ precipitation\ values \\ are\ based\ on\ the \\ three\ selected\ months \\ of\ Q_{Tmin} \end{array} \right.$
Elevation	Digital Elevation Model (DEM)	Elevation of a location	Meters	NA
Slope	Digital Elevation Model (DEM)	Slope of a terrain	Degrees	NA
Aspect	Digital Elevation Model (DEM)	Aspect of a terrain	NA	NA
evi_avg	Average Enhanced Vegetation Index (EVI)	10-year (2011-2020) average EVI by considering all months	NA	NA
evi_mon	Peak monsoon Enhanced Vegetation Index (EVI)	10-year (2011-2020) average EVI by considering the months of June, July and August	NA	NA
evi_dry	Peak summer Enhanced Vegetation Index (EVI)	10-year (2011-2020) average EVI by considering the months of March, April and May	NA	NA

Notations:
$i = month$; $Tmax = monthly\ mean\ of\ daily\ maximum\ temperatures\ (°C)$; $Tmin = monthly\ mean\ of\ daily\ minimum\ temperatures\ (°C)$;
$Tavg_i = \frac{Tmax_i}{Tmin_i}$; $PPT = total\ monthly\ precipitation\ (mm)$

Appendix III. Pearson's correlation coefficient between environmental variables used for developing Maxent models for selected species

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
aspect	BIO 17	-0.015	-0.100	-0.316	0.216	-0.065	-0.068
aspect	BIO 18	0.846	0.239	0.352	-0.675	0.141	0.163
aspect	BIO 19	0.110	0.132	0.287	-0.184	0.074	0.086
aspect	BIO 2	-0.545	-0.099	-0.269	-0.757	-0.061	-0.087
aspect	BIO 3	0.971	-0.005	-0.084	-0.384	-0.029	-0.036
aspect	BIO 4	-0.276	-0.036	-0.212	-0.070	-0.047	-0.082
aspect	BIO 5	-0.510	0.084	-0.037	-0.725	-0.006	0.000
aspect	BIO 6	-0.067	0.125	0.023	0.180	0.036	0.045
aspect	BIO 7	-0.325	-0.097	-0.264	0.624	-0.055	-0.078
aspect	BIO 8	-0.292	0.116	-0.011	-0.199	0.023	0.034
aspect	BIO 9	-0.309	0.115	0.000	-0.171	0.023	0.032
aspect	elevation	0.349	-0.110	-0.003	0.140	-0.018	-0.027
aspect	evi_avg	-0.393	0.025	0.097	0.556	0.044	0.046
aspect	evi_dry	-0.500	0.076	0.182	0.677	0.079	0.101
aspect	evi_mon	-0.206	-0.029	0.057	0.465	0.031	0.020
aspect	slope	-0.019	0.009	0.048	0.306	0.029	0.034
BIO 1	aspect	-0.281	0.115	-0.010	-0.235	0.014	0.023
BIO 1	BIO 17	-0.414	-0.354	-0.483	0.245	-0.128	-0.073
BIO 1	BIO 18	-0.163	-0.264	-0.473	-0.172	-0.123	-0.101
BIO 1	BIO 19	0.104	0.137	0.305	-0.487	0.021	0.107
BIO 1	BIO 2	0.214	-0.471	-0.072	0.242	-0.051	-0.289

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 1	BIO 3	-0.181	-0.105	-0.855	0.963	-0.311	-0.292
BIO 1	BIO 4	0.148	0.011	0.707	0.963	0.272	0.135
BIO 1	BIO 5	-0.141	0.912	0.995	-0.059	0.915	0.934
BIO 1	BIO 6	0.073	0.966	0.992	-0.047	0.928	0.967
BIO 1	BIO 7	-0.515	-0.434	0.150	-0.329	-0.003	-0.229
BIO 1	BIO 8	0.107	1.000	0.999	0.982	0.995	0.996
BIO 1	BIO 9	0.232	0.999	0.999	0.977	0.985	0.990
BIO 1	elevation	-0.187	-0.993	-0.997	-0.976	-0.975	-0.991
BIO 1	evi_avg	0.099	0.435	-0.028	-0.085	-0.054	0.079
BIO 1	evi_dry	0.277	0.296	-0.094	-0.115	-0.115	0.050
BIO 1	evi_mon	-0.140	0.364	0.004	-0.069	0.011	0.096
BIO 1	slope	0.000	0.023	-0.209	-0.309	-0.018	-0.159
BIO 10	aspect	-0.158	0.110	-0.025	-0.297	0.006	0.014
BIO 10	BIO 1	0.123	0.993	0.999	0.982	0.988	0.993
BIO 10	BIO 17	-0.414	-0.391	-0.463	0.214	-0.201	-0.125
BIO 10	BIO 18	0.275	-0.339	-0.499	-0.097	-0.197	-0.176
BIO 10	BIO 19	0.959	0.032	0.267	-0.479	-0.032	0.090
BIO 10	BIO 2	0.908	-0.367	-0.025	0.325	0.096	-0.187
BIO 10	BIO 3	-0.058	-0.187	-0.841	0.992	-0.331	-0.315
BIO 10	BIO 4	0.991	0.128	0.740	0.954	0.410	0.242
BIO 10	BIO 5	-0.123	0.953	0.999	0.022	0.963	0.966

