Impact of climate change on two high-altitude restricted and endemic flycatchers of the Western Ghats, India

E. R. Sreekumar* and P. O. Nameer

Department of Wildlife Science, College of Forestry, Kerala Agricultural University, Thrissur 680 656, India

Climate change has been influencing bird species in different ways. Some documented changes include reduction in geographic range, decline in abundance and changes in the seasonality of migratory bird species in spring after overwintering in the tropics. We undertook a study on two species of high-elevation dependant, restricted-range flycatchers: Black-and-orange Flycatcher (BOF) *Ficedula nigrorufa* (Jerdon, 1839) and Nilgiri Flycatcher (NIF) *Eumyias albicaudatus* (Jerdon, 1840), to determine how they respond to the predicted climate change scenarios. We used 194 and 300 independent occurrence points for BOF and NIF to develop climate models and understand the species responses to climate change scenarios using MaxEnt algorithm. We also used isothermality, mean temperature of coldest quarter and slope for developing the BOF model. For NIF, we used isothermality, mean temperature of coldest quarter, precipitation of driest month, precipitation of warmest quarter, slope and enhanced vegetation index. The mean temperature of coldest quarter (BIO 11) was the most crucial variable influencing climate suitability for both the species. The model predicted the current extent of occurrence of 6532 sq. km as suitable for BOF and 12,707 sq. km for NIF, within their ranges. However, only 27% and 24% of the existing suitable area of BOF and NIF respectively, falls within the protected area network in the Western Ghats. Future predictions suggest suitable area loss to the tune of 20–31% for BOF and 36–46% for NIF by 2050.

Keywords: Biodiversity hotspots, climate change, habitat loss, species distribution modelling.

ANTHROPOGENIC climate change and increased environmental degradation have put millions of species at risk of extinction[1]. According to a recent report of the Intergovernmental Panel for Climate Change (IPCC), anthropogenic activities will cause global temperature to rise by 1.2°C between 2030 and 2052 compared to pre-industrial levels[2]. Erratic environmental conditions, decline in species abundances and widespread extinctions are some of the significant predicted effects of climate change[3,4]. An estimated 4–8% of the vertebrate species from across the world would lose half of their current suitable habitats if global temperature increases by 1.5–2°C (ref. 2). Therefore, climate change threatens the global biodiversity and ultimately the structure and ecosystem functioning[3,5,6].

Mountain ecosystems, in particular, are more sensitive to climate change and are expected to experience unprecedented rates of warming during the 21st century[7]. The climate on mountains changes rapidly with elevation over a relatively short vertical distance, a feature unique to these ecosystems[8]. Hence these ecosystems are valuable indicators of climate change[9]. The oscillating climate and unique floral structure in the montane ecosystems provide special microclimatic conditions and habitat for the species, and such montane ecosystems are known as 'sky islands'[10,11]. The Western Ghats (WG), considered as one of the 36 biodiversity hotspots in the world[12], is situated in southwest India and consists of such sky islands. Palakkad Gap is the major discontinuity in the entire stretch of the 1600 km long WG. Since 2012, WG is also a World Heritage Site[13], and two hill ranges in the region (Nilgiri Hills and Agasthyamalai Hills) have been recognized as Biosphere Reserves by the United Nations Educational, Scientific and Cultural Organization (UNESCO)[14,15]. The WG mountain range exhibits high endemism with several species restricted to a narrow elevational range[16]. This specialized habitat is now deteriorating due to changing climatic conditions and anthropogenic activities[17–19]. Under the looming threat of global warming and climate change-driven habitat loss, it is vital to assess the fate of habitat specialists of WG, so that remedial conservation strategies can be planned.

Black-and-orange Flycatcher (BOF; *Ficedula nigrorufa*) and Nilgiri Flycatcher (NIF; *Eumyias albicaudatus*) are monotypic species endemic to the southern WG and confined to higher elevations. BOF prefers the understorey of shola forests, especially *Strobilanthes* and bamboo thickets, among the stunted evergreen forest patches in the sky islands of WG and distributed above ~700 m altitude, but more common around 1500 m and above[20,21]. The NIF is also found above ~600 m elevation but more frequently above 1200 m (ref. 22). Degraded forests and plantations of timber, tea, coffee and cardamom adjacent

*For correspondence. (e-mail: sreekumarcof@gmail.com)

