MODELLING HABITAT SUITABILITY AND CLIMATE CHANGE IMPACTS ON ENDEMIC BIRDS OF SOUTHERN WESTERN GHATS, KERALA, INDIA

by

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THESIS

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DECLARATION

I, hereby declare that this thesis entitled **"MODELLING HABITAT SUITABILITY AND CLIMATE CHANGE IMPACTS ON ENDEMIC BIRDS OF SOUTHERN WESTERN GHATS, KERALA, 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 HABITAT SUITABILITY AND CLIMATE CHANGE IMPACTS ON ENDEMIC BIRDS OF SOUTHERN WESTERN GHATS, KERALA, INDIA"** is a record of research work done independently by Mr. Sreehari. K. Mohan 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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INTRODUCTION

1 INTRODUCTION

Among the numerous anthropogenic factors responsible for the decline of biodiversity, two are considered to have overwhelming importance, global climatic change and the destruction, fragmentation and disturbance of habitats (Parmesan, 2006; Kampichler *et al.*, 2014). Although human-induced land use is considered to be the primary driving force of today's species decline, climate change is also being attributed as a significant causative factor. Drastic alterations in the distributions and abundances of species' have been connected to elevating temperatures (Spooner *et al.*, 2018; Cook *et al.*, 2020). Correlational studies over large numbers of regions and taxa have disclosed clear associations between climate change and observed changes in geographical range and suitability of many plant and animal taxa (Hickling *et al.*, 2006; Stephens *et al.*, 2016; Spooner *et al.*, 2018; Mason *et al.*, 2019).

Each of the previous four decades has been successively warmer than any decade that preceded it since 1850. In 2019, atmospheric CO_2 concentrations were higher than at any time in at least 2 million years. The frequency and intensity of heavy precipitation events have increased since the 1950s over the most land area (IPCC, 2021). We have already started experiencing intermittent extreme climate events in floods, cyclones, unprecedented rain spells and severe drought. So, it is urgently needed to understand the possible effect of global change on biodiversity. Global temperature surge of 1.5°C to 2°C is highly likely to lead us to a situation of losing half of the suitable habitats of 4% to 8% of the world's vertebrates (IPCC, 2018)

Unfortunately, our understanding of regional biodiversity patterns in the subcontinent of India remains feeble (Ramachandran *et al.*, 2017). At the same time, tropical montane ecosystems are highly diverse and harbour high endemicity (Ricketts *et al.*, 2005; Lele *et al.*, 2020). These regions are extinction risk hotspots as they hold threatened species with restricted distributions (Ricketts *et al.*, 2005;

Hoffmann *et al.*, 2010). Montane habitat specialists may also be pressurized by climate change, forcing them to move to a higher elevation (Stuhldreher & Fartmann, 2018). Where such movements are inhibited by topography, species may face habitat decline and eventually local extinctions (Parmesan, 2006; Lele *et al.*, 2020).

The Western Ghats mountain range in south India is the hottest hotspot of biodiversity (Myers *et al.*, 2000) that also includes locations of high extinction risk (Ricketts *et al.*, 2005). Two significant landscapes in the WG (Nilgiri and Agasthyavanam) have been recognized as Biosphere Reserves by the United Nations Educational, Scientific and Cultural Organization (UNESCO) (UNESCO, 2012, 2016). The sky islands at the highest elevations of the Western Ghats (WG) hold a naturally bi-phasic mosaic of evergreen forests and grasslands known as the shola ecosystem (Lele *et al.*, 2020). This ecosystem is dominated by montane grasslands (Thomas & Palmer, 2007; Das *et al.*, 2015), which harbour unique species assemblages (Sankaran, 2009).

Many birds are endemic to the sky islands of WG. Ashambu Laughingthrush *Montecincla meridionalis* and Nilgiri Pipit *Anthus nilghiriensis* are included in this list. Ashambu Laughingthrush is endemic to the Agasthyamalai landscape of southern WG (del Hoyo *et al.*, 2020), whereas Nilgiri Pipit is endemic to the Nilgiris and Palani-Anamalai hills of WG. Understanding their habitat suitability and distribution is essential since climate change could influence them, and the time is already late. Understanding the habitat preferences and dispersal ability of such sensitive species would help prevent them from becoming extinct, and it can address long-term conservation of the species as well (Peterson and Robins, 2003)

The prime objective of this research is to detect the environmental and climatic variables that influence the distribution of such endemic birds of the WG. Along with that, the study also intended to map the suitable habitats and their quality for these birds and predicts the future changes in their habitat suitability and quality change under different climate change scenarios such as RCP 4.5, RCP 6.0, and RCP 8.5 for the time the 2070s (2061-2080) by using the MaxEnt algorithm.

REVIEW OF LITERATURE

2 REVIEW OF LITERATURE

2.1 SPECIES DISTRIBUTION AND FACTORS

Comprehensive knowledge of species' ecological and geographic distributions is essential for conservation planning (Ferrier 2002; Funk and Richardson 2002; Rushton *et al.,* 2004; Elith *et al.,* 2006), and for understanding ecological and evolutionary factors of spatial patterns of biodiversity (Rosenzweg 1995, Brown and Lomolino 1998, Ricklefs 2004, Graham *et al.,* 2006; Elith *et al.,* 2006). But factors affecting the species distribution was an unsolved problem in ecology (Araujo and Guisan, 2006) and species distribution studies need understanding of how organisms interact with the abiotic and biotic factors that constitute species environment (MacArthur 1984; Gaston 2003; Chase and Leibold 2004; Spence and Tingley 2020). Such information on species distribution is useful for population monitoring (Shaffer *et al.,* 1998), biodiversity mapping (Bojo´rquez-Tapia *et al.,* 1995), and conservation management (Corsi *et al.,* 1999).

Availability of feeding habitat is one of the major concerns for the distribution of specie. Jordano (1993) evaluated the significance of distribution of Junipers as a major diet supplier of frugivorous thrushes. Similarly, Beale *et al.,* (2006) concluded that the decline in the population of Turdus torquatus (Ring Ouzel) in Britain was mainly due to the increase in summer temperature and at the same time decrease in summer precipitation. Adverse weather conditions were also a likely factor in the population decline of the song thrush Turdus philomelos in Britain (Robinson *et al.,* 2014)

Scheffers *et al.,* (2016) commented that researchers are leaned towards understanding how species are currently responding to a changing environment, and in predicting how species will respond to upcoming changes in a period pf rapid human-induced environmental change. Climate change is likely to induce vegetation change that will force wild plant and animal species to shift their range in response to the newer environmental variable (IPCC, 2001). Species' populations and distributions are also modified by many factors other than prevailing climate (Clavero *et al.*, 2011), and local climate adaptation may lead to different responses in different parts of a species range (Visser *et al.*, 2003; Mason *et al.*, 2019), so such unexplained variation can also occur.

2.2 CLIMATE CHANGE IN WESTERN GHATS

Like most of the other biogeographic zones in India, Western Ghats also face risks associated with prevailing global climate change. Rajendran and Kitoh (2008) noted a likely surge in the monsoon rainfall over the interior zones of the Indian subcontinent under the future climatic conditions and a drastic reduction in orographic rainfall over the west coasts of Kerala and Karnataka states. The rainfall reduction over parts of Western Ghats were mostly to the south of 16° N and was accompanied by a significant reduction in the south-westerly winds and moisture transport into the region. Several studies have also proposed the possibility of the weakening and normalization of the tropical large-scale overturning circulation in response to global warming conditions (Sugi *et al.*, 2002; Cherchi *et al.*, 2010). Robinson (1994) who considered past climatic changes in WG suggest that the vegetational changes may also be influenced by CO2 rather than soil moisture alone. Ravindranath *et al.*, (1997) had projected climate change impact under the 'most-likely' scenario was an expansion in the area under evergreen forests due to increased precipitation and an increase in dry thorn forest due to increased temperature. Furthermore, there was a noticeable decline in dry deciduous forest and modest decrease in montane forest/grassland.

The indigenous species in Western Ghats are undergoing adverse pressures because of anthropogenic disturbances, such as land use land cover changes, presence of invasive species, forest fire etc. A study by Gopalakrishnan *et al.*, (2011) shows that under the A1B conditions the forests of central and Northern Western Ghats are prone to climate change, while another study by Krishnakumar *et al.*, (2011) shows that the tropical evergreen forests of Southern Western Ghats are shown to be resilient with a predicted surge in its precipitation. However, few studies from this region highlights the importance of climate change in changing distributions of endemic species using niche modeling approaches (Sen et al., 2016a, 2016b). The results are alarming which shows a decrease in their suitable habitats and range. The third assessment of IPCC (2001) also caution that apart from habitat loss, wild species are at risk from changes in environmental conditions that favor forest fires and drought. If the frequency of these extreme events increases, the frequency of forest fire also increases.

2.3 IMPACT OF CLIMATE CHANGE ON BIRDS

Climate change may negatively affect an animal species through changes in vegetation and environment affecting the suitability of its habitat, which take time to occur, leading to an extinction debt (Kuussaari et al. 2009; Mason et al. 2019). Birds have the capacity to be considered as strong bio-indicators, since birds are very popular and have an iconic status all over the world (Crick, 2004). Katti and Price (1996) have recorded a decrease in the density and persistence of Green Leaf Warblers on their wintering grounds in the WG in response to drought.

However, Thomas et al. (2006) highlighted the likely artifactual perception that because of climate change, range expansions and population increases are more common than range retractions and population decline. In support of this findings, Stephens et al. (2016) and Mason et al. (2019) also concluded similar positive relationship between population trend and climate suitability

2.4 RESPONSES OF ORGANISMS TOWARDS CLIMATE CHANGE

Globally, many species have already shifted their extant to evade elevating temperatures and track historic climate, either by poleward shifts (Parmesan and Yohe 2003), to greater elevations (Moritz et al. 2008, Chen et al. 2011), to deeper waters (Perry et al. 2005, Dulvy et al. 2008), or the forest floor (Scheffers et al. 2013). Spence and Tingley (2020) further investigated and found out regardless of species moving poleward, upslope or deeper, all three thermal gradients covary with other environmental variables that can have dominant and substantial effects on the biology and biogeography of species in the future.

Nevertheless, despite our limited understanding of species-specific responses to varying abiotic factors, we know organisms have three primary mechanisms to cope up with abiotic challenges of novel environments (Spence and Tingley, 2020). First, either through behavioral variation or innate tolerance, organisms need not require any physiological adaptations to flourishingly colonize an area with novel conditions (Parmesan and Yohe 2003). Second, species may display physiological flexibility and acclimatory potential to get rid of the abiotic challenge after an initial exposure (Somero 2010, Valladares et al. 2014). Third, populations may be locally resilient to varying abiotic conditions across the range, and intraspecific variation may furnish evolutionary potential to overcome the conditions (Diamond 2018). However, those species which are unable show innate tolerance, physiological or the genetic potential to evolve to absurd abiotic factors, these factors may even diminish the ability for that population to shift its range to keep away from rising temperatures (Spence and Tingley, 2020).

2.5 CLIMATE CHANGE AND BIRDS DISTRIBUTIONAL RANGE

The general effect of projected human induced climate change is that the habitats of many species will move towards higher latitudes from their present location. It is also worth noting that organisms will migrate at different rates through fragmented landscapes, and ecosystems dominated by long-lived trees may change slowly (Singh, 2011). Abraham and Jefferies (1997) found out that the breeding ranges of some migratory birds, such as waterfowl, have been expanding poleward in response to climate amelioration. Both amphibians and birds in Great Britain have been forced to prepone their breeding dates by about 7 to 21 days since the 1970s in association with temperature surge (Beebee 1995; Crick et al. 1997; Hansen et al. 2001).

To compute the changes in distribution of a species, it is important to understand the likely responses of each species with respect to the changing environment. An increased temperature and decreased precipitation would almost certainly stress the habitat specialists (Ravindranath *et al.*, 1997). It is also noteworthy that, in the case of montane forests (or sholas), the increase in temperature may smoothen the migration of plant species from lower elevation forests to the montane areas, thus causing a reduction in montane forests. Species having limited climatic ranges or restricted habitat requirements or small population (endemic mountain species and birds restricted to islands, peninsulas) tend to be the most threatened to face the risk of extinction (Singh, 2011).

2.6 IMPORTANCE OF RANGE DISTRIBUTION STUDIES

To convey regional biogeographic patterns, it needs either large phylogenetic datasets at small spatial scales (Agarwal *et al.* 2014; Vijayakumar *et al.* 2014) or community-level distribution studies (Tamma and Ramakrishnan, 2015; Ramachandran *et al.*, 2016). Even though birds of the Indian sub-continent have poor phylogenetic data (Reddy 2014), there have been extensive bird distributional surveys over the last two centuries (Oates and Blanford 1889; Stuart Baker 1930; Ali and Ripley 1987; Rasmussen and Anderton 2012) with clear understanding on geographical limits of species. Ramachandran *et al.*, (2016) identified six potential biogeographic barriers in Western Ghats, which are (starting from north) Narmada River, Goa Gap, Cauvery River, Chaliyar River, Palghat Gap and Shenkottah Gap.

2.7 MODELLING OF SPECIES HABITAT SUITABILITY

2.7.1 IMPORTANCE OF HABITAT SUITABILITY MODELLING

Root and Schneider (1993) found an evident correlation between population distribution and climatic factors in 148 wintering terrestrial birds. Similarly, Mason *et al.* (2019) examined the relationship between species-specific regional population changes and climate suitability trends, using long-term information of population change for 525 breeding bird species in Europe and in USA and concluded that population is varying positively and negatively for different taxa of birds. They've used multiple species distribution models for obtaining correlation between varying factors. Habitat Suitability Modelling (HSM) OR Species Distribution Modelling (SDM) establish the relationship between species records in an area and environmental characteristics and spatial characteristics of those areas (Franklin, 2009; Kumar and Stohlgren, 2009; Elith *et al.*, 2011).

They represent an empirical method to draw statistical conclusions about the drivers of species distribution under various conservation, ecological and evolutionary processes (Zimmermann *et al.*, 2010). Particularly, in those areas where systematic surveys have not been conducted, distribution models help conservation practitioners in estimating and assessing the extent of suitable areas for the species of interest (Elith, 2002). By using known distribution of the species, environmental variables are defined, and this information is used in identifying similar regions with similar environmental variables and the new distribution can be modelled (Pearson and Dawson, 2003).

Overlays of geospatial species samples with environmental variables such as elevation, vegetation and land use were often used to understand wildlife-habitat relationships and predict distributions (Stoms *et al.*, 1992; Anderson *et al.*, 2003). The only way to test the hypothesis foretelling the future is by waiting for the future to unfold or testing the past changes and comparing it with the current distribution (Araujo *et al.*, 2005).

An understanding of climate warming and their impact on projections of species distributions will benefit in communicating and reducing climate-related uncertainty in the output of SDMs (Beaumont *et al.*, 2008). These models were widely used as a tool to understand the various hypotheses in ecology, evolution and conservation (Elith *et al.*, 2006). Apart from predicting range shifts associated with future climatic scenarios, SDMs are also used to understand environmental correlates of species occurrences (Wollan *et al.*, 2008; Monterroso *et al.*, 2009; Elith *et al.*, 2011), predict and explore expanding distribution of invasive species (Ward, 2007; Wang *et al.*, 2007; Elith *et al.*, 2011) and understanding genetic diversity, endemism and evolutionary niche dynamics (Young *et al.*, 2009; Lamb *et al.*, 2009). Pautesso *et al.*, (2011) concluded that when the species range shift occurs, current protected area networks may not be able to provide adequate protection to the species considering the fact that the species distribution may shift to outside of the protected area.

2.7.2 PROCESS OF HSM

2.7.2.1 STEPS IN HSM

Major steps followed in case of modelling of species distribution; (1) Available present data of occurrences of the selected species (Peterson et al., 1998; Peterson and Stockwell, 2001); (2) Developing ecological niche models and testing with the distribution (Guisan and Zimmerman, 2000; Kobler and Adamic, 2000); (3) Change in species distribution is projected based on the general circulation models of climate change; (4) Ecological niche model of the species is projected onto the predicted landscape distribution (Soberon and Peterson, 2005) and using this, model could derive the probability of occurrence of a species for any given area or trace the specific environmental variable that suits (Elith *et al.*, 2011)

2.7.2.2 TESTING ACCURACY AND RESOLUTION

The accuracy of model description depends upon the degree of environmental gradients that define the species distributional limits (Pearson et al., 2007). Various rules in different models were made up of individual algorithms and the areas would be identified within and outside the realized niche based on these rules (Peterson, 2001). In other words, models were built mainly based on correlations between the variables and pattern of distribution and this did not consider the causal relationship due to autocorrelation among the interacting variables (Bahn and McGill, 2007; Beale et al., 2008). To improve the interpretation of the responses of the species distribution, large geographical landscapes were studied. This reduces the correlation of environmental variables with climatic variables (Maclean *et al.*, 2008). It can be used to resolve ambiguities due to correlated predictors, but it may fail to find out the spurious correlations among the environmental variables which was used to define distribution (Ashcroft *et al.*, 2011). The problem of accuracy may become more important when models are developed for undulating terrain with heterogeneous topography, where vegetation is distributed with sharp transitions from one vegetation type to another (Fischer, 1994; Zimmermann and Kienast, 1999)

Concerns of the accuracy of species prediction are addressed based on varying climatic conditions and testing the climatic envelope models (Pearson *et al.*, 2006). However, it is implicit in distribution modelling that a perfect truth is hard to obtain (Oreskes *et al.*, 1994; Guisan and Zimmerman, 2000). There is now a plethora of methods for modelling species' distributions that vary in how we want to model the distribution, select relevant predictor variables, define fitted functions for variable, quantify variable contributions, allow for interactions, and predict geographic patterns of occurrence (Guisan and Zimmerman 2000, Burgman *et al.*, 2005; Elith *et al.*, 2006; Elith *et al.*, 2011).

2.8 SPECIES DISTRIBUTION STUDIES

Correlational studies over many species, regions and similar taxa have revealed clear bonding between recent climate fluctuations and observed changes in geographical range and abundance of many plant and animal taxa (Hickling *et al.*, 2006; Spooner *et al.*, 2018; Stephens *et al.*, 2016). Change in distribution of a species may fall into three categories; (1) range reduction (Peterson *et al.*, 2002; Thuiller *et al.*, 2005); (2) range expansion (Mason *et al.*, 2019; Sanjo and Nameer, 2019); and (3) range shifts (Pearson *et al.*, 2002; Mason *et al.*, 2019). These varying results were also explained in detail using associated environmental variables (Maclean *et al.*, 2008). However, positive changes in species abundance in response to beneficial climate change is generally perceived to be robust and more plentiful than for populations expected to be negatively affected (Parmesan and Yohe 2003; Root *et al.*, 2003; Thomas *et al.*, 2006). But, Mason *et al.*, (2019) warns that results associated with range expansion should be approached with caution as it only considers climate change but not climate change associated with vegetation change. Meanwhile, Goetz *et al.*, (2014) found out a strong correlation between temperature variation and richness of forest birds and at the same time precipitation has a severe influence on richness of open woodland birds.

2.9 DATA USED FOR MODELLING

2.9.1 PRESENCE AND ABSENCE RECORD

Most of the studies on progress of distribution modelling approaches have focused on generating models using presence/absence or abundance data, where regions of interest have been sampled systematically (Hirzel and Guisan 2002; Cawsey *et al.*, 2002; Elith *et al.*, 2006). Clear majority of this data consists of occurance records from herbariums and museum collections (Elith *et al.*, 2006) which are electronically accessible (Heutmann, 2005). Since the intent and method of collecting are relatively unknown, absence cannot be concluded with certainty (Elith *et al.*, 2006). This information can also have biases and errors (Hijmans *et* *al.*, 2000). For example, field surveys can incorrectly identify a species as present that is absent in a certain location (false presence) and may fail to detect a species that is present (false absence) (Reese *et al.*, 2005). In either situation, the prevalence of false absence or false presence records may affect attempts to predict species distributions based on environmental variables (Tyre *et al.*, 2003). For enhancing evaluation of model performance in predicting distributions of species, it is advisable to use independent, structured presence-absence information for validation (Elith *et al.*, 2006). Due to poor sampling or missing species occurrences during field survey, absence data won't be available for methods which require both the data set. In this case, it is advisable to use 'pseudo-absences'. instead of real absence data (Ferrier *et al.*, 2002) or some methods used background data for the entire study area (Hirzel *et al.*, 2002).

In today's world, species occurrence data is widely available and can be easily accessed through communications as they are created using satellite imageries. But it is challenging to validate the absence data since wildlife-habitat connection was absent even though there exists a potential for a species to be seen at a site (MacKenzie *et al.*, 2004; Gu and Swihart, 2004). However, with the prevailing datasets, Reese *et al.*, (2005) assumed that false presence is less likely to occur as compared to false absence. At the same time Baldwin (2009) used presence only data and showed that the necessity of absence data is minimal.

2.10 REPRESENTATIVE CONCENTRATION PATHWAYS

The IPCC fifth assessment report (AR5) introduced 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/m2).

