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Where are they? Where will they be? In pursuit of current and future whereabouts of endangered Himalayan musk deer

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ABSTRACT

Conservation and management of environmentally suitable areas, that support survival and persistence of species, are keys to protect wildlife in their natural habitat. Populations of Himalayan musk deer *Moschus leucogaster*, an endemic species in Asia, are listed as endangered in the IUCN red list, requiring immediate conservation actions before their extinction in the wild. In order to model and map the current and future (under projected climate change settings) climatically-suitable area for the species, Maxent modeling technique, that requires presence-only records, was employed. As predictors, we extracted 19 bioclimatic variables from 'WorldClim' database with a ~1 km spatial resolution and used 10 uncorrelated bioclimatic variables as inputs. As indicated by a high area under ROC curve (AUC) value (>0.9), Maxent well performed and predicted climatically-suitable habitat for the species along the Hindukush Himalaya, where the species is known to occur. Annual mean temperature appeared to most influence the distribution of potential habitat for the species. An expansion of species' habitat was noticed in the Indian and Tibetan part of species range, suggesting a potential future effect of climate change on the species distribution. The findings of this study could assist wildlife managers in devising conservation plans for the current and future conservation of the species in the context of climate change. This is the first study to model and map the current and future distribution of the species in its range.

Introduction

With different levels of biodiversity increasingly being endangered or threatened with extinction by manifold factors (both deterministic and stochastic), one of the biggest challenge conservationists face today is to turn this tide and maintain integrity and functionality of ecosystems (Millenium Ecosystem Assessment, 2005). This challenge has been further amplified by effects of climate change with an array of varying consequences over space and time (Parmesan and Yohe, 2003; Thomas et al., 2004; van Gils et al., 2016). Numerous conservation strategies, varying with type, scale, and magnitude of threats, have been developed by conservationists (Brooks et al., 2006). Within these contexts, species distribution models (SDMs) have been widely developed to estimate, predict, and map species geographic ranges over time (Elith and Leathwick, 2009).

Various algorithms, with increasing computational capabilities, have been devised for SDMs and their use vary with objectives and available data (Guisan and Zimmermann, 2000; Elith and Graham, 2009). These techniques establish relationships between sites of known species occurrences and environmental factors that are presumed to affect their presences or absences. These relationships allow to interpolate and extrapolate geographic distributions in novel areas and/or under a changed scenario setting (for example, scenarios predicted under climate change). Among the SDMs, Maximum Entropy Modeling (Maxent) technique, that requires presence-only records (i.e., latitude/longitude of species occurrence points) of the species, is being widely used for estimation and prediction of a species' geographical range (Phillips et al., 2006). Moreover, increasing availabilities of species occurrence data have extended its application in conservation biogeography, especially regarding rare and declining species with incomplete information (Phillips et al., 2006). Consequently, Maxent appear as important

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tool to gain insights into current ranges and potential range-shifts due to climate change effects over time (see Phillips et al., 2006; Franklin, 2010).

A rare species whose distribution has not yet been modeled, is the Himalayan musk deer Himalayan musk (*Moschus leucogaster)*. This species inhabits high alpine environments of Bhutan, northern India, Pakistan, Nepal, and China (Green, 1986; Grubb, 2005; Yang et al., 2003); i.e., high altitude region along the Hindukush Himalaya. This species is also treated as a subspecies of alpine musk deer (*Moschus chrysogaster*). Actually literatures indicate that both *M. leucogaster* and *M. chrysogaster* are interchangeably treated as Himalayan musk deer and/or alpine musk deer in these regions. However, range map from IUCN red list specifies that the musk deer species in this range is Himalayan musk deer (i.e., *M. leucogaster*). Hence, the species of concern in this study is treated as *M. leucogaster*. Populations of musk deer are declining primarily due to habitat loss and overexploitation (Yang et al., 2003; Timmins and Duckworth, 2015). Consequently, the species have been listed in Appendix A of CITES and as endangered in red list of International Union for Conservation of Nature (IUCN). However, studies of the species are so far scattered, largely local and confined to small geographic scale. Hence, the identification of climatically-suitable areas for the survival and persistence of the species could potentially aid in the current and future conservation of the species. The current study is directed towards modeling and mapping, for the first time, the current distributional range of the species, and attempts to predict the future range under projected climate change scenario, using a Maxent model. In addition, it aims to provide qualitative insights into the climatic variables that potentially affect the habitat distribution of the species.

