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Niche models inform the effects of climate change on the endangered Nilgiri Tahr (*Nilgiritragus hylocrius*) populations in the southern Western Ghats, India

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A R T I C L E I N F O

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A B S T R A C T

Large mammals are declining globally due to habitat loss and fragmentation. Climate change is one of the factors known to alter the range of several mammalian species. An early understanding of the effect of climate change on species distributions can provide critical information for conservation planning. *Nilgiritragus hylocrius* (Nilgiri Tahr) is an endangered ungulate that is restricted to the montane grasslands of the Western Ghats, India. Currently, the Nilgiri Tahr is restricted to a fraction of its former range and is also prone to risks due to several ongoing anthropogenic pressures. However, the impact of global climate change on this emblematic species has seldom been estimated. The goal of our study was to use ecological niche models to quantify the effect of climate change on the habitats of Nilgiri Tahr. Using the maximum entropy (MaxEnt) algorithm, we modelled the potential distribution of Nilgiri Tahr in its native range. The models were developed under the current climatic conditions and then projected onto two future climate change scenarios (RCP4.5 and RCP8.5) and for three different time frames in the future (years 2030, 2050 and 2080). We identified that most of the climatically suitable habitats of Nilgiri Tahr would become unsuitable when global warming intensifies. Our models predicted a complete loss of suitable habitats in many existing protected areas in the Western Ghats. We use insights provided by our modeling results to propose conservation management plans to increase the likelihood of persistence of Nilgiri Tahr in the Western Ghats.

1. Introduction

The 21st century is predicted to witness rapid changes in climate, which will have tremendous impacts on biodiversity at multiple levels (Cordellier et al., 2012). Studies indicate that in lieu of proper mitigation measures, the median global annual mean temperature may rise to 4 °C by 2100 (Warren et al., 2013). Severe reduction in species range size and abundance are the major predicted consequences of this climate change (Malcolm et al., 2006; Thomas et al., 2004; Warren et al., 2013). In case of large mammals, habitat loss, human wildlife conflicts, land use change, dispersal limitations and hunting along with rapid climate change have been identified to increase their extinction risk throughout the world (Adams-Hosking et al., 2015; Hoffmann et al., 2015; Schloss et al., 2012). Adopting sophisticated approaches to identify the species likely to be at risk and mapping the latent extinction risk, are critical for avoiding defaunation, especially in the present era of climate change (Dirzo et al., 2014).

One way to predict the latent threat to species due to climate change is to use ecological niche models (ENMs) to predict a species' potential distribution under various scenarios of environmental change. Theoretically, ENMs use the relationship between a species and its habitat to identify a species' potential distribution at un sampled locations (Guisan and Thuiller, 2005). Niche based models are informative in delimiting a species' ecological requirements and predicting potential suitable habitats by using the known distribution of a species (spatial coordinates) with a given set of environmental variables (Graham et al., 2004; Peterson, 2006). These models are used widely to predict and quantitatively estimate the impact of projected climate warming (Adams-Hosking et al., 2015; Aragón et al., 2010; Bleyhl et al., 2015; Khanum et al., 2013; Kujala et al., 2013; Legault et al., 2013; Luo

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et al., 2015; Rödder and Weinsheimer, 2009; Rubidge et al., 2011; Ulrey et al., 2016).

The Western Ghats is considered as one of the hottest biodiversity hotspots in the world (Cincotta et al., 2000, Myers et al., 2000). These mountains provide critical habitats for several endemic flora and fauna (Myers et al., 2000). Recently the native species in Western Ghats are undergoing several threats as a result of anthropogenic pressures, 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 scenario the forests of central and Northern Western Ghats. are vulnerable 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 increase in its rainfall. Even though such studies exist the role of global climate change in the endemic mammal species of Western Ghats have been less explored. However, few studies from this region highlights the importance of climate change in altering distributions of its endemic species using niche modeling approaches (see Sen et al., 2016a, 2016b). The results are alarming which shows a decline in their future suitable habitats.

Nilgiritragus hylocrius (henceforth mentioned as 'Tahr') is an endangered mountain ungulate that belongs to the subfamily Caprinae (Ropiquet and Hassanin, 2005). Tahr is the only mountain ungulate in South India among the 12 ungulate species that occur in India (Fox and Johnsingh, 1997; Predit et al., 2015). The tahr is endemic to the Western Ghats-Sri Lanka biodiversity hotspot it is restricted to the montane grasslands (Myers et al., 2000). Historically, the species occurred throughout the Western Ghats, which is now restricted to around 3000 individuals in less than one-tenth of its former range in Kerala and Tamil Nadu states in the southern Western Ghats within an altitude range of 1100 m to 2695 m. However, the Tahr populations declined over the years due to hunting, conflict with livestock grazing and habitat loss (Esa et al., 2010; Predit et al., 2015; Rice, 1984; Schaller, 1970). In addition, Sukumar (2000) highlighted the importance of climate mediated habitat loss of Tahr resulting in the reduction of natural grasslands in the Western Ghats. Despite this, there has been no further research on predicting the impact of global climate change on this species, which is essential for long-term conservation planning.