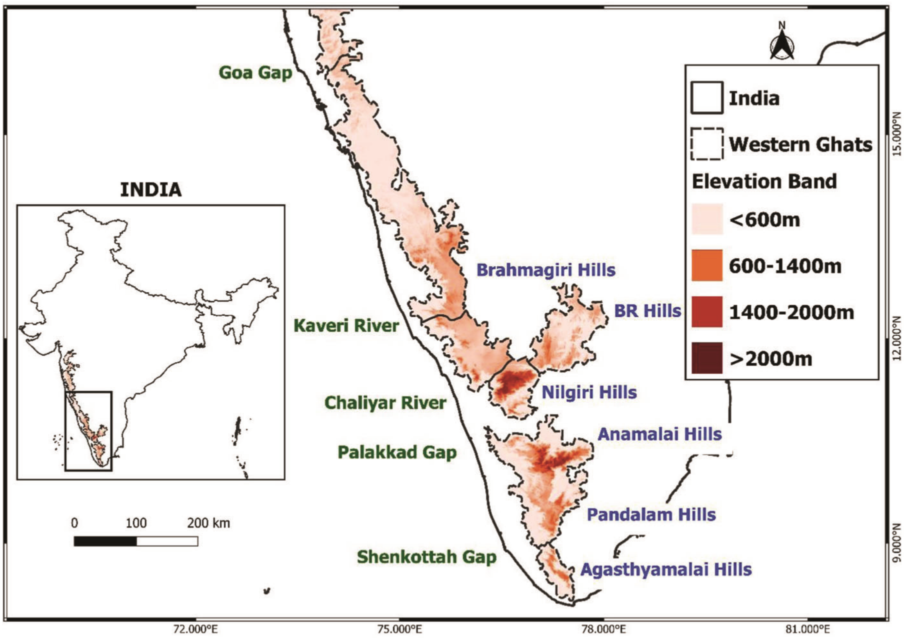

Figure 1. Landscapes and elevation bands of southern Western Ghats, India.

to the forest areas are also considered suitable habitats. NIF mainly feeds on invertebrates; however, it also consumes fruits and berries of *Vaccinium* spp., *Syzygium* spp., *Cestrum* spp., etc.[21]. Both these flycatchers are categorized as 'Least Concern' (LC) according to the IUCN Redlist[23,24] and fall under 'moderate' conservation concern according to the current state of India's Birds report[25].

It is essential to recognize the effect of climate change on endemic species because of their restricted distribution and specific habitat requirements[26]. Species distribution models (SDMs) are practical tools to understand the relationship between species occurrence and environmental factors[27,28]. SDMs also help determine the previously unknown areas of a species from the known species occurrence points and predictor variables[29–31]. Understanding the spatial distribution and future changes in the distribution of a species would be helpful for long-term conservation, and the SDM is a valuable tool for the same[32].

The main objectives of this study are: (a) To determine the environmental variables that influence the distribution pattern of BOF and NIF. (b) To determine the extent of suitable areas of BOF and NIF in WG. (c) To predict future changes in the climatic suitability of the habitats of BOF and NIF across WG under different climate change scenarios for 2050s using species distribution modelling.

Materials and methods

Background

The selection of background area is critical in SDM studies for better predictive power and model performance. The background area should contain suitable habitats for the taxa in question and consider the species' ability to dispersal. In this study, we have selected the southern Western Ghats (SWG) (8°–13.5°N and 75°–77.5°E) as the background in which the entire distribution of both species is included (Figure 1). The Brahmagiri Hills, Nilgiri Hills, Biligiri Rangana Hills (BR Hills), Anamalai Hills, Pandalam Hills and Agasthyamalai Hills are significant landscapes within SWG. The highest peak in WG, the 'Anamudi' (2695 m altitude), is in the Anamalai Hills. The high-elevation locations (above 1400 m) of SWG support a unique montane habitat known as shola forests, a mosaic of forests restricted to the mountain folds and surrounded by rolling grasslands in the valleys[18]. The shola forests are considered the best suitable habitat for both BOF and NIF[20–22].

Occurrence data collection and processing

We obtained the occurrence records of BOF and NIF from eBird[33], which also includes data from the recent (2015–20) Kerala Bird Atlas (KBA)[33]. The KBA provides gridded bird occurrences collected from across Kerala and uploaded to the eBird database. The eBird data are published after multi-level, rigorous review processes[34], thereby enabling its usage for various scientific analyses, including the species distribution modelling and conservation planning[35–37]. There are other occurrence data of both species available on multiple platforms like iNaturalist and India Biodiversity Portal, but they lack a reliable vetting process and hence not suitable for this study. A total of 893 and 1395 unique occurrence points were obtained for BOF and NIF respectively, from the eBird primary dataset (version: EBD_relJan-2021).

We downloaded vetted eBird data and filtered them as detailed below. We (a) included all checklists having travelling and stationary protocols; (b) excluded all checklists with more than or equal to 300 min of duration; (c) excluded all checklists if the travelled distance was 5 km or more and (d) excluded those checklists with more than ten observers[38]. The authenticity of the records was ensured by checking the review status and media availability. We removed the occurrence points without adequate supporting evidence from unusual habitats, unusual elevation or isolated locations from the analysis. We used spatial thinning to avoid overfitting the model by spatial clustering of occurrence data due to the spatial coverage bias of the citizen-science dataset[39,40]. Occurrence data were thinned at 2 km resolution using 'spThin'[41] in R version 4.0.3 (ref. 42).