Material and methods

Eighty-five unique geographic coordinates (i.e. Latitude/Longitude) of the species' occurrences were used in the study. These geographic coordinates represent presence locations of the species and were recorded based on sightings of fecal pellets of the species. Musk deer have easily recognizable 'latrine-sites' (with heap of fecal pellets) that make recording of the species' presence easy. These data were collected from randomly surveyed potential habitat of the species in Bhutan, Nepal, India, and Pakistan in between 2013 and 2015; hence the occurrence points are from the geographic range of the species along the Hindukush Himalaya from Pakistan to Bhutan (for details about the area and data collection see, Abbas et al., 2015; Ilyas, 2014; Khadka and James, 2016). Nineteen bioclimatic variables with a 30 arc-second spatial resolution (approximately 1 km resolution) for two time periods: 'current' and 'future' (for the year 2050), were used as predictors and extracted from the 'WorldClim' database (url: worldclim.org; Hijmans et al., 2005). The database consists of projected climate for the years 2050 and 2070, with four different scenarios of greenhouse gas trajectories i.e., Representative Concentration Pathways (RCPs). Because of varying level of greenhouse gas concentration trajectories envisioned for the future and their inherent effect on climate, climatic surfaces data for a modest scenario i.e., RCP6.0 averaged from three randomly selected General Circulation Models (GCM: BCC-CSM1-1, CCSM4, GISS-E2-R) for the year 2050 were used for projecting the future geographic range of the species.

Pearson's correlation coefficients among the current nineteen bioclimatic variables in the database were determined (see Appendix), and when the correlation coefficient between the variables was found to be significant (i.e. $r \geq 0.9$, $p < 0.01$), only one variable from a set of highly correlated variables was used to reduce the problems due to multi-collinearity (Dormann et al., 2013). Consequently, of the 19 bioclimatic variables extracted from 'WorldClim', 10 bioclimatic variables i.e. annual mean temperature, mean diurnal range, isothermality, temperature seasonality, mean temperature of wettest quarter, annual precipitation, precipitation of driest month, precipitation seasonality, precipitation of warmest quarter, and precipitation of coldest quarter were used as inputs for the model. Since the ecology of the species is largely unknown, we used all the 10 uncorrelated variables as inputs rather than filtering them out to variables that otherwise would be considerably linked to the survival of the species. Moreover, our major focus was to map climatically-suitable geographic area (i.e., prediction) rather than description of the process (i.e., explanation). We used Maxent (version 3.3.3k; http://www.cs.princeton.edu/~schapire/maxent/; Phillips et al., 2006) as a modeling platform (with auto features, 5000 iterations and default settings). For background samples (i.e. pseudo-absences), to estimate the bioclimatic layers across the entire extent, Maxent was made to select only the countries with presence locations (i.e., Bhutan, Nepal, India and Pakistan). In so doing, we limited the pseudo-absences to areas that were surveyed for the species, potentially providing the background samples with the same bias as presence locations (Elith et al., 2011).

Model was developed in Maxent using the occurrence points (i.e. latitude and longitude) and current climatic variables and was projected for the future climatic variables. The model was replicated 100 times in order to get an average estimate (since machine learning techniques are notorious for their inability to produce unique solutions), and hence the output is an average of 100 replications. Maxent produces a continuous raster map of habitat suitability with values ranging from 0 to 1 (0 indicating a non-suitability, 1 indicating a perfect suitability). Continuous map produced by Maxent was exported to ArcGIS (version: 10.4.1). A binary map of climatically-suitable and unsuitable geographical areas was created in ArcMap using 'maximum test sensitivity plus specificity logistic threshold' in the Maxent output file called 'maxentResults'. This threshold was found to maximize the sum of sensitivity and specificity and hence was considered to perform as well as the 'presence/absence' models (see Liu et al., 2016). Performance of the model was evaluated using a metric called 'Area Under the ROC (receiver operating characteristic) curve' or 'AUC' (Swets, 1988) and test omission error (i.e., fraction of presences predicted absent). The AUC metric, whose value ranges between 0 and 1, is a threshold-independent measure of a model's ability to discriminate presence from absence (or background). An AUC value of 0.5 indicates that the model performance is not better than random, while value >0.9 indicates high model performance (Peterson et al., 2011). 'Subsampling' procedure was executed in Maxent for model validation. Seventy percent of the occurrences data were used to train the model while the remaining 30 percent were used to test it. The relative contribution of different bioclimatic predictors to the distribution model was evaluated using percent variable contribution and jackknife procedures in Maxent (Elith et al., 2011).