According to the IPCC future emissions classification, there are four scenarios, 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 high level (RCP 8.5). The RCP 2.6 is the ambitious pathway, and it shows an early peak in atmospheric CO2 level then fall due to various CO2 removal activities. The RCP 8.5 predicted a high CO2 level in the atmosphere beyond 2100 due to little effort and failure in the CO2 removal activities. The atmospheric CO2 equivalent of RCP 2.6 and RCP 8.5 are 490ppm and >1370ppm, respectively. For the RCP 4.5 and RCP 6.0, the CO2 level is 650ppm and 850ppm, respectively (IPCC, 2014).

2.11 SHARED SOCIOECONOMIC PATHWAYS

IPCC sixth assessment report (AR6) introduced considering Climate Model Inter-comparison Project Phase six (CMIP6) where a new set of emission scenarios come into play. Which is named as Shared Socioeconomic Pathways (SSPs). It discusses how particular trends in social, economic, and environmental developments make changes to the world. The SSPs have been developed to provide five distinctly different pathways about future socioeconomic developments as they might unfold in the absence of explicit additional policies and measures to limit climate forcing or to enhance adaptive capacity. They are intended to enable climate change research and policy analysis, and are designed to span a wide range of combinations of challenges to mitigation and adaptation to climate change (Riahi *et al.*, 2017). SSPs describe plausible alternative trends in the evolution of society and natural systems over the 21st century at the level of the world and large world regions (Kriegler *et al.*, 2012)

There are five SSPs and the likely scenarios are as follows;

SSP1 Sustainability – Taking the Green Road (Low challenges to mitigation and adaptation). The world shifts gradually, toward a more sustainable path, emphasizing more inclusive development that respects environmental boundaries. Driven by an increasing commitment to achieving development goals, inequality is reduced both across and within countries.

SSP2 Middle of the Road (Medium challenges to mitigation and adaptation). The world follows a path in which social, economic, and technological trends do not shift markedly from historical patterns. Development and income growth proceeds unevenly, with some countries making relatively good progress while others fall short of expectations.

SSP3 Regional Rivalry – A Rocky Road (High challenges to mitigation and adaptation). A resurgent nationalism, concerns about competitiveness and security, and regional conflicts push countries to increasingly focus on domestic or, at most, regional issues. Investments in education and technological development decline. Economic development is slow, consumption is material-intensive, and inequalities persist or worsen over time.

SSP4 Inequality – A Road Divided (Low challenges to mitigation, high challenges to adaptation) Highly unequal investments in human capital, combined with increasing disparities in economic opportunity and political power, lead to increasing inequalities and stratification both across and within countries. Technology development is high in the high-tech economy and sectors. The globally connected energy sector diversifies, with investments in both carbon-intensive fuels like coal and unconventional oil, but also low-carbon energy sources.

SSP5 Fossil-fueled Development – Taking the Highway (High challenges to mitigation, low challenges to adaptation). This world places increasing faith in competitive markets, innovation and participatory societies to produce rapid technological progress and development of human capital as the path to sustainable development. There are also strong investments in health, education, and institutions to enhance human and social capital. At the same time, the push for economic and social development is coupled with the exploitation of abundant fossil fuel resources and the adoption of resource and energy intensive lifestyles around the world. All these factors lead to rapid growth of the global economy, while global population peaks and declines in the 21st century.

The RCPs and SSPs can be brought together into a two-dimensional RCP/SSP matrix. Here, each cell can describe a plausible trajectory of emissions and concentrations resulting in a given level of forcing by 2100 that is consistent with and superimposed on pathways of socio-economic development (van Vuuren, 2013). When SSPs are combined with radiative forcing pathways or climate change outcomes in integrated scenarios, policy assumptions will be necessary to produce emissions that would achieve the desired climate outcomes, as well as to characterize adaptation measures (van Vuuren, 2011). The new framework combines so-called Shared Socioeconomic Pathways (SSPs) and the RCPs (and other climate scenarios) in a Scenario Matrix Architecture (Riahi *et al.*, 2017).

2.12 ASSESSMENT OF CLIMATIC CHANGES

For assessing the likely effects of climate change on biodiversity, many tools can be used which include global climate models, regional climate models, species bioclimatic envelope models, dynamic and equilibrium vegetation models and site-specific sensitivity analysis (Sulzman *et al.*, 1995). The most detailed information on future climate is given by General Circulation Models (GCMs), often refined with regional climate models (RCMs) and with empirical-statistical post-processing methods (Maraun, 2013; Mendlik and Gobiet, 2015). Despite being a sophisticated model, GCMs are also subjected to considerable uncertainties (Mendlik and Gobiet, 2015). And these uncertainties are often investigated using Multi Model Ensembles (MMEs). As per Masson and Knutti (2011) the aim of ensemble design should be to maximize model diversity to seize model uncertainty properly while ensuring better model performance. These model simulations are considered as the best possible alternatives of the future (Hansen *et al.*, 2001). Both equilibrium and transient model scenarios are used in species assessment to incorporate a broad range of possible futures (Aber *et al.*, 2001). GCMs and RCMs are generally used by dynamic vegetation models, biome envelope models and species envelope models to reveal different aspects of the biogeography because of the future climate change (Cramer *et al.*, 2000).

2.13 HSM TYPES AND TECHNIQUES

2.13.1 FOREST GAP MODEL

The Forest Gap Model became widely popular among forest ecologists as it addresses a wide range of applied research questions. It can be effectively used to understand the impacts of environmental alteration on long-term dynamics of forest structure, biomass, vegetation and composition (Bugmann, 2001). However, our attempt to synthesize knowledge about vegetation dynamics or to distinguish different assumptions regarding forest growth faces severe challenges because of the complexity of a forest ecosystem (Botkin *et al.*, 1972). Bugmann *et al.*, (1996) also mentioned the complexity of each forest and the requirement of additional region-specific sub-models to improve model performance. The model runs based on several assumptions which are; (1) The forest is considered as a composite of many small fragments in which each vegetation can have a different age and successional stage; (2) Tree position within a patch is not taken into account; i.e., patches are horizontally homogeneous; (3) the canopy or the leaf layer of each tree are located in an indefinitely thin layer at the top of the trunk; and (4) there are no functional interactions between each patch; i.e., successional processes are described on each patch separately These simplifications made it possible to analyze mixed-species, uneven-aged forests, which had been difficult previously mainly because of computing limitations (Bugamann, 2001).

2.13.2 SPECIES BIOCLIMATIC ENVELOPE MODEL

For assessing conservation planning measures, species-specific climate interaction needs to be studied and the bioclimatic envelope model provides the best alternative for it. Bioclimatic models in their purest form consider climatic variables only and do not consider processing other environmental factors that influence the distribution of species, such as soil parameters and land-cover type (Pearson and Dawson, 2003). Adding to it, other studies have questioned its validity by pointing out factors other than climate such as biotic interactions, evolutionary change and dispersal ability (Davis *et al.*, 1998; Lawton, 2000; Woodward and Beerling, 1997; Pearson and Dawson, 2003). Bioclimatic envelope shares the same principle of biome envelope models, where which the current distribution of species was used to 'train' a model for the future incorporating the predicted climatic conditions (Hannah *et al.*, 2002)

2.13.3 GENERALIZED DISSIMILARITY MODELS (GDM)

Generalized dissimilarity modelling (GDM) is a statistical tool for analyzing and predicting spatial patterns of turnover in community composition i.e., beta diversity across large landscapes (Ferrier *et al.*, 2007). For the estimation of probability of occurrence of species distribution, kernel regression algorithm is used within the transformed environmental space produced by GDM (Lowe, 1995). The approach can be applied to range of assessment activities including visualization of spatial patterns in community composition, constrained environmental classification, distributional modellingof community types or species, survey gap analysis, conservation assessment (Ferrier *et al.*, 2007)

2.13.4 GLM AND GAM MODELS

GLM and GAM were widely used in species distribution modelling because ecological and environmental relationships can be modelled realistically and can be explained with strong statistical foundations (Austin, 2002). In addition to that GAMs can also be effectively used for time series studies of air pollution (He *et al.*, 2005). It can also model complex ecological responses than GLM because of greater flexibility (Yee and Mitchell, 1991).

2.13.5 MULTIVARIATE ADAPTIVE REGRESSION SPLINES (MARS)

Multivariate Adaptive Regression Splines is a method for better modelling of high dimensional data (Friedman and Roosen, 1995). The advantage of MARS lies in its ability to capture the intrinsic complicated data mapping in multi-dimensional patterns and produce uncomplicated, easier-to-interpret models (Zhang and Goh, 2016). It is very easy to use in GIS applications for making prediction maps and are faster compared to GAMs and can analyze community data (MARS-COMM) (Leathwick *et al.*, 2005)

2.13.6 GENENTIC ALGORITHM FOR RULE-SET PREDICTION (GARP)

GARP is an integrated spatial analysis system for predicting distributions of both plants and animals. It is having two versions; (1) DK-GARP which is used for modelling data obtained from natural history collections; and (2) OM-GARP, a new open modeler implementation, where both uses a genetic algorithm for selecting a set of rules for adaptations of regression and range specifications, thus predicting species suitability (Stockwell and Peters, 1999). The algorithm of GARP can generate pseudo-absence points as it works using presence-absence data.

2.13.7 MAXIMUM ENTROPY MODELLING (MAXENT)

For some species, detailed account on presence/absence data may be available. But in the case of most species, absence data may not be available (Phillips *et al.*, 2006). In such cases, MaxEnt can be used for effectively modelling distribution of a species. MaxEnt estimates species' distributions by learning the distribution of maximum entropy subject to the constraint that the expected value of each environmental variable or interactions under this estimated distribution matches its empirical mean (Phillips *et al.*, 2006). MaxEnt can precisely build a model even if there are a smaller number of presence records and it again an advantage since there is a chance for not getting dependable locations for mapping spreading of species (Baldwin, 2009). It was observed that MaxEnt have done better than other similar modelling techniques (Elith *et al.*, 2006; Hernandez *et al.*, 2006; Philips *et al.*, 2006). MaxEnt achieved higher success rate and it marked the differences even at low sample sizes as compared to other models (Pearson *et al.*, 2007).

2.13.8 BOOSTED REGRESSION TREES (BRT)

BRT is a technique that look to improve the performance of a single model by fitting many models and combining them for prediction (Elith *et al.*, 2008). And it is modelled in stage wise manner, where several modifications are made in each step (Friedman *et al.*, 2000). Over fitting of data are avoided by using cross-validation. This is to grow the models progressively during the predictive accuracy testing on withheld portions of the data (Elith *et al.*, 2006). It combines the strengths of two algorithms; (1) regression trees and boosting (an adaptive method for combining simple models to improve predictive performance) (Elith *et al.*, 2008).

2.14 FACTS ABOUT THE SPECIES

2.14.1 ASHAMBU LAUGHINGTHRUSH (ASHAMBU CHILAPPAN) *Montecincla meridionalis*

Ashambu Laughingthrush is a high-altitude endemic bird of Southern WG. Earlier the species was treated as a subspecies of Kerala Laughingthrush *Trochalopteron fairbanki* (Rasmussen and Anderton, 2005); *Strophocincla fairbanki* (Praveen and Nameer, 2013). But later analysis indicated considerable divergence and suggested erection of a new species (Praveen and Nameer, 2013; Robin *et al.*, 2017; del Hoyo *et al.*, 2020) in the name of *Montecincla meridionalis* where a dedicated generic name has given to it as it inhabits the montane evergreen-shola ecosystems of Southern WG (Robin *et al.*, 2017). Within Southern WG, the species disjunct and restricted distribution is confined to Ashambu (Agasthyamalai) hills (Sashikumar *et al.*, 2011; Chandran and Praveen, 2013) which is located South of Shenkottah/Achenkovil Gap, in extreme south WG (del Hoyo *et al.*, 2020).

Being a habitat specialist, they are found in the altitude above 1200m and prefers edges of broadleaved evergreen forest, Ochlandra reeds, secondary forest; also, plantations (including tea and cardamom), especially those with thicket-lined streams running through them (del Hoyo *et al.*, 2020). It can be found in altitudes up to 2135m as per del Hoyo *et al.*, (2020) and IUCN (2016). However, it is arguable that the upper-limit is lower than this, since the highest peak in the landscape is Agasthyamalai which spans 1878m above msl. They forage in parties of 6-14 individuals and are omnivorous in nature. Their diet includes insects, berries and fruits (Rasmussen and Anderton, 2005; del Hoyo *et al.*, 2020).

Chandran and Praveen (2013) points out that nearly 90% of the species habitat falls under protected area networks including wildlife sanctuaries and tiger reserves. This says that the potential habitat is legally protected. However, they also warn that the spread of Ochlandra may impact the distribution of the species in future. Since the species requires highly specialized habitat, it is believed that the population of the species may lie in between 2,500-10,000 (del Hoyo *et al.*, 2020; IUCN, 2016). It is classified as 'Vulnerable' as per IUCN (IUCN, 2016). And the population is declining because of habitat loss, degradation, increased anthropogenic pressure and associated land use change (Somasundaram and Vijayan, 2007; Chandran and Praveen, 2013; IUCN, 2016; del Hoyo *et al.*, 2020).

2.14.2 NILGIRI PIPIT *Anthus nilghiriensis*

The Nilgiri pipit is a high-altitude specialist bird endemic to the montane grasslands of Southern Western Ghats (Sashikumar *et al.*, 2011; Robin *et al.*, 2014; Lele *et al.*, 2020). It inhabits upland grassland, open grassy and rocky hills, also in coffee plantations, preferably 100-2300m above msl (may be even higher up to 2600m) (Tyler, 2020). It is a locally common insectivore, resident in its breeding range, Also the species has no records of long-distance movements and are mostly sedentary (Vinod, 2007).

They forage on ground, in short grass and when disturbed, flies to nearest bush or tree (Tyler, 2020). Even though they are insectivores, they also been reported consuming seeds of grasses found in their habitats (Vinod, 2007; IUCN, 2016). They breed during the month of March to July. Nest a shallow cup of coarse grass and roots, lined with finer grass, hair and stems, built among roots or in tuft of grass or in depression at base of bush on open hillside (Tyler, 2020) or in marshy grasslands with slightly taller grasses and sedges, particularly near streams (Vinod 2007).

Increase in the reports of the species from different parts of the Western Ghats over the past few decades have led to a substantial extension of its known range (Robin *et al.*, 2014). This includes WG regions of South Karnataka, relatively lower elevations of WG of Kerala and Tamil Nadu, Periyar landscapes, Ponmudy hills etc. However, extensive field study by Robin *et al.*, (2014) couldn't detect the presence of this species from much of the locations except for high-altitude grasslands of Nilgiris, Anamalai and Palani hills. Besides, they questioned the occurrence records from Periyar – Agasthyamalai landscapes and Brahmagiris by pointing out possible misidentification with nominate Paddyfield Pipit *Anthus rufulus* and proposed that the Nilgiri plateau and the Anamalai Hills (including the Palani Hills) be considered as distributional limits for this species. The species is 'Vulnerable' as per IUCN

By considering it habitat specificity and requirement of high-elevation landscapes the spcies is under the threat of climate change and associated landscape alteration (IUCN, 2016). Land use changes, habitat loss, expanding plantations of tea, cardamom, wattles and eucalyptus, tourism activities are all major threat for the species (Robin *et al.*, 2014; IUCN, 2016; Tyler, 2020)

2.15 THE SOUTHERN WESTERN GHATS

Ramachandran *et al.* (2017) defined southern Western Ghats as part of the WG found south of the Goa gap. These regions are again divided into biogeographic units bounded by geographic barriers. The major biogeographic units include south of Goa gap, south of Cauvery river, south of Chalayar river, south of Palghat Gap and south of Shenkottah Gap. It has much more endemicity as compared to the northern WG (Ramachandran *et al.*, 2017). According to Vijayakumar *et al.* (2016) and Haffer (1969) palaeoclimate-based models or the 'refuge model', the isolation of populations during dry glacial periods in forest refuge areas is hypothesized to have led to vicariance and speciation. This hypothesis can also be applied in the case of Western Ghats where there are several geographical barriers that contribute for species isolation (Vijayakumar *et al.*, 2016)

MATERIALS AND METHODS

3 MATERIALS AND METHODS

3.1 SELECTED SPECIES

Based on the availability of occurrence data and ecological information, two Western Ghats endemic bird species were selected for the current study. These species are Ashambu Laughingthrush (ALT), *Montecincla meridionalis* and Nilgiri Pipit (NP) *Anthus nilghiriensis* (Plate 1). Both ALT and NP are categorized as 'Vulnerable' according to IUCN, and both are listed under schedule IV of Wildlife (Protection) Act, 1972, and both have High conservation concerns in the State of India's Birds (SoIB) report (WPA, 1972; SoIB, 2018; IUCN, 2021) (Table 1)

Table 1. Species selected for the study

English Common Name	**Malayalam Common Name**	**Scientific Name**	**IUCN status**	**SoIB status**
Ashambu Laughingthrush (Ashambu Chilappan)	അശാംബു ചിലപ്പൻ	*Montecincla meridionalis*	Vulnerable	High
Nilgiri Pipit	മലവരമ്പൻ	*Anthus nilghiriensis*	Vulnerable	High

Ashambu Laughingthrush

Nilgiri Pipit

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

3.2 BACKGROUND (LANDSCAPE OF INTEREST)

The background is nothing but the landscape of interest used to perform the species distribution modelling. The selection of background is a crucial step in SDM, and it determines the model's predictive power. The requirement for selecting the background is that; (1) it should represent suitable habitats of the species of interest, and (2) the dispersal ability of a species by considering migration and local movement. Based on the extent of distribution and dispersion capacity, background selection differs between species (Elith *et al.*, 2011; Merow *et al.*, 2013).

Both species selected for the study (ALT and NP) are endemic to Southern WG. Each species is distributed in different geographical landscapes within WG due to the geographic, vegetational and climatic barriers present in the WG (Ramachandran *et al.*, 2017). These landscapes are further studied in the name of Sky islands (Robin *et al.*, 2010; Robin and Nandini, 2012). Background for each species selected based on the birds' distribution and dispersion capacity concerning the biogeographic and climatic barriers present in the region (Figure 1).

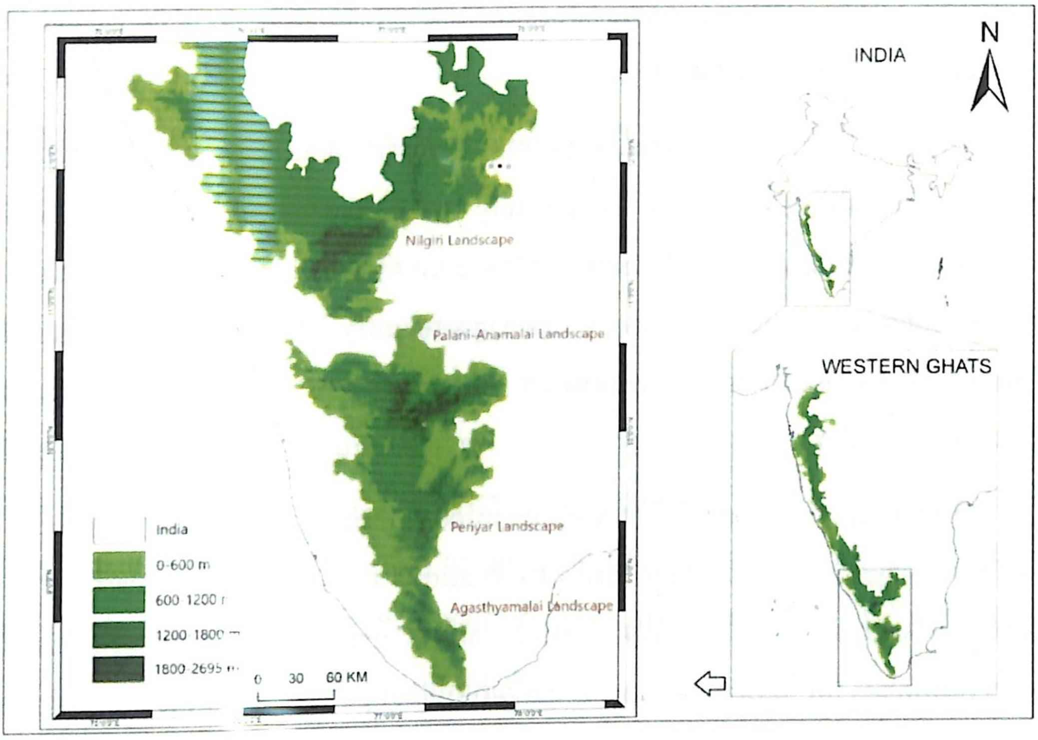

Figure 1. Landscapes fall within Southern WG and its elevation class

3.3 SPECIES PRESENCE RECORDS

Species presence records or occurrence points are the prime input for SDM. These are georeferenced point data that include longitude and latitude besides species names. It can also contain the date and time of point taken, location name, elevation and additional comments by the observer.

3.3.1 Gathering Occurrence Points

The method of point count is used to record species presence. Every point count was taken for 15 minutes and consisted of the following information; species, date, time, geo-coordinates of the point using Global Positioning System (GPS). The survey was conducted from February 2020 to April 2021 by visiting various locations like Agasthyavanam Biological Park, Shenduruney Wildlife Sanctuary, Periyar Tiger Reserve, Eravikulam National Park, Munnar Territorial Division, Marayur Sandal Division, Silent Valley National Park and Mannarkkad Forest

Division. All collected data were uploaded to the website eBird India (www.ebird.org/India) database.

