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Identifying Climatic Niche Shift of The Endemic Avifauna of Western Ghats

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Abstract

Climate change poses a threat to endemic species by altering their habitats and reducing their chances of survival. These species, uniquely adapted to their environments, face the risk of extinction as climate patterns shift rapidly. Western Ghats is one of the global biodiversity hotspots and home to diverse endemic species. Despite the unique species present in the Western Ghats, limited studies have attempted to understand the climate-related risks to them. This study employs an ensemble modeling approach to assess the current distribution and predict the future climatic niches of 29 endemic bird species in the Western Ghats. Results indicate a substantial loss of climatic niche for most species under both scenarios, with certain species experiencing a decline of more than 70% in their climatic niche. The four laughingthrush species are exceptionally vulnerable, potentially losing up to 99% of their suitable climatic niche. Furthermore, we emphasize the critical importance of mid-altitude regions with Wet Evergreen Forest in the Western Ghats, as potential climate-change refugia for these species. Ensuring that the temperature remains below 2°C is imperative, necessitating urgent conservation efforts, including habitat preservation. This study provides essential insights to inform conservation strategies and underscores the necessity for continued research and proactive measures to safeguard the Western Ghats' unique biodiversity in the face of escalating climate change challenges.

Keywords: Species distribution modelling, Biodiversity hotspot, Climate change, Endemic species

Introduction

Climate change stands as a significant factor contributing to the global decline in biodiversity (Parmesan & Yohe, 2003; Warren & Seifert, 2011; Bellard *et al*., 2012; Pacifici *et al*., 2015; Urban 2015). The climate factors that influence the geographic distribution of a species, known as its 'Climate Envelopes' (Guisan & Zimmermann, 2000; Pearson & Dawson, 2003), play a pivotal role in shaping the spatial presence of species. If a species is unable to disperse to areas with favorable climatic conditions, it undergoes either shifts in its geographic ranges or faces local extinction (Guisan & Zimmermann, 2000; Bellard *et al.*, 2012).

Small-ranged endemic species are vulnerable to climate change as they have a limited geographic range, limited dispersal capacity, specialized environmental niche, low population, and poor adaptive capacity (Chichorro *et al.*, 2019; Staude *et al.*, 2020). These species will face a higher climate risk as they may not have any climate refugia under small ranges (Catford *et al.*, 2012; Lucas *et al.*, 2019; IPCC, 2019). Additionally, endemic species often have lower genetic diversity, limiting their capacity to adapt to new conditions (López-Pujol *et al.,* 2013). In contrast, species with large geographic ranges are less vulnerable to climate change and are likely to have climate refugia within their ranges (Lucas *et al.*, 2019).

Birds are highly sensitive to change in climate conditions, and their responses have been well-documented, making climate change a significant concern for birds worldwide (King *et al*., 2013). Research has shown that globally, approximately one-eighth of all bird species face a significant risk of extinction in the coming decades, which will necessitate human intervention to conserve them (King *et al.*, 2013). Furthermore, if global temperatures rise by 3.5˚C, about 600 to 900 species of birds are projected to become extinct by 2100, with the tropics accounting for 89% of these extinctions (Scridel *et al.*, 2018). In India, 18 of the 79 endemic bird species are vulnerable, as per the IUCN Red List database. Of these 79 species, 23% are globally threatened, 3% lack sufficient data, 19% are nearly threatened, 34% are of least concern, and the status of 20% of the species is unknown (Jathar & Rahmani, 2006).

The Western Ghats, recognized as one of India's four global biodiversity hotspots (Myers, 2000) and one of the twelve endemic bird areas, boasts a rich avifauna exhibiting diverse habitat preferences, ranging from generalist species thriving in orchards and tea plantations to specialized ones exclusive to high-elevation shola woods and grasslands (Ramesh *et al*., 2017). This region harbours 29 endemic bird species (Table 1), including one Critically Endangered, three Endangered, two Near Threatened, six Vulnerable, and seventeen Least Concerned species (Ramesh *et al.*, 2017; BirdLife International, 2020). Notably, some species inhabit the transition zone between the Western Ghats and the Deccan plateau, extending beyond the confines of the Western Ghats (Supplementary Figure S1). Among the 508 bird species recorded in this region, 29 endemics, such as the Malabar grey hornbill (*Ocyceros griseus*), Malabar barbet (*Psilopogon malabaricus*), and Nilgiri wood-pigeon (*Columba elphinstonii*), are predominantly habitat specialists with limited geographic ranges and lower climate tolerance levels, rendering them particularly susceptible to the impacts of climate change (Chang *et al.*, 2018). Considering the importance of endemic species in the Western Ghats, there are hardly any studies focusing on their climate risk (Ramesh *et al*., 2017). This study aims to identify the current suitable climatic niche of all endemic bird species of the Western Ghats and how different climatic variables can influence or alter the climatic niche of these species.

Materials and Methods

Study area:

The Western Ghats (Figure 1) is an extensive mountain range stretching 1,600 km along the western coast of the Indian peninsula. Covering an area of 160,000 km^2, it typically reaches heights of approximately 1,200 m. Spanning across the states of Gujarat, Maharashtra, Goa, Karnataka, Kerala, and Tamil Nadu, this region is acknowledged as one of India's four biodiversity hotspots and holds the designation of an Endemic Bird Area (EBA).

The climate of the Western Ghats varies with altitude and proximity to the equator. In lower elevations, a tropical and humid climate prevails, influenced by the nearby sea. With increasing elevation, a more temperate climate is observed, with temperatures averaging around 15 °C at higher elevations of 1,500 m in the north and 2,000 m in the south. The average annual temperature is 20 °C in the south and 24 °C in the north (Mudbhatkal & Amai, 2018). Significant monsoon rainfall is received in the Western Ghats with the total annual precipitation ranging from 2550 mm to 3750 mm. Evergreen rainforests are surrounded by small patches of tropical semi-evergreen rainforest. In areas with lower and more seasonal rainfall, tropical moist deciduous forests thrive, primarily on the eastern side of the Ghats. Wet temperate forests are situated at elevations above approximately 1,500 m in the southern hills. Sholas, or patches of evergreen forest, exist in sheltered sites on rolling montane grassland, while subtropical broadleaf hill forests flourish at elevations between 1,000 and 1,700 m (Champion & Seth, 1968; Whitmore, 1984).