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 10	BIO 6	0.030	0.931	0.985	-0.037	0.863	0.935
BIO 10	BIO 7	-0.249	-0.328	0.196	-0.385	0.145	-0.123
BIO 10	BIO 8	0.984	0.994	0.999	0.989	0.987	0.987
BIO 10	BIO 9	0.978	0.990	0.996	0.979	0.961	0.982
BIO 10	elevation	-0.973	-0.976	-0.993	-0.974	-0.935	-0.975
BIO 10	evi_avg	-0.001	0.376	-0.050	-0.130	-0.143	0.027
BIO 10	evi_dry	-0.056	0.207	-0.122	-0.166	-0.221	-0.012
BIO 10	evi_mon	0.028	0.397	-0.011	-0.100	-0.043	0.063
BIO 10	slope	-0.025	0.008	-0.212	-0.335	-0.020	-0.174
BIO 11	aspect	-0.349	0.116	0.000	-0.134	0.024	0.032
BIO 11	BIO 1	0.186	0.999	0.999	0.975	0.976	0.993
BIO 11	BIO 10	0.975	0.991	0.996	0.974	0.939	0.980
BIO 11	BIO 17	-0.405	-0.346	-0.494	0.302	-0.088	-0.081
BIO 11	BIO 18	0.066	-0.255	-0.458	-0.311	-0.081	-0.065
BIO 11	BIO 19	0.890	0.151	0.330	-0.588	0.122	0.147
BIO 11	BIO 2	0.969	-0.484	-0.113	0.106	-0.228	-0.357
BIO 11	BIO 3	-0.245	-0.099	-0.868	0.942	-0.372	-0.358
BIO 11	BIO 4	0.992	-0.006	0.677	0.994	0.077	0.050
BIO 11	BIO 5	-0.016	0.906	0.990	-0.190	0.834	0.913
BIO 11	BIO 6	0.043	0.970	0.996	-0.011	0.974	0.979
BIO 11	BIO 7	-0.179	-0.447	0.111	-0.279	-0.169	-0.283
BIO 11	BIO 8	0.988	0.999	0.998	0.986	0.963	0.990
BIO 11	BIO 9	0.995	1.000	1.000	0.997	0.993	0.996
BIO 11	elevation	-0.993	-0.994	-0.998	-0.996	-0.994	-0.995