Results

Average test AUC value for the model was 0.98 (±0.003 SD) and average training AUC value was 0.992 (±0.0007 SD). Also, average test omission error for the threshold used was 0.01 indicating a good performance of the model. Annual mean temperature was the strongest predictor of musk deer habitat distribution with 71.4% contribution. Similarly, the other climatic variables that were noted important for musk deer habitat distribution were precipitation seasonality (i.e., coefficient of variation), temperature seasonality (SD*100), and annual precipitation. Annual mean temperature of ~6° C, precipitation seasonality of ~68, temperature seasonality of ~5690, and annual precipitation of ~721 mm were noted as the

Table 1
Relative contribution of different bioclimatic variables to Maxent model for climatically-suitable habitat distribution of Himalayan musk deer. Percent contribution values are averaged over 100 replicate runs. General statistics show the bioclimatic profile of the species. Only the variables with contribution >1% are shown.

Variable	Percent Contribution	Mean	Standard Deviation
Annual Mean Temperature (°C)	71.4	6.18	0.28
Precipitation seasonality (CV)	7.6	68.2	0.8
Temperature seasonality (SD × 100)	5.5	5690	179
Annual precipitation (mm)	5.3	721	52
Precipitation of Coldest Quarter (mm)	4	124.6	10.3
Mean Diurnal Range (°C) (Mean of monthly (max temp – min temp))	2.5	10.5	0.09
Precipitation of Driest Month (mm)	1.2	9.9	0.91

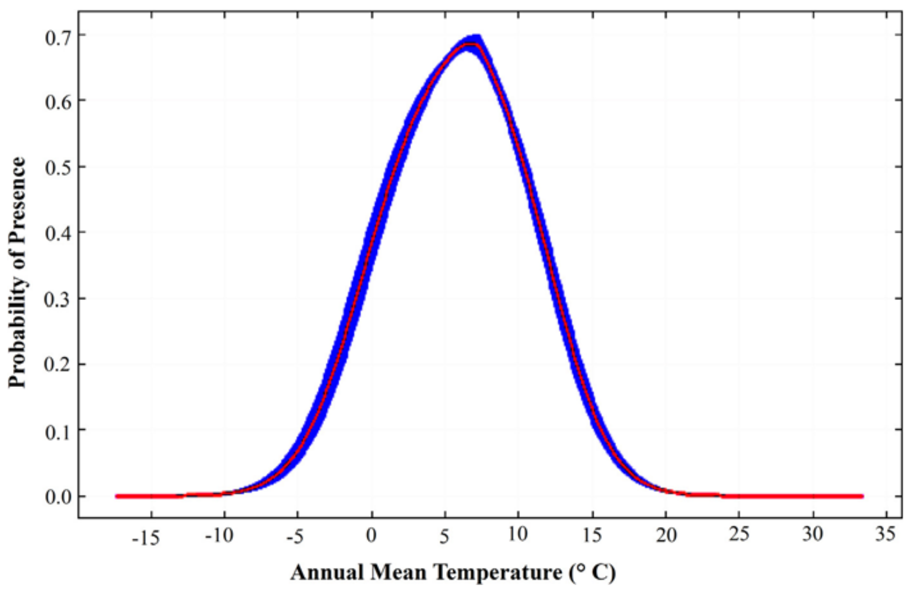

Fig. 1. Relationship between annual mean temperature and probability of presence of musk deer. The curve depicts the mean (±SD) response calculated over 100 replicates.