The Western Ghats boast a rich biodiversity, including more than 7,402 angiosperm species, 1,814 gymnosperm species, 508 bird species, 227 reptile and amphibian species, 290 freshwater fish species, and 6,000 insect species. Notably, at least 325 globally endangered species find their habitat in this region (Myers *et al.*, 2000; Dahanukar *et al.*, 2004).

Species Occurrence Data:

GBIF (Global Biodiversity Information Facility), the world's largest global network and data infrastructure, supported by governments worldwide, offers open-access data covering all life forms on earth. Through the compilation of numerous datasets from across the globe, GBIF provides a wealth of information. In our study, we obtained 622,702 occurrence records (presence-only) for 29 endemic bird species in the Western Ghats region from the beginning of the year 2000 to the end of 2020, sourced from GBIF (GBIF.org, accessed on January 30, 2023, GBIF Occurrence Download: 10.15468/dl.aj3b6x). To ensure data accuracy, post-download records underwent verification procedures aimed at minimizing locational inaccuracies. To improve model performance (Hu *et al.*, 2020), we used the 'spatially rarefy tool' in SDMtool box (Brown, 2014) in ArcGIS 10.8 and retained a single record per 1 km^2 grid to remove duplicate points and minimise potential spatial clusters in the presence locations (Supplementary Figure S1).

Climatic Data:

We selected eight bioclimatic variables (Table 2) recommended by Warren *et al.*, 2013, that represent annual, seasonality, and extreme trends; and influence the species present in the tropical and subtropical regions (Sarkar & Talukdar, 2023). Selected variables represents annual mean temperature (Bio 1), annual precipitation (Bio 12), maximum temperature of warmest month (Bio 5), precipitation of the wettest quarter (Bio 16), minimum temperature of the coldest month (Bio 6), precipitation the driest quarter (Bio 17), temperature seasonality (Bio 4) and precipitation seasonality (Bio 15) (Table 2). We downloaded Near-current climatic scenario (1970-2000) and end-century climatic scenarios (2081-2100) from Worldclim (Fick & Hijmans, 2017) at ~1km^2 resolution. For future projection, we considered Shared Socioeconomic Pathway (SSP) based bioclimatic layers SSP2-4.5 and SSP5-8.5. These future bioclimatic layers are CMIP6 based and projects possible future climatic conditions in 2100 compared to pre-industrial period. The SSPs also provide several possibilities for population demographics, urbanization, and economic growth. (Riahi *et al.*, 2017). Scenarios SSP2-4.5 and SSP5-8.5 reflect rising levels of global warming, with mean temperatures changing by 2 and 4°C from 1995-2014 period to 2100, respectively (Riahi *et al.*, 2017).

Identification of suitable climatic niche:

We used four modeling algorithms from the 'biomod2' R package v3.5-1 (Thuiller *et al*., 2021), including Generalised Linear Model (GLM; McCullagh & Nelder, 1989), Generalized Additive Model (GAM; Hastie & Tibshirani, 1990), Random Forest (RF; Breiman 2001), and Maximum Entropy (MAXENT; Phillips *et al.*, 2004).

Figure 1: Location of the Western Ghats

The employed modeling strategies were designed to complement each other's strengths and weaknesses. For instance, GLMs are limited in capturing intricate nonlinear relationships, prompting the utilization of GAMs due to their flexibility in modeling nonlinear responses. Nonetheless, GAMs are susceptible to overfitting if regularization measures are not appropriately implemented. To address this concern, RFs were employed, given their resilience against overfitting and ability to furnish variable importance metrics. However, RF models may exhibit reduced interpretability compared to GLMs or GAMs. Consequently, for ease of interpretation, the Maxent model was selected, as it presents results in a straightforward presence-absence format. For each species, each ensemble model consisted of 20 runs using occurrence data that was split into two subsets, with 70% (training) and 30% (testing) data. A total of 10,000 randomly selected pseudo-absence points were used in each species model. We trained the Models in present condition and projected to future SSP scenarios for identifying suitable future climate niche.

Table 1: Details of the studies species along with their scientific names, and IUCN status

Sl no.	Species	Scientific name	IUCN status
1	Sahyadri sunbird	*Aethopyga vigorsii*	LC
2	Nilgiri pipit	*Anthus nilghiriensis*	VU
3	Rufous babbler	*Argya subrufa*	LC
4	Grey-headed Bulbul	*Brachypodius priocephalus*	NT
5	Nilgiri Woodpigeon	*Columba elphinstonii*	VU
6	White-bellied Blue-flycatcher	*Cyornis pallidipes*	LC
7	White-bellied Treepie	*Dendrocitta leucogastra*	LC
8	Nilgiri Flowerpecker	*Dicaeum concolor*	LC
9	Nilgiri Flycatcher	*Eumyias albicaudatus*	LC
10	Black-and-orange Flycatcher	*Ficedula nigrorufa*	LC
11	Malabar Lark	*Galerida malabarica*	LC
12	Wynaad Laughingthrush	*Garrulax delesserti*	LC
13	Crimson-backed Sunbird	*Leptocoma minima*	LC
14	Nilgiri Laughingthrush	*Montecincla cachinnans*	EN
15	Palani Laughingthrush	*Montecincla fairbanki*	NT
16	Banasura Laughingthrush	*Montecincla jerdoni*	EN
17	Ashambu Laughingthrush	*Montecincla meridionale*	VU
18	Malabar Grey Hornbill	*Ocyceros griseus*	VU
19	Malabar Barbet	*Psilopogon malabaricus*	LC
20	White-cheeked Barbet	*Psilopogon viridis*	LC
21	Malabar Parakeet	*Psittacula columboides*	LC
22	Flame-throated Bulbul	*Rubigula gularis*	LC
23	Broad-tailed Grassbird	*Schoenicola platyurus*	VU
24	White-bellied Sholakili	*Sholicola albiventris*	VU
25	Nilgiri Sholakili	*Sholicola major*	EN
26	Malabar Starling	*Sturnia blythii*	LC
27	Malabar Woodshrike	*Tephrodornis sylvicola*	LC
28	Grey-fronted Green-pigeon	*Treron affinis*	LC
29	Nilgiri Thrush	*Zoothera neilgherriensis*	CR

Table 2: Climatic variables used in the study to develop present and future distribution of the 29 bird species.