In this study, we used maximum entropy modeling approach (MaxEnt; Phillips et al., 2006) to estimate the amount and distribution of potential suitable habitat for Tahr both under current climate and future climate change scenarios; and provide suggestion to identify areas for conserving the existing populations.

2. Materials and methods

2.1. Study area and occurrence records

The study was conducted in the Western Ghats biodiversity hotspot (between 8° N to 12° N latitudes) of peninsular India from 2010 to 2011 where Tahr inhabits the montane grasslands of the southern Western Ghats above an elevation of 1100 m (Fig. 1). The existing habitats of the Tahr were identified from the previous literature and in consultation with the experts and forest officials. The experts included the scientists and researchers who have previously worked on Tahr. The number of existing Tahr habitats identified counted upto ten. These ten Tahr habitats were visited and repeatedly searched for the presence of the species for an average of five days per locality. The survey team constituted of three to six individuals- with one or more species expert, and forest officers. The total number of animals sighted were counted and noted down The geographic coordinates were marked from the nearest locations possible from the first sighting of the animal. Indirect evidence such as the presence of pellets was also considered and geolocated under reliable circumstances. Other than this primary data from ten Tahr habitats, secondary data points were collected from reliable published sources (See Supplementary file S1 for complete dataset).

For developing ENMs, the study area was divided into 236,269 map pixels of 1 km^2 resolution which collectively encompass the known distribution area of Tahr. A total of 318 known Tahr occurrence were collected from primary and secondary data sources.

2.2. Environmental covariates

A set of 23 candidate predictor variables that characterize the environment surrounding Tahr locations were chosen for modeling the impact of climate change. Predictors included 19 bioclimatic variables available from WorldClim data set (Hijmans et al., 2005; http://www.worldclim.org) and aridity (measure of humidity, http://csi.cgiar.org/aridity/) three topographic variables altitude (http://www.worldclim.org), slope aspect (calculated using ArcGIS version 10.3 (ESRI 2013), were included in model fitting. All variables were treated as continuous for the current study. Northness (sin(aspect*pi/180)) and eastness (cos (aspect*pi/180)) were calculated using ArcGIS version 10.3 (ESRI 2013) and incorporated as separate predictor variables. The final set of variables where chosen carefully after accounting for multicollinearity among the predictors. This was done by calculating Pearson's correlation coefficient, $|r| < 0.70$) and the variance inflation factors (VIFs) using R (package *usdm*, Naimi, 2013). Predictor variables with VIFs > 5 were removed from the analysis since even mildly correlated layers are known to influence the accuracy of species distribution models (Veloz, 2009).

2.3. Model building and validation

To reduce the effects of spatial autocorrelation among the occurrence points, we first calculated the climatic heterogeneity of the study site using principal component analysis (PCA) of all the climatic variables. A climate heterogeneity map was then developed by combining the three principal component axes using SDMToolBox (Brown, 2014). The spatial aggregation among occurrence records within an area was then subsequently reduced by spatially filtering the occurrence records (Boria et al., 2014). After removing spatially auto-correlated occurrence points and reducing multiple occurrence records in single cell, the total number of occurrence points was reduced to 169 from 318 (See Supplementary file Fig. S2).

To develop climatic habitat suitability maps, we used a maximum entropy modeling approach implemented in the software program MaxEnt (version 3.3.3 k; Phillips et al., 2006). We performed 10-fold cross-validation tests with 5000 iterations; the convergence threshold being set to 1×10^{-6}. A logistic output was chosen, which can be interpreted as the probability of presence of a species given the environmental variables (Merow et al., 2013). Current models were tuned by varying the regularization multiplier (RM) values from 1.0 to 2.5. An increase in the value of RM reduces model complexity by reducing the number of parameters entered into the model (Phillips et al., 2006). The complexity of the current models was further varied by changing different feature types (i.e., linear, product, quadratic and hinge) in MaxEnt (Table 1). We used the R package ENMeval (Muscarella et al., 2014) to tune the best current model. The model with lowest omission rates was chosen for the future projections. Jackknife tests were used to evaluate variable importance. We employed a logistic threshold of minimum training presence for converting continuous MaxEnt predictions to binary layers (i.e., suitable/unsuitable habitat). We selected this conservative threshold for two reasons. (1) omission of some occurrences from the training were not appropriate for the current dataset. and (2) the goal of the study was to identify suitable areas to conserve an endangered species, where an over estimation is considered to be less dangerous than missing areas of suitable habitats.