Environmental variables

Environmental variables and other factors like behaviour, competition, etc. are the core determining factors of species distribution[28,43]. Based on the available data, 19 bioclimatic variables[44] were downloaded from the Climatologies at High-resolution for the earth's land surface areas (CHELSA) climate data[45]. The digital elevation model (DEM) was obtained from the global data (GTOPO30) available with the United States Geological Survey (USGS) database. Aspect and slope were extracted from DEM using QGIS 3.16. We obtained enhanced vegetation index (EVI) layers for 2011–20 from the USGS database. We utilized EVI data to obtain the following layers in ArcGIS: average EVI (evi_avg), EVI in peak monsoon, June–August (evi_mon) and EVI in peak summer, March–May (evi_dry). All variables were set to a spatial resolution of 30 arc sec (~1 km) and the projection of World Geodetic System 84 EPSG:4326 (WGS 1984). We eliminated variables with high correlation (Pearson correlation coefficient, $|r| > 0.75$) to avoid multicollinearity[46,47]. We selected variables with multicollinearity below the threshold.

MaxEnt modelling

Maximum entropy algorithm implemented in MaxEnt version 3.4.4 was used to determine the distribution pattern (current and future) of BOF and NIF[48,49]. We used the ENMeval R package to get an initial model suggestion based on the Akaike Information Criterion (AIC) and associated model settings[50]. Value of regularization multiplier and the number of background points were also determined with the ENMeval tool. The model with the lowest AIC value was selected from different model suggestions to choose the preliminary model. We built the initial model using MaxEnt and calculated the contribution and permutation importance of variables. We discarded the lowest contributing and permutation importance variables, re-ran the model with different MaxEnt features and regularization multiplier, evaluated it with the ENMeval tool, and noted the change in AIC value. We identified the model with low AIC value as best performing. Different sets of variables were used for BOF and NIF, based on the model performance evaluation. We ran the MaxEnt program with 10-folds of cross-validation, with the number of background points set as 10,000 and iterations as 5000 for both species.

The 'complementary log–log' (cloglog) was selected as the MaxEnt output type, which is the most appropriate format for estimating the probability of species presence[48]. The importance of the predictor variables in model building and species suitability determining variables was understood by estimating the permutation importance of the variables and test gain of the jackknife analysis – both estimates are present in the MaxEnt output.

Future simulations

The future distributions of BOF and NIF were predicted under different representative concentration pathways (RCPs, 4.5 and 8.5) for 2050s (2041–60). Future bioclimatic variables and static variables like DEM were used to predict the future distributions. We removed the EVI layers from analysis due to unavailability of future EVI values. To compare future simulations with the current scenario, we developed a separate model that excludes EVI layers. We selected Earth system models (ESMs) with dissimilar model constructing codes that helped reduce the uncertainty in future predictions[51,52]. The three different ESMs under Coupled Model Intercomparison Project Phase 5 (CMIP 5), the Beijing Climate Centre Climate System Model 1.1 (BCC CSM1.1), Model for Interdisciplinary Research on Climate version 5 (MIROC5) and Hadley Centre Global Environmental Model 2 – Earth System (HadGEM2-ES) were used for analysis. We calculated the average of the three models with the raster calculator tool in QGIS.

Model performance evaluation

One of the criteria to assess model performance is area under the receiver operating characteristic (ROC) curve (AUC). It measures how well a parameter can be distinguished between two diagnostic groups (random and background points). AUC can be calculated from the ROC curve by plotting sensitivity against '1 – specificity' across the range of possible thresholds. The AUC ranges from 0 to 1, and the best performing model is indicated by values close to or equal to one. It is not good to evaluate the model performance with AUC value alone, because it is not entirely reliable and informative[49].

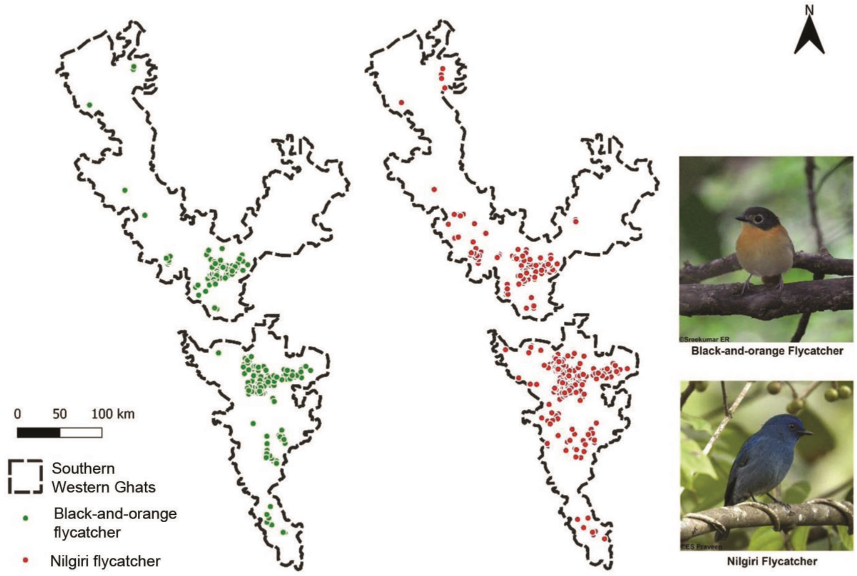

Figure 2. Occurrence points used for model construction of black-and-orange flycatcher and Nilgiri flycatcher, southern Western Ghats, India.