Data Type	Variables
Climatic data from Worldclim (1970-2000 and 2081-2100)	Bio1- Annual mean temperature
	Bio4- Temperature Seasonality
	Bio5- Maximum temperature of the warmest month
	Bio6- Minimum temperature of the coldest month
	Bio12- Annual Precipitation
	Bio15- Precipitation Seasonality
	Bio16- Precipitation of wettest quarter
	Bio17- Precipitation of driest quarter

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Cross-validation procedure was used to evaluate the model accuracy (Fielding & Bell, 1997). Two main evaluation measures were used to assess the final models: the area under the receiver operating characteristic (ROC) curve, or AUC, and the true skill statistic (TSS). The TSS has an advantage over the Kappa statistic in that it is unaffected by the size of the validation set or the prevalence of the species (Allouche *et al.*, 2006). The TSS ranges from 1 to +1, with +1 denoting agreement between predictions and observations and values of 0 or below denoting agreement no better than random partitioning (Landis & Koch, 1977). Despite this advantage, the Kappa statistic was also retained along with the TSS and AUC. AUC is a commonly used measure to assess the prediction accuracy of Ecological Niche Models (ENMs). It typically falls between 0.5 and 1.0, and models with an AUC of >0.9 are considered to be robust (Mousavi & Erfanian, 2020).

The final models with a TSS score of >0.7 were taken into consideration for creating the ensemble model of each species using the weighted mean suitability (weighted by TSS values of the models). For further analysis, binary presence-absence rasters were created based on the TSS cut-off threshold, which maximized the sensitivity and specificity (Table 3) (Liu *et al.*, 2013).

Species Dispersal, Richness, Refugia, and Centroid Shift

We considered partial future dispersal of the modelled species to provide a more realistic scenario. The dispersal limit for the future climatic scenario was set at 150 km from the present suitable climate niche using the "Limit dispersal in future SDMs" tool in the SDMToolbox v2.5 (Brown, 2014).

To determine species richness, the previously derived binary presence-absence rasters were extracted based on the dispersal limit and used with the 'Estimate Richness and Endemism' function in the SDMToolbox 2.5 (Brown, 2014). The 'Minus' tool in ArcGIS Pro v3.0.3 (ESRI, 2022) was then used to calculate the difference between current and future richness, which helped identify the areas that are sustaining more species and are stable, as well as those that are not.

To determine how much area each species will gain or lose in the future, the 'Distribution Changes using Binary SDMs' tool in SDMToolbox v2.5 (Brown, 2014) was used with the same binary data. The 'Centroid Changes' function in SDMToolbox v2.5 (Brown, 2014) was used to calculate the direction of each species' shift in the climatic niche. Areas which were able to sustain >75% of modeled species richness in the future; those areas were reclassified as a binary raster to determine the climate-change refugia (Warren *et al.*, 2013). Output maps were created using ArcGIS Pro v3.0.3 (ESRI, 2022).

Results

Model Score and Important Climatic Variables

The ROC-AUC, TSS and Kappa scores were used to evaluate the model performance; the range of all the statistics was between 0.7 and 1 (Supplementary Table S1). These scores suggest that the models performed robustly. Out of the eight bioclimatic variables selected, the annual precipitation, the minimum temperature of the coldest month, and maximum temperature of the warmest month contributed highest for most of the species. In contrast, precipitation of the driest month and precipitation of the coldest month had the least contribution (Supplementary Figure S2).

Present Distribution

Current suitable climatic niche was calculated for all the twenty-nine endemic bird species. The highest climatically suitable areas were found for Malabar lark (199,411.89 km^2), followed by the white-cheeked barbet (155,293.23 km^2) likely because of their wide distribution range. Among the other species which do not have ranges beyond the Western Ghats, the crimson-backed sunbird (134,862.41 km^2), followed by the grey-fronted green-pigeon (133,785.28 km^2), have the highest climatically suitable areas. Models predicted low climatically suitable areas for two species of laughingthrushes; the Banasura laughingthrush (1,680.59 km^2), followed by the Ashambu Laughingthrush (3,986.96 km^2). Calculation of species richness for the endemic birds depicted the highest species richness at the mid-elevation areas of Nilgiris, Annamalai, and Agastyamalai hills. Whereas the Northern Western Ghats and the Eastern Nilgiri have the lowest species richness (Figure 2).

Future Distribution under SSP2-4.5 and SSP5-8.5

Richness Change

Future climatic niche of most of the endemic birds of the Western Ghats will contract, especially if the temperature is increased by 4°C (Figure 3). Similar to the present scenario, the highest richness of the modelled species is projected at the mid-elevation areas i.e., 900-1800m, surrounding the peaks of Nilgiri, Annamalai, and Agastyamalai hills. The Sahyadri region of the Northern Western Ghats and the Eastern parts of the Nilgiri hills will experience a significant decline in species richness (Figure 3).

Richness change (Figure 4) in the projected future scenarios reveals that areas with comparatively lower elevation, *i.e.*, ≤900 m, such as the seaward side of the Western Ghats range, the western coast, the Palghat gap, and the high-elevation areas (1800-2600 m), including the peaks and highlands, will be unable to maintain a suitable climatic niche for the modelled species (Figure 5).