Collected species occurrence points (Primary data) can only represent the extant species falling within the Kerala state. Since the species (both ALT and NP) prefer montane ecosystems of Southern Western Ghats, additional occurrence data that fall outside the state boundary can significantly help frame the species' full extent. This extra data was downloaded from eBird primary dataset and constitute the secondary data.

eBird is a freely available web-enabled community of bird watchers who collect, manage and store their bird observations in a globally accessible unified database (Sullivan *et al.*, 2009). eBird data is used by Birders, scientists, and conservationists for understanding avian biological patterns and the environmental, anthropogenic factors that influence them. A proper multi-level review process makes the eBird data pure and available for research and conservation programmes, including the development of species distribution models (Sullivan *et al.*, 2017). So, the species presence data was downloaded from eBird, including primarily collected data. eBird basic dataset version 'EBD_relJun-2021' used to extract occurrence data. Details of the occurrence data are provided under Appendix I.

3.3.2 Vetting of occurrence points

Since secondary occurrence data were collected from a public database, the. quality of data would highly be depended on the recognition capabilities of the observer, spatial and temporal coverage by the contributor, detectability of a species, the rare bird recording method of the database and attention given by the reviewer to vet the data (Isaac *et al.*, 2014; Kamp *et al.*, 2016). So, it is advisable to recheck the data and further filter it before making it usable. Filtering methods were modified after Strimas-Mackey *et al.* (2020) and included the following filtering techniques; (a) included all checklists having travelling and stationary protocols; (b) excluded all checklists with more than or equal to 120 minutes of duration; (c) removed checklists with transect distance of 2km or more; (d) removed checklists with more than ten observers. Modifications were made by considering habitat specificity of the species, abrupt elevation gain and vegetation change in the habitat.

After vetting occurrence points, spatial thinning was also done to avoid spatial clustering. When multiple occurrence points get clustered at specific regions, it may lead to overfitting of the model. Thinning was carried out in R using the package spThin (Aiello-Lammens *et al.,* 2015). According to the number of available points and the nature of clustering, records of NP were thinned at 1km. Whereas in the case of ALT, due to minimal data, thinning was not carried out. Figure 2 and Figure 3 shows the occurrence records of ALT and NP respectively. All of which is gathered from southern WG.

Since ALT is endemic to the Agasthyamalai landscape (south of Shenkottah pass), there are no records from the north. In NP, this bird is confined only to high-ranges of the southern WG, including Nilgiri hills and Palani-Anamalai hills. Hence, there are two disjunct populations of this species on either side of the Palghat gap. The topography of this gap makes the species isolated on either side with no dispersal between its disjunct population.

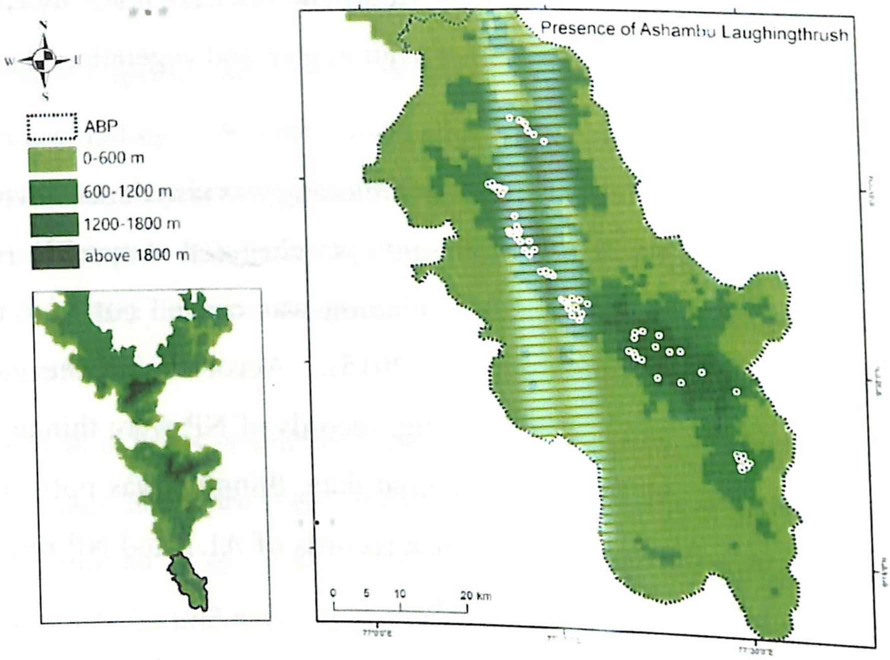

Figure 2. Occurrence points of Ashambu Laughingthrush from Western Ghats

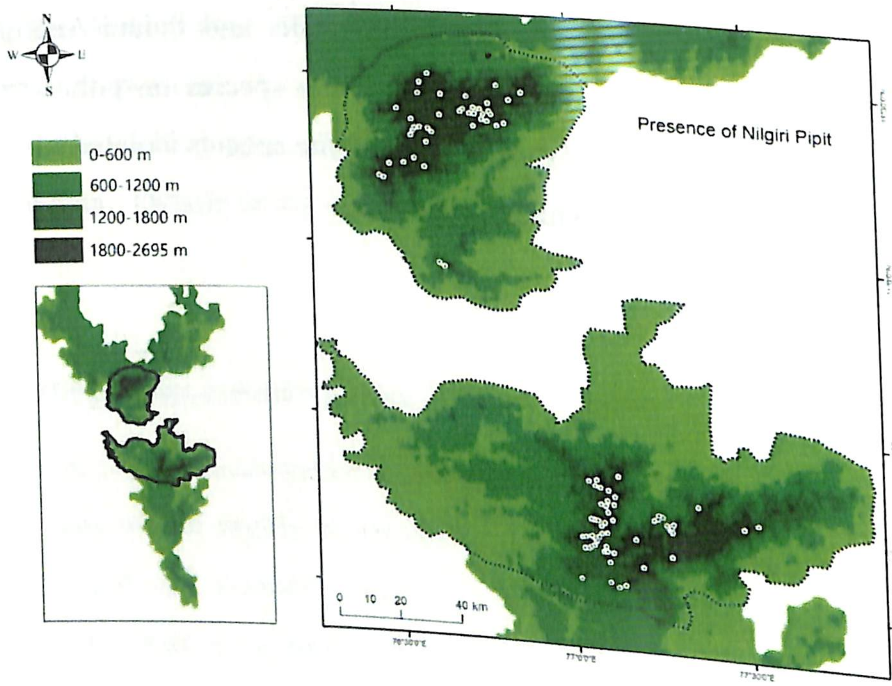

Figure 3. Occurrence points of Nilgiri Pipit from the Western Ghats

3.4 ENVIRONMENTAL VARIABLE

Patterns in species diversity and dissimilarity of species composition across geographic space are a function of environmental heterogeneity (Graham *et al.*, 2005). Hence determining environmental variables and estimating their contribution to species of interest is essential in modelling studies (Araújo and Guisan, 2006)

The following environmental variables are considered based on species ecology and extant; bioclimatic variables (BIO 1-19) (Hijmans *et al.*, 2005), Digital Elevation Model (DEM) and Enhanced Vegetation Index (EVI) (Appendix II). The dataset was downloaded from the website; Climatologies at high resolution for the earth's land surface areas (CHELSA) climate dataset (Karger *et al.*, 2017). The DEM (GTOPO30) was downloaded from the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre. Topographic variables like altitude, slope, and aspect are calculated using QGIS (version 3.16) from the obtained DEM file. Enhanced Vegetation Index is like Normalised Difference Vegetation Index NDVI, but it is more responsive to canopy variations, canopy type and architecture, and plant physiognomy (Heute *et al.*, 2002).

All EVI layers were downloaded at the spatial resolution of 30 arc seconds (~1 km) from the USGS Landsat dataset and projected to WGS 84 EPSG:4326 (WGS 1984). The satellite has a revisit period of 28 days. EVI layers of each month ranging from 2011-2020 were accessed. Thus, downloaded data then averaged out in three ways; (1) by taking an average of EVI for the whole ten years (evi_avg); (2) 10-year average EVI of the wettest quarter of the year (peak monsoon; June-August) (evi_wet); (3) 10-year average EVI of the driest quarter (peak summer; March-May) (evi_dry). All these three layers were used along with other variables for the SDM process.

3.4.1 List of environmental variables used for SDM

3.4.1.1 Bioclimatic variables

1. Bio1 (Mean Annual Temperature): refers to the average of the maximum and minimum temperatures of a year. This corresponds to the total energy inputs for an ecosystem
2. Bio2 (mean Diurnal Range): the mean difference between the monthly maximum and minimum temperature averaged for a year.
3. Bio3 (Isothermality): quantifies how large the day-to-night temperatures oscillate relative to the summer-to-winter (annual) oscillations ((Bio2/Bio7) x100). This can determine the influence of monthly variation of temperature comparable to that of a year.
4. Bio4 (Temperature Seasonality): this is a measure of temperature variation over a year relative to monthly temperature averages. More significant variability in temperature is inferred from a larger standard deviation.
5. Bio5 (Maximum temperature of the warmest month): this is a measurement of the temperature of the hottest month, which can be used for determining species distribution changes related to warm temperature anomalies.
6. Bio6 (Minimum temperature of the coldest month): indicates the lowest temperature of the coldest month
7. Bio7 (Temperature annual range): quantifies the variation in temperature over a year determined by taking the difference between Bio5 and Bio6 (Bio5-Bio6)
8. Bio8 (Mean temperature of the wettest quarter): quarter is three months (1/4th of a year). It is the measure of the average temperature of the wettest season.
9. Bio9 (Mean temperature of the driest quarter): a measure of the average dry season temperature of a year.
10. Bio10 (Mean temperature of the warmest quarter): average temperature of the hottest season of the year

11. Bio11 (Mean temperature of the coldest quarter): average temperature of the coldest season of the year.
12. Bio12 (Annual precipitation): it is the cumulative total of rainfall over 12 months. It gives an account of total water inputs.
13. Bio13 (Precipitation of the wettest month): total rainfall of the month which has got the highest rainfall
14. Bio14 (Precipitation of the driest month): total rainfall of the month which has got the least rainfall
15. Bio15 (Precipitation seasonality) is the ratio of the standard deviation of monthly precipitation to the monthly mean precipitation.
16. Bio16 (Precipitation of the wettest quarter): total rainfall of the wettest quarter (three months) of a year
17. Bio17 (Precipitation of the driest quarter): total rainfall of the driest season of a year
18. Bio18 (Precipitation of the warmest quarter): total rainfall of the hottest season of a year
19. Bio19 (Precipitation of the coldest quarter): total rainfall of the coldest season of a year

3.4.1.2 Digital Elevation Model (DEM)

20. Altitude
21. Slope
22. Aspect

3.4.1.3 Enhanced Vegetation Index

23. Evi_avg: 10-year average of enhanced vegetation index for the year 2011-2020
24. Evi_wet: 10-year average of enhanced vegetation index of the wettest quarter (June - August) for the year 2011-2020
25. Evi_dry: 10-year average of enhanced vegetation index of the driest quarter (March-May) for the year 2011-2020

The temperature is measured in °C (degree celsius), and precipitation is in mm (millimetres). All the bioclimatic variables (bio1 - bio19) are calculated from monthly rainfall and minimum, mean and maximum monthly temperature. And data layers were generated by interpolating average monthly data available from regional weather stations. As per the World Meteorological Organization (WMO), the climate is defined as the measurement of the mean and variability of relevant quantities of variables (such as temperature, precipitation or wind) over some time, ranging from months to thousands of years. The classical period is 25-30 years.

CHELSA (Climatologies at high resolution for the earth's land surface areas) is a very high resolution (30 arc sec, ~1km) global climate data set currently hosted by the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL). It is built to provide free access to high-resolution climate data for research and application and is constantly updated and refined. It includes climate layers for various periods and variables, ranging from the Last glacial maximum to current times to several future scenarios. CHELSA is based on a mechanistic statistical downscaling of global reanalysis data or global circulation model output and is freely available.

3.4.2 MULTICOLLINEARITY TEST

Collinearity among environmental predictors is regarded as an essential source of model uncertainty. It may decrease its statistical power (Júnior and Nóbrega, 2018) So, it is always better to perform a multicollinearity analysis to eliminate highly correlated variables and improve model performance. In this study, variables with high correlation with each other, i.e., Pearson correlation coefficient $|r| > 0.75$, were calculated using SDMtoolbox and removed before model building. If the value $|r| > 0.75$ between two variables, then SDMtoolbox could eliminate one ecologically less significant variable. Thus, variables with less correlation are selected for the model building of each species. The multicollinearity results suggested 12 variables for ALT whereas ten for NP (Appendix III).

3.5 SPECIES DISTRIBUTION MODELLING USING MAXENT

Maximum entropy (Phillips *et al.*, 2006, 2017) algorithm (MaxEnt version 3.4.4) is used to develop species distribution models. Feeding data for the modelling is presence-only occurrence points of the species.

To moderate goodness-of-fit with model complexity and to evaluate models with spatially independent data, there is a need to smoothing model performance and calibrate overfitting. R package ENMeval (Muscarella *et al.*, 2014) (Ecological Niche Model Evaluation) can be used for this. It can also provide us with model settings like the selection of Maxent features, regularization multiplier (RM) and the number of background points for building a Maxent model. Regularization or Regularization Multiplier (RM) is a relaxation component added to Maxent to constrain the estimated distribution, thereby allowing the average value of each sampled variable to approximate its empirical average and thereby reducing the overfitting of the model (Baldwin, 2009). It could also provide us with a bias file for building Maxent models. ENMeval results could also give a value of Akaike Information Criterion (AIC), which is a measure of model performance and model suggestions. The lower the AIC value, the higher the performance of the model. The initial model developed by Maxent allows us to analyze the variable contribution, permutation importance, area under the curve (AUC), and jackknife test output to understand the contribution of each variable in the process of model building. Several models must be run discarding variables with the most negligible contribution, and the model with the lowest AIC value is selected from the ENMeval results. Thus, it identifies the best performing model with the lowest AIC and AUC values by running Maxent and ENMeval multiple times.

Different types of analysis are available in Maxent, and here complementary log-log (cloglog) output was selected for the study. Cloglog type of output was a recently released analysis by the Maxent development team and is considered the most appropriate output for explaining the species habitat suitability (Phillips *et al.*, 2017). Maxent replication run type selected as cross-validation and number of iterations set as 5000. The number of backgrounds points, features, and RM were adjusted, referring ENMeval output. All other settings are kept as default.

3.6 FUTURE SIMULATIONS

Habitat suitability was then modelled using future simulations. The projections developed under different Representative Concentration Pathways (RCPs) like RCP 2.6, RCP 4.5 and RCP 8.5 for 2061 – 2080 (the 2070s). Bioclimatic variables associated with future climate models and static topographic variables used to build prediction outputs. The EVI layers were excluded from the prediction models because of the unavailability of such layers in the future.

Four different ESMs such as the Community Climate System Model version 4 (CCSM4), Model for Interdisciplinary Research on Climate version 5 (MIROC5), Norwegian Earth System Model 1 (NorESM1-M) and Model for Interdisciplinary Research on Climate Earth System Model Chemistry (MIROC-ESM-CHEM) downloaded. All these models were used to build habitat suitability predictions for both species.

Evaluation of model performance is an unavoidable step in the process of SDM. Among indices available for assessing model performance, Area Under the Receiver Operating Characteristic Curve (AUC) value assessment is one method. AUC measures how well parameters can distinguish between two diagnostic groups (random and background points). It is computed from the Receiver Operating Characteristic (ROC) curve by checking the sensitivity against '1-specificity' across the range of possible thresholds. The AUC ranges from 0 to 1, and the model's goodness is indicated by values close to one. This measure of model performance provided the results of Maxent out. Since AUC value alone could not evaluate model performance due to its limitations (Phillips *et al.*, 2006), another model evaluation measurement is the True Skill Statistic (TSS), which can be defined as 'sensitivity + specificity – 1'. TSS ranges from –1 to +1, and values close to one indicate high accuracy. Model robustness can be understood by calculating the AIC value and here. used AIC, AUC and TSS for model performance evaluation.

3.7 ASSESSMENT OF HABITAT SUITABILITY

The Maxent output provides prediction maps in raster file format (Ascii file '.asc'). Obtained raster files are then converted into a binary map by using a threshold value. Maximum test sensitivity plus specificity (maxSSS) of cloglog is considered as the best threshold for Maxent output reclassification for habitat suitability determination (Liu *et al.*, 2013). All the habitat values which are less than this threshold can be regarded as unsuitable habitats, whereas greater values are suitable. Based on this, current and future raster output could be reclassified to binary raster with two values, 0 (unsuitable) and 1 (suitable), by using ArcGIS or QGIS.

Binary maps hence formed can be used to plot and assess habitat suitability change. This can be done using the function raster calculator in QGIS 3.16 by subtracting the current binary map from the future binary maps. The resultant map will have three-pixel values; a value of 0 indicates no change in species suitability (either suitable or unsuitable both in current and future scenarios). A value of 1 indicates areas that will be converted into suitable habitat in the future from an unsuitable habitat in the current situation, and –1 represents areas that will be changing from suitable habitat in the present to an unsuitable habitat in the future; lost habitats!

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

3.8 HABITAT SUITABILITY INDEXING

Since maximum test sensitivity plus specificity (maxSSS) of cloglog is considered as the best threshold for Maxent output reclassification for habitat suitability determination (Liu *et al.*, 2013), it can also be used effectively for indexing habitat suitability. Values that are greater than maxSSS indicate suitable habitats, and it ranges up to 1. Further, it can be reclassified into four subclasses: Highly suitable habitat (0.8-1.0), Moderately suitable habitat (0.6-0.8), Less suitable habitat (maxSSS-0.6) and Non-suitable habitats (less than maxSSS). It could give us an idea about the extent and quality of suitable habitats of a species.

This analysis is done for both current and future scenarios of the species. Subtracting these raster layers (future minus current) could give an idea about the change of quality of a species habitat.

RESULTS

4 RESULTS

4.1 SELECTION OF THE MODEL BASED ON IMPORTANT PREDICTIVE VARIABLES

The contribution and permutation importance of the variables in the finalised model; the model with the lowest AIC value, highest TSS and AUC value were selected. The significance of variables was also evaluated by doing a jackknife test, and a different set of variables appeared in the suggested models. The response curves of each gave the best suitable conditions of the species concerning the variable

4.1.1 Ashambu Laughingthrush

Ten models have been developed for the species ALT based on the permutation importance of environmental variable, AIC, AUC and TSS values. Out of these models, Model eight is selected as the final model with five variables and Maxent features as Linear (L), Quadratic (Q) Hinge (H) and Product (P) with one as regularisation multiplier (RM). Low AIC value, high AUC value and moderately good TSS value show the final model's robustness. Overall accuracy can also be used as an additional value for assessing model performance (Table 2).

Table 2. Model development and associated accuracy indices of the Ashambu Laughingthrush

Model No	Variables	RM	AIC	TSS	AUC
1	Bio1, Bio2, Bio3, Bio11, Bio12, Bio14, Bio19, aspect, slope, evi_wet, evi_dry	3	1105.1	0.807	0.934
2	Bio1, Bio2, Bio12, Bio14, Bio15, aspect, slope, evi_wet, evi_dry	4	1057.4	0.811	0.934
3	Bio1, Bio2, Bio3, Bio11, Bio12, Bio14, evi_wet	2.5	1098.1	0.823	0.925
4	Bio1, Bio3, Bio11, Bio12, Bio14, evi_wet	2.5	1101.5	0.819	**0.922**
5	Bio1, Bio2, Bio11, Bio12, Bio14, evi_wet	2	1117.1	0.767	0.911
6	Bio1, Bio2, Bio3, Bio11, Bio12, Bio14, Bio15, evi_wet	3	1078.9	0.734	0.929
7	Bio1, Bio11, Bio12, Bio14, Bio15, evi_wet	3	1077.1	0.860	0.929
8	**Bio1, Bio12, Bio14, Bio15, evi_wet**	**1**	**1050.1**	**0.881**	**0.932**
9	Bio1, Bio12, Bio14, Bio15	0.5	1054.6	0.874	0.924
10	Bio1, Bio12, Bio14	2	1098.3	0.729	0.902

All five variables contributed to the model building with noticeable permutation importance. BIO 1 has the highest percentage of contribution and permutation importance, whereas evi_wet is identified as the least essential variable (Table 3)

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

Variables	PC	PI	MAX	MIN	MEAN	SD
BIO 1	87.6	60.6	28.67	17.03	22.85	3.36
BIO 12	5	19.2	228.7	72	150.4	45.3
BIO14	4.2	11.3	5.02	1.18	3.1	1.11
BIO15	2.8	7.7	79.6	48.4	64	9.02
EVI_WET	0.4	1.2	6575.4	810.6	3693	1666.6

PC: Percentage Contribution; PI: Permutation Importance; SD: Standard Deviation

Jackknife analysis also shows the importance of the BIO 1 in model testing. The evi_wet has a minor test gain in the jackknife analysis (Figure 4). When referring to the response curves of the variables, the best suitable conditions of the ALT are defined around 18.5°C of BIO 1 and 2287 mm of average annual precipitation (BIO 12) (Figure 5).