Another model evaluation measurement is the true skill statistic (TSS), defined as 'sensitivity + specificity – 1'. TSS ranges from –1 to +1, and values close to or equal to one indicate high accuracy of the model. In this study, we used AIC, AUC and TSS for model performance evaluation (Supplementary Table 1).

Species suitability calculation

The cloglog outputs were converted into a binary raster based on the 'maximum test sensitivity plus specificity cloglog threshold' (max SSS) value[53]. Values below the threshold were considered as unsuitable areas for the species and these above the threshold as suitable. We calculated the species suitability changes using the raster calculator tool in QGIS application by subtracting the current binary map from the future binary maps. We calculated the change in suitable areas by subtracting the current binary map from the future binary maps using the raster calculator tool in QGIS. We interpreted the values of the subtracted layer and identified areas of no change in suitability (both future and current maps having the same value for the overlapping cells), predicted increase in suitable areas in future (gain of suitable area) and predicted decrease in suitable areas in future (loss of suitable area).

Results

Modelling

We had 194 records of BOF and 300 records of NIF after spatial thinning of occurrence data (Figure 2). Mean diurnal range (BIO 2), isothermality (BIO 3), mean temperature of coldest quarter (BIO 11), precipitation of driest month (BIO 14), precipitation of wettest quarter (BIO 16), precipitation of warmest quarter (BIO 18), aspect, slope and evi_avg were used for the preliminary model construction of BOF, and BIO 2, BIO 3, BIO 11, precipitation of wettest month (BIO 13), BIO 14, BIO 18, aspect, slope and evi_avg for the preliminary model building of NIF. For the final model construction for BOF, we used BIO 3, BIO 11; and slope, but for NIF, BIO 3, BIO 11, BIO 14, BIO 18, slope and evi_avg were used (Table 1; Supplementary Table 2).

Important environmental variables

We identified BIO 11 as the most crucial variable for both BOF and NIF for climate suitability prediction. It had more than 90% permutation importance and high test gain in the jackknife analysis. Isothermality and slope did not contribute much to model building. They did not have any permutation importance in model construction for both BOF and NIF, but they did play a role in model predictive power based on the jackknife test result (Table 1, Supplementary Figures 1–3). Therefore, model building without these variables results in a higher AIC value than the currently selected model.

Current suitability

For BOF, the best model (AIC = 3668.34) contained three variables (Table 1), and the model predicted 6532 sq. km (threshold = 0.609) as suitable for BOF within WG

Table 1. Percentage contribution and permutation importance of variables in model construction

Variable	Black-and-orange flycatcher		Nilgiri flycatcher	
	Percentage of contribution	Permutation importance (%)	Percentage of contribution	Permutation importance (%)
Isothermality (BIO 3)	0.6	1	0	0
Mean temperature of coldest quarter (BIO 11)	99.3	98.9	95.2	92.4
Precipitation of driest month (BIO 14)	–	–	0.2	0
Precipitation of warmest quarter (BIO 18)	–	–	2.4	4.2
Slope	0.1	0	0	0
Enhanced vegetation index (10-year average)	–	–	2.2	3.4