The location data in our study may be biased due to logistical reasons, as a result our sampling across the geographic range of Tahr can be non-random. For example, use of Tahr locations from the secondary data sources can result in over representation of few localities. The systematic sampling efforts in general can also be geographically biased

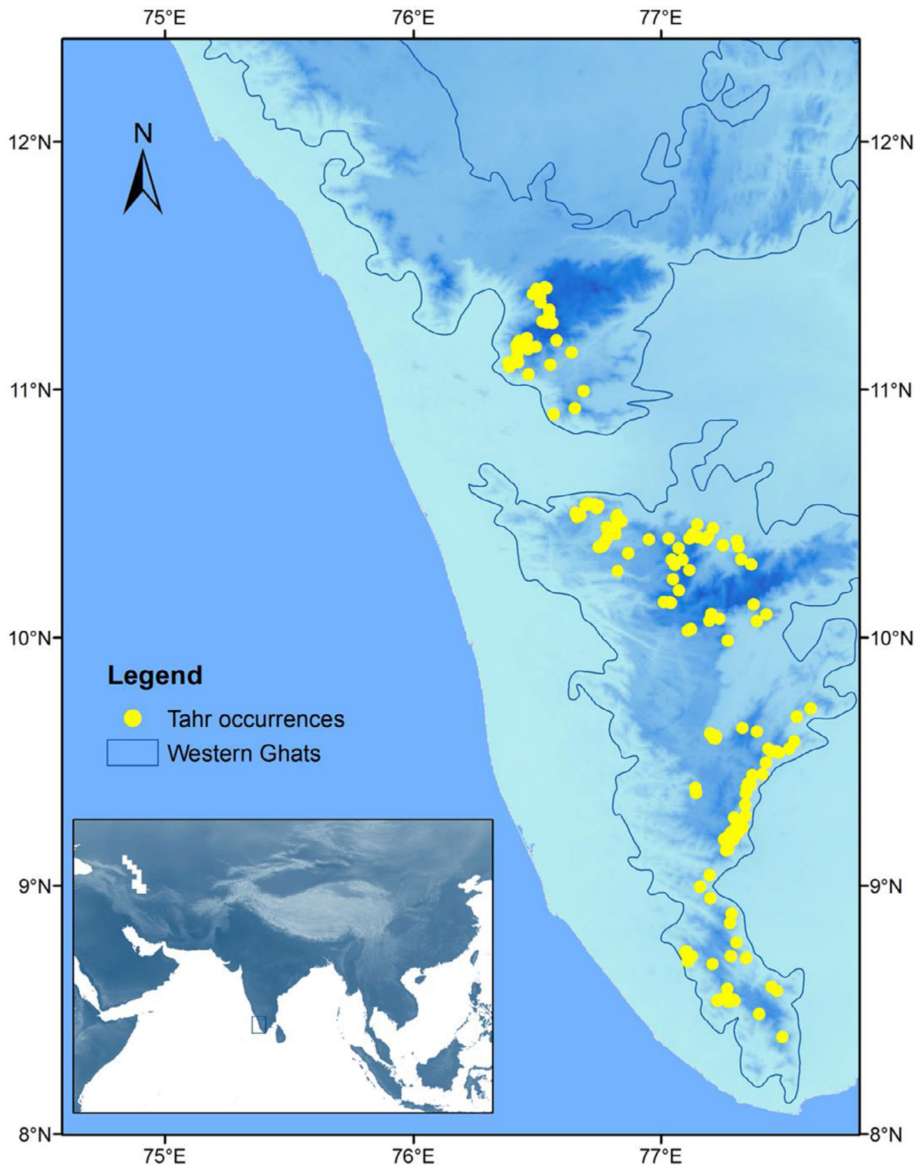

Fig. 1. Sampling locations of Nilgiri Tahr in the Western Ghats mountain chains in India.

towards readily accessible areas. Hence, to account for the sampling bias in the location data, a bias grid was created by calculating Gaussian kernel density of sampling localities using SDMtoolbox (Supplementary file Fig. S3). In the bias file, values of 1 reflect locations with no sampling bias, whereas higher values represent higher sampling bias in the landscape (Elith and Leathwick, 2009). Fifteen different models were developed with varying levels of complexity and different regularization multiplier values. The best model with smallest omission rate was selected for future projections. Model outputs from both scenarios were compared using a niche identity test implemented in ENMTools V1.3. (Warren et al., 2010).

2.4. Forecasting habitat changes in response to climate change

For future climate projections, climatic layers were downloaded from the Consultative Group on International Agricultural Research's (CGIAR) Research Program on Climate Change, Agriculture and Food Security (CCAFS) climate data archive (data available from http://www.ccafs-climate.org/data/). The future climate projections are based on representative concentration pathways or RCPs (IPCC, 2014), which assume different greenhouse gas concentration trajectories based on a range of radiative forcing. The RCP 4.5 represents an optimistic emission scenario, where emissions will peak around 2040 and then decline, and RCP 8.5 assumes increased greenhouse gas emission throughout the 21st century. We developed the models for three future time periods 2030s (2021–2050), 2050s (2040–2069) and 2080s (2070–2099) for both the RCPs. In order to reduce the uncertainty in global circulation models (GCMs), we developed models for the future using four GCMs. These models were based on layers developed by Hadley Coupled Model V3 (HadCM3_AO), Canadian earth system model (canesm2), Model for Interdisciplinary Research on Climate (MIROC-ESM) and Commonwealth Scientific and Industrial Research Organization (CSIRO_MK). The topographic layers were treated as static during the future projections. The dynamic non-climatic variables that are expected to change in future were included in the model. These layers were also treated as static for the future projections (see Stanton et al., 2012). The reliability of future predictions was checked by performing a multivariate environment similarity surface (MESS) analysis (Elith and Leathwick, 2009). This analysis was performed in order to check where novel climate exists in the MaxEnt predictions. MESS also indicates the locations where future models can be the most uninformed (Elith and Leathwick, 2009). Further, to understand the degree of