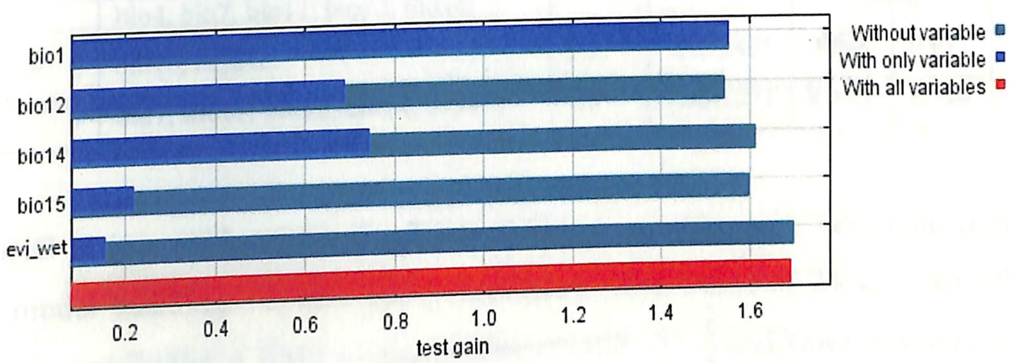

Figure 4. Jackknife test graphs showing the test gain of different variables used in the model building of Ashambu Laughingthrush

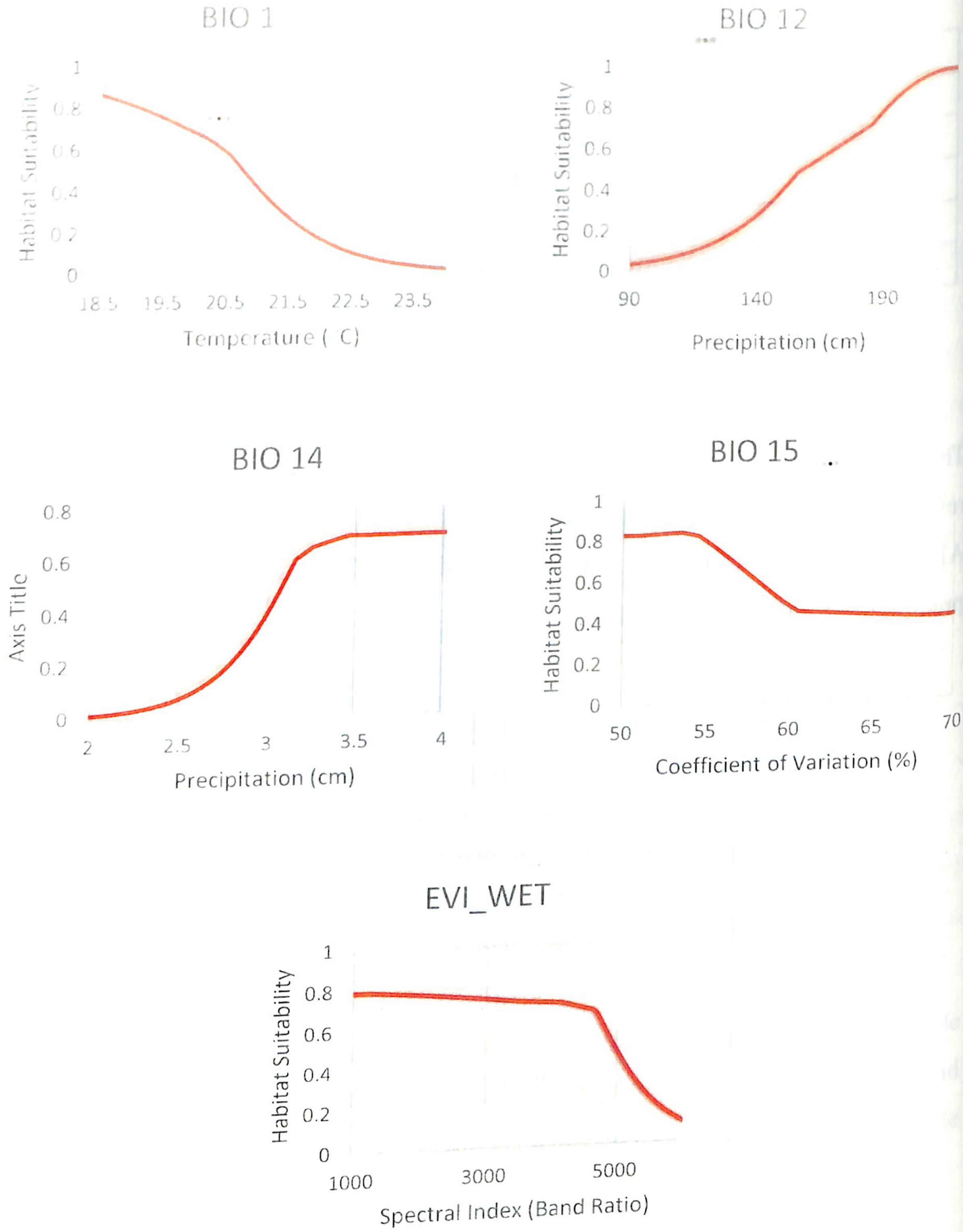

Figure 5. Response curves of the variables used for the model building of Ashambu Laughingthrush

4.1.2 NILGIRI PIPIT

Three models have been developed for the species NP based on the permutation importance of environmental variables, AIC, AUC and TSS values. Out of these models, Model three is selected as the final model with five variables and Maxent features as Linear (L), Quadratic (Q) and Hinge (H) with 1.5 as regularisation multiplier (RM). Low AIC value, high AUC value and moderately good TSS value show the final model's robustness. Overall accuracy can also be used as an additional value for assessing model performance (Table 4).

Table 4. Model development and associated accuracy indices of the Nilgiri Pipit

Model No	Variables	RM	AIC	TSS	AUC
1	bio3, bio4, bio7, bio11, bio12, bio14, bio18, bio19, wetave, dryave	3.5	1,441.847	0.868	0.901
2	bio4, bio7, bio11, bio12, bio14, bio18, dryave	1.5	1,433.438	0.848	0.911
3	**bio7, bio11, bio12, bio14, dryave**	**1.5**	**1,435.271**	**0.843**	**0.920**

BIO 11 is considered the single most crucial variable, with 74% contributing to the model building. It also has permutation importance of 74%. All other variables contributed a little to the model (Table 5). Jackknife analysis also indicates the importance of BIO 11, and it has a higher test gain (Figure 6). Furthermore, the species' habitat suitability is higher when the mean temperature of the coldest quarter (BIO 11) is around 12°C.

Table 5. Variables included in the final model of Nilgiri Pipit and associated calculations

Variable	PC	PI	MAX	MIN	MEAN	SD
BIO 11	74.2	73.8	27.71	10.8	19.25	4.9
EVI_DRY	11.4	4.8	6261.4	592.6	3427	1638.9
BIO 12	6.4	9.8	394.24	39.76	217	102.4
BIO 7	5.5	4.1	18.15	12.75	15.45	1.56
BIO14	2.5	7.5	3.23	0.47	1.85	0.79

PC: Percent Contribution; PI: Permutation Importance; SD: Standard Deviation

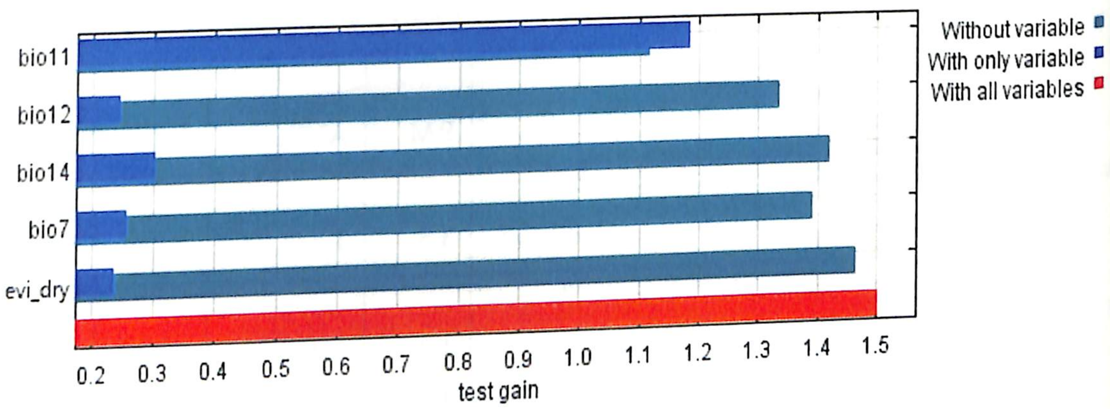

Figure 6. Jackknife test graphs showing the test gain of different variables used in the model building of Nilgiri Pipit

When referring to the response curves of the variables, the best suitable conditions of the ALT defined around 12.5°C of BIO 11 and 2885 mm of average annual precipitation (BIO 12) (Figure 7).

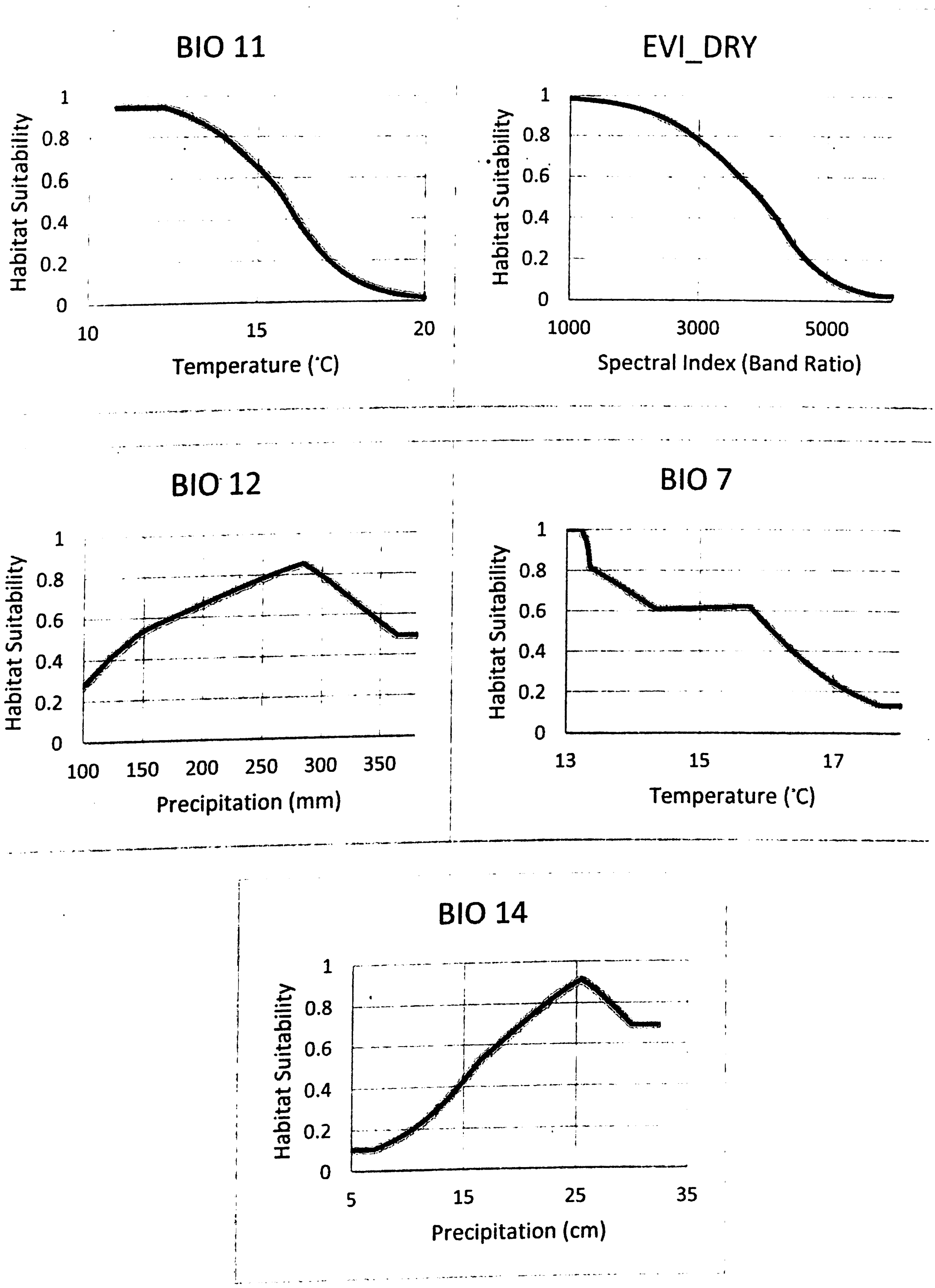

Figure 7. Response curves of the variables used for the model building of Nilgiri Pipit

4.2 CURRENT HABITAT SUITABILITY ANALYSIS

4.2.1 Ashambu Laughingthrush

The best performing model of the ALT (AIC = 1050.1) predicted an area of 303 km2 as suitable habitat across the background. The suitable habitat covered 9% of the background area used in the Maxent modelling (Table 6). Out of the total suitable area, 80.5% fall under the protected area network of Kerala and Tamil Nadu state. The model also predicted a new suitable habitat, where previous records were unavailable, particularly the eastern part of Kalakkad - Mundanthurai Tiger Reserve (Figure 8).

Table 6. Suitable habitat available for both species under current climate scenarios

Species	**maxSSS***	**Suitable Habitat**	**Total background area**	**Percentage of suitable habitat**
Ashambu Laughingthrush	0.4169	303	3356	9.03
Nilgiri Pipit	0.3901	1792	8628	20.77

*Maximum test sensitivity plus specificity cloglog threshold

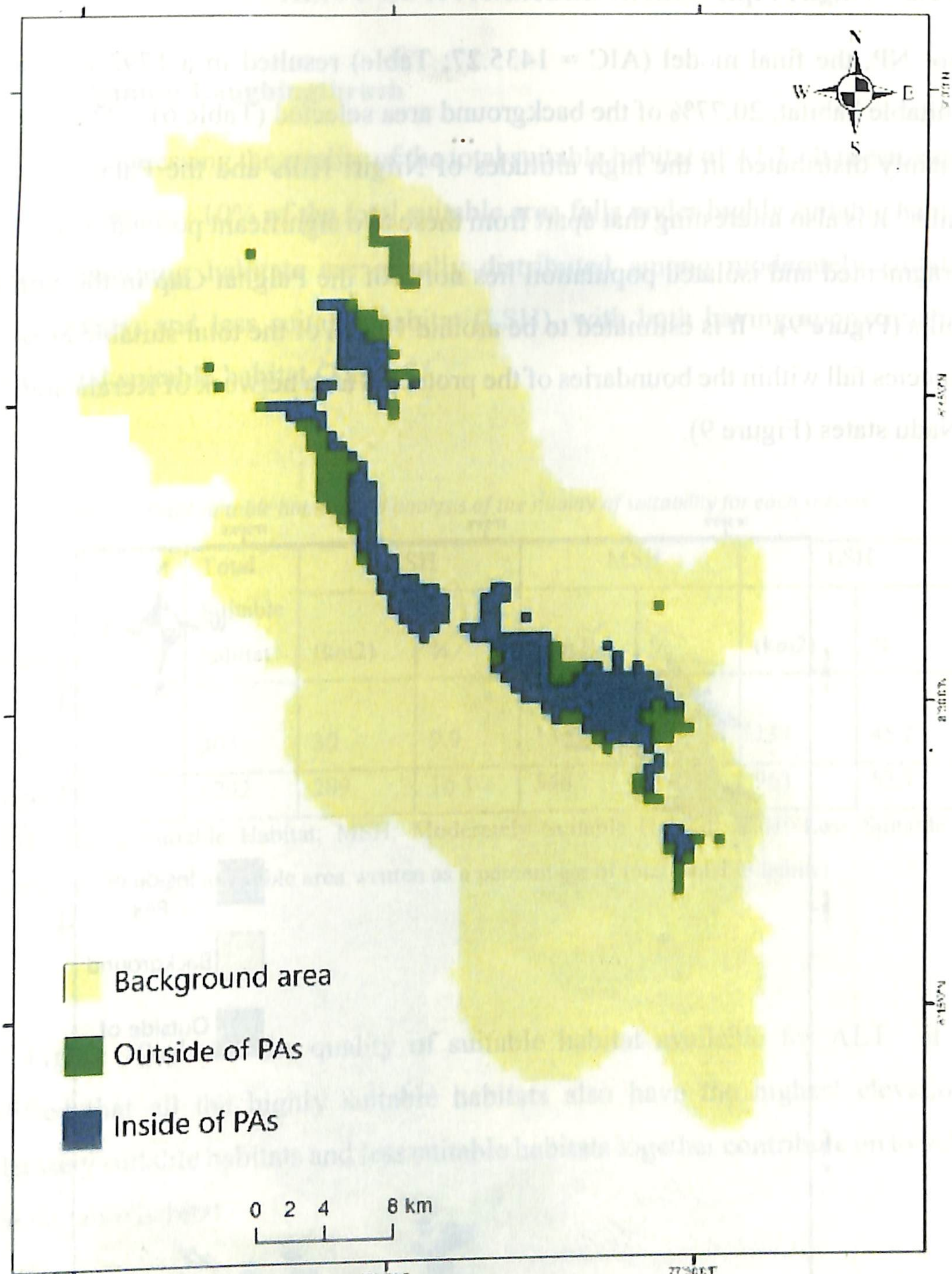

Figure 8. Predicted habitat suitability of Ashambu Laughingthrush

4.2.2 Nilgiri Pipit

For NP, the final model (AIC = 1435.27; Table) resulted in a 1792 km^2 area as suitable habitat, 20.77% of the background area selected (Table 6). The species is mainly distributed in the high altitudes of Nilgiri Hills and the Palani-Anamalai hills. It is also interesting that apart from these two significant populations, a highly fragmented and isolated population lies north of the Palghat Gap in the Shiruvani hills (Figure 9). It is estimated to be around 18.7% of the total suitable area of the species fall within the boundaries of the protected area network of Kerala and Tamil Nadu states (Figure 9).

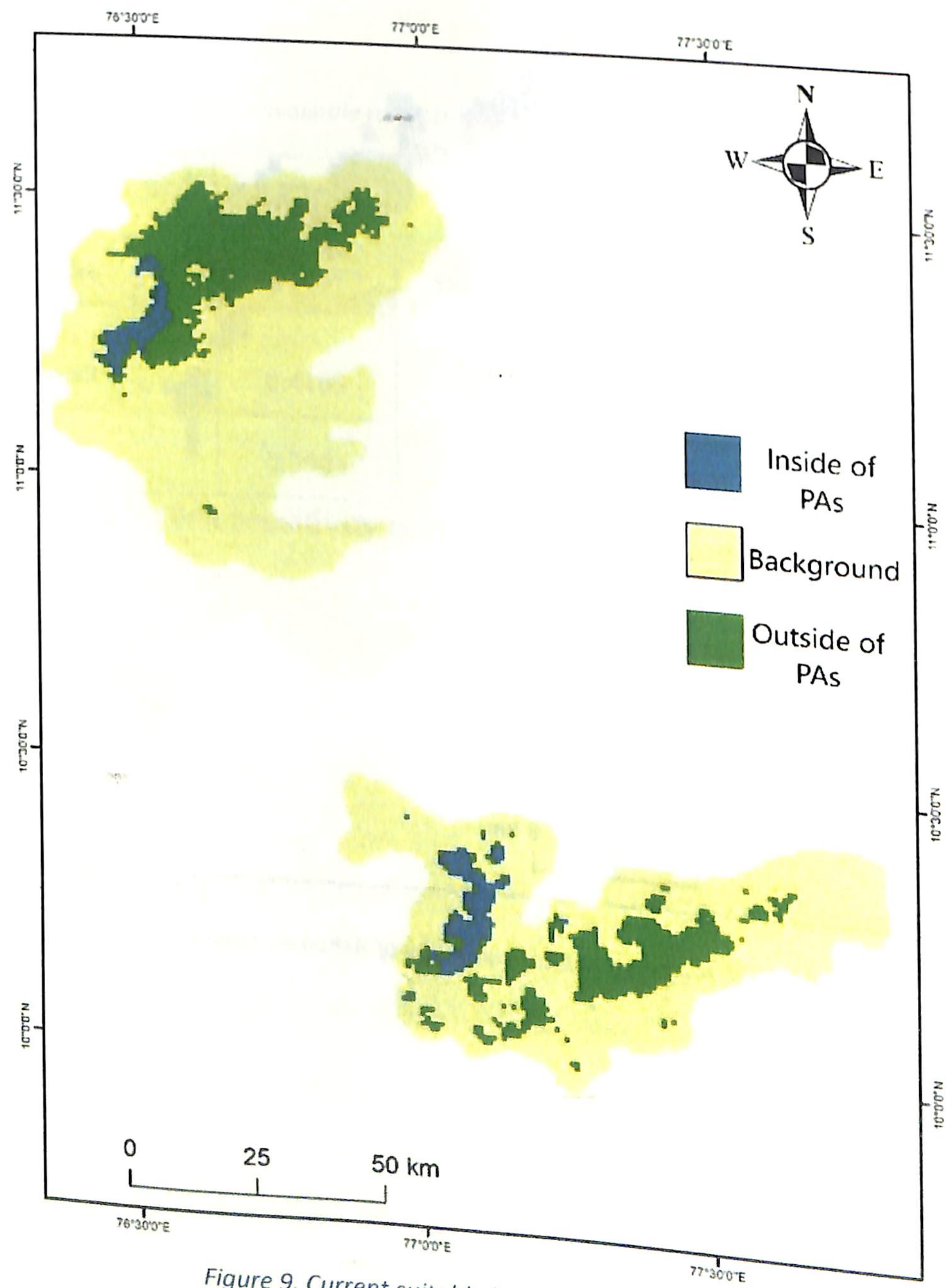

Figure 9. Current suitable habitat of Nilgiri Pipit

4.3 ESTIMATING QUALITY OF AVAILABLE HABITAT

4.3.1 Ashambu Laughingthrush

While assessing the quality of the total suitable habitat of ALT. It is estimated that approximately 10% of the total suitable area falls under highly suitable habitat (HSH), remaining habitats are equally distributed among moderately suitable habitat (MSH) and less suitable habitat (LSH), with both having approximately 45% of total suitable habitat (Table 7)

Table 7. Total suitable habitat and analysis of the quality of suitability for each species

	Total Suitable	HSH		MSH		LSH	
Species	habitat	(km2)	%	(km2)	%	(km2)	%
Ashambu Laughingthrush	303	30	9.9	136	44.9	137	45.2
Nilgiri Pipit	1792	289	16.1	540	30.1	963	53.7

HSH: Highly Suitable Habitat; MSH: Moderately Suitable Habitat; LSH: Less Suitable Habitat; Percentage: available area written as a percentage of total suitable habitat

Figure 10 shows the quality of suitable habitat available for ALT. It is identified that all the highly suitable habitats also have the highest elevation. Moderately suitable habitats and less suitable habitats together contribute up to 90% of the suitable habitat.