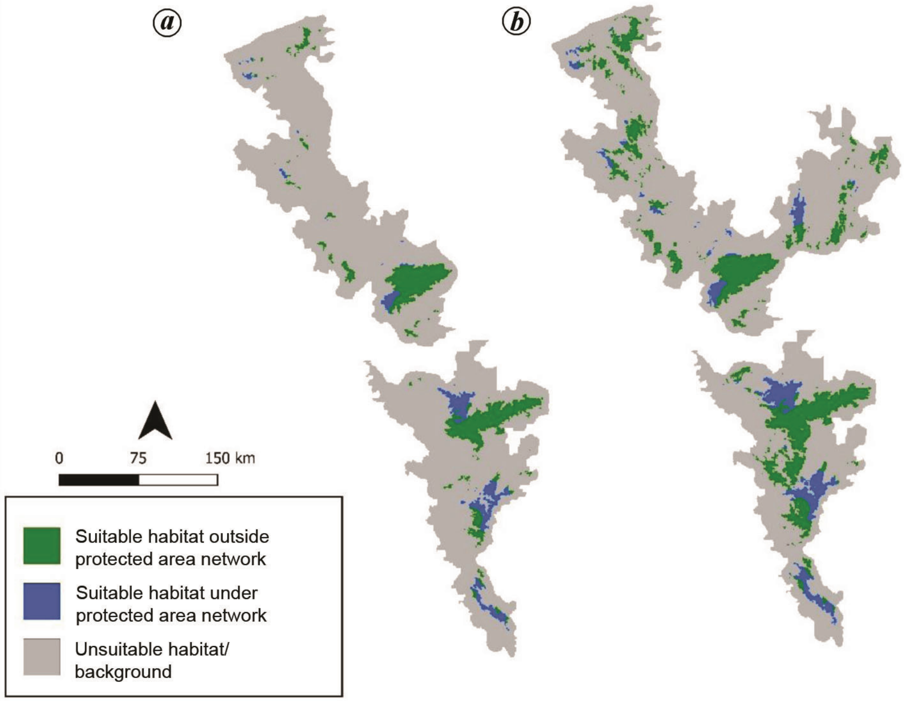

Figure 3. Predicted suitability of (***a***) black-and-orange flycatcher and (***b***) Nilgiri flycatcher with indication of suitable areas available within the protected area network.

(Figure 3). Out of the total suitable area, 61.20% is distributed south of the Palakkad Gap and the remaining north of the Palakkad Gap. The model also predicted some new and hitherto unknown suitable locations in Talakaveri Wildlife Sanctuary (WLS) and Pushpagiri WLS in Karnataka for BOF. Out of the total suitable area for BOF, only 26.50% is distributed inside the protected area network and nearly 75% lies outside the protected area network in the region.

For NIF, the best model (AIC = 6052.20) included six variables (Table 1). A total of 12,707 sq. km (threshold = 0.631) is considered as suitable area for NIF (Figure 3). Out of this, 52.30% is distributed in southern part of the Palakkad Gap and the remaining in the northern part of the Palakkad Gap. Similar to BOF, in the case of NIF also, nearly 75% of its suitable area lies outside the protected area network of WG. However, the model predicted some potentially suitable areas in Kudremukh National Park, Pushpagiri WLS, Talakaveri WLS, Cauvery WLS and Biligiri Rangaswamy Temple WLS, where the species has not been reported so far.

Future suitability changes

Future predictions for BOF indicate a 30.82% loss in suitable area under RCP 8.5 (Table 2). Therefore, noticeable suitability contraction would occur in the Anamalai and Agasthyamalai Hills in the RCP 4.5 and RCP 8.5 scenarios. On the other hand, future predictions also suggest that BOF would gain some new suitable areas in the Nilgiri Hills compared to the current suitability. The model also predicts loss of 34% (RCP 4.5) to 46% (RCP 8.5) of suitable area within the protected area network (Supplementary Figure 4).

Future prediction models for NIF indicate loss of suitability in both climate change scenarios, viz. RCP 4.5 and

Table 2. Relative changes in the area of suitable habitat to the current predicted distribution under various climate change scenarios for 2050s

Species	Representative concentration pathway scenario	Threshold	No change	Unsuitable area	Suitable area	Total predicted suitable area (km^2)	Percentage of range contraction
Black-and-orange	4.5	0.603	51440	1465	128	5195	20.5
flycatcher	8.5	0.606	50972	2037	24	4519	30.8
Nilgiri flycatcher	4.5	0.613	59512	4911	21	8733	35.9
	8.5	0.613	58180	6255	9	7377	45.8

RCP 8.5. The model predicts extreme loss under RCP 8.5 (45.85%) (Table 2). We noted a loss of suitable areas throughout the species' current distribution extent. The suitability contracted within the protected area network by 34% (RCP 4.5) to 45% (RCP 8.5), according to the model predictions (Supplementary Figure 5).

Discussion

Suitable areas of BOF and NIF

The present study predicts suitable locations along the high-altitude regions for two species of restricted distributed flycatchers in WG. Among the two, NIF has more widely distributed suitable areas available in SWG. BOF is restricted to the high-elevation pockets and is more isolated in distribution than NIF. Few occurrence data are available in the Brahmagiri Hills for both species[54]. In the case of NIF, the model predicts additional suitable areas in BR Hills, but the species may not be found there because of the unavailability of montane habitat. Also, NIF is not a long-distance migrant and such predicted suitable areas are 50–100 km away from the known range of the species. Regions within the Agasthyamalai Hills, Pandalam Hills, Anamalai Hills and Nilgiri Hills are the core habitats for both species of flycatchers. Both BOF and NIF have a high preference for montane habitats[20,22]. The present study also predicts majority of suitable areas in the high-elevation regions of WG. The values of permutation importance and jackknife test gain suggests that BIO 11 is the most crucial variable predicting suitable areas for both BOF and NIF.