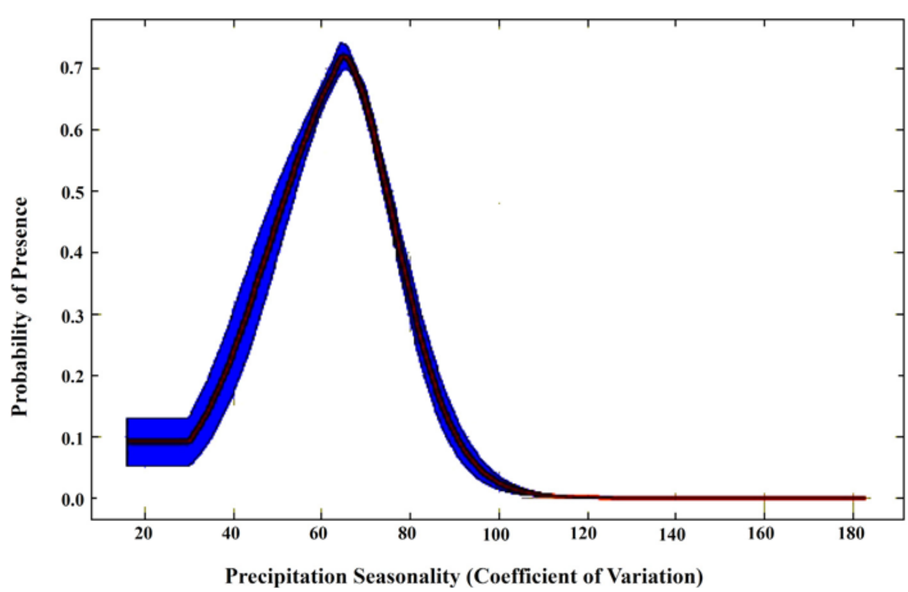

Fig. 2. Relationship between precipitation seasonality and probability of presence of musk deer. The curve depicts the mean (±SD) response calculated over 100 replicates.

optimal bioclimatic conditions for musk deer's habitat distribution (Table 1; Figs. 1–4). Jackknife results showed 'annual mean temperature' as the most useful information by itself, and having the most information that is not present in other variables, for model predictability (i.e., with highest regularized training gain and AUC value). Model predictions matched the collected occurrences of musk deer in Bhutan, Nepal, India, and Pakistan and also showed potential geographic range in China (Fig. 5 and 6). Future geographic distribution of the species is predicted to expand mostly in the Indian and Tibetan region of China (Fig. 6).

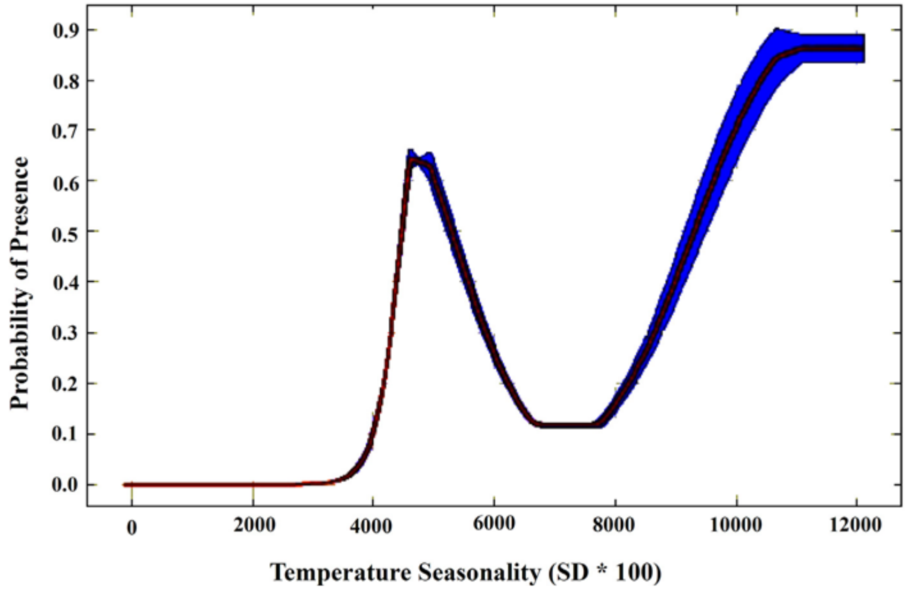

Fig. 3. Relationship between temperature seasonality and probability of presence of musk deer. The curve depicts the mean (±SD) response calculated over 100 replicates.