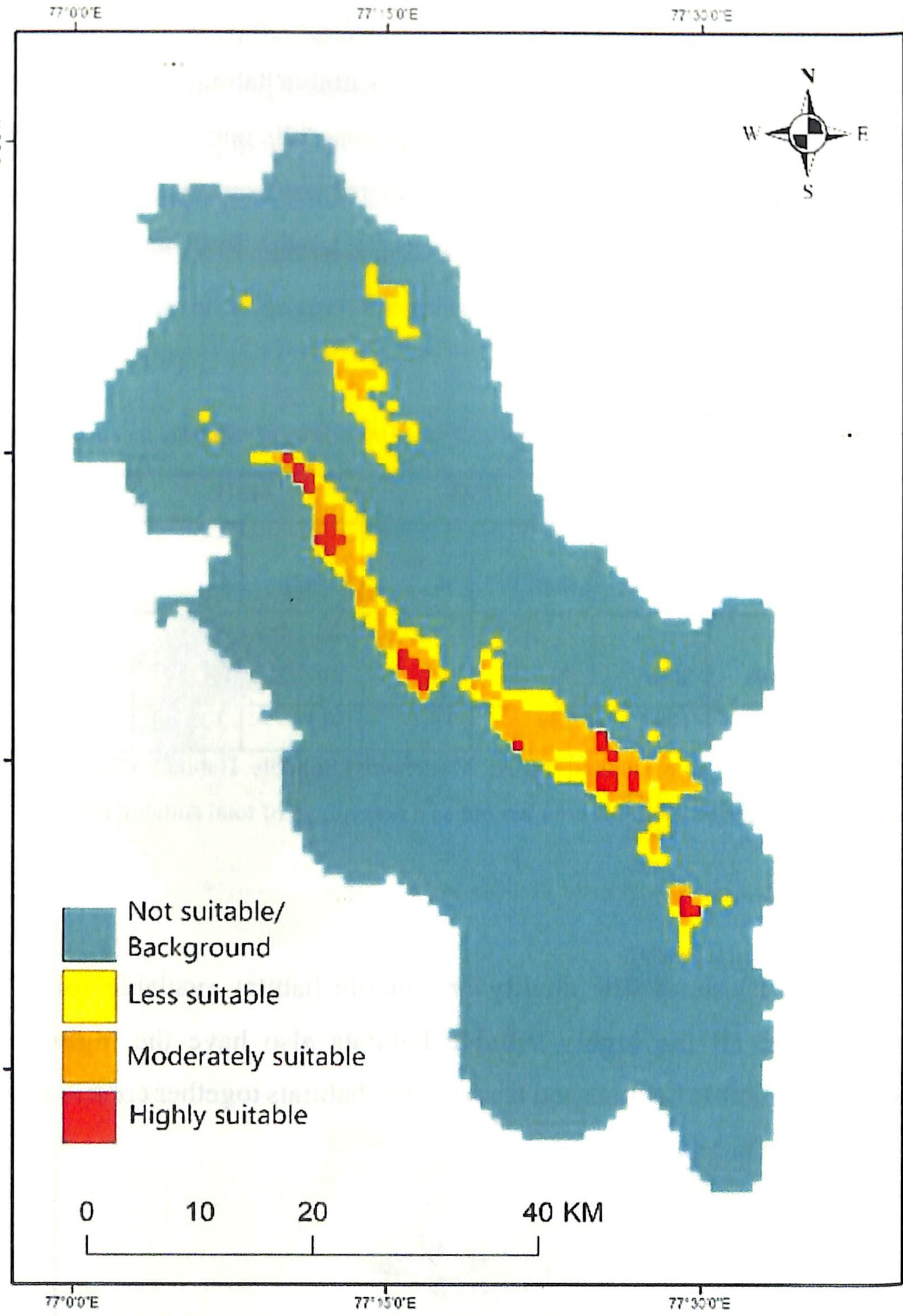

Figure 10. Extent of suitable habitat and its quality for Ashambu Laughingthrush

4.3.2 Nilgiri Pipit

More than half (~53%) of the current suitable habitat of NP falls under less suitable areas. 30% of available habitat is moderately suitable, while the remaining 16% is estimated to be falling under HSH (Table 7). Figure 11 shows the extent of habitats falling in these criteria. It is interesting to note that HSHs are all situated in higher elevations. Eravikulam National Park holds a significant share in providing HSH for this species, particularly for its southern population (south of Palghat Gap)

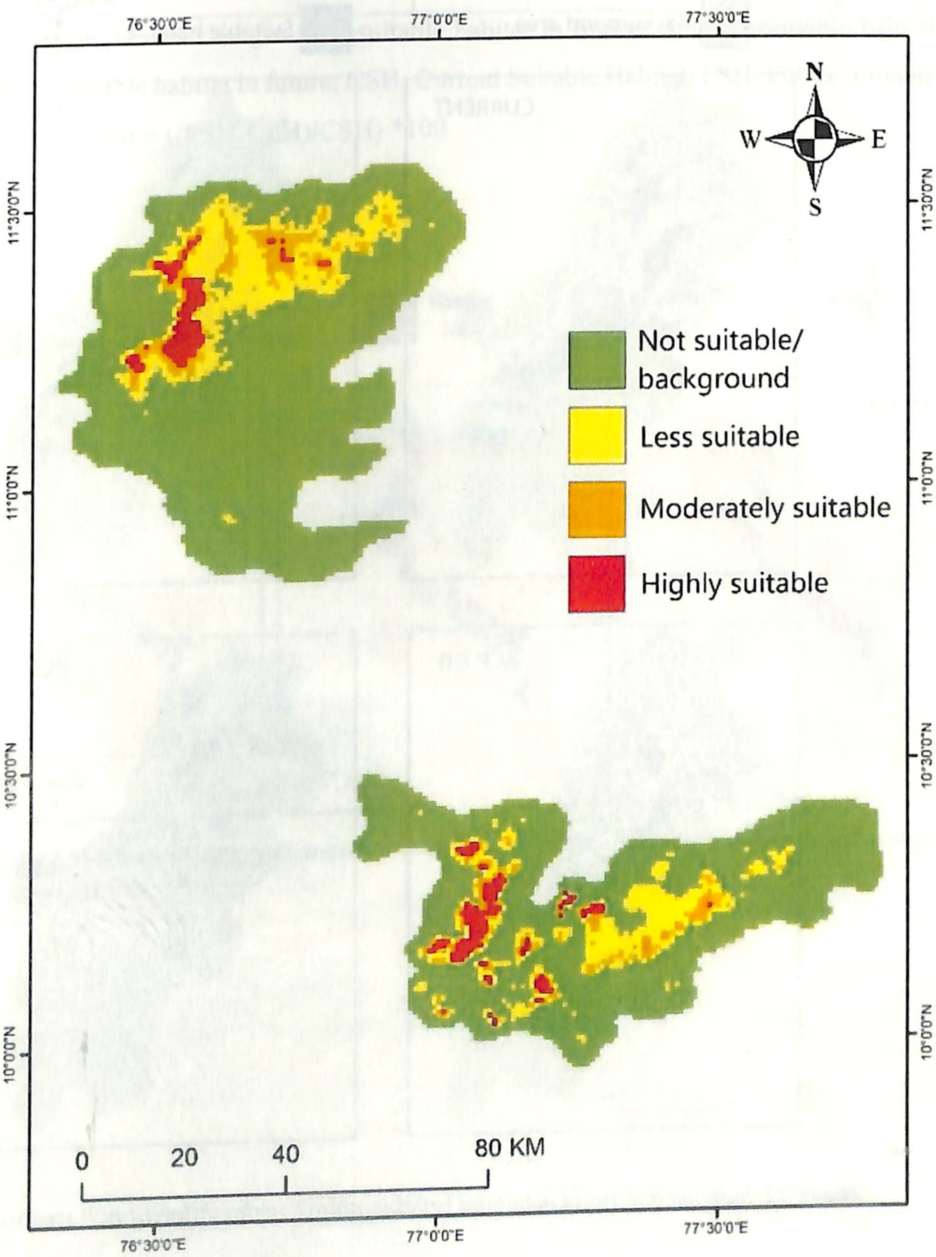

Figure 11. Extent of suitable habitat and its quality for Nilgiri Pipit

4.4 PREDICTING FUTURE HABITAT CHANGES AND SUITABILITY

4.4.1 Ashambu Laughingthrush

According to selected RCP scenarios, maxent could predict a considerable loss in the suitable habitat of ALT. The species would be losing 20.5% of its current suitable area in the RCP 4.5 (the 2070s) scenario, 40% in RCP 6.0 (2070s) and a drastic 76.6% loss in the RCP 8.5 (2070s) scenario (Table 8). Thus, under the extreme climate change scenario, the NP would lose four-fifths of its suitable area within 50 years (Figure 12 and Figure 13).

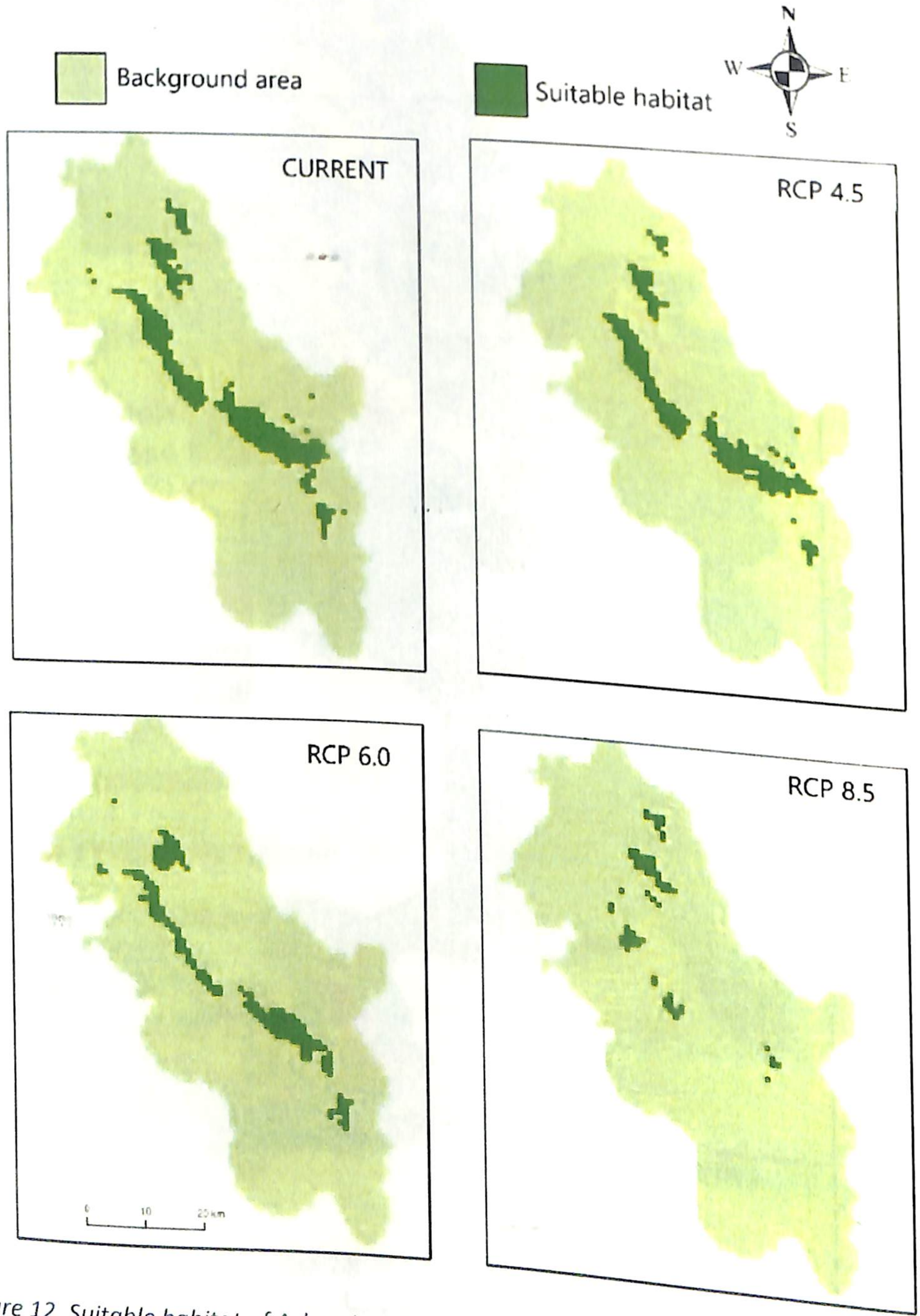

Figure 12. Suitable habitat of Ashambu Laughingthrush under different RCP scenarios

Table 8. Habitat loss and gain of Ashambu Laughingthrush

RCP Scenario	maxSSS Threshold	Loss (km^2)	Gain (km^2)	CSH (km2)	FSH (km^2)	Net Gain (%)
4.5 (the 2070s)	0.3487	65	3	303	241	-20.5
6.0 (the 2070s)	0.3104	229	108	303	182	-39.9
8.5 (the 2070s)	0.3284	241	9	303	71	-76.6

Loss: Suitable habitat changes to unsuitable habitat in future; Gain: Unsuitable habitat changes to suitable habitat in future; CSH: Current Suitable Habitat; FSH: Future Suitable Habitat; Net Gain = ((FSH-CSH)/CSH) *100

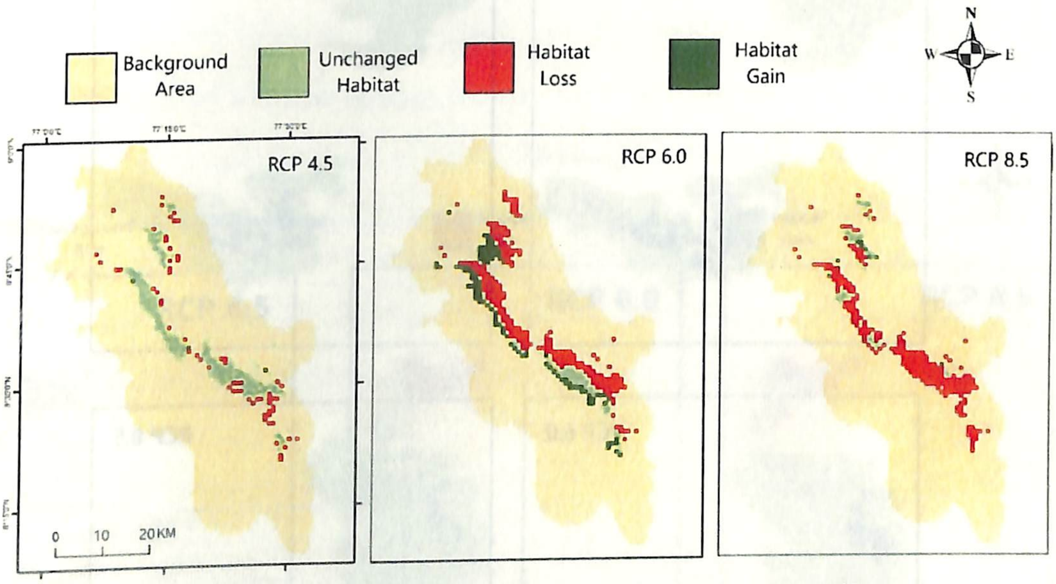

Figure 13. Probable habitat quality change for Ashambu Laughingthrush under different RCP scenarios

4.4.2 Nilgiri Pipit

In all the three RCP scenarios, maxent could predict a considerable loss in the suitable habitat of NP. The species would be losing 41.2% of its current suitable area in the RCP 4.5 (the 2070s) scenario, 50.45% in RCP 6.0 (2070s) and a drastic 79% loss in the RCP 8.5 (2070s) scenario (Table 9). Thus, under the extreme climate change scenario, the NP would lose four-fifth of its suitable area within 30 years (Figure 14 and Figure 15)

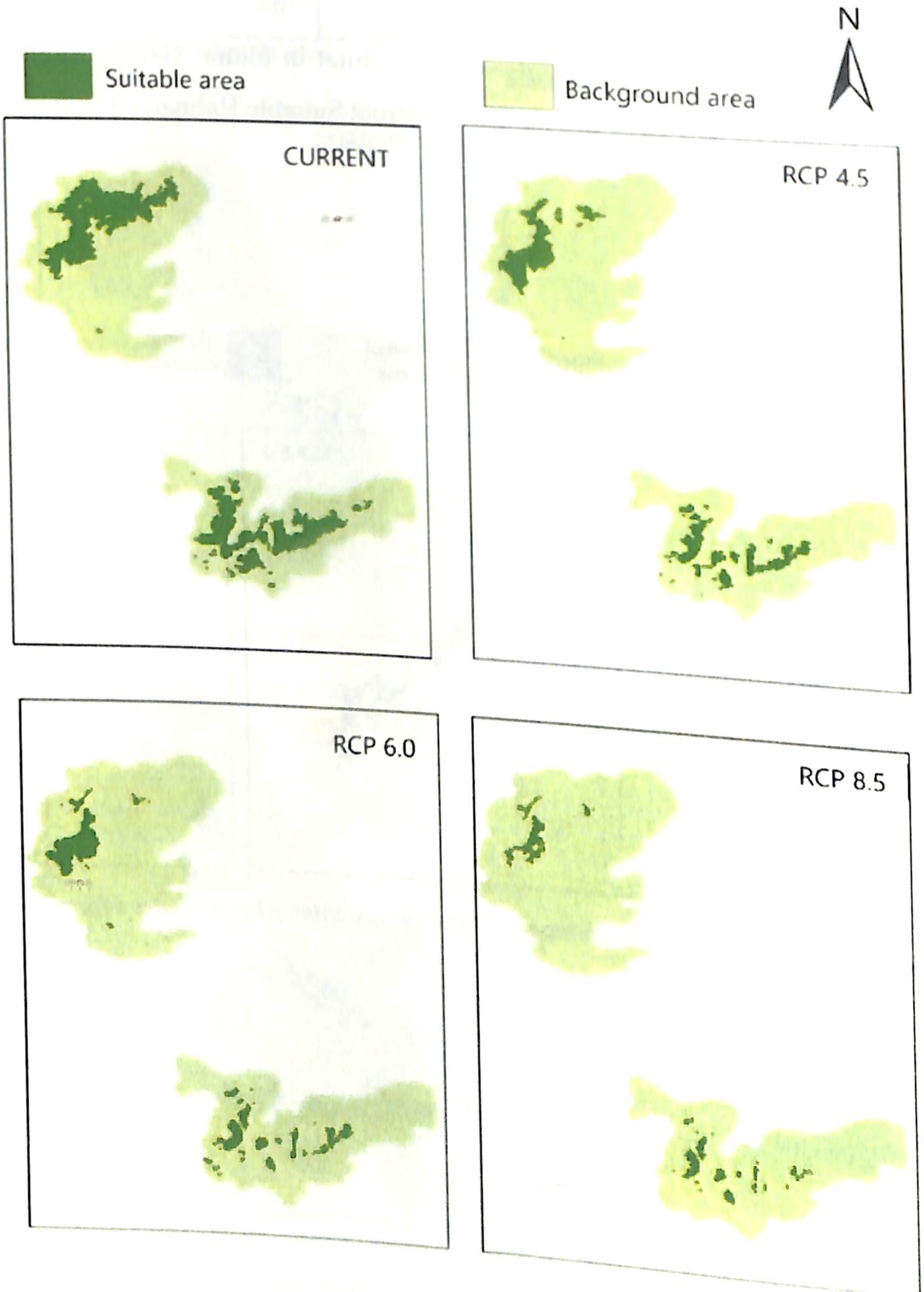

Figure 14. Available habitat for Nilgiri Pipit in 2070s according to different RCP scenarios