Suitable areas of BOF and NIF within the protected area network in WG

Out of the total predicted distributional range of BOF and NIF, only around 25% of the suitable areas is distributed within the protected area network. Future climate change may threaten more than 40% of the available suitable areas for both species. The most suitable locations for these two flycatchers in the Anamalai and Nilgiri Hills lie outside the protected area network. Specialized habitats like shola are under threat from various anthropogenic activities and invasive plant species. The loss of shola forests is slow in the existing protected areas, but is rapid in Reserve Forests[19]. Realigning the boundaries of the existing protected area network to include the suitable regions of the two species of flycatchers may ensure the long-term conservation of both species. Long-term isolation of populations can even lead to the local extinction of the species[55]. The wildlife managers must take actions to ensure proper corridor connectivity between the isolated montane habitats for avoiding such extinctions.

Climate change impact and suitability changes

More net suitable area loss was predicted for NIF (35.90–45.85%) than for the BOF (20.47–30.82%). We observed the loss of suitable areas of NIF in its entire range. In the case BOF, loss of suitable locations occurred in the Anamalai, Pandalam and Agasthyamalai Hills compared to other regions. Several studies suggest that climate change can adversely affect several species, and they may lose their potential habitat, shift their range or become locally extinct[56,57]. Montane habitat specialist species may react to climate change by elevational range shift[58]. However, further elevational shift may not be possible for both BOF and NIF because they already exist in the highest elevation within WG. Sukumar *et al.*[11] predicted the deterioration of montane shola ecosystems and associated species extinction risks due to climate change. Land-use changes due to anthropogenic activities and climate change impacts may negatively affect the restricted distributed species like BOF and NIF.

Limitations of the present study

We obtained the occurrence points of both BOF and NIF from eBird, which is a citizen-based data collection tool[33]. The eBird data quality depend on the observer's identification skills, spatial and temporal coverage by participants, detectability of a species, rare bird recording method and the care taken by the reviewer to vet the data[59,60]. Furthermore, we only used the variables related to climate, topography and vegetation. Other environmental factors that may also affect the species distribution, like insect population density, fruit tree distribution, etc. were not included in this study because of the unavailability of such data[61]. Species-specific microclimatic studies are needed to standardize the variables for species distribution modelling.

Conclusion

We developed SDMs for two endemic flycatchers (BOF and NIF) to understand the current potential suitability and possible responses of the species to future climate change with regard to changes in suitability using MaxEnt algorithm. The models predicted substantial loss of suitable areas under different climate change scenarios for both species, which will be more severe for NIF than BOF.

Moreover, about 75% of the currently suitable areas of both species lie outside the protected area network. Respective wildlife managers in Kerala, Karnataka and Tamil Nadu may need to take urgent actions to realign the boundaries of the protected area network by including suitable regions to ensure the long-term conservation of these two high range-restricted species. These endemic species need more specific conservation prescriptions, for which more detailed autecological studies must be carried out.

Conflicts of interest: The authors declare that there is no conflict of interest.