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 11	evi_avg	0.102	0.447	-0.016	0.008	0.064	0.127
BIO 11	evi_dry	0.071	0.310	-0.077	-0.005	0.031	0.105
BIO 11	evi_mon	0.094	0.366	0.012	0.028	0.091	0.139
BIO 11	slope	-0.019	0.024	-0.206	-0.282	-0.016	-0.150
BIO 12	aspect	-0.391	0.177	0.380	0.698	0.136	0.162
BIO 12	BIO 1	0.797	0.136	-0.204	-0.045	-0.091	0.014
BIO 12	BIO 10	0.052	0.030	-0.246	-0.093	-0.173	-0.027
BIO 12	BIO 11	0.146	0.148	-0.175	0.076	0.044	0.077
BIO 12	BIO 17	-0.430	0.158	-0.381	0.655	-0.193	-0.381
BIO 12	BIO 18	-0.350	0.786	0.829	-0.726	0.230	0.197
BIO 12	BIO 19	-0.002	0.957	0.772	-0.609	0.882	0.868
BIO 12	BIO 2	0.183	-0.826	-0.832	-0.679	-0.544	-0.360
BIO 12	BIO 3	-0.279	0.662	-0.051	-0.151	-0.308	-0.391
BIO 12	BIO 4	0.092	-0.888	-0.743	0.130	-0.586	-0.432
BIO 12	BIO 5	0.198	-0.238	-0.288	-0.663	-0.247	-0.049
BIO 12	BIO 6	0.146	0.351	-0.099	0.167	0.124	0.112
BIO 12	BIO 7	-0.428	-0.843	-0.864	0.168	-0.487	-0.270
BIO 12	BIO 8	0.082	0.132	-0.219	-0.042	-0.128	-0.004
BIO 12	BIO 9	0.158	0.150	-0.174	0.072	0.030	0.103
BIO 12	elevation	-0.166	-0.211	0.158	-0.049	-0.052	-0.084
BIO 12	evi_avg	0.209	0.432	0.383	0.492	0.473	0.366
BIO 12	evi_dry	0.429	0.731	0.602	0.599	0.650	0.554
BIO 12	evi_mon	-0.130	-0.357	0.216	0.416	0.152	0.060
BIO 12	slope	0.014	0.184	0.145	0.202	0.015	0.114

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 13	aspect	-0.225	0.172	0.382	0.577	0.116	0.131
BIO 13	BIO 1	0.827	0.140	-0.094	-0.001	-0.048	0.022
BIO 13	BIO 10	0.114	0.036	-0.135	-0.041	-0.114	-0.002
BIO 13	BIO 11	0.163	0.153	-0.067	0.105	0.066	0.070
BIO 13	BIO 12	0.950	0.993	0.985	0.975	0.972	0.952
BIO 13	BIO 17	-0.563	0.080	-0.464	0.731	-0.363	-0.572
BIO 13	BIO 18	-0.135	0.777	0.775	-0.641	0.056	-0.049
BIO 13	BIO 19	0.104	0.972	0.813	-0.595	0.950	0.953
BIO 13	BIO 2	0.152	-0.793	-0.818	-0.571	-0.429	-0.202
BIO 13	BIO 3	-0.087	0.642	-0.140	-0.085	-0.373	-0.459
BIO 13	BIO 4	0.127	-0.874	-0.649	0.156	-0.466	-0.257
BIO 13	BIO 5	0.026	-0.218	-0.177	-0.572	-0.158	0.018
BIO 13	BIO 6	0.121	0.345	0.007	0.169	0.119	0.072
BIO 13	BIO 7	-0.630	-0.810	-0.826	0.008	-0.363	-0.097
BIO 13	BIO 8	0.109	0.136	-0.110	-0.008	-0.091	-0.007
BIO 13	BIO 9	0.184	0.155	-0.065	0.112	0.069	0.110
BIO 13	elevation	-0.189	-0.217	0.050	-0.080	-0.073	-0.076
BIO 13	evi_avg	0.085	0.438	0.364	0.417	0.396	0.272
BIO 13	evi_dry	0.288	0.732	0.586	0.517	0.567	0.452
BIO 13	evi_mon	-0.222	-0.351	0.200	0.341	0.080	-0.026
BIO 13	slope	0.004	0.169	0.106	0.174	0.011	0.072
BIO 14	aspect	-0.289	-0.136	-0.315	0.402	0.075	-0.088
BIO 14	BIO 1	-0.516	-0.276	-0.484	-0.528	-0.006	-0.125
BIO 14	BIO 10	-0.286	-0.320	-0.465	-0.569	-0.018	-0.171