Table 9. Habitat suitability changes in the future for Nilgiri Pipit

RCP Scenario	max SSS Threshold	Loss (km^2)	Gain (km^2)	CSH (km^2)	FSH (km^2)	Net Gain (%)
4.5 (the 2070s)	0.3688	893	154	1792	1053	-41.24
6.0 (the 2070s)	0.3620	1032	128	1792	888	-50.45
8.5 (the 2070s)	0.3601	1417	0	1792	375	-79.07

Loss: Suitable habitat changes to unsuitable habitat in future; Gain: Unsuitable habitat changes to suitable habitat in future; CSH: Current Suitable Habitat; FSH: Future Suitable Habitat; Net Gain = ((FSH-CSH)/CSH) *100

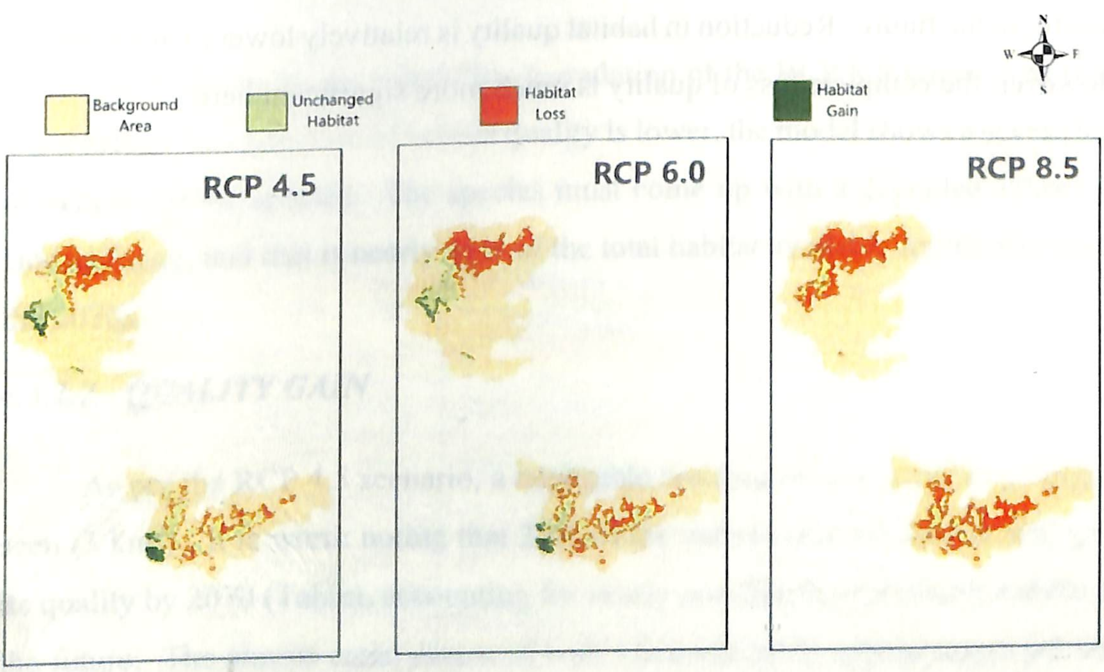

Figure 15. Probable habitat changes for Nilgiri Pipit under different RCP scenarios

4.5 ANALYSING HABITAT QUALITY CHANGE

4.5.1 ASHAMBU LAUGHINGTHRUSH

4.5.1.1 QUALITY REDUCTION

Upon calculating the reduction in habitat quality (Table 10) under the RCP 4.5 scenario, it is estimated that 2070s will deteriorate nearly 14% of the current suitable habitat. This account for more than 17% of the available habitat. HSH will not suffer from complete loss, but 20% of it will deteriorate and will have MSH status in the future. Total habitat loss will be severe in the case of LSH. 26% of it will be lost entirely, but at the same time, another 36km2 area will be downgraded to LSH from MSH.

RCP 6.0 suggests much more loss than the previous scenario (Table 10), with 22% of the current available habitat being degraded, close to 37% of the suitable habitat. 80% (109 km2) of LSH in the current habitat will not be available for the species in the future. Reduction in habitat quality is relatively lower in this scenario. However, the complete loss of quality is much more significant here.

Table 10. Habitat quality reduction of Ashambu Laughingthrush under different RCP scenarios

RCP Scenario	Complete habitat loss			Reduction in habitat quality			Total habitat quality reduced		
	HSH to NSH (km^2)	MSH to NSH (km^2)	LSH to NSH (km^2)	HSH to LSH (km^2)	HSH to MSH (km^2)	MSH to LSH (km^2)	Total* (km^2)	% of the initial area %	%. of the remaining area %
4.5 (the 2070s)	0	3	62	0	6	36	42	13.9	17.4
6the .0 (2070s)	21	99	109	4	60	3	67	22.1	36.8
8the .5 (the 2070s)	15	113	113	13	2	17	32	10.6	45.1

HSH: Highly Suitable Habitat; MSH: Moderately Suitable Habitat; LSH: Less Suitable Habitat; *Tota al: a total area that has reduced its quality (excluding complete loss); Initial area=303 km2; remaining area: FSH of Table 8

The table shows the suitability degradation of the RCP 8.5 scenario as well. Even though the reduction of habitat quality is lower, the model shows a severe loss of habitat for the species. The species must come up with a degraded 32km2 of land in future, and that is nearly 45% of the total habitat available for the species in the 2070s.

4.5.1.2 QUALITY GAIN

As per the RCP 4.5 scenario, a negligible erection of new possible habitat is seen (3 km^2). It is worth noting that 20% of the current suitable habitat will gain its quality by 2070 (Table), accounting for nearly one-fourth of available habitat in the future. The almost equal extent of both LSH and MSH will be upgraded into MSH and HSH, respectively.

RCP 6.0 predicted a bit differently. There will be new areas available for the species in future; at the same time, nearly 49 km^2 suitable area will become much more suited for the species climatic preference (see Table 11).

RCP 8.5 is the worst scenario among the three where the only negligible area will be upgraded and created in the future. $2km^2$ area of LSH will become MSH and some $8km^2$ area will be added to the list of LSH.

Table 11. Habitat quality gain of Ashambu Laughingthrush under different RCP scenarios

RCP	Complete habitat gains			Gain in habitat quality			Total habitat quality gain		
	NSH to LSH (km^2)	NSH to MSH (km^2)	NSH to HSH (km^2)	LSH to MSH (km^2)	MSH to HSH (km^2)	LSH to HSH (km^2)	Total (km^2)	% initial area %	% of the remaining area %
4.5 (the 2070s)	3	0	0	28	30	0	58	19.1	24.07
6.0 (the 2070s)	51	20	37	3	30	16	49	16.2	26.92
8.5 (the 2070s)	8	1	0	2	0	0	2	0.7	2.82

HSH: Highly Suitable Habitat; MSH: Moderately Suitable Habitat; LSH: Less Suitable Habitat; *Total: a total area that has gained its quality (excluding complete gain); Initial area=303 km2; remaining area: FSH of Table 8

4.5.2 Nilgiri Pipit

4.5.2.1 QUALITY REDUCTION

A dramatic decline is observed in the case of NP in all three RCP scenarios (Table 12). The most habitat loss is seen in LSH. In RCP 4.5, nearly half of the current suitable habitat will be lost by the 2070s. At the same time, the 323km^2 area of MSH will be changed to LSH. The bird will be forced to live in a habitat with 40% of deteriorated habitat compared to the current suitable habitat.

The same trend exists in RCP 6.0 as well. 22% of the current suitable habitat will likely be facing quality deterioration. Nearly half of the LSH (863 km^2) will not be available for the species to survive. It is slightly larger than that of RCP 4.5. Almost 45% of the future habitat will be in a state of deterioration.

Drastic habitat loss and quality reduction are seen in the RCP 8.5 scenario. Deteriorated habitat of around 367km^2 accounts for almost 98% of the future habitat of NP. 67% of the HSH will be converted into LSH (196 km^2), whereas 18% of HSH will become MSH.

Table 12. Habitat quality reduction of Nilgiri Pipit under different RCP scenarios

	Complete habitat loss			Reduction in quality			Total quality reduced		
	HSH to NSH	MSH to NSH	LSH to NSH	HSH to LSH	HSH to MSH	MSH to LSH	Total	% of the initial area	% of the remaining area
RCP	(km^2)	(km^2)	(km^2)	(km^2)	(km^2)	(km^2)	(km^2)	%	%
4.5 (the 2070s)	12	63	818	14	86	323	423	23.60	40.17
6.0 (the 2070s)	14	155	863	40	101	256	397	22.15	44.70
8.5 (the 2070s)	40	419	958	196	52	119	367	20.48	97.87

HSH: Highly Suitable Habitat; MSH: Moderately Suitable Habitat; LSH: Less Suitable Habitat; *Total: a total area that has reduced its quality (excluding complete loss); Initial area=303 km2; remaining area: FSH of Table 9

4.5.2.2 *QUALITY GAIN*

According to RCP 4.5, 12% of the remaining habitat will be gaining its quality, out of which 13km² area will be converted into HSH from NSH. 155 km2 additional area will be available for the bird to survive.

RCP 6.0 indicates a bit more increase in a new suitable area for NP, around 171 km² (Table 13). Out of which 101 km² comes under LSH. It shows a significant improvement in habitat quality, of which about 28 km² of LSH will be converted into HSH in the future.

It is noteworthy that there will be no new areas and quality upgrades for the RCP 8.5 scenario. A fraction of suitable habitat may remain but will be degrading (see Table 13)

Table 13. Habitat quality gain of Nilgiri Pipit under different RCP scenarios

RCP	Complete habitat gains			Gain in habitat quality			Total quality gained		
	NSH to LSH (km²)	NSH to MSH (km²)	NSH to HSH (km²)	LSH to MSH (km²)	MSH to HSH (km²)	LSH to HSH (km²)	Total (km²)	% of the initial area %	% of the remaining area %
4.5 (the 2070s)	77	64	13	14	81	39	134	7.48	12.72
6.0 (the 2070s)	101	64	6	29	78	28	135	7.53	15.2
8.5 (the 2070s)	0	0	0	0	0	0	0	0	0

HSH: Highly Suitable Habitat; MSH: Moderately Suitable Habitat; LSH: Less Suitable Habitat; *Total: a total area that has gained its quality (excluding complete gain); Initial area=303 km2; remaining area: FSH of Table 9

DISCUSSION

5 DISCUSSION

5.1 CONTRIBUTION OF VARIABLES IN BUILDING THE MODEL

The selection of predictor variables is a significant step in almost all modelling studies (Guisan & Zimmermann, 2000; Heikkinen *et al.*, 2006; Araujo & Guisan, 2006). This variable should also reflect the ecology of the species and could explain the habitat requirement of a species (Austin and Van Niel, 2011). Altogether, 25 environmental variables were used in the current based on the availability of the variable and the current understanding of the ecology of the species. After careful examination and statistical analysis, an adequate number of variables are finally selected for the model building. The species in this study (ALT and NP) are high-altitude specialists (del Hoyo *et al.*, 2020). Even though altitude seems a significant predictor variable for the species, it is the other bioclimatic variable (temperature and precipitation) that are shaped by the altitude, contribute to the species habitat selection. It was also proven statistically using a multicollinearity test where altitude correlated with other variables and got removed. It is thus evident and significant that global temperature rise is likely to cause an impact on species suitability regardless of the topography of the landscape.

Different temperature, precipitation and vegetation variables contribute significantly to both the species habitat selection. Among them, temperature variables were identified as the major contributing factors on which the species is highly dependent. Mean annual temperature (BIO 1) and mean temperature of the coldest quarter (BIO 11) are the critical variable for ALT and NP, respectively. Apart from that, annual precipitation and precipitation seasonality also help form the required habitat of both species. Not only temperature and precipitation, but vegetation structure is also significant for both species. Field studies indicate that the ALT prefers thick evergreen forests and forest edges of the high-altitude region. In contrast, NP prefers shola grasslands and open lands found in high-altitude areas and avoided canopies. It can be concluded that a change in these bioclimatic predictors may significantly affect the survival of the species in question.

5.2 CURRENT SUITABLE HABITAT AVAILABLE FOR THE SPECIES

5.2.1 Ashambu Laughingthrush

del Hoyo (2020) classify this species as an inhabitant of evergreen forests over an altitude of 1200m, reaching at least 2135m above MSL. It is adequately observed in the case of the lower reach. We couldn't find the bird below that elevation anywhere in the surveyed region, and we could observe the bird as soon as we got past that elevation mark. But, having said that the bird is endemic to the Agasthyamalai landscape (Sashikumar *et al.*, 2011; Chandran and Praveen, 2013; del Hoyo *et al.*, 2020), and the upper reach of this landscape is the Agasthyamalai peak that spans 1868m above MSL (Amarnath *et al.*, 2003), the species' upper limit of elevation can be updated to below 1868m. In this research, it was 1466m (4812 ft). In fact, it shows a very restricted distribution. The model also suggested a suitable habitat for the species in Tamil Nadu. There are no records available for the species from that region, namely the Kuttalam reserve forest, lying northeast of Pandimotta (Shenduruney WLS). Proper field survey should be carried out in those hills as it can provide suitable habitat for the species, which can be regarded as the northern boundary for the species.

5.2.2 Nilgiri Pipit

NP seems like an overlooked species among birdwatchers! According to Ali (1999), the bird inhabits an altitude from 1050 onwards. This was then supported by Sashikumar *et al.*, (2011) and Tyler (2020). But, despite intense field data collection from the state of Kerala covering all significant landscapes, the study couldn't find any bird below the altitude of 1600m, even from Palani Hills). This was also backed up by Robin *et al.* (2014). According to Robin *et al.* (2014), the bird is less likely to be found in an elevation less than 1800m except for the Siruvani hills of Palakkad district. This intense field survey couldn't spot/catch a single bird from north of Nilgiris and south of Palani and Anamalai hills. Also, they did observe similar-looking Paddyfield Pipit (*Anthus rufulus*), Richard's Pipit (*Anthus richardi*) and Long-billed Pipit (*Anthus similis travancoriensis*) from these locations. They postulate that the historical records of Nilgiri Pipit could have been other similarly looking pipits as they are a potential candidate for misidentification.

So, by following Robin *et al.* (2014), a study could identify potential habitat available for the NP now. High-altitude mountain ranges running across the Nilgiri Landscape in the north of the Palghat gap and Palani-Anamalai landscape in the south has been shown as the suitable current habitat for NP. As it inhabits grassy, rocky hilltops interspersed with sholas (Ali, 1999; Sashikumar *et al.,* 2011; Robin *et al.,* 2014; Taylor, 2020), the health of the habitat is crucial for its survival. 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 and Palghat gap, which is a 30km plain

5.3 HABITAT QUALITY OF THE CURRENT SUITABLE HABITAT

Mountain peaks and associated high-elevation forests indicate highly suitable habitats (HSH) in the case of both ALT and NP. Similarly, less suitable habitats are located at the periphery of the species suitability map.

HSH for ALT lies in the Agasthyavanam Biological Park (ABP) as a chain running along with the highest peaks in that system. Areas including Chemunjimotta, Pandipath, Agasthyamalai, Kodayar and Mahendragiri are identified as HSH. Moderately Suitable Habitats (MSH) lie surrounding HSH, followed by Less Suitable Habitats (LSH). From this trend, it can be concluded that due to global temperature rise, species are likely to be climbing up the hill seeking suitable habitat.

A similar trend can be observed in the case of NP as well. Half of the suitable habitat of NP is, in fact, LSH, which is under severe threat. New Amarambalam WLS in the north of the Palghat gap and Eravikulam NP in the south of the Palghat gap are the HSH for the species as per the present conditions owing to their high elevated topography. HSH found in Ooty and Kodaikanal faces a significant threat from anthropogenic pressures as they are currently unprotected.

5.4 CLIMATE CHANGE IMPACT AND HABITAT SUITABILITY

Based on the above discussion, it is evident that both the species would be losing their suitable habitats under extreme climate change scenarios. One of the possible responses of species' especially birds, against adverse climate conditions is shifting their habitat either locally or by migration extinct (Parmesan, 2006). If the species fail to migrate or are unable to relocate themselves, they should change their physiology as an adaptation (Dantzer *et al.*, 2014). Species failing to do so become locally/globally extinct (Bellard *et al.*, 2012). The elevational shift may be a possible solution to overcome climate warming (Stuhldreher and Fartmann, 2018). These elevational shifts may eventually lead to conflict for space and resources among other habitat specialists, including birds and other taxa.

5.4.1 Ashambu Laughingthrush

According to different RCP scenarios, the Maxent model could predict severe habitat loss ranging from 20% to 77%. Even though the bird is likely to be expanding its habitat in all these scenarios, it will not be able to balance areas that it will lose. Upon careful examination of sites that will be gone in the future, it can be concluded that most of the lost regions are found in the outer boundary of the current habitat, i.e. areas with relatively lower elevation. Centrally aligned elevated mountain ranges seem to be maintaining the habitat in future, especially areas surrounding Agasthyamalai peak and Chemunjimotta of Peppara WLS. However, Ravindranath and Sukumar (1998) predicted a likely expansion of the evergreen forest in the future due to an increase in mean annual precipitation. A detailed study is needed whether this expansion benefits the species in future.

5.4.2 Nilgiri Pipit

A 40% to 80% reduction in habitat is calculated under different RCP scenarios. A slight habitat gain is also noticed in the case of NP. It is noteworthy that the significant share of areas that will be lost in the future are situated along the western slopes of WG, falling in the state of Tamil Nadu. And the area gain in NP is primarily observed along the eastern slope of WG. This suggests a drastic but gradual temperature increase in the leeward side of WG, which also lie adjacent to the drier plains of Tamil Nadu. A dramatic westward shift in habitat is clearly observed in the case of NP. Within the available habitat, higher elevation ranges seem to be free from the immediate temperature increase. But the altitudinal shift of the species may then pave the way for intense competition among species' sharing the same niche. Future expansion of evergreen forest (after Ravindranath and Sukumar, 1998) may lead to a decline in grassland ecosystem (Sukumar *et al.*, 1995) which is again a threat for this grassland bird. The evergreen forest has already started licking grasslands from the valleys of Eravikulam national Park, as observed from the field.

5.5 SUITABLE HABITAT UNDER PROTECTED AREA NETWORK

Close to four-fifths of the suitable habitat of ALT is estimated to be falling inside the PA network of Kerala and Tamil Nadu state. In that sense, most of its habitat is legally well protected. Even then, hill ranges exist, especially in the extreme north of the species habitat, that require conservation importance. Kuttalam reserve forest in TN, adjacent to Shenduruney WLS, is one such area that should be notified as part of PA Kalakkad-Mundanthurai TR of TN.

Even though most of these habitats are protected, forests adjoining Agasthyamalai peak are getting severe anthropogenic pressure born from ecotourism and pilgrimage tourism. Panigrahi and Jins (2018) were also raised this issue as one of the significant threats for the habitat of birds thriving in that region. An urgent management intervention is recommended to regulate the flow of the tourist and pilgrims to the peak before it adversely affects these high-altitude forests.

Only 18% of the current suitable habitat of NP falls within the boundary of the PA network of Kerala and Tamil Nadu. Eravikulam national park, Silent Valley national park of Kerala and New Amarambalam WLS of TN are the major PAs that provide the necessary conditions for the species survival. The rest of the NP habitat falls under reserve forests, eucalyptus, tea and cardamom plantations, degraded lands tourism centres. Among the major tourist destinations in South India, Ooty in Nilgiris and Kodaikanal in Anamalais are also home to NP. These areas are unprotected and highly vulnerable to land-use changes. Apart from that; these are the areas where a significant loss of future habitat is projected. So, these landscapes need immediate policy intervention, land restoration and conservation action.

5.6 QUALITY DEGRADATION OF AVAILABLE FUTURE HABITATS

We have already discussed the future habitat loss of ALT and NP. In addition to that, the quality of the habitat is also going to degrade severely as per the analysis. Half of the remaining habitat of ALT will be degraded as per the worst-case scenario (RCP 8.5). Owing to its extended area, NP shows a significant degradation of its habitat. This degradation in its habitat will be even severe if the global temperature rise accompanies added anthropogenic pressures. Wildfire, invasive species, deliberate planting of exotic trees (Joshi *et al.*, 2018) and competition for resources will complicate this dilemma. If the habitats become disconnected due to forest deterioration, then the species populations become isolated. Long-term isolation of the fragmented populations would lead to the local extinction of the species (Wilcox and Murphy, 1985). 97% of the remaining habitat of NP will be degraded as per the RCP 8.5 situation. In that case, a handful of mountain peaks may support this species in the nametag of HSH, that too with severe competition.