Distribution Change

The Banasura laughingthrush is projected to face a range contraction of 99.40%, followed by the Ashambu laughingthrush with an 83.53% contraction if the temperature increases by 4°C. If the temperature increases by 2°C, the Banasura laughingthrush will face a 79.73% range contraction, followed by the Nilgiri laughingthrush with a 63.89% contraction. Interestingly, the Nilgiri sholakili is the only species that is projected to face a climatic niche expansion of 139.94% and 132.79% if the temperature increases by 4°C and 2°C, respectively. However ecologically, it is not possible because there are several other factors which can restrict a species range. Nilgiri thrush and broad-tailed grassbird were projected to face a 46.66% and 19% range contraction, respectively, at 2°C increased temperature, but a range expansion of 16.71% and 2.17%, respectively, at 4°C increased temperature. Also, the Malabar starling is projected to face a 2.98% range expansion if the temperature is increased by 2°C but a 58.9% range contraction if the temperature is increased by 4°C (Figure 5).

Centroid Shift

At a 2°C temperature increase, the major shift in the centroid is projected towards the north and northeast. At 4°C, the shift towards the south, southeast, and southwest is associated with species facing range expansion (*e.g.*, Nilgiri Sholakili and broad-tailed grassbird). Conversely, the shift towards the north, northeast, and northwest is

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Table 3: Merged TSS cut-off generated from ensemble models to create binary maps.

Species	Merged cut-off
Sahyadri Sunbird	433
Nilgiri Pipit	253
Rufous Babbler	382
Grey-headed Bulbul	411
Nilgiri Woodpigeon	272
White-bellied Blue-flycatcher	341
White-bellied Treepie	414
Nilgiri Flowerpecker	423
Nilgiri Flycatcher	333
Black-and-orange Flycatcher	303
Malabar Lark	293
Wynaad Laughingthrush	373
Crimson-backed Sunbird	373
Nilgiri Laughingthrush	394
Palani Laughingthrush	308
Banasura Laughingthrush	466
Ashambu Laughingthrush	292
Malabar Grey Hornbill	433
Malabar Barbet	433
White-cheeked Barbet	545
Malabar Parakeet	443
Flame-throated Bulbul	423
Broad-tailed Grassbird	252
White-bellied Sholakili	490
Nilgiri Sholakili	61
Malabar Starling	443
Malabar Woodshrike	474
Grey-fronted Green-pigeon	251
Nilgiri Thrush	272

associated with species facing range contraction, such as the Banasura laughingthrush and Ashambu laughingthrush (Figure 6).

Climate-change Refugia
The southern Western Ghats, including the Nilgiri, Annamalai, and Agastyamalai, will function as the climate-change refugia for these endemic species. At 4°C, the area under refugia will decrease in the northern areas (Figure 7).

Discussion

An ensemble modeling approach using biomod2 was employed to map the current distribution and predict the future climatic niche of 29 endemic birds of the Western Ghats. The models projected the climatically suitable regions of these 29 species with two warming scenarios. The models were prepared using eight bioclimatic variables and presence-only data of the species. The results indicate a significant loss of more than 50% at the end of the century for 18 of the 29 species if the temperature increases by 2°C and for 22 of the 29 species if the temperature increases by 4°C from the 1995-2000 scenario (Figure 4).

The four laughingthrushes studied are projected to lose at least 70% of their climatic niche if the temperature increases by 4°C, and the Banasura laughingthrush is projected to lose 99% of its suitable climatic niche. These species prefer dense and moist vegetation with thick along with exhibiting site fidelity towards the shola forest (Chandran & Praveen, 2013). A study by Chaturvedi et al. in 2010 projected that the tropical evergreen forest will undergo a change of more than 50% due to climate change, and the Shola forests *(i.e.*, high montane forests of the Western Ghats) are currently decreasing due to human activities (Gupta, 1990). This loss of habitats can further augment decline of these endemic species.

The Nilgiri sholakili bird is projected to gain >100% of its current climatic niche at the end of the century. The species has a very fragmented habitat shaped by the Shola Forest in a small area (BirdLife International, 2023). The output showed a result that displayed the suitable climatic niche, which is much broader than the realized niche of a species. Thus, although Nilgiri sholakili will have the highest suitable climatic niche among all the modelled species, their realized niche will be much smaller due to their specialized habitat preference (*i.e.,* the shola forests).

Earlier studies found that species richness declines with increased elevation (Grinnell & Storer, 1924; Whittaker, 1952, 1960; McCain, 2009); and birds and non-flying small mammals have the highest richness at mid-elevations due to stable climatic conditions (Grinnell *et al.,* 1930; McCain, 2009). Similarly, in this study, it has been observed that at the end of the century, the mid-altitude region (*i.e.*, 900-1800m) of the Western Ghats with Wet Evergreen Forest can act as climate-change refugia for most of the studied species.

Species projected to have a range expansion or comparatively low range contraction, is shifting toward the Southern direction. In the future, the arid and semi-arid region of India will expand at a rapid rate, and the expansion will take place at the Northern Western Ghats also (Ramarao et al., 2018). This justifies the southward movement as the species will try to escape the expansion of arid regions in the northern western ghats. This will also be the reason for the presence of climate-change refugia at the Southernmost part of the Western Ghats.

The high values of AUC-ROC, TSS, and Kappa do not guarantee that ENMs accurately capture the complexity of the climatic niche, as these models cannot consider all biotic and abiotic factors. However, even with these limitations, the study meets the ENM best practices standards outlined by Araújo *et al.* (2019).