1. IPBES, *IPBES Global Assessment Summary for Policymakers* (eds Díaz, S. *et al.*), Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, Secretariat, Bonn, Germany, 2019.
2. Allen, M. *et al.*, Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. *Sustain. Develop. Efforts Eradicate Poverty*, 2018, p. 616.
3. Thomas, C. D. *et al.*, Extinction risk from climate change. *Nature*, 2004, **427**, 145–148.
4. Malcolm, J. R., Liu, C., Neilson, R. P., Hansen, L. and Hannah, L., Global warming and extinctions of endemic species from biodiversity hotspots. *Conserv. Biol.*, 2006, **20**, 538–548.
5. Walther, G. R. *et al.*, Ecological responses to recent climate change. *Nature*, 2002, **416**, 389–395.
6. Walther, G. R., Community and ecosystem responses to recent climate change. *Philos. Trans. R. Soc. London, Ser. B.*, 2010, **365**, 2019–2024.
7. Nogués-Bravo, D., Araújo, M. B., Errea, M. P. and Martínez-Rica, J. P., Exposure of global mountain systems to climate warming during the 21st century. *Global Environ. Change*, 2007, **17**, 420–428.
8. Whiteman, C. D., *Mountain Meteorology: Fundamentals and Applications*, Oxford University Press, Oxford, United Kingdom, 2000.
9. Rogora, M. *et al.*, Assessment of climate change effects on mountain ecosystems through a cross-site analysis in the Alps and Apennines. *Sci. Total Environ.*, 2018, **624**, 1429–1442.
10. McCormack, J. E., Huang, H. and Knowles, L. L., Sky islands. *Encycl. Islands*, 2009, **4**, 841–843.
11. Sukumar, R., Suresh, H. S. and Ramesh, R., Climate change and its impact on tropical Montane ecosystems in Southern India. *J. Biogeogr.*, 1995, **22**, 533–536.
12. Myers, N., Mittermeier, R. A., Mittermeier, C. G., Da Fonseca, G. A. B. and Kent, J., Biodiversity hotspots for conservation priorities. *Nature*, 2000, **403**, 853–858.
13. UNESCO World Heritage Committee, Decisions Adopted during the 41st Session of the World Heritage Committee, Krakow, Poland, 2017.
14. UNESCO, Nilgiri Biosphere Reserve, India, 2012; https://en.unesco.org/biosphere/aspac/nilgiri (accessed on 29 March 2021).
15. UNESCO, Agasthyamala Biosphere Reserve, India; 2016; https://en.unesco.org/biosphere/aspac/agasthyamala (accessed on 29 March 2021).
16. Ricketts, T. H. *et al.*, Pinpointing and preventing imminent extinctions. *Proc. Natl. Acad. Sci. USA*, 2005, **102**, 18497–18501.
17. Robin, V. V., Sinha, A. and Ramakrishnan, U., Ancient geographical gaps and paleo-climate shape the phylogeography of an endemic bird in the sky Islands of Southern India. *PLoS ONE*, 2010, **5**, e13321.
18. Robin, V. V. and Nandini, R., Shola habitats on sky islands: status of research: on montane forests and grasslands in southern India. *Curr. Sci.*, 2012, **103**,1427–1437.
19. Arasumani, M., Khan, D., Vishnudas, C. K., Muthukumar, M., Bunyan, M. and Robin, V. V., Invasion compounds an ecosystem-wide loss to afforestation in the tropical grasslands of the Shola sky islands. *Biol. Conserv.*, 2019, **230**, 141–150.
20. Clement, P., Black-and-orange flycatcher (*Ficedula nigrorufa*), version 1.0. In *Birds of the World* (eds del Hoyo, J. *et al.*), Cornell Lab of Ornithology, Ithaca, New York, USA, 2021.
21. Khan, M. A. R., Ecology of the black-and-orange flycatcher *Muscicapa nigrorufa* (Jerdon) in southern India. *J. Bombay Nat. Hist. Soc.*, 1979, **75**, 773–791.
22. Clement, P., Nilgiri flycatcher (*Eumyias albicaudatus*), version 1.0. In *Birds of the World* (eds del Hoyo, J. *et al.*), Cornell Lab of Ornithology, Ithaca, NY, USA, 2021.
23. BirdLife International, *Ficedula nigrorufa*. IUCN Red List of Threat and Species2017 e.T22709415A118488735, 2017.
24. BirdLife International, *Eumyias albicaudatus*. IUCN Red List Threat and Species 2017 e.T22709449A118490523, 2017.
25. SoIB, State of India's Birds 2020: Range, trends and conservation status. The SoIB Partnership, 2018; https://www.stateofindiasbirds.in/
26. Jones, M. C. *et al.*, Predicting the impact of climate change on threatened species in UK waters. *PLoS ONE*, 2013, **8**, e54216.
27. Root, T., Energy constraints on avian distributions and abundances. *Ecology*, 1988, **69**, 330–339.
28. Root, T. L. and Schneider, S. H., Can large-scale climatic models be linked with multiscale ecological studies? *Conserv. Biol.*, 1993, **7**, 256–270.
29. Allouche, O., Tsoar, A. and Kadmon, R., Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *J. Appl. Ecol.*, 2006, **43**, 1223–1232.
30. Peterson, A. T., Papeş, M. and Soberón, J., Rethinking receiver operating characteristic analysis applications in ecological niche modeling. *Ecol. Modell.*, 2008, **213**, 63–72.
31. Cobos, M. E., Peterson, A. T., Barve, N. and Osorio-Olvera, L., kuenm: an R package for detailed development of ecological niche models using Maxent. *Peer J.*, 2019, **7**, e6281.
32. Peterson, A. T. and Robins, C. R., Using ecological-niche modeling to predict barred owl invasions with implications for spotted owl conservation. *Conserv. Biol.*, 2003, **17**, 1161–1165.
33. Praveen, J. and Nameer, P. O., *An Atlas of the Birds of Kerala*, Kerala Agricultural University and Bird Count India, 2021, p. 219.
34. Sullivan, B. L., Wood, C. L., Iliff, M. J., Bonney, R. E., Fink, D., and Kelling, S., eBird: a citizen-based bird observation network in the biological sciences. *Biol. Conserv.*, 2009, **142**, 2282–2292.
35. Pacifici, K. *et al.*, Integrating multiple data sources in species distribution modeling: a framework for data fusion. *Ecology*, 2017, **98**, 840–850.
36. Sullivan, B. L. *et al.*, Using open access observational data for conservation action: a case study for birds. *Biol. Conserv.*, 2017, **208**, 5–14.