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 14	BIO 11	-0.228	-0.268	-0.496	-0.523	0.062	-0.142
BIO 14	BIO 12	-0.453	0.205	-0.375	0.078	0.728	-0.418
BIO 14	BIO 13	-0.640	0.130	-0.456	-0.019	0.842	-0.587
BIO 14	BIO 17	0.773	0.939	0.998	-0.203	-0.711	0.967
BIO 14	BIO 18	-0.439	0.163	-0.069	-0.001	-0.290	0.559
BIO 14	BIO 19	-0.425	0.126	-0.489	0.440	0.878	-0.632
BIO 14	BIO 2	-0.081	-0.314	0.362	-0.345	-0.083	-0.322
BIO 14	BIO 3	-0.459	0.303	0.582	-0.585	-0.581	0.651
BIO 14	BIO 4	-0.223	-0.416	-0.083	-0.514	-0.137	-0.333
BIO 14	BIO 5	0.375	-0.446	-0.452	-0.129	0.036	-0.326
BIO 14	BIO 6	-0.076	-0.133	-0.518	-0.186	0.026	-0.026
BIO 14	BIO 7	0.978	-0.328	0.226	0.847	0.014	-0.462
BIO 14	BIO 8	-0.196	-0.279	-0.487	-0.539	-0.054	-0.090
BIO 14	BIO 9	-0.273	-0.266	-0.498	-0.551	0.103	-0.206
BIO 14	elevation	0.227	0.246	0.504	0.503	-0.056	0.113
BIO 14	evi_avg	0.154	0.209	0.122	0.177	0.226	0.031
BIO 14	evi_dry	0.119	0.313	0.044	0.190	0.328	-0.002
BIO 14	evi_mon	0.167	-0.070	0.044	0.099	0.031	0.041
BIO 14	slope	0.027	0.097	0.146	0.300	-0.003	0.131
BIO 15	aspect	0.080	0.130	0.363	0.155	-0.083	0.077
BIO 15	BIO 1	0.656	0.235	0.131	0.236	-0.177	0.040
BIO 15	BIO 10	0.212	0.140	0.091	0.228	-0.243	0.049
BIO 15	BIO 11	0.194	0.252	0.157	0.286	-0.145	0.077
BIO 15	BIO 12	0.684	0.813	0.893	0.682	-0.225	0.739

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 15	BIO 13	0.848	0.861	0.947	0.806	-0.377	0.877
BIO 15	BIO 14	-0.865	-0.059	-0.629	-0.358	-0.708	-0.806
BIO 15	BIO 17	-0.771	-0.103	-0.640	0.708	0.970	-0.808
BIO 15	BIO 18	0.226	0.561	0.597	-0.322	0.529	-0.352
BIO 15	BIO 19	0.294	0.897	0.825	-0.494	-0.469	0.885
BIO 15	BIO 2	0.093	-0.704	-0.795	-0.139	-0.418	0.053
BIO 15	BIO 3	0.261	0.432	-0.338	0.222	0.634	-0.615
BIO 15	BIO 4	0.178	-0.800	-0.466	0.315	-0.411	0.016
BIO 15	BIO 5	-0.195	-0.065	0.052	-0.240	-0.399	0.142
BIO 15	BIO 6	0.068	0.397	0.226	0.143	-0.007	0.018
BIO 15	BIO 7	-0.864	-0.709	-0.750	-0.405	-0.517	0.189
BIO 15	BIO 8	0.151	0.226	0.115	0.214	-0.157	-0.003
BIO 15	BIO 9	0.226	0.253	0.159	0.312	-0.226	0.135
BIO 15	elevation	-0.218	-0.312	-0.173	-0.267	0.118	-0.069
BIO 15	evi_avg	-0.044	0.580	0.319	0.185	0.156	0.181
BIO 15	evi_dry	0.051	0.756	0.517	0.238	0.166	0.290
BIO 15	evi_mon	-0.188	-0.111	0.196	0.128	0.105	-0.006
BIO 15	slope	-0.017	0.066	0.021	0.029	0.019	-0.025
BIO 16	aspect	-0.275	0.175	0.371	0.574	0.112	0.135
BIO 16	BIO 1	0.823	0.168	-0.073	0.027	-0.066	0.043
BIO 16	BIO 10	0.125	0.062	-0.114	-0.015	-0.127	0.015
BIO 16	BIO 11	0.184	0.181	-0.046	0.133	0.045	0.093
BIO 16	BIO 12	0.967	0.997	0.983	0.975	0.957	0.970
BIO 16	BIO 13	0.997	0.998	0.999	0.998	0.997	0.996