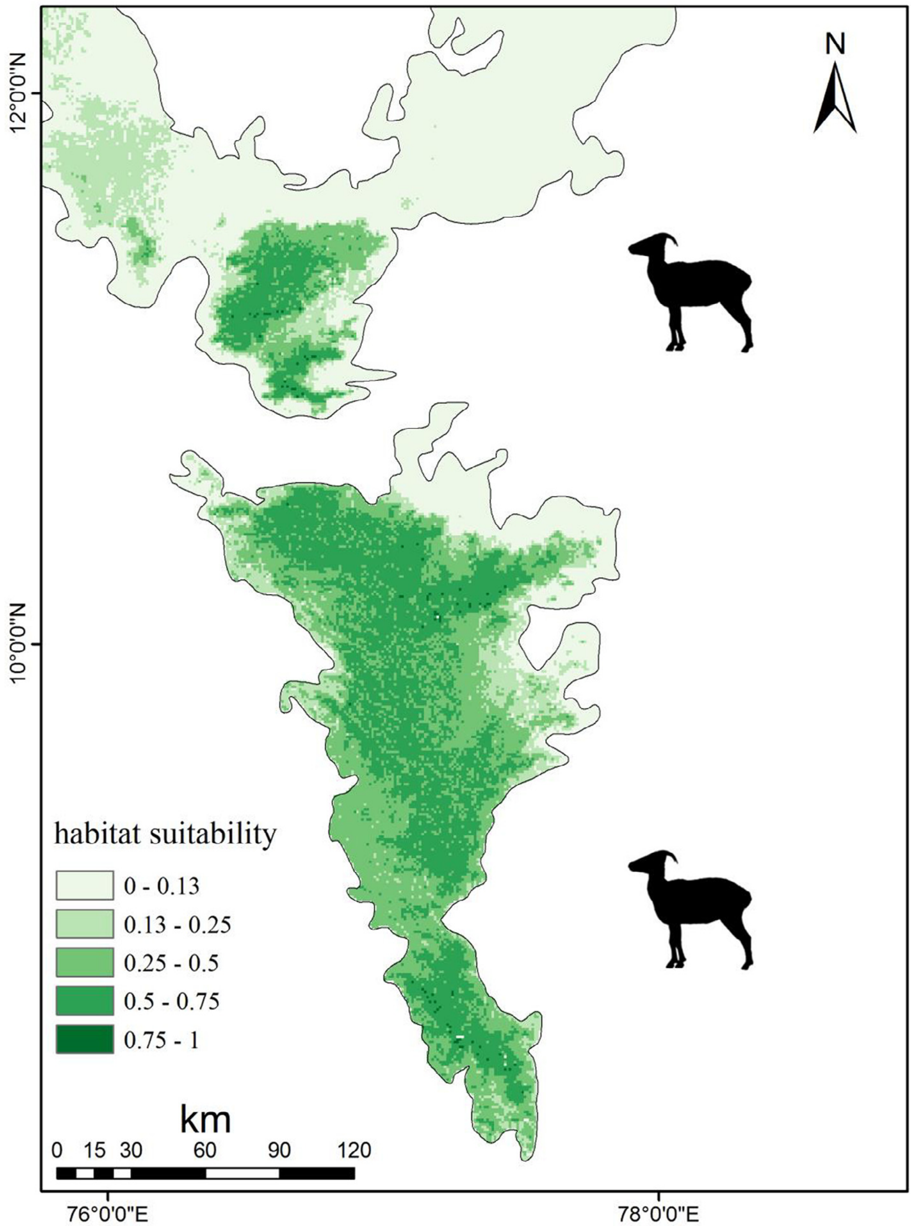

Fig. 2. Climatic habitat suitability for Nilgiri Tahr in Western Ghats under the current climatic conditions predicted using MaxEnt. The warmer colors indicate areas with high suitability scores.

extrapolation we examined the results of most dissimilar variables (MOD) analysis in MaxEnt.

Model performances were evaluated using two metrics, AUC (Area under the receiver operating characteristic (ROC) curve) and TSS (True Skill Statistics). AUC is a threshold-independent metric which measures the models' ability to distinguish between random and background points. Usage of AUC alone for evaluating model performance has been widely criticized (Austin, 2007; Lobo et al., 2008). A high AUC score does not always reflect that the models are highly informative (Phillips et al., 2006). Hence, TSS scores were calculated, which is a threshold dependent measure of accuracy. TSS is defined as sensitivity + specificity − 1, where sensitivity and specificity are calculated based on the probability threshold for which their sum is maximized (Allouche et al., 2006).