The endemic bird species of the Western Ghats face threats from habitat degradation and loss, particularly since they are confined to a small region throughout the year. Climate change will exacerbate these threats, directly and indirectly impacting their populations. As these species are endemic, they are unlikely to disperse much under the future climate scenario, resulting in a narrower realized niche. Protecting the mid-latitude regions of the Southern Western Ghats should be a priority as these areas are projected to sustain higher species

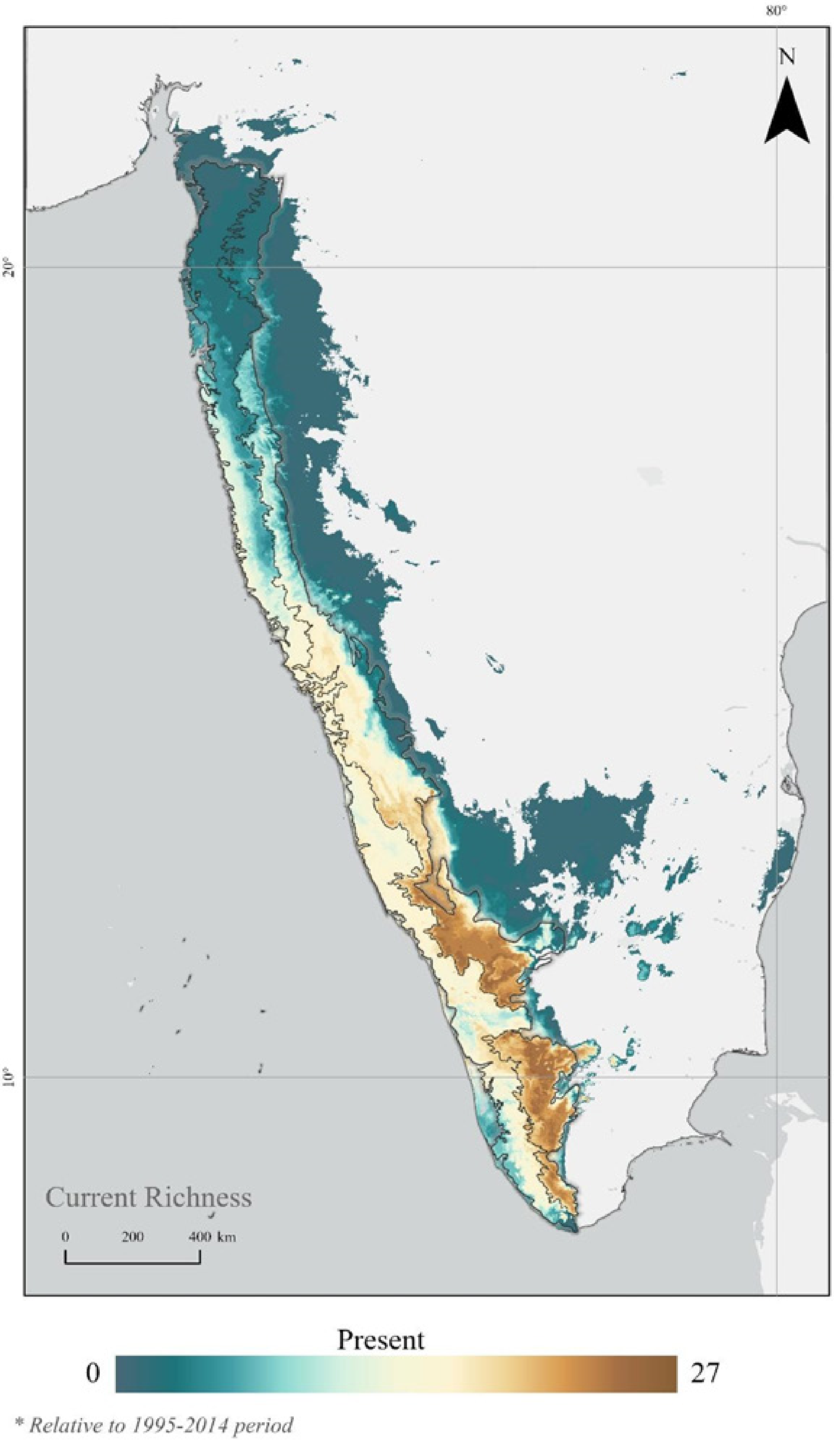

Figure 2: Present species richness for the 29 endemic birds of Western Ghats.