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 16	BIO 14	-0.608	0.154	-0.449	-0.021	0.865	-0.553
BIO 16	BIO 15	0.823	0.849	0.948	0.808	-0.409	0.853
BIO 16	BIO 17	-0.543	0.104	-0.456	0.743	-0.396	-0.536
BIO 16	BIO 18	-0.179	0.764	0.772	-0.655	0.018	-0.007
BIO 16	BIO 19	0.102	0.967	0.826	-0.609	0.958	0.944
BIO 16	BIO 2	0.185	-0.826	-0.830	-0.572	-0.396	-0.248
BIO 16	BIO 3	-0.140	0.649	-0.156	-0.060	-0.389	-0.442
BIO 16	BIO 4	0.145	-0.884	-0.639	0.185	-0.444	-0.295
BIO 16	BIO 5	0.064	-0.202	-0.157	-0.584	-0.161	0.022
BIO 16	BIO 6	0.124	0.377	0.030	0.156	0.089	0.105
BIO 16	BIO 7	-0.597	-0.842	-0.836	0.014	-0.327	-0.148
BIO 16	BIO 8	0.129	0.164	-0.089	0.018	-0.109	0.015
BIO 16	BIO 9	0.203	0.183	-0.044	0.139	0.051	0.131
BIO 16	elevation	-0.209	-0.244	0.029	-0.108	-0.052	-0.100
BIO 16	evi_avg	0.109	0.446	0.373	0.424	0.378	0.294
BIO 16	evi_dry	0.315	0.738	0.597	0.523	0.549	0.474
BIO 16	evi_mon	-0.207	-0.346	0.202	0.348	0.063	-0.007
BIO 16	slope	0.006	0.174	0.105	0.167	0.011	0.078
BIO 17	BIO 18	-0.270	0.204	-0.078	-0.478	0.617	0.658
BIO 17	BIO 19	-0.484	0.089	-0.493	-0.525	-0.467	-0.630
BIO 17	BIO 2	-0.278	-0.249	0.364	-0.306	-0.453	-0.373
BIO 17	BIO 3	-0.243	0.230	0.578	0.186	0.599	0.613
BIO 17	BIO 4	-0.367	-0.372	-0.082	0.352	-0.438	-0.388
BIO 17	BIO 5	0.207	-0.501	-0.450	-0.411	-0.367	-0.288

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 17	BIO 6	-0.044	-0.216	-0.517	0.057	0.049	0.032
BIO 17	BIO 7	0.746	-0.262	0.229	-0.210	-0.545	-0.503
BIO 17	BIO 8	-0.350	-0.357	-0.485	0.219	-0.105	-0.033
BIO 17	BIO 9	-0.427	-0.344	-0.496	0.328	-0.175	-0.152
BIO 17	elevation	0.395	0.329	0.502	-0.291	0.060	0.052
BIO 17	evi_avg	0.069	0.123	0.114	0.256	0.206	0.093
BIO 17	evi_dry	0.063	0.225	0.032	0.304	0.221	0.072
BIO 17	evi_mon	0.049	-0.054	0.040	0.247	0.153	0.095
BIO 17	slope	0.024	0.079	0.144	0.030	0.018	0.128
BIO 18	BIO 19	0.496	0.733	0.490	0.600	-0.099	-0.176
BIO 18	BIO 2	-0.135	-0.426	-0.514	0.876	-0.450	-0.562
BIO 18	BIO 3	0.882	0.487	0.303	0.018	0.329	0.321
BIO 18	BIO 4	0.150	-0.653	-0.710	-0.388	-0.415	-0.651
BIO 18	BIO 5	-0.562	-0.503	-0.527	0.972	-0.331	-0.337
BIO 18	BIO 6	-0.048	-0.097	-0.401	-0.108	0.049	0.061
BIO 18	BIO 7	-0.474	-0.452	-0.621	-0.346	-0.499	-0.629
BIO 18	BIO 8	0.126	-0.266	-0.484	-0.193	-0.091	-0.059
BIO 18	BIO 9	0.109	-0.254	-0.454	-0.283	-0.141	-0.123
BIO 18	elevation	-0.067	0.208	0.446	0.295	0.052	0.040
BIO 18	evi_avg	-0.444	0.142	0.336	-0.601	0.356	0.353
BIO 18	evi_dry	-0.566	0.446	0.548	-0.692	0.407	0.447
BIO 18	evi_mon	-0.246	-0.400	0.144	-0.575	0.244	0.223
BIO 18	slope	-0.032	0.157	0.247	-0.151	0.017	0.176
BIO 19	BIO 2	0.762	-0.780	-0.782	0.279	-0.341	-0.156