3. Results

3.1. Model building and validation

The best model included five bioclimatic variables (Precipitation of Wettest Month, Precipitation of Driest Quarter, Precipitation of Warmest Quarter, Isothermality and Temperature seasonality), and four topographic layers (altitude, slope, Northness and Eastness) after the cross correlation tests (see Supplementary Table T1 and Fig. S1). Furthermore, the choice toretain the precipitation variables were not arbitrary. These variables are known to affect the net primary productivity of grasslands in general, and the grasslands where Tahr inhabit areas which receives an annual rainfall of over 1500 mm with relatively short dry seasons. The final model had a combination of linear, quadratic, and product features (L,Q,P) and a regularization multiplier value of 2. All the models during the tuning experiments performed better than random. The best performing model had an average AUCcv = 0.859 and TSS value of 0.609. Precipitation of the

Table 1
Summary of model evaluation statistics for Nilgiri Tahr using ENMeval with varying model complexities. L,Q,P,T,H are the linear, product, threshold, and hinge features in MaxEnt. RM is the regularization multiplier. AUC_{CV} represents the mean AUC values for the 10-fold cross validated models developed during the evaluation process. TEST OR represents the omission rates at 0% and 10%. The models were ranked based on the omission rates.

MaxENT Features	Variables	RM	AUCcv	TEST OR 0%	TEST OR 10%	Rank
LH	slope, bio4, bio3, bio13, bio17, bio18, altitude	1	0.862	0.011	0.159	4
LH		2	0.861	0.017	0.155	8
LH		1.5	0.862	0.173	0.095	14
LQH		1.5	0.869	0.011	0.165	5
LQH		1	0.863	0.017	0.182	11
LQH		2	0.863	0.0173	0.126	12
LQP		**2**	**0.862**	**0.005**	**0.124**	**1**
LQP		1.5	0.862	0.011	0.108	2
LQP		1	0.859	0.0118	0.13	6
LQPT		2	0.874	0.011	0.154	3
LQPT		1	0.87	0.0118	0.263	7
LQPT		1.5	0.875	0.11	0.17	13
LQPTH		1	0.871	0.005	0.258	5
LQPTH		1.5	0.871	0.017	0.16	9
LQPTH		2	0.871	0.017	0.16	10

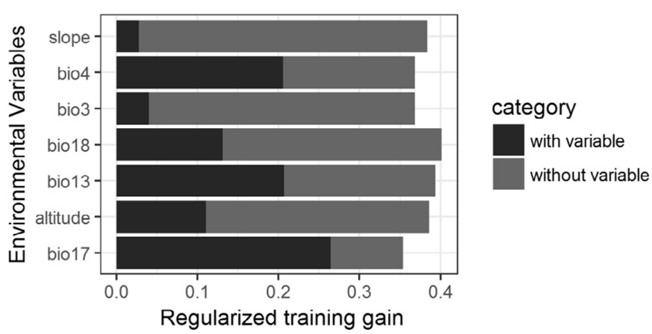

Fig. 3. Jackknife test showing the relative importance of different environmental predictors in MaxEnt models for Nilgiri Tahr.

driest quarter (bio17), temperature seasonality (bio4) and precipitation of the wettest month (bio13) and precipitation of warmest quarter (bio18) had the highest effect on predicting Tahr habitats compared to the other predictors estimated by jackknife test (Fig. 3). This suggests the importance of precipitation variables in determining the distribution of Tahr. For example, the logistic output (interpreted as portability of presence) of Tahr peaked towards the higher value of the variables, precipitation of warmest quarter (bio18) and precipitation of driest quarter (bio17). Similarly, for the variable, precipitation of wettest month (bio13), the probability peaked on values ranging from 1500 to 3000 mm (Fig. 4). We found that the probabilities peaked around low values of temperature seasonality (bio4) which suggests that Tahr species select climatically stable areas. The climate-topography model also performed well with an average AUC_{cv} = 0.864 and TSS = 0.584. Niche identity test of both the climate-topography and the combined models showed 98.2% similarity across models. This test suggests that there were no significant changes in the model outcomes while using vegetation layers as predictors along with climatic variables when compared to a climate-topography model (Supplementary file Fig. S4).

3.2. Characteristics of realized niche in current and future scenarios

The results from all the GCMs were congruent and showed a decrease in suitable habitats for all the future projections. The final future predictions were obtained by an ensemble approach (averaging results of the two models) (Araujo and New, 2007). Current suitable habitats were predicted from 8° to 12° latitudes in the Western Ghats region of Southern India. The montane grasslands in the Western Ghats are the most suitable habitat in the current scenario (Fig. 2). The model predicted 21,448 km^2 as suitable in the current scenario within the Western Ghats. When projected to future time periods, a drastic loss of the existing Tahr habitats was observed for all the future time periods. The extreme climate change scenario RCP 8.5 for 2030, 2050 and 2080 predicted the maximum range loss as expected (61.2%, 61.4 and 63% of current habitats respectively; Fig. 5 and Supplementary file Table 2). In all the future scenarios, remaining suitable habitats were restricted to < 8500 km^2 in the Western Ghats (Table 2). As per our model predictions, the relatively optimistic climate change scenario (RCP4.5) predicted a gain of more novel habitats compared to the extreme climate change scenario (See Table 2, Supplementary file Fig. S6). Interestingly, the extreme climate change scenario during 2030 predicted more suitable habitats compared to all other scenarios. By 2080, we notice that under the extreme climate change scenario, our models predicted that only an area of 31,297 km^2 will be suitable through time (Supplementary file Table 2). Even though our model predicts a drastic loss in suitable habitats during 2030s we also notice that the areas with stable climatic conditions are relatively high compared to other scenarios during this time period.