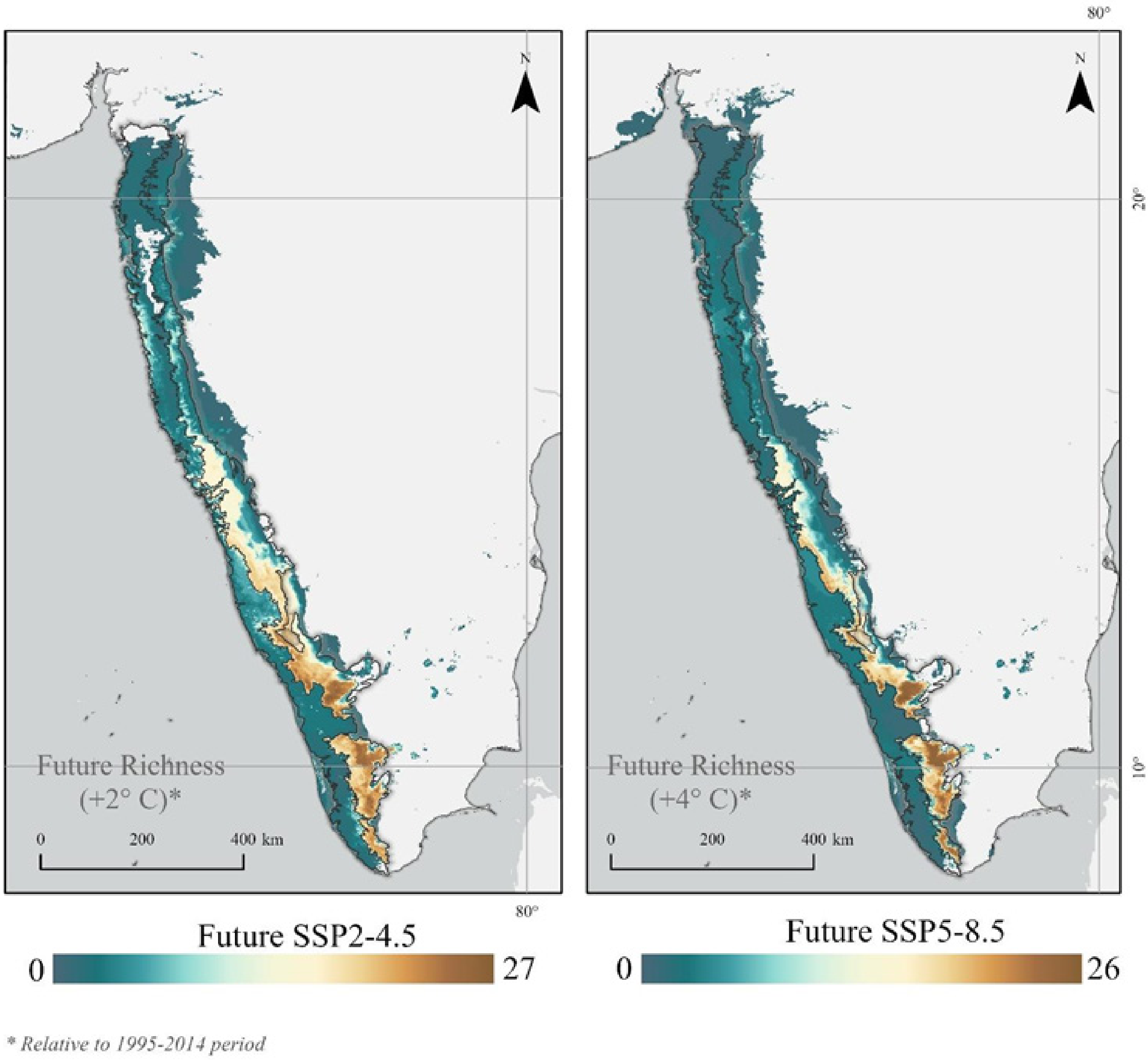

Figure 3: Future species richness for the 29 endemic birds of Western ghats in different warming scenarios (SSP2-4.5 (~2°C) and SSP5-8.5 (~4°C)).

richness, and these are the only areas that will be working as the refugia for these species.

The 29 endemic bird species in the Western Ghats have different IUCN statuses, ranging from 'Endangered' to 'Critically Endangered,' indicating their vulnerability to extinction. Therefore, maintaining the temperature increase well below 2°C (SSP2-4.5) is necessary to conserve their climatic niche.

The study is the first to analyze how the climatic niche of endemic bird species in the Western Ghats' biogeographic zone may change in two different warming scenarios. By identifying projected range shifts and a temperature threshold of 2 °C increase under the SSP245 scenario, the study provides valuable information that can provide insights into conservation strategies for these species.

Conclusion

Our study, utilizing an ensemble modeling approach, comprehensively assesses the current distribution and predicts the future climatic niches of 29 endemic bird species in the Western Ghats. The results underscore the significant and impending threat posed by climate change to these unique and vulnerable species, with projections indicating substantial habitat loss, particularly under a scenario of 4°C temperature increase. The four laughingthrush species are particularly at risk, facing potential losses of up to 99% of their suitable climatic niche. Furthermore, our findings highlight the utmost importance of mid-altitude regions within the Western Ghats, especially those with Wet Evergreen Forest, as potential climate-change refugia for these species. This research has excluded some pertinent parameters because of the spatial scale employed. These factors encompass the potential spread of disease pathogens and pests, inter-species

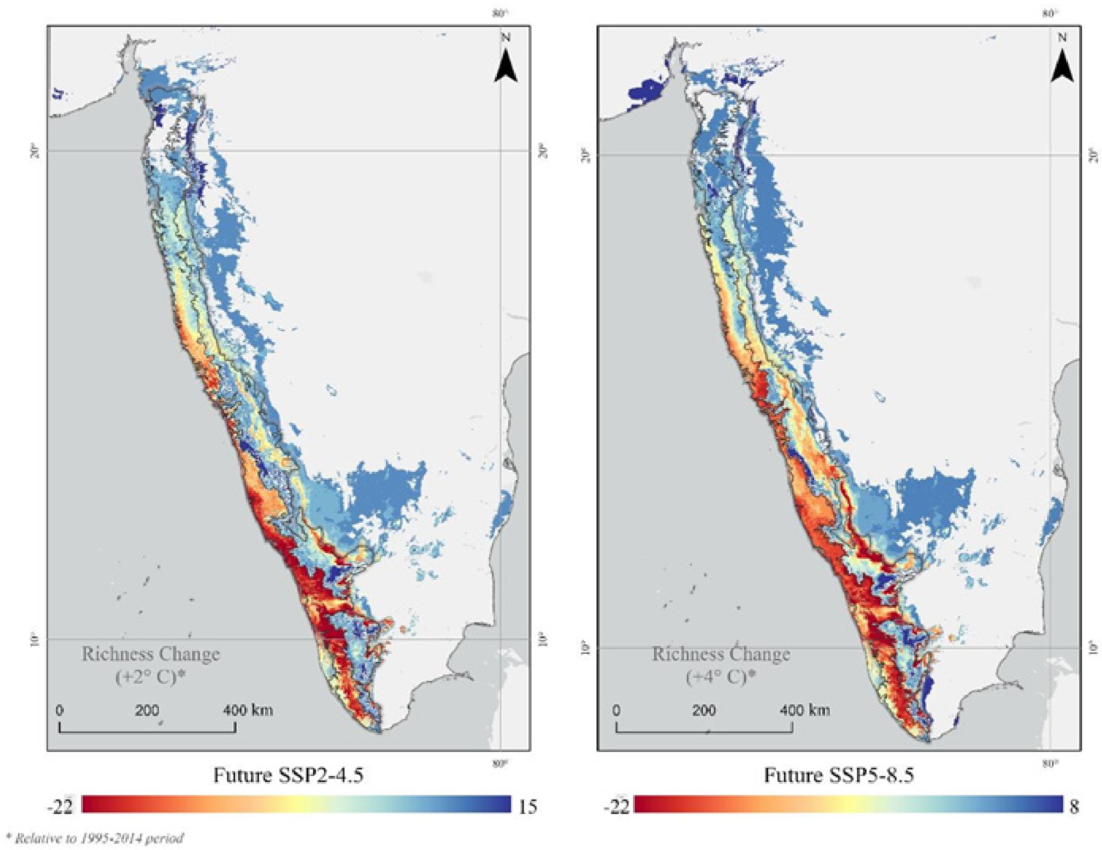

Figure 4: Change in species richness under future climatic scenario (SSP2-4.5 (~2°C) and SSP5-8.5 (~4°C)). A positive value denotes increase in species richness, whereas a negative value denotes richness decline.