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 19	BIO 3	0.218	0.585	-0.451	-0.445	-0.431	-0.492
BIO 19	BIO 4	0.917	-0.879	-0.320	-0.602	-0.370	-0.171
BIO 19	BIO 5	-0.283	-0.214	0.227	0.409	-0.055	0.123
BIO 19	BIO 6	0.017	0.338	0.397	-0.072	0.150	0.136
BIO 19	BIO 7	-0.395	-0.794	-0.710	0.214	-0.267	-0.046
BIO 19	BIO 8	0.902	0.130	0.290	-0.493	-0.027	0.072
BIO 19	BIO 9	0.908	0.153	0.332	-0.594	0.137	0.194
BIO 19	elevation	-0.883	-0.216	-0.346	0.548	-0.126	-0.151
BIO 19	evi_avg	-0.089	0.471	0.420	-0.230	0.335	0.235
BIO 19	evi_dry	-0.170	0.738	0.579	-0.272	0.486	0.390
BIO 19	evi_mon	-0.008	-0.299	0.260	-0.264	0.055	-0.023
BIO 19	slope	-0.031	0.144	0.052	0.152	0.006	0.028
BIO 2	BIO 3	-0.465	-0.570	0.324	0.430	0.014	0.079
BIO 2	BIO 4	0.953	0.852	0.645	0.033	0.912	0.859
BIO 2	BIO 5	0.100	-0.069	0.026	0.923	0.340	0.049
BIO 2	BIO 6	0.051	-0.681	-0.196	-0.110	-0.416	-0.518
BIO 2	BIO 7	-0.035	0.998	0.970	-0.567	0.987	0.976
BIO 2	BIO 8	0.952	-0.465	-0.054	0.221	-0.032	-0.312
BIO 2	BIO 9	0.957	-0.486	-0.108	0.141	-0.144	-0.316
BIO 2	elevation	-0.964	0.538	0.127	-0.114	0.239	0.373
BIO 2	evi_avg	0.179	-0.588	-0.421	-0.615	-0.576	-0.452
BIO 2	evi_dry	0.174	-0.755	-0.574	-0.720	-0.689	-0.521
BIO 2	evi_mon	0.130	0.098	-0.261	-0.560	-0.371	-0.334
BIO 2	slope	-0.012	-0.143	-0.038	-0.304	-0.014	-0.090

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 3	BIO 4	-0.184	-0.693	-0.406	0.911	-0.087	-0.053
BIO 3	BIO 5	-0.537	-0.395	-0.827	0.145	-0.382	-0.386
BIO 3	BIO 6	-0.054	0.076	-0.880	-0.047	-0.280	-0.271
BIO 3	BIO 7	-0.487	-0.598	0.117	-0.452	-0.138	-0.127
BIO 3	BIO 8	-0.203	-0.104	-0.851	0.967	-0.286	-0.266
BIO 3	BIO 9	-0.202	-0.098	-0.865	0.953	-0.411	-0.396
BIO 3	elevation	0.246	0.045	0.868	-0.941	0.326	0.312
BIO 3	evi_avg	-0.393	0.184	-0.041	-0.205	-0.042	-0.105
BIO 3	evi_dry	-0.495	0.419	-0.017	-0.250	-0.037	-0.113
BIO 3	evi_mon	-0.208	-0.378	-0.054	-0.171	-0.095	-0.142
BIO 3	slope	-0.025	0.116	0.165	-0.359	0.013	0.105
BIO 4	BIO 5	-0.053	0.409	0.772	-0.277	0.602	0.437
BIO 4	BIO 6	0.036	-0.238	0.615	-0.004	-0.096	-0.107
BIO 4	BIO 7	-0.181	0.871	0.792	-0.249	0.916	0.864
BIO 4	BIO 8	0.996	0.019	0.719	0.973	0.297	0.109
BIO 4	BIO 9	0.989	-0.008	0.681	0.991	0.164	0.092
BIO 4	elevation	-0.991	0.076	-0.666	-0.991	-0.070	-0.033
BIO 4	evi_avg	0.055	-0.490	-0.329	0.063	-0.588	-0.476
BIO 4	evi_dry	0.015	-0.752	-0.475	0.056	-0.726	-0.570
BIO 4	evi_mon	0.057	0.290	-0.210	0.080	-0.357	-0.336
BIO 4	slope	-0.021	-0.130	-0.191	-0.257	-0.017	-0.157
BIO 5	BIO 6	0.129	0.777	0.975	-0.101	0.707	0.821
BIO 5	BIO 7	0.441	-0.028	0.247	-0.455	0.395	0.127
BIO 5	BIO 8	-0.006	0.914	0.996	-0.083	0.914	0.919