37. Robinson, O. J., Ruiz-Gutierrez, V., Fink, D., Meese, R. J., Holyoak, M. and Cooch, E. G., Using citizen science data in integrated population models to inform conservation. *Biol. Conserv.*, 2018, **227**, 361–368.
38. Strimas-Mackey, M. *et al.*, Best practices for using eBird data. Cornell Lab of Ornithology, Ithaca, New York, USA, 2020.
39. Kadmon, R., Farber, O. and Danin, A., Effect of roadside bias on the accuracy of predictive maps produced by bioclimatic models. *Ecol. Appl.*, 2004, **14**,401–413.
40. Williams, P. H., Margules, C. R. and Hilbert, D. W., Data requirements and data sources for biodiversity priority area selection. *J. Biosci.*, 2002, **27**, 327–338.
41. Aiello-Lammens, M. E., Boria, R. A., Radosavljevic, A., Vilela, B. and Anderson, R. P., spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography*, 2015, **38**, 541–545.
42. R Core Team, R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, 2021.
43. Root, T., Environmental factors associated with avian distributional boundaries. *J. Biogeogr.*, 2006, **15**, 489.
44. Fick, S. E. and Hijmans, R. J., WorldClim 2: new 1 km spatial resolution climate surfaces for global land areas. *Int. J. Climatol.*, 2017, **37**, 4302–4315.
45. Karger, D. N. *et al.*, Climatologies at high resolution for the earth's land surface areas. *Sci. Data*, 2017, **4**, 1–20.
46. Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E. and Yates, C. J., A statistical explanation of MaxEnt for ecologists. *Divers. Distrib.*, 2011, **17**, 43–57.
47. Merow, C., Smith, M. J. and Silander, J. A., A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography*, 2013, **36**, 1058–1069.
48. Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E. and Blair, M. E., Opening the black box: an open-source release of Maxent. *Ecography*, 2017, **40**, 887–893.
49. Phillips, S. J., Anderson, R. P. and Schapire, R. E., Maximum entropy modeling of species geographic distributions. *Ecol. Modell.*, 2006, **190**, 231–259.
50. Muscarella, R. *et al.*, ENMeval: an R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. *Methods Ecol. Evol.*, 2014, **5**, 1198–1205.
51. Sanderson, B. M., Knutti, R. and Caldwell, P., A representative democracy to reduce interdependency in a multimodel ensemble. *J. Climate*, 2015, **28**, 5171–5194.
52. Knutti, R., Masson, D. and Gettelman, A., Climate model genealogy: generation CMIP5 and how we got there. *Geophys. Res. Lett.*, 2013, **40**, 1194–1199.
53. Liu, C., White, M. and Newell, G., Selecting thresholds for the prediction of species occurrence with presence-only data. *J. Biogeogr.*, 2013, **40**, 778–789.
54. eBird, eBird: an online database of bird distribution and abundance. Cornell Lab of Ornithology, Ithaca, New York, USA, 2021.
55. Wilcox, B. A. and Murphy, D. D., Conservation strategy: the effects of fragmentation on extinction. *Am. Nat.*, 1985, **125**, 879–887.
56. Parmesan, C., Ecological and evolutionary responses to recent climate change. *Annu. Rev. Ecol. Evol. Syst.*, 2006, **37**, 637–669.
57. Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W. and Courchamp, F., Impacts of climate change on the future of biodiversity. *Ecol. Lett.*, 2012, **15**, 365–377.
58. Stuhldreher, G. and Fartmann, T., Threatened grassland butterflies as indicators of microclimatic niches along an elevational gradient – implications for conservation in times of climate change. *Ecol. Indic.*, 2018, **94**, 83–98.
59. Kamp, J., Oppel, S., Heldbjerg, H., Nyegaard, T. and Donald, P. F., Unstructured citizen science data fail to detect long-term population declines of common birds in Denmark. *Divers. Distrib.*, 2016, **22**, 1024–1035.
60. Isaac, N. J. B., van Strien, A. J., August, T. A., de Zeeuw, M. P. and Roy, D. B., Statistics for citizen science: extracting signals of change from noisy ecological data. *Methods Ecol. Evol.*, 2014, **5**, 1052–1060.
61. Araújo, M. B. and Guisan, A., Five (or so) challenges for species distribution modelling. *J. Biogeogr.*, 2006, **33**, 1677–1688.

ACKNOWLEDGEMENTS. We thank Ashish Jha, Josh Banta, Ashwin Viswanathan, R. Sreehari, J. Praveen and Suhel Quader for help in developing the methodology and analysis, and the Director, Kerala State Council for Science, Technology and Environment, Thiruvananthapuram and the Dean of Faculty, College of Forestry, Kerala Agricultural University, Thrissur for financial support. We also thank the Kerala Forest and Wildlife Department, Thiruvananthapuram for permission (No. KFDHQ-2027/2019-CWW/WL 10 dated 16 April 2019) to conduct birds surveys throughout the state, and anonymous reviewers for the suggestions that helped improve the manuscript.

Received 8 January 2021; revised accepted 27 September 2021

doi: 10.18520/cs/v121/i10/1335-1342