5.7 LIMITATIONS OF THE STUDY

This study is mainly focused on quantifying species distribution changes in response to global temperature and changing climate. For that purpose, bioclimatic variables, digital elevation model, and enhanced vegetation index were effectively used to develop the present and future models. In turn, the qualification of the model depends mainly on the goals of the study that explain the qualification criteria and the usability of the model (Guisan and Zimmermann, 2000). Species habitat selection is highly varied and can be complex than we think. Other than temperature and precipitation, many other factors influence the distribution of a species. Prey-predator relationship, inter, intra-specific competition, an abundance of food and water, availability of healthy breeding ground and movements, to name a few (after McEven and Wingfield, 2003)

But most of such variable layers are unavailable in the required format to perform SDMs. This current study has tried incorporating the utmost variables as possible to generate the statistically meaningful model. A detailed account on species-specificity, habitat specialisation, dependants of the species to the prevailing microclimate of the location would throw more light into the accurate mapping of species suitable habitat. The resolution and quality of the available layers may also vary among different models released by other climate organisations. The high-resolution climate model rooted in different families were selected to overcome this problem.

A new array of socioeconomic scenarios (Shared Socioeconomic Pathways; SSPs) may soon be available for modelling (Neill *et al.*, 2013). This incorporates the social structure, development, education, administrational power, inter-governmental relations and economic structure of the world (after Riahi *et al.*, 2016). That, coupled with the current emission scenarios, would likely give a much more accurate model as it incorporates the human-modified world in all its essence.

SUMMARY

6 SUMMARY

Prevailing anthropogenic pressure on earth and associated global temperature rise affect many taxa, including birds. Understanding these phenomena and how they influence birds can be studied effectively by choosing endemic high-altitude-dependent birds. Since montane habitat is more vulnerable to global temperature rise, resident birds in these habitats can be selected as bioindicators. Modelling habitat suitability is considered one of the best analyses for understanding the relationship between a species and its environment. HSM can be done very effectively by using Maxent because of its accuracy and ability to function irrespective of species absence records.

This study aims to quantify the influence of environmental variables on the distribution of selected endemic birds of the Western Ghats. The study also seeks to identify the suitable habitats of the selected endemic birds of the Western Ghats. Another quest in this study is to analyse the quality of available habitats for the selected endemic birds of WG. 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 2070s (2061-2080) by using the Maxent algorithm.

Habitat Suitability Models can be rendered by using the software maxent. It can develop models by analysing presence-only information of the species of interest. Rigorous field surveys within selected habitat could provide an adequate number of presence data for the species. Occurrence data lying outside the state can be retrieved from the eBird database, an online citizen science-based bird monitoring platform. Bioclimatic variables (BIO 1 to BIO 19), digital elevation model (elevation, slope and aspect) and 10-year averaged enhanced vegetation index developed the HSM. Pearson's multicollinearity test is used to eliminate highly correlated ($|R|>0.75$) variables. The ENM (Ecological Niche Modelling) evaluation tool (ENMeval) was used to determine the Maxent features, several background points and regularisation. To reduce model bias, future predictions were made by taking an average of five different earth system models under

Coupled Model Inter-comparison Project 5 (CMIP5). Two other species, Ashambu Laughingthrush (Ashambu Chilappan), *Montecincla meridionalis* and Nilgiri Pipit *Anthus nilghiriensis*, are selected for the modelling study owing to their endemicity and habitat specialisation.

The highlights of the results are summarised below:

- Mean annual temperature (BIO 1) and mean temperature of the coldest quarter (BIO 11) was found to be the variables having the highest importance for the species ALT and NP, respectively.
- An area of 303 km^2 is calculated as suitable habitat for ALT. It only covers 9% of the total background area chosen for the study
- For NP, the model could identify an extent of 1792 km^2 as a suitable habitat, which covers one fifth (20%) of the total background area
- 80.5% of the total habitat of ALT and 18.7% of total habitat of NP are distributed within the protected area network of Kerala and Tamil Nadu state
- Out of the suitable habitat of ALT, 9.9% of the area are HSH. 44.9% are MSHs, and the remaining 45.2% are LSH
- 16.1% of the available habitat of the NP currently comes under HSH, one-third of its habitat is moderately suitable, and half of its suitable habitat comes under LSH
- Upon future climatic modelling, it is estimated that ALT will be facing a net loss in its habitat ranging from 20.5% to 76.6% under different climate change scenarios.
- In the case of NP, net habitat loss is predicted to range from 41.2% to 79%
- The quality of the future habitat is also severely affected in the case of both ALT and NP. According to different RCP scenarios, ALT would have to survive in degraded land in the future, where the remaining habitat will be severely degraded by 40 to 97%. However,, there will be a quality gain too, which will be around 24%, 26% and 2% in RCP 4.5, RCP 6.0 and RCP 8.5, respectively.
- An average of 25% of the current suitable habitat will deteriorate in the case of NP. And the bird will have a future with a 97% degraded habitat. Nearly 15% of the remaining habitat seems to be gaining its quality in RCP 6.5, whereas there will be no gain in the case of RCP 8.5
- Potentially suitable habitats which are lying outside of PAs should be identified. Redrawing a protected area network in the WG is thus recommended to ensure the long-term conservation of both species.
- Restoring degraded forests, woodlands and grasslands should be the prior management policy

Future Recommendations:

- Conducting periodic bird surveys in WG is needed for understanding the most accurate distribution of the species and changes in population dynamics
- Understanding of niche structure and habitat suitability of other endemic birds of the WG
- Standardise earth system models for the Western Ghats
- A collaborative effort on emission reduction, equitable sharing of resources and policy implementation is urgently needed

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7 REFERENCES

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ABSTRACT

MODELLING HABITAT SUITABILITY AND CLIMATE CHANGE IMPACTS ON ENDEMIC BIRDS OF SOUTHERN WESTERN GHATS,

KERALA, INDIA

by

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ABSTRACT

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8 ABSTRACT

Finding factors influencing change in species distribution is of great importance to scientific research. Dramatic alterations in species distributions and abundances have been connected to elevating global temperature. The habitat specialists restricted to montane ecosystems could be used as ecological indicators of global temperature rise as they are sensitive to climate change. In this study, habitat suitability models of two high-altitude dependent birds thriving in the sky islands of the Western Ghats were developed, studied and analyzed to understand the patterns of their distribution in the wake of changing climate.

The maximum entropy (MaxEnt) algorithm was selected as the modelling tool for the study. ENM Evaluate tool was used to determine the settings for the model, and the best-performing model was selected based on the True Skill Statistic (TSS) and Akaike Information Criterion (AIC) value. Two birds analyzed in this study are Ashambu Laughingthrush *Montecincla meridionalis* (ALT), a highly restricted-range species endemic to Agasthyamalai hills of the southern Western Ghats, and Nilgiri Pipit *Anthus nilghiriensis* (NP), which is endemic to Nilgiri and Palani-Anamalai hills of WG. Both are threatened, high-altitude habitat specialists. Different environmental variables were incorporated to generate the models for each of these species. Mean annual temperature (BIO 1) is identified as the most influencing variable for ALT, whereas the mean temperature of the coldest quarter (BIO 11) is the crucial one for NP.

Suitable habitats currently available for ALT and NP are estimated to be 303 km^2 and 1792 km^2, respectively. These habitats are further classified into highly relevant, moderately suitable and less suitable habitats as well. Future models predicted severe degradation and loss of suitable habitat for both species under various climate change scenarios. It is estimated that 2070s will lose 20%-76% of the suitable habitat of ALT under different emission or RCP scenarios. In the case of NP, a net loss of 40%-79% is estimated for various RCP scenarios. 82% of the

suitable habitat of NP and 20% of that of ALT come outside the boundary of the PA network.

Realignment of the protected area network of the WG considering suitable habitat of these birds, elevating their conservation status, collaborative effort for educating the public to ensure CO_2 and other greenhouse gas emission reduction, equitable sharing of resources and policy implementations are urgently needed to ensure the long-term conservation of these species.

ANNEXURES

9 APPENDIX

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

Species	Longitude	Latitude
ALT	77.2107	8.82927
ALT	77.21687	8.827843
ALT	77.21718	8.827496
ALT	77.21695	8.827659
ALT	77.21184	8.82941
ALT	77.2174	8.827395
ALT	77.21082	8.829418
ALT	77.19808	8.832059
ALT	77.21937	8.824478
ALT	77.23329	8.626594
ALT	77.17279	8.744785
ALT	77.17282	8.744761
ALT	77.36393	8.512117
ALT	77.38395	8.488717
ALT	77.34767	8.52282
ALT	77.48611	8.47583
ALT	77.36643	8.55008
ALT	77.35627	8.54773

Species	Longitude	Latitude
ALT	77.35497	8.540735
ALT	77.1824	8.7376
ALT	77.26101	8.588936
ALT	77.18068	8.739632
ALT	77.26069	8.588524
ALT	77.18099	8.73819
ALT	77.18503	8.73739
ALT	77.18756	8.737578
ALT	77.18873	8.737823
ALT	77.2607	8.588972
ALT	77.20084	8.701535
ALT	77.18836	8.736875
ALT	77.18349	8.737441
ALT	77.26003	8.589151
ALT	77.21274	8.654842
ALT	77.18072	8.738133
ALT	77.18017	8.739099
ALT	77.1802	8.738094

Species	Longitude	Latitude
ALT	77.18063	8.739465
ALT	77.19359	8.679557
ALT	77.17333	8.7427
ALT	77.17194	8.74111
ALT	77.1708	8.7422
ALT	77.16666	8.7433
ALT	77.17222	8.74527
ALT	77.17555	8.7388
ALT	77.19222	8.68166
ALT	77.19388	8.6775
ALT	77.19444	8.67972
ALT	77.19888	8.6775
ALT	77.20444	8.67583
ALT	77.20666	8.68194
ALT	77.20277	8.6725
ALT	77.20333	8.68722
ALT	77.25027	8.62166
ALT	77.24194	8.623611
ALT	77.24694	8.62611
ALT	77.24055	8.62805
ALT	77.21916	8.65
ALT	77.21944	8.66805
ALT	77.2075	8.6669
ALT	77.26388	8.58777

Species	Longitude	Latitude
ALT	77.26861	8.58194
ALT	77.26888	8.576944
ALT	77.27444	8.59138
ALT	77.2841	8.58944
ALT	77.27944	8.57888
ALT	77.27361	8.5675
ALT	77.29472	8.58416
ALT	77.28666	8.57027
ALT	77.28305	8.56166
ALT	77.44194	8.49916
ALT	77.4144	8.48416
ALT	77.41472	8.525
ALT	77.3877	8.5452
ALT	77.22194	8.815277
ALT	77.23	8.81
ALT	77.24305	8.8011
ALT	77.18333	8.73027
ALT	77.38277	8.529722
ALT	77.4008	8.52416
ALT	77.3532	8.521426
ALT	77.35558	8.518917
ALT	77.35468	8.520208
ALT	77.49173	8.37844
ALT	77.49374	8.377572

Species	Longitude	Latitude
ALT	77.49416	8.37871
ALT	77.49475	8.383931
ALT	77.48424	8.39256
ALT	77.48623	8.38732
ALT	77.5005	8.38217
ALT	77.49245	8.391414

Species	Longitude	Latitude
ALT	77.4887	8.375831
ALT	77.4961	8.376277
ALT	77.35624	8.515348
ALT	77.49038	8.37263
ALT	77.17865	8.736145
ALT	77.22647	8.65626

Species	Longitude	Latitude
NP	77.13561	10.04169
NP	77.139	10.04292
NP	77.13153	10.03926
NP	77.09654	10.04329
NP	77.09257	10.04682
NP	77.00915	10.05196
NP	77.10361	10.13306
NP	77.27135	10.13476
NP	77.27133	10.13489
NP	77.27201	10.1407
NP	77.03562	10.1428
NP	77.03637	10.14301
NP	77.03995	10.14309
NP	77.04124	10.1436
NP	77.04004	10.14371

Species	Longitude	Latitude
NP	77.0351	10.14666
NP	77.08229	10.14972
NP	77.05544	10.16475
NP	77.01555	10.17178
NP	77.02229	10.1731
NP	77.01491	10.17372
NP	77.0476	10.17377
NP	77.02276	10.17387
NP	77.05091	10.17447
NP	77.02478	10.17519
NP	77.06283	10.1776
NP	77.06256	10.17776
NP	77.16809	10.1778
NP	77.0419	10.178
NP	77.04219	10.17876

Species	Longitude	Latitude
NP	77.07089	10.18774
NP	77.08656	10.19014
NP	77.2732	10.20722
NP	77.07	10.21
NP	77.2662	10.2144
NP	77.07382	10.21745
NP	77.07073	10.21813
NP	77.07972	10.22019
NP	77.07675	10.22026
NP	77.07663	10.22089
NP	77.07708	10.22154
NP	77.06014	10.22617
NP	77.05	10.227
NP	77.04754	10.22743
NP	77.07767	10.22774
NP	77.05285	10.22818
NP	77.04152	10.22917
NP	77.05735	10.22931
NP	77.041	10.23
NP	77.03992	10.23145
NP	77.08435	10.27122
NP	77.10781	10.27538
NP	77.08914	10.28551
NP	77.06986	10.32292

Species	Longitude	Latitude
NP	77.07107	10.323
NP	77.05455	10.3276
NP	76.44871	11.19524
NP	76.58325	11.22611
NP	76.52244	11.23617
NP	76.56115	11.24836
NP	76.59078	11.29955
NP	76.54499	11.31923
NP	76.552	11.333
NP	76.59573	11.3416
NP	76.55663	11.34215
NP	76.56056	11.34245
NP	76.57075	11.3446
NP	76.54679	11.36706
NP	76.73369	11.3905
NP	76.63576	10.93666
NP	76.61957	10.94715
NP	76.71946	11.39103
NP	76.73586	11.40113
NP	76.77094	11.36964
NP	76.75417	11.37527
NP	76.75882	11.39051
NP	76.77639	11.39878
NP	76.7829	11.39056

Species	Longitude	Latitude
NP	76.74918	11.40532
NP	76.81945	11.36473
NP	76.835	11.43592
NP	76.77335	11.42324
NP	76.79973	11.47819
NP	76.71089	11.44192
NP	76.63121	11.38282
NP	76.56804	11.44652
NP	76.63525	11.4457
NP	76.50464	11.3981
NP	77.122	10.35993
NP	77.05947	10.34487
NP	77.03643	10.34021
NP	77.09267	10.31681
NP	77.11069	10.29877
NP	77.09	10.25194
NP	77.10317	10.2294
NP	76.59658	11.3411
NP	76.73072	11.40874
NP	76.73441	11.41271
NP	77.07073	10.27447
NP	77.23217	10.24513
NP	77.27662	10.2319
NP	77.25719	10.2285

Species	Longitude	Latitude
NP	77.26601	10.21819
NP	77.27125	10.22194
NP	77.11714	10.03418
NP	77.09988	10.04248
NP	77.01425	10.04955
NP	77.04176	10.14398
NP	77.03569	10.14236
NP	77.03204	10.14204
NP	77.02935	10.14197
NP	77.02359	10.14511
NP	77.02068	10.14231
NP	77.0409	10.14757
NP	77.0494	10.15164
NP	77.07522	10.13525
NP	77.085	10.13553
NP	77.09223	10.138
NP	77.09278	10.10487
NP	77.10026	10.10919
NP	77.24683	10.25083
NP	77.22122	10.23889
NP	77.23497	10.25507
NP	77.06283	10.32386
NP	76.46138	11.1897
NP	77.18796	10.09804

Species	Longitude	Latitude
NP	77.34808	10.28984
NP	76.4799	11.23246
NP	77.51692	10.25059
NP	76.69924	11.40279
NP	77.47673	10.23596
NP	76.59734	11.50546
NP	77.48108	10.23188
NP	76.72972	11.35418

Species	Longitude	Latitude
NP	76.69172	11.39611
NP	77.06168	10.16969
NP	76.60723	11.33018
NP	76.5535	11.25111
NP	76.79931	11.35667
NP	76.87104	11.45967
NP	76.57397	11.47946

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	˚C	$\frac{\sum_{i=1}^{i=12} Tavg_i}{12}$
BIO 2	Mean Diurnal Range	The mean of the monthly temperature ranges	˚C	$\frac{\sum_{i=1}^{i=12} Tmax_i - Tmin_i}{12}$
BIO 3	Isothermality	It quantifies how large the day-to-night temperatures oscillate relative to the summer-to-winter (annual) oscillations	˚C	$\frac{BIO\ 2}{BIO\ 7} \times 100$
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	˚C	$SD\{Tavg_1, \ldots, Tavg_{12}\}$
BIO 5	Max Temperature of Warmest Month	The maximum monthly temperature occurrence over a given year (time-series) or averaged span of years (normal)	˚C	$max\{Tavg_1, \ldots, Tavg_{12}\}$

BIO 6	Min Temperature of Coldest Month	The minimum monthly temperature occurrence over a given year (time-series) or averaged span of years (normal)	˙C	$min\{Tavg_1, \ldots, Tavg_{12}\}$
BIO 7	Temperature Annual Range	A measure of temperature variation over a given period	˙C	$BIO\ 5 - BIO\ 6$
BIO 8	Mean Temperature of Wettest Quarter	This quarterly index approximates mean temperatures that prevail during the wettest season	˙C	$\frac{\sum_{i=1}^{i=3} Tavg_i}{3} \left\{ \begin{matrix} \text{Where monthly} \\ \text{temperature} \\ \text{averages are based} \\ \text{on the three selected} \\ \text{months of } Q_{PPTmax} \end{matrix} \right.$ $Q_{PPTmax} = \max \left[\left[\begin{matrix} \sum_{i=1}^{i=3} PPT_i, \\ \sum_{i=2}^{i=4} PPT_i, \\ \ldots\ldots\ldots, \\ \sum_{i=11}^{i=1} PPT_i, \\ \sum_{i=12}^{i=2} PPT_i, \end{matrix} \right]\right] \left\{ \begin{matrix} \text{Where precipitation} \\ \text{is evaluated for} \\ \text{12 consicutive} \\ \text{sets of 3 months.} \\ \text{The last two sets} \\ \text{span two years} \\ \text{for time} - \text{series} \\ \text{data} \end{matrix} \right.$

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

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

			⋮	$Q_{T_{min}} = \min \left\| \begin{matrix} \sum_{i=1}^{i=3} Tavg_i, \\ \sum_{i=2}^{i=4} Tavg_i, \\ \cdots\cdots\cdots \\ \sum_{i=11}^{i=1} Tavg_i, \\ \sum_{i=12}^{i=2} Tavg_i, \end{matrix} \right\| \left\{ \begin{matrix} \textit{Where temperatures} \\ \textit{are evaluated for} \\ \textit{12 consicutive} \\ \textit{sets of 3 months.} \\ \textit{The last two sets} \\ \textit{span two years} \\ \textit{for time − series} \\ \textit{data} \end{matrix} \right.$
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}	$\max([PPT_i, \dots\dots, PPT_{12}])$
BIO 14	Precipitation of Driest Month	This index identifies the total precipitation that prevails during the driest month	kg m^{-2}	$\min([PPT_i, \dots\dots, PPT_{12}])$
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	kg m^{-2}	$\frac{SD\{PPT_1, \dots, PPT_{12}\}}{1 + \left(BIO\ 12/_{12}\right)} \times 100$

		monthly total precipitation to the mean monthly total precipitation		
BIO 16	Precipitation of Wettest Quarter	This quarterly index approximates total precipitation that prevails during the wettest quarter	kg m^{-2}	$\max\left[\left[\begin{array}{c}\sum_{i=1}^{i=3} PPT_i, \\ \sum_{i=2}^{i=4} PPT_i, \\ \ldots\ldots\ldots, \\ \sum_{i=11}^{i=1} PPT_i, \\ \sum_{i=12}^{i=2} PPT_i,\end{array}\right]\right] \left\{\begin{array}{c}\textit{Where precipitation} \\ \textit{is evaluated for 12} \\ \textit{consecutive sets} \\ \textit{of 3 months.} \\ \textit{The last two} \\ \textit{sets span} \\ \textit{two years for} \\ \textit{time -- series data}\end{array}\right.$
BIO 17	Precipitation of Driest Quarter	This quarterly index approximates total precipitation that prevails during the driest quarter	kg m^{-2}	$\min\left[\left[\begin{array}{c}\sum_{i=1}^{i=3} PPT_i, \\ \sum_{i=2}^{i=4} PPT_i, \\ \ldots\ldots\ldots, \\ \sum_{i=11}^{i=1} PPT_i, \\ \sum_{i=12}^{i=2} PPT_i,\end{array}\right]\right] \left\{\begin{array}{c}\textit{Where precipitation} \\ \textit{is evaluated for 12} \\ \textit{consecutive sets} \\ \textit{of 3 months.} \\ \textit{The last two} \\ \textit{sets span} \\ \textit{two years for} \\ \textit{time -- series data}\end{array}\right.$