The multivariate environmental similarity (MESS) analysis predicted few areas with novel climate across the range in the future predictions. The most dissimilar variable (MOD) map shows that the novel climate conditions found were due to the influence of slope variable and Bio18 (Precipitation of the warmest quarter). However, these areas were found outside the training range of our model (Supplementary file Figs. S5–S10).

3.3. Habitat stability and loss in protected areas

The protected area network within the Western Ghats was found to have climatically suitable conditions for Thar in the current scenario. However, most of the existing protected areas (PAs) will become unsuitable under future climate scenarios (Supplementary file Table 3). Our models suggest that > 60% of the current suitable habitats in the southern Western Ghats will be lost as a result of the climate warming. To be specific, Kalakkad Mundanthurai Tiger reserve, Peppara WLS, Neyyar WLS, Schenduruny WLS and Srivilliputhur WLS shows a complete absence of suitable climatic conditions for Tahr in the future scenario. In addition, other PAs in this region such as Peechi-Vazhani Wildlife Sanctuary (WLS), Parambikulam Tiger Reserve (TR), Chinnar WLS, Silent Valley National Park (NP), and Srivilliputhur WLS are also vulnerable to extreme climate changes scenarios. The abiotically stable areas under both the climate change scenarios were located in Periyar TR, Eravikulam, Mukurthy NP, Kalakkad Mundanthurai TR, Indira Gandhi NP, and Anamalai WLS (Supplementary file Table 3). Even though there are stable habitats predicted by the model, these PA's are expected to experience a drastic habitat loss as a result of the future climate change.

4. Discussion

The results of our study suggest a drastic loss of Tahr's current suitable habitat even under moderate future climate change scenarios. The extreme climate scenario for the time period 2030s and 2050s was subjected to more habitat loss as compared to the moderate climate change scenario except for 2050. As per the current model outputs the current habitats may face the most severe risk from climate change in the near future. We recommend immediate conservation attention for vulnerable habitats.

Apart from threats posed by climate change, the species is also known to face serious threats due to hunting and other human-induced disturbances. Vegetation change in the native habitat of Tahr due to the

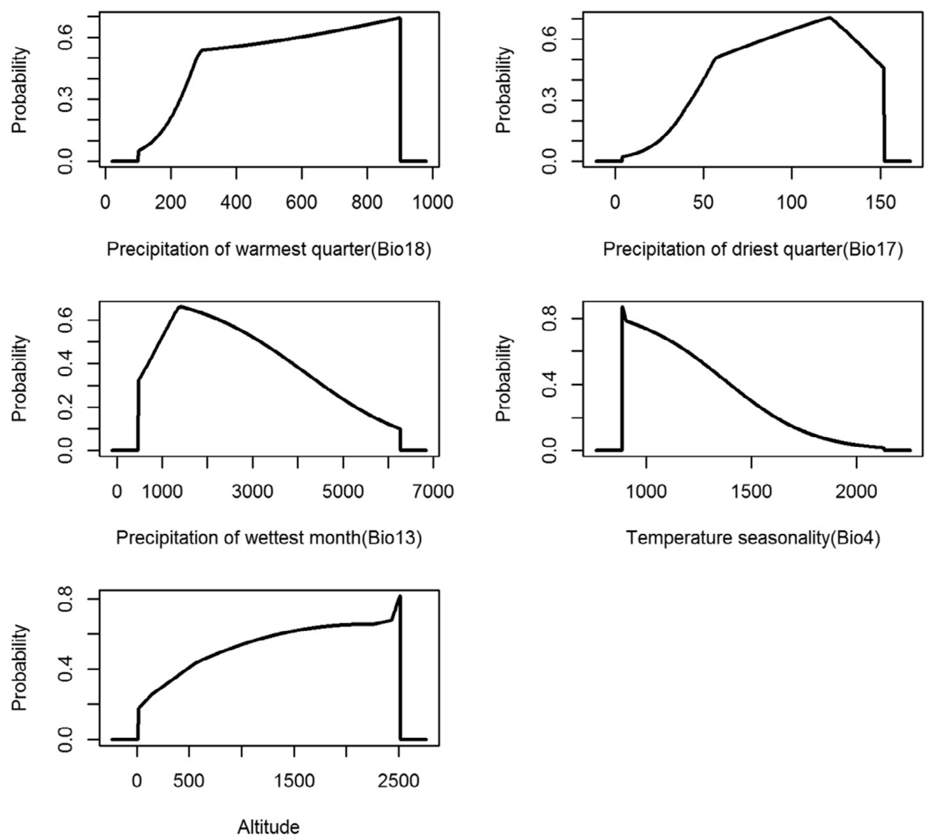

Fig. 4. Response curves showing relationships between the important environmental variables and probability of presence of Nilgiri Tahr. The values shown are an average of 10 replicates of cross-validated Maxent models.

replacement of short grasses by tall grass cover as a result of the ongoing protection against forest fire is also shown be detrimental to the survival of Tahr (Hopeland et al., 2016). Recent studies have shown that out of the overall 10–25 populations which sums to a total of 3122 individuals of the species in the Western Ghats, eight are very small populations (Predit et al., 2015; Hopeland et al., 2016). All these factors can further aggravate the chances of local extinctions in addition to climate change.