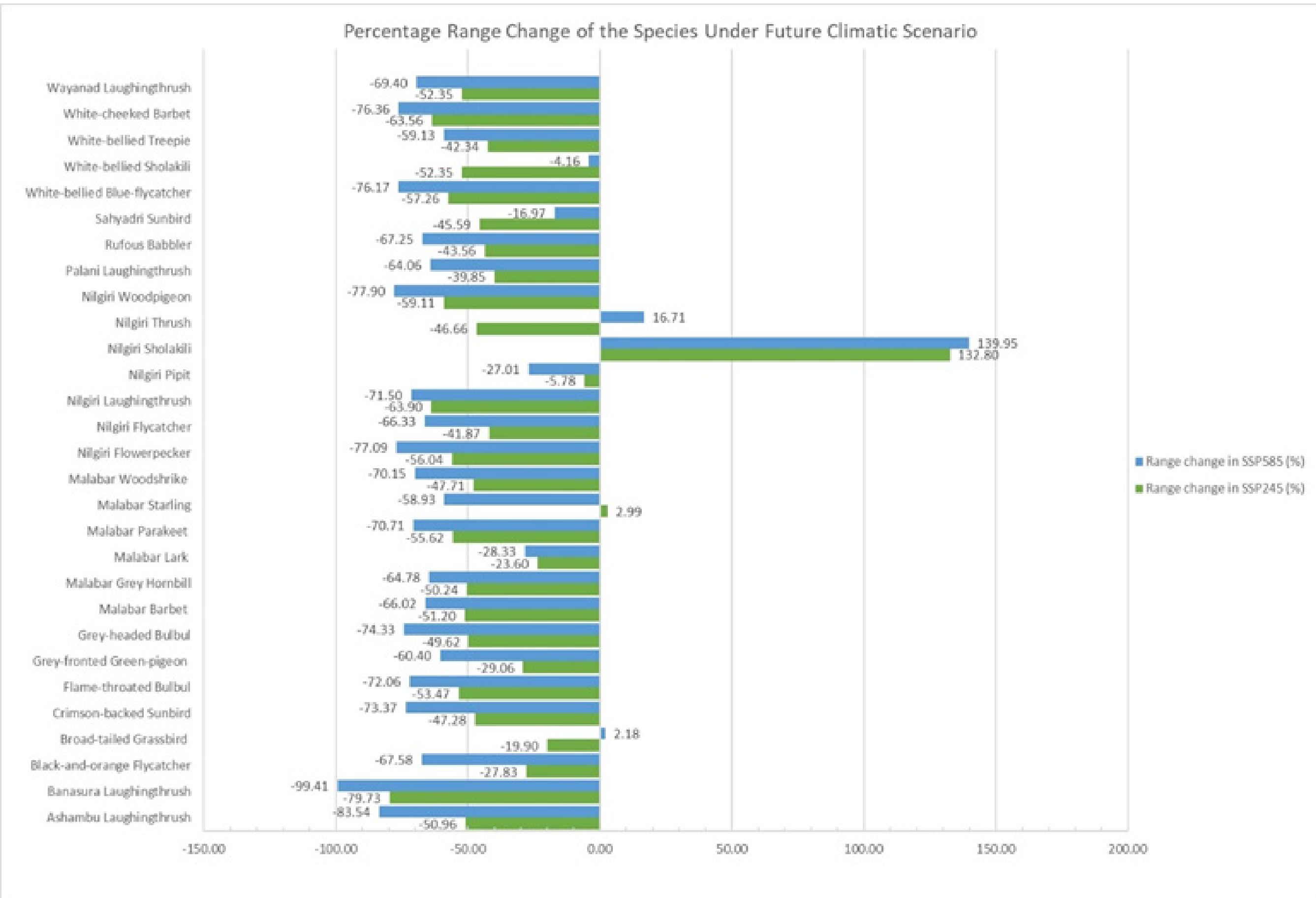

Figure 5: Range change of the endemic species under future climatic scenario

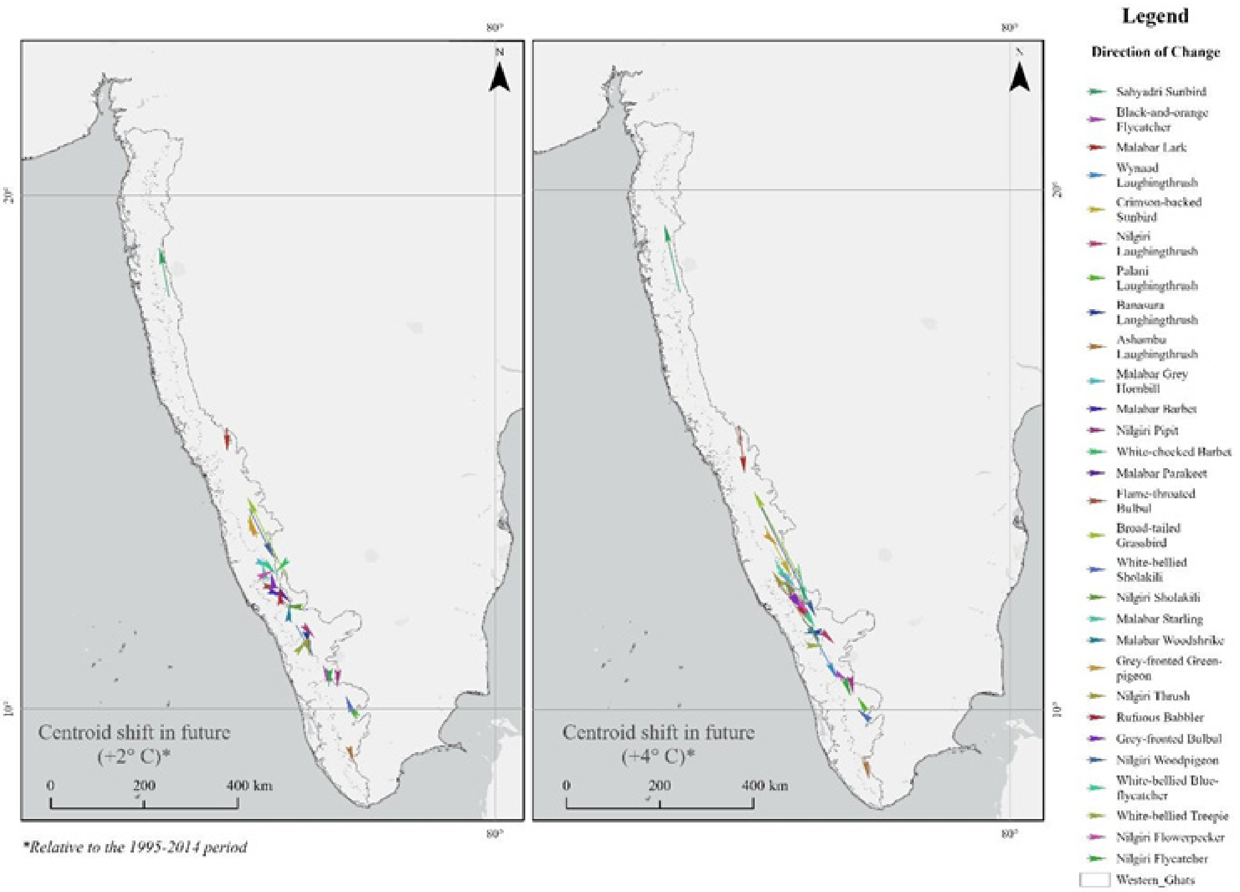

Figure 6: Centroid shift in the distribution in different warming scenarios (SSP2-4.5 (~2°C) and SSP5-8.5 (~4°C))

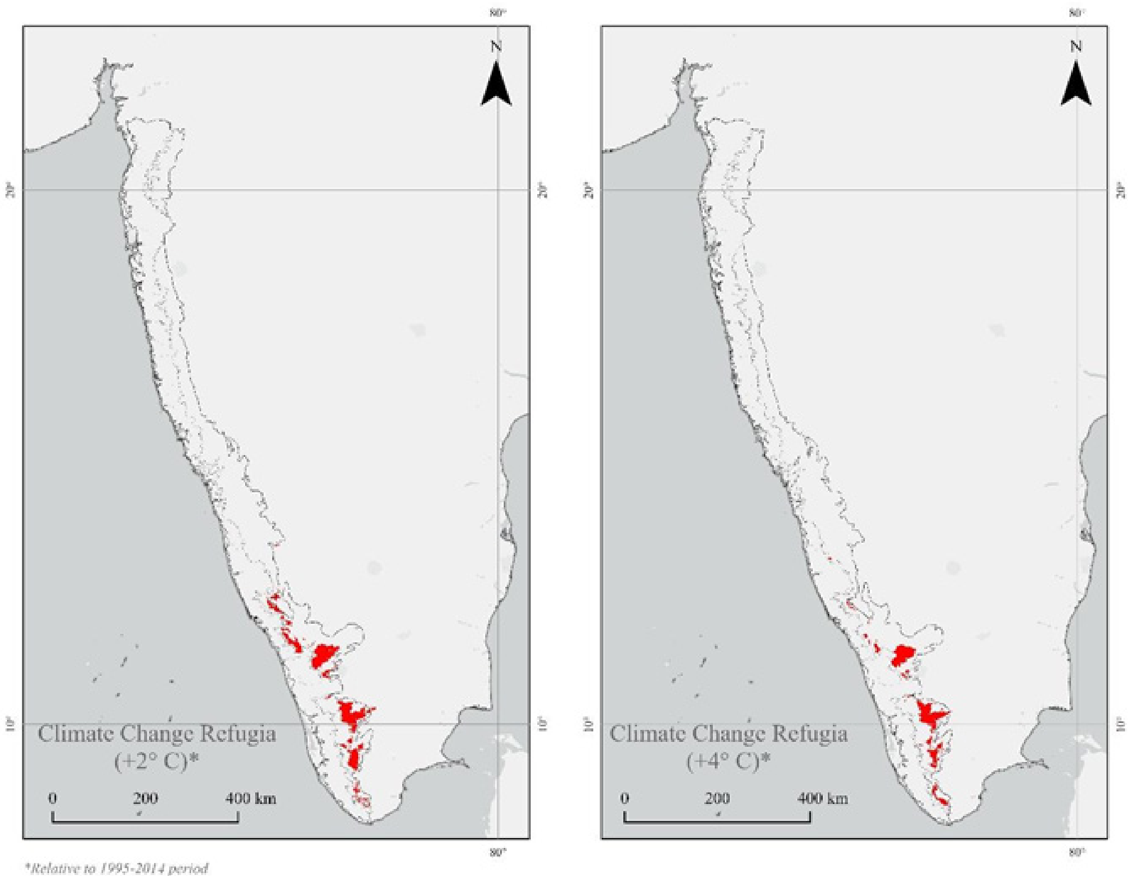

Figure 7: Climate change refugia for the endemic birds of Western Ghats in different warming scenarios (SSP2-4.5 (~2°C) and SSP5-8.5 (~4°C)).

interactions (such as food availability, predator-prey relationships, and competitive interactions), and the impacts of extreme climatic events.

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TO DOWNLOAD SUPPLEMENTARY MATERIAL CLICK [HERE]

CONFLICT OF INTEREST
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

DATA AVAILABILITY
The original contributions generated for the study are included in the article, further inquiries can be directed to the corresponding author/s.

AUTHORS' CONTRIBUTION
All authors have contributed equally to the paper.

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