BIO 18	Precipitation of Warmest Quarter	This quarterly index approximates total precipitation that prevails during the warmest quarter	kg m^{-2}	$\sum_{i=1}^{i=3} PPT_i \begin{cases} \textit{Where monthly} \\ \textit{precipitation values} \\ \textit{are based on the} \\ \textit{three selected months} \\ \textit{of } Q_{Tmax} \end{cases}$
BIO 19	Precipitation of Coldest Quarter	This quarterly index approximates total precipitation that prevails during the coldest quarter	kg m^{-2}	$\sum_{i=1}^{i=3} PPT_i \begin{cases} \textit{Where monthly} \\ \textit{precipitation values} \\ \textit{are based on the} \\ \textit{three selected months} \\ \textit{of } Q_{Tmin} \end{cases}$
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_wet	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

i. Ashambu Laughingthrush

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
altitude	evi_avg	-0.01359
altitude	evi_dry	0.097812
altitude	evi_wet	-0.10558
aspect	evi_avg	0.060332
aspect	evi_dry	0.130203
aspect	evi_wet	0.044775
aspect	altitude	-0.04863
bio1	evi_avg	0.005171
bio1	evi_dry	-0.1086
bio1	evi_wet	0.093288
bio1	altitude	-0.99566
bio1	aspect	0.06158
bio1	slope	-0.27083
bio1	bio19	-0.63202
bio1	bio18	-0.52075
bio1	bio17	-0.68005
bio1	bio16	-0.77343
bio1	bio15	0.287955

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio1	bio14	-0.6555
bio1	bio13	-0.64918
bio1	bio12	-0.50673
bio1	bio11	0.999166
bio1	bio10	0.999554
bio1	bio9	0.999346
bio1	bio8	0.996878
bio1	bio7	-0.25031
bio1	bio6	0.986369
bio1	bio5	0.980697
bio1	bio4	0.275967
bio1	bio3	-0.68547
bio1	bio2	-0.34782
bio10	evi_avg	0.003587
bio10	evi_dry	-0.10731
bio10	evi_wet	0.088159
bio10	altitude	-0.9954
bio10	aspect	0.057826

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio10	slope	-0.26738
bio10	bio19	-0.62586
bio10	bio18	-0.52266
bio10	bio17	-0.66817
bio10	bio16	-0.76893
bio10	bio15	0.281297
bio10	bio14	-0.64865
bio10	bio13	-0.64541
bio10	bio12	-0.50244
bio10	bio11	0.998365
bio11	evi_avg	0.020058
bio11	evi_dry	-0.09148
bio11	evi_wet	0.110651
bio11	altitude	-0.99537
bio11	aspect	0.071465
bio11	slope	-0.27634
bio11	bio19	-0.65418
bio11	bio18	-0.50069
bio11	bio17	-0.69831
bio11	bio16	-0.7668
bio11	bio15	0.2745
bio11	bio14	-0.67694

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio11	bio13	-0.63705
bio11	bio12	-0.4868
bio12	evi_avg	0.330523
bio12	evi_dry	0.56258
bio12	evi_wet	0.184642
bio12	altitude	0.496223
bio12	aspect	0.255318
bio12	slope	0.169509
bio12	bio19	-0.06308
bio12	bio18	0.86421
bio12	bio17	0.202179
bio12	bio16	0.831663
bio12	bio15	-0.57714
bio12	bio14	-0.01733
bio12	bio13	0.916313
bio13	evi_avg	0.236258
bio13	evi_dry	0.445397
bio13	evi_wet	0.082528
bio13	altitude	0.642026
bio13	aspect	0.230951
bio13	slope	0.285737
bio13	bio19	0.164425

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio13	bio18	0.805135
bio13	bio17	0.346993
bio13	bio16	0.923862
bio13	bio15	-0.31862
bio13	bio14	0.200029
bio14	evi_avg	-0.17675
bio14	evi_dry	-0.1828
bio14	evi_wet	-0.24411
bio14	altitude	0.651818
bio14	aspect	-0.33173
bio14	slope	0.262317
bio14	bio19	0.989883
bio14	bio18	-0.10445
bio14	bio17	0.932746
bio14	bio16	0.46799
bio14	bio15	0.059374
bio15	evi_avg	-0.29157
bio15	evi_dry	-0.43356
bio15	evi_wet	-0.23738
bio15	altitude	-0.27759
bio15	aspect	-0.04607
bio15	slope	-0.0065

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio15	bio19	0.130781
bio15	bio18	-0.57734
bio15	bio17	-0.16352
bio15	bio16	-0.31094
bio16	evi_avg	0.168805
bio16	evi_dry	0.34906
bio16	evi_wet	0.028867
bio16	altitude	0.763599
bio16	aspect	0.083269
bio16	slope	0.308851
bio16	bio19	0.446007
bio16	bio18	0.68619
bio16	bio17	0.603351
bio17	evi_avg	-0.11391
bio17	evi_dry	-0.05939
bio17	evi_wet	-0.23769
bio17	altitude	0.672039
bio17	aspect	-0.32422
bio17	slope	0.279141
bio17	bio19	0.925627
bio17	bio18	0.043577
bio18	evi_avg	0.27376

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio18	evi_dry	0.473218
bio18	evi_wet	0.162924
bio18	altitude	0.516445
bio18	aspect	0.296202
bio18	slope	0.147107
bio18	bio19	-0.15101
bio19	evi_avg	-0.21909
bio19	evi_dry	-0.23753
bio19	evi_wet	-0.28682
bio19	altitude	0.628846
bio19	aspect	-0.34212
bio19	slope	0.262106
bio2	evi_avg	-0.01729
bio2	evi_dry	0.150955
bio2	evi_wet	-0.19883
bio2	altitude	0.34416
bio2	aspect	-0.13576
bio2	slope	0.211018
bio2	bio19	0.426023
bio2	bio18	0.165774
bio2	bio17	0.66828
bio2	bio16	0.442605

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio2	bio15	-0.41723
bio2	bio14	0.477666
bio2	bio13	0.381533
bio2	bio12	0.361625
bio2	bio11	-0.3656
bio2	bio10	-0.32512
bio2	bio9	-0.35141
bio2	bio8	-0.35862
bio2	bio7	0.991251
bio2	bio6	-0.49617
bio2	bio5	-0.16101
bio2	bio4	0.769169
bio2	bio3	0.871162
bio3	evi_avg	-0.04101
bio3	evi_dry	0.114892
bio3	evi_wet	-0.20294
bio3	altitude	0.683153
bio3	aspect	-0.15043
bio3	slope	0.28142
bio3	bio19	0.69145
bio3	bio18	0.240886
bio3	bio17	0.8226

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio3	bio16	0.62633
bio3	bio15	-0.27869
bio3	bio14	0.745673
bio3	bio13	0.512174
bio3	bio12	0.381615
bio3	bio11	-0.70283
bio3	bio10	-0.66908
bio3	bio9	-0.69212
bio3	bio8	-0.69565
bio3	bio7	0.809531
bio3	bio6	-0.78792
bio3	bio5	-0.54933
bio3	bio4	0.471549
bio4	evi_avg	-0.13943
bio4	evi_dry	-0.08462
bio4	evi_wet	-0.25718
bio4	altitude	-0.2736
bio4	aspect	-0.16022
bio4	slope	0.06863
bio4	bio19	0.177485
bio4	bio18	-0.32295
bio4	bio17	0.320619

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio4	bio16	-0.11429
bio4	bio15	-0.0637
bio4	bio14	0.196837
bio4	bio13	-0.14031
bio4	bio12	-0.13929
bio4	bio11	0.249774
bio4	bio10	0.298774
bio4	bio9	0.265074
bio4	bio8	0.251508
bio4	bio7	0.813262
bio4	bio6	0.119049
bio4	bio5	0.442193
bio5	evi_avg	0.011029
bio5	evi_dry	-0.07076
bio5	evi_wet	0.066205
bio5	altitude	-0.97739
bio5	aspect	0.042501
bio5	slope	-0.24344
bio5	bio19	-0.59456
bio5	bio18	-0.49759
bio5	bio17	-0.58666
bio5	bio16	-0.71576

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio5	bio15	0.198781
bio5	bio14	-0.60849
bio5	bio13	-0.59335
bio5	bio12	-0.43981
bio5	bio11	0.977162
bio5	bio10	0.985061
bio5	bio9	0.980172
bio5	bio8	0.976461
bio5	bio7	-0.05793
bio5	bio6	0.936238
bio6	evi_avg	0.011369
bio6	evi_dry	-0.12181
bio6	evi_wet	0.124108
bio6	altitude	-0.98194
bio6	aspect	0.082175
bio6	slope	-0.28877
bio6	bio19	-0.66369
bio6	bio18	-0.50685
bio6	bio17	-0.74816
bio6	bio16	-0.78992
bio6	bio15	0.335588
bio6	bio14	-0.6943

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio6	bio13	-0.66325
bio6	bio12	-0.52564
bio6	bio11	0.989116
bio6	bio10	0.982124
bio6	bio9	0.986773
bio6	bio8	0.985935
bio6	bio7	-0.40451
bio7	evi_avg	-0.00452
bio7	evi_dry	0.161692
bio7	evi_wet	-0.18238
bio7	altitude	0.246327
bio7	aspect	-0.1236
bio7	slope	0.186585
bio7	bio19	0.340082
bio7	bio18	0.144332
bio7	bio17	0.600556
bio7	bio16	0.382339
bio7	bio15	-0.43513
bio7	bio14	0.390624
bio7	bio13	0.340295
bio7	bio12	0.34849
bio7	bio11	-0.26734

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio7	bio10	-0.2269
bio7	bio9	-0.25286
bio7	bio8	-0.2602
bio8	evi_avg	0.028332
bio8	evi_dry	-0.07885
bio8	evi_wet	0.115394
bio8	altitude	-0.99268
bio8	aspect	0.085404
bio8	slope	-0.27444
bio8	bio19	-0.67044
bio8	bio18	-0.48425
bio8	bio17	-0.71103
bio8	bio16	-0.75653
bio8	bio15	0.277302
bio8	bio14	-0.69098
bio8	bio13	-0.61563
bio8	bio12	-0.4678
bio8	bio11	0.997999
bio8	bio10	0.996268
bio8	bio9	0.997783
bio9	evi_avg	0.017193
bio9	evi_dry	-0.09235

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio9	evi_wet	0.105338
bio9	altitude	-0.99552
bio9	aspect	0.068408
bio9	slope	-0.27394
bio9	bio19	-0.64881
bio9	bio18	-0.50264
bio9	bio17	-0.69044
bio9	bio16	-0.76481
bio9	bio15	0.272984
bio9	bio14	-0.67161
bio9	bio13	-0.63565
bio9	bio12	-0.48614
bio9	bio11	0.999623
bio9	bio10	0.998926
evi_dry	evi_avg	0.903947
evi_wet	evi_avg	0.86647
evi_wet	evi_dry	0.706116
slope	evi_avg	0.040273
slope	evi_dry	0.048053
slope	evi_wet	-0.01318
slope	altitude	0.26912
slope	aspect	-0.05832

ii. Nilgiri Pipit

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
altitude	bio7	-0.28151
altitude	bio16	0.063017
aspect	bio7	-0.15962
aspect	bio16	0.329714
aspect	altitude	0.028382
aspect	evi_avg	-0.0366
aspect	evi_wet	-0.0651
aspect	slope	0.011533
aspect	evi_dry	0.102902
aspect	bio9	-0.02365
aspect	bio8	-0.0263
aspect	bio6	-0.01111
aspect	bio5	-0.05446
aspect	bio4	-0.18249
aspect	bio3	-0.06931
aspect	bio2	-0.2159
aspect	bio19	0.179268
aspect	bio18	0.226119
aspect	bio17	-0.30137
bio1	bio7	0.322825
bio1	bio16	-0.11264

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio1	altitude	-0.9949
bio1	evi_avg	0.144523
bio1	evi_wet	0.133431
bio1	slope	-0.05369
bio1	evi_dry	-0.00327
bio1	bio9	0.99442
bio1	bio8	0.998014
bio1	bio6	0.992758
bio1	bio5	0.996834
bio1	bio4	0.638116
bio1	bio3	-0.64104
bio1	bio2	-0.03541
bio1	bio19	0.338165
bio1	bio18	-0.48386
bio1	bio17	-0.47674
bio1	aspect	-0.03756
bio10	bio7	0.341159
bio10	bio16	-0.14284
bio10	altitude	-0.99188
bio10	evi_avg	0.139791
bio10	evi_wet	0.134379

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio10	slope	-0.05356
bio10	evi_dry	-0.01691
bio10	bio9	0.991293
bio10	bio8	0.99741
bio10	bio6	0.987715
bio10	bio5	0.998837
bio10	bio4	0.664407
bio10	bio3	-0.62486
bio10	bio2	0.000354
bio10	bio19	0.311635
bio10	bio18	-0.49153
bio10	bio17	-0.45887
bio10	aspect	-0.0469
bio10	bio1	0.999163
bio11	bio7	0.292051
bio11	bio16	-0.05689
bio11	altitude	-0.99549
bio11	evi_avg	0.132194
bio11	evi_wet	0.114098
bio11	slope	-0.0588
bio11	evi_dry	0.002495
bio11	bio9	0.999595

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio11	bio8	0.992439
bio11	bio6	0.997483
bio11	bio5	0.987933
bio11	bio4	0.561962
bio11	bio3	-0.71278
bio11	bio2	-0.12254
bio11	bio19	0.378242
bio11	bio18	-0.50419
bio11	bio17	-0.51799
bio11	aspect	-0.02273
bio11	bio1	0.994512
bio11	bio10	0.991187
bio11	bio15	0.208671
bio11	bio14	-0.51562
bio11	bio13	-0.07297
bio11	bio12	-0.19807
bio12	bio7	-0.5419
bio12	bio16	0.96986
bio12	altitude	0.203056
bio12	evi_avg	0.048812
bio12	evi_wet	-0.17026
bio12	slope	0.050615

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio12	evi_dry	0.388692
bio12	bio9	-0.20369
bio12	bio8	-0.25726
bio12	bio6	-0.16191
bio12	bio5	-0.31753
bio12	bio4	-0.73113
bio12	bio3	-0.18709
bio12	bio2	-0.78045
bio12	bio19	0.467974
bio12	bio18	0.527286
bio12	bio17	-0.26407
bio12	aspect	0.329611
bio12	bio1	-0.25705
bio12	bio10	-0.28633
bio12	bio15	0.756231
bio12	bio14	-0.25354
bio12	bio13	0.969384
bio13	bio7	-0.43985
bio13	bio16	0.998443
bio13	altitude	0.080008
bio13	evi_avg	0.054396
bio13	evi_wet	-0.15606

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio13	slope	0.038403
bio13	evi_dry	0.393298
bio13	bio9	-0.0758
bio13	bio8	-0.13434
bio13	bio6	-0.03592
bio13	bio5	-0.18873
bio13	bio4	-0.6427
bio13	bio3	-0.28653
bio13	bio2	-0.77998
bio13	bio19	0.591893
bio13	bio18	0.44175
bio13	bio17	-0.42841
bio13	aspect	0.342751
bio13	bio1	-0.12938
bio13	bio10	-0.15958
bio13	bio15	0.877559
bio13	bio14	-0.41503
bio14	bio7	-0.0666
bio14	bio16	-0.40025
bio14	altitude	0.49717
bio14	evi_avg	0.0674
bio14	evi_wet	0.039374

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio14	slope	0.087558
bio14	evi_dry	-0.00681
bio14	bio9	-0.52001
bio14	bio8	-0.47869
bio14	bio6	-0.52541
bio14	bio5	-0.45982
bio14	bio4	-0.00022
bio14	bio3	0.646689
bio14	bio2	0.429047
bio14	bio19	-0.56442
bio14	bio18	0.329257
bio14	bio17	0.982128
bio14	aspect	-0.30395
bio14	bio1	-0.4811
bio14	bio10	-0.46473
bio14	bio15	-0.69983
bio15	bio7	-0.17831
bio15	bio16	0.875167
bio15	altitude	-0.19663
bio15	evi_avg	0.071308
bio15	evi_wet	-0.07171
bio15	slope	-0.01085

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio15	evi_dry	0.32776
bio15	bio9	0.210205
bio15	bio8	0.146608
bio15	bio6	0.239744
bio15	bio5	0.112517
bio15	bio4	-0.37472
bio15	bio3	-0.47887
bio15	bio2	-0.68654
bio15	bio19	0.68612
bio15	bio18	0.142395
bio15	bio17	-0.70718
bio15	aspect	0.306573
bio15	bio1	0.160712
bio15	bio10	0.133869
bio16	bio7	-0.44669
bio17	bio7	-0.11496
bio17	bio16	-0.413
bio17	altitude	0.495025
bio17	evi_avg	0.06149
bio17	evi_wet	0.051737
bio17	slope	0.094975
bio17	evi_dry	-0.02665

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio17	bio9	-0.52292
bio17	bio8	-0.47484
bio17	bio6	-0.52489
bio17	bio5	-0.45522
bio17	bio4	0.04585
bio17	bio3	0.690072
bio17	bio2	0.464859
bio17	bio19	-0.58521
bio17	bio18	0.339202
bio18	bio7	-0.3851
bio18	bio16	0.44714
bio18	altitude	0.475146
bio18	evi_avg	0.107069
bio18	evi_wet	-0.07268
bio18	slope	0.097872
bio18	evi_dry	0.342771
bio18	bio9	-0.51089
bio18	bio8	-0.4751
bio18	bio6	-0.46533
bio18	bio5	-0.51438
bio18	bio4	-0.30989
bio18	bio3	0.583711

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio18	bio2	-0.0733
bio18	bio19	-0.01731
bio19	bio7	-0.17487
bio19	bio16	0.593741
bio19	altitude	-0.36885
bio19	evi_avg	0.157173
bio19	evi_wet	0.061926
bio19	slope	0.013259
bio19	evi_dry	0.331167
bio19	bio9	0.385129
bio19	bio8	0.324589
bio19	bio6	0.413717
bio19	bio5	0.291593
bio19	bio4	-0.23079
bio19	bio3	-0.51911
bio19	bio2	-0.64478
bio2	bio7	0.519333
bio2	bio16	-0.78264
bio2	altitude	0.100083
bio2	evi_avg	-0.03673
bio2	evi_wet	0.106733
bio2	slope	0.015326

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio2	evi_dry	-0.26956
bio2	bio9	-0.11817
bio2	bio8	-0.03196
bio2	bio6	-0.15368
bio2	bio5	0.030057
bio2	bio4	0.726911
bio2	bio3	0.579489
bio3	bio7	-0.09869
bio3	bio16	-0.28835
bio3	altitude	0.673666
bio3	evi_avg	0.031586
bio3	evi_wet	0.057858
bio3	slope	0.084105
bio3	evi_dry	0.02125
bio3	bio9	-0.71545
bio3	bio8	-0.63554
bio3	bio6	-0.69896
bio3	bio5	-0.62471
bio3	bio4	0.070432
bio4	bio7	0.543962
bio4	bio16	-0.63088
bio4	altitude	-0.58445

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio4	evi_avg	0.082244
bio4	evi_wet	0.17353
bio4	slope	-0.01274
bio4	evi_dry	-0.18193
bio4	bio9	0.564859
bio4	bio8	0.63799
bio4	bio6	0.545372
bio4	bio5	0.680849
bio5	bio7	0.370164
bio5	bio16	-0.17293
bio5	altitude	-0.98751
bio5	evi_avg	0.130141
bio5	evi_wet	0.134654
bio5	slope	-0.05606
bio5	evi_dry	-0.03543
bio5	bio9	0.988589
bio5	bio8	0.994918
bio5	bio6	0.981684
bio6	bio7	0.253638
bio6	bio16	-0.0189
bio6	altitude	-0.99543
bio6	evi_avg	0.15002

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
bio6	evi_wet	0.122721
bio6	slope	-0.05463
bio6	evi_dry	0.031767
bio6	bio9	0.996893
bio6	bio8	0.99033
bio8	bio7	0.318336
bio8	bio16	-0.11852
bio8	altitude	-0.99317
bio8	evi_avg	0.139167
bio8	evi_wet	0.128366
bio8	slope	-0.05337
bio8	evi_dry	-0.0085
bio8	bio9	0.99201
bio9	bio7	0.29913
bio9	bio16	-0.06
bio9	altitude	-0.99481
bio9	evi_avg	0.132663
bio9	evi_wet	0.117928
bio9	slope	-0.06008
bio9	evi_dry	0.002101
evi_avg	bio7	-0.01434
evi_avg	bio16	0.066323

Layer 1	Layer 2	Pearson's Correlation Coefficient (R)
evi_avg	altitude	-0.14748
evi_dry	bio7	-0.16546
evi_dry	bio16	0.403096
evi_dry	altitude	-0.01571
evi_dry	evi_avg	0.847386
evi_dry	evi_wet	0.584857
evi_dry	slope	0.10358
evi_wet	bio7	0.078809
evi_wet	bio16	-0.15296
evi_wet	altitude	-0.12852
evi_wet	evi_avg	0.855863
slope	bio7	-0.0513
slope	bio16	0.040649
slope	altitude	0.05456
slope	evi_avg	0.09801
slope	evi_wet	0.06374