The present study shows even though PAs such as Chinnar WLS, Eravikulam NP (which holds comparatively larger populations of the species in the Western Ghats), and Parambikulam TR will have some stable areas under different climate change scenarios, while the other areas are predicted to experience severe habitat loss in the future. This ultimately might lead to the chances of large-scale local extinction of the species in those locations.

Globally, several studies suggest that rapid climate change will lead to severe range contraction, range shifts and local extinctions of species (Parmesan 2006; Bellard et al., 2012). Species unable to disperse or adapt to this change will be extinct. A recent study revealed the first Mammal species- Bramble Cay melomys (*Melomys rubicola*), a marsupial found in Australia- became extinct due to climate change (Watson, 2016). Even though the habitat requirements of the species were well understood, along with its vulnerability to sea level rise, Watson (2016) concluded that the species went extinct due to the lack of 'proactive conservation planning.' Knowledge of the threats experienced by a species and its habitats, coupled with timely management decision making, is thus critical to the conservation of endangered species (Martin et al., 2012). A global analysis by Warren et al. (2013) showed that without proper mitigation strategies the median global annual mean temperature might rise to 4 °C above pre-industrial levels by 2100. Warren et al. (2013) also predicted 34 ± 7% of the animals and 57 ± 6% of the plants may lose 50% or more of their geographic range by the 2080s. According to the 5th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2014), the global surface temperature is projected to exceed 1.5 °C for the scenario RCP4.5 and will exceed 2 °C under RCP8.5. In this context, the current conservation management process may not be sufficient to mitigate these conditions due to simultaneous alteration in the existing habitats (Hoegh-Guldberg et al., 2008). All these lead to the contemporary necessity of evaluating the climate vulnerability of every species, especially those with limited geographic distributions.

The climate vulnerability of current Tahr habitats and other threats to the species and its habitats call for an immediate conservation attention and planning. Several habitat dynamics studies in high altitude grasslands including the Tahr's substantiate the modeling results and need for conservation planning. For example, the conversion of grasslands in high rainfall areas into woody vegetation (Bond and Parr, 2010; Sukumar et al., 1995; Vergis et al., 2011) can also result in habitat loss of the species. The absence of fire as a result of better surveillance and forest management practices occurring in the region can intensify the ecological succession of woody vegetation in existing grasslands which reduce foraging opportunities for Tahr and make them more susceptible to predators (Hopeland et al., 2016). In summary, the modeling results, as well as the ecological study results from the Tahr habitats together, demand an immediate, proactive conservation and management strategy with a strong focus on the protection of both existing Tahr habitats and areas that may be suitable for Tahr in the future.

4.1. Management implications and caveats

Here, using ecological niche models, we provide an opportunity to evaluate the future needs for conserving Tahr habitat by considering the ongoing global climate change. Our study shows drastic loss of Tahr