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 5	BIO 9	-0.084	0.905	0.991	-0.157	0.880	0.931
BIO 5	elevation	-0.006	-0.873	-0.987	0.185	-0.823	-0.899
BIO 5	evi_avg	0.280	0.224	-0.072	-0.629	-0.262	-0.058
BIO 5	evi_dry	0.381	-0.015	-0.154	-0.718	-0.359	-0.109
BIO 5	evi_mon	0.115	0.467	-0.022	-0.590	-0.119	0.004
BIO 5	slope	0.026	-0.042	-0.213	-0.221	-0.023	-0.203
BIO 6	BIO 7	-0.063	-0.650	0.026	-0.122	-0.369	-0.462
BIO 6	BIO 8	0.045	0.965	0.989	-0.007	0.916	0.970
BIO 6	BIO 9	0.043	0.971	0.996	-0.013	0.951	0.967
BIO 6	elevation	-0.039	-0.980	-0.996	0.021	-0.976	-0.982
BIO 6	evi_avg	0.030	0.533	0.027	0.058	0.169	0.193
BIO 6	evi_dry	0.072	0.465	-0.019	0.097	0.156	0.184
BIO 6	evi_mon	0.009	0.276	0.039	0.069	0.153	0.179
BIO 6	slope	0.027	0.061	-0.201	0.059	-0.012	-0.117
BIO 7	BIO 8	-0.150	-0.429	0.169	-0.316	0.012	-0.258
BIO 7	BIO 9	-0.231	-0.450	0.115	-0.327	-0.079	-0.233
BIO 7	elevation	0.178	0.504	-0.096	0.265	0.186	0.308
BIO 7	evi_avg	0.197	-0.577	-0.443	0.349	-0.564	-0.427
BIO 7	evi_dry	0.169	-0.757	-0.611	0.396	-0.675	-0.492
BIO 7	evi_mon	0.206	0.125	-0.268	0.285	-0.355	-0.306
BIO 7	slope	0.026	-0.148	-0.083	0.274	-0.016	-0.111
BIO 8	BIO 9	0.979	0.999	0.998	0.985	0.972	0.983
BIO 8	elevation	-0.989	-0.992	-0.995	-0.987	-0.963	-0.989
BIO 8	evi_avg	0.060	0.427	-0.044	-0.062	-0.071	0.084

Layer 1	Layer 2	WLT	BLT	NLT	PLT	NIF	BOF
		Pearson's Correlation Coefficient (R)					
BIO 8	evi_dry	0.019	0.287	-0.113	-0.088	-0.139	0.054
BIO 8	evi_mon	0.060	0.361	-0.007	-0.039	0.006	0.103
BIO 8	slope	-0.019	0.024	-0.210	-0.301	-0.017	-0.152
BIO 9	elevation	-0.986	-0.995	-0.998	-0.993	-0.986	-0.989
BIO 9	evi_avg	0.092	0.449	-0.012	-0.015	0.021	0.117
BIO 9	evi_dry	0.060	0.312	-0.073	-0.031	-0.022	0.095
BIO 9	evi_mon	0.092	0.364	0.017	0.008	0.065	0.131
BIO 9	slope	-0.021	0.025	-0.206	-0.294	-0.018	-0.157
elevation	evi_avg	-0.100	-0.480	0.004	-0.003	-0.076	-0.140
elevation	evi_dry	-0.075	-0.362	0.062	0.011	-0.046	-0.125
elevation	evi_mon	-0.077	-0.342	-0.023	-0.020	-0.088	-0.137
elevation	slope	0.019	-0.032	0.205	0.276	0.015	0.140
evi_avg	evi_dry	0.874	0.847	0.901	0.933	0.907	0.896
evi_avg	evi_mon	0.784	0.545	0.891	0.912	0.816	0.810
evi_avg	slope	0.177	0.068	0.129	0.291	0.024	0.136
evi_dry	evi_mon	0.486	0.087	0.685	0.799	0.582	0.560
evi_dry	slope	0.046	0.147	0.121	0.265	0.023	0.155
evi_mon	slope	0.029	-0.091	0.085	0.271	0.017	0.059