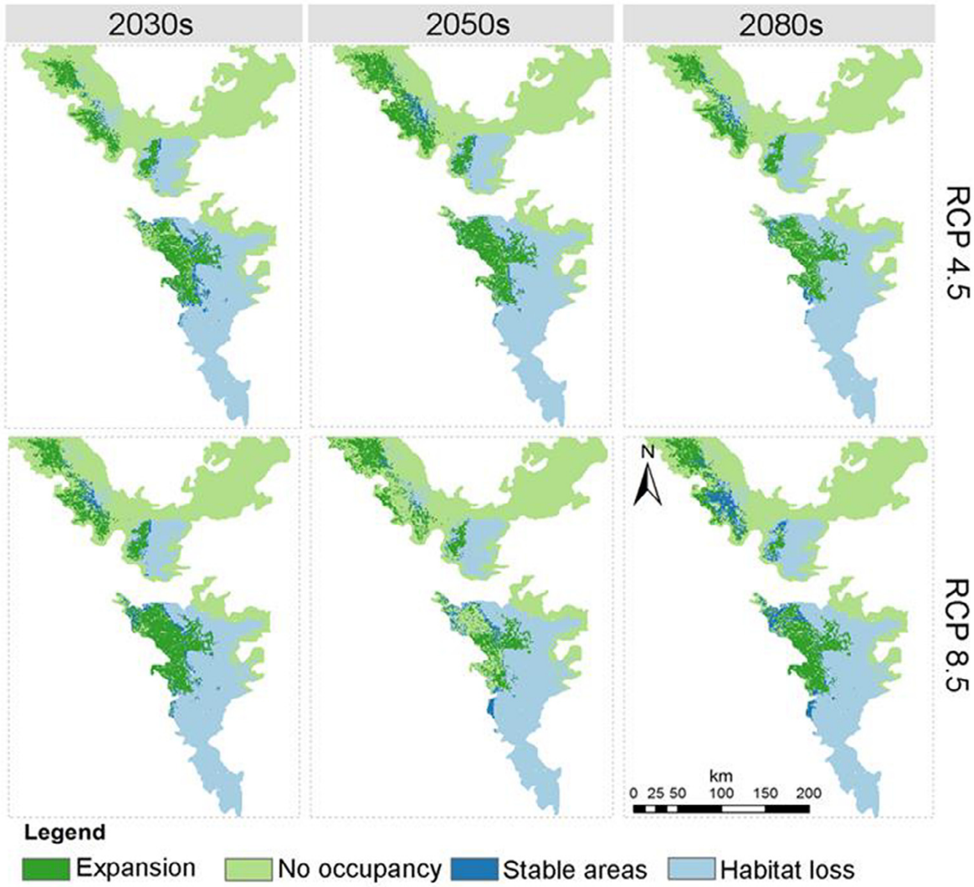

Fig. 5. Change maps representing the predicted future (stable/no change, contraction/loss, expansion/gained) climatic habitats for Nilgiri Tahr. for the years 2030s, 2050s and 2080s under RCP4.5 and RCP8.5 climate change scenarios.

Table 2
Area (km^2) which were found suitable/stable, lost and gained for Nilgiri Tahr with in the Western Ghats hotspot compared to the current scenario.

Future scenario	Stable	Gain	Lost
2030 RCP4.5	1242	4482	15,666
2030 RCP8.5	1254	2148	15,324
2050 RCP4.5	1087	5540	15,557
2050 RCP8.5	1118	2422	15,917
2080 RCP4.5	897	3954	16,188
2080 RCP8.5	2062	3197	16,019

habitats compared to the present and is the first of its kind which uses ecological niche models to predict the suitable habitats for Tahr in the Western Ghats. Niche models are perceived as a best-suited method while dealing with uncertainties such as future climate change for conservation prioritization and reserve selection process (Tulloch et al., 2016). For example Ecological niche models were successfully employed in identifying critical habitats and understand the effect of climate change in the distribution of the endangered ungulate Przewalski's gazelle (*Procapra przewalskii*) in China (Hu and Jiang, 2011). Niche models were also used to understand suitable habitats of the *Hoplocephalus bungaroides*, the most endangered snake of Australia in the future climate warming scenarios (Penman et al., 2010). These studies shed light to the need to conservation of areas which are more suitable for its persistence in the future scenarios. Creation of additional protected areas in suitable habitats outside the existing PA network within in the range will be helpful to curb the effect of climate change on Tahr as well as its associated species. Several small populations of Tahr are subjected to illegal hunting. Rai and Johnsingh, (1992) reported the incidence of hunting and population decline from Kalakkad-Mundanthurai Tiger reserve, Interestingly, our models predict a major loss of suitable habitats of tahr in this region, in such situations we recommend suitable steps to control hunting and preserve its existing habitats along with increased awareness of species conservation under climate change. Monitoring small populations in areas were habitat loss are shown to be prominent must be carried out immediately since local catastrophic events such as human mediated land transformation, diseases outbreaks and poaching in conjunction with climate change could easily cause extinction of Tahr in these habitats. Similarly, site-specific management programs, informed by ENMs, can be crucial in conservation planning of the Tahr. Based on our results we recommend site specific conservation measures to those locations where the existing habitats are predicted to be lost under climate change. These locations can be potentially vulnerable and it is advisable to protect and improve the existing conditions of these habitats. We also recommend to avoid any man made alterations in areas which are predicted to have stable habitat conditions for future.

While considering the results of the study we also acknowledge several caveats. For example, the WorldClim data used for the niche modeling can be less accurate in regions like Western Ghats with few weather stations. Hence, we see the possibility that the models presented here are subject to change with the availability of better climatic forecast. The accuracy of future models is also questionable in precisely forecasting future changes in local climate. Our models predicted novel habitats in human-dominated lowlands outside the Western Ghats.

Nevertheless, it in noteworthy to mention that these habitats will be of no use with regard to the in-situ conservation of the species. This prediction might have occurred due to the choice of rainfall variables in our model building, and it's also noteworthy to mention that the locations outside the Ghats, in general, receive high rainfall. Our choice of minimum training presence threshold in determining habitat suitability can be very subjective, especially without reliable absence data, and can change the areas predicted to be suitable. Even though several caveats exist, niche models are recommended to incorporate for prioritization studies (Tulloch et al., 2016), which will ensure that valuable conservation opportunities will not be missed in the wake of global climate change.

5. Conclusions

The present study demonstrates that the existing Nilgiri Tahr habitats are vulnerable to future climate change. Under rapid climate change most of its current habitats will not provide suitable climatic conditions for this species to persist in the wild conditions. The current protected area networks in the Western Ghats are predicted to lose most of their suitable habitats for Tahr as a result of future climate change. Our model results suggest that the existing protected area networks may not be effective in conserving the current Tahr population in the Western Ghats, unless mitigation measures are incorporated in the management plans considering the climate vulnerability of the species. We recommend immediate surveys for improving connectivity and habitat quality of those locations which are predicted to lose its climatic conditions in the future.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecoleng.2018.06.017.

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