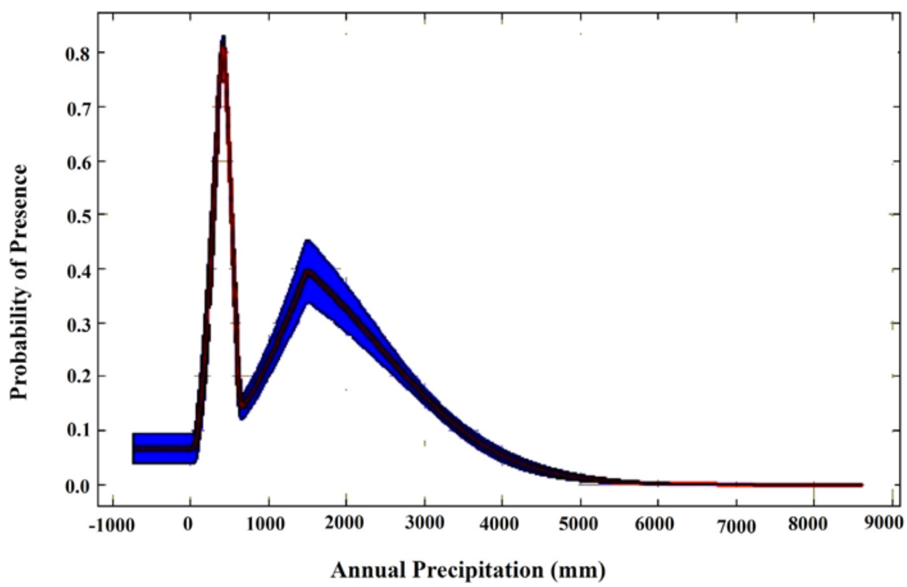

Fig. 4. Relationship between annual precipitation and probability of presence of musk deer. The curve depicts the mean (±SD) response calculated over 100 replicates.

Discussion

This is the first study to model and map the potential current and future distribution of climatically-suitable habitat of Himalayan musk deer in its whole range. Maxent accurately predicted the currently available occurrences; hence the maps created maps could be used to design detailed surveys to explore populations of the species in the predicted geographic area. It appears that the species has a narrowly-distributed climatically-suitable habitat, along the Hindukush Himalaya, with majority of climatically-suitable current habitat in Indian and the Tibetan region of species' range. The current distribution of climatically-suitable area, as predicted from the study, did not completely match the expert-based IUCN range map of the species (red contours in Figs. 5 and 6). Yet, notable is the potential habitat range in Pakistan and Tibetan region of China which is not encompassed in the IUCN range map although the species have been recorded in those areas (see Yang et al., 2003; Abbas et al., 2015). Hence, the current distribution map from the study offers an avenue for further exploration of the species in the area predicted suitable in the study. We believe that the current distribution map, as predicted from this study, meets the necessity of identifying potential areas that demand conservation concern. We recommend the protection and management of potentially suitable key areas predicted by the model even if the species don't currently occur there. This might require cooperation between countries and the design of a joint, international management plan.

The expansion of climatically-suitable habitat in the future in Indian and Tibetan part of the species' range suggest a potential reshuffling of species' distribution in the future (see Parmesan and Yohe, 2003); presumably to track the optimum or adaptive climatic niches and keep pace with the effects of changing climate for survival. This is in accordance with the theoretical predictions of climate change on a wide variety of taxa and climates (Hersteinsson and Macdonald, 1992; Pounds et al., 1999; Warren et al., 2001; Parmesan and Yohe, 2003). The geographic range of the species is distributed in between the latitudinal range of 30^0–38^0 N (i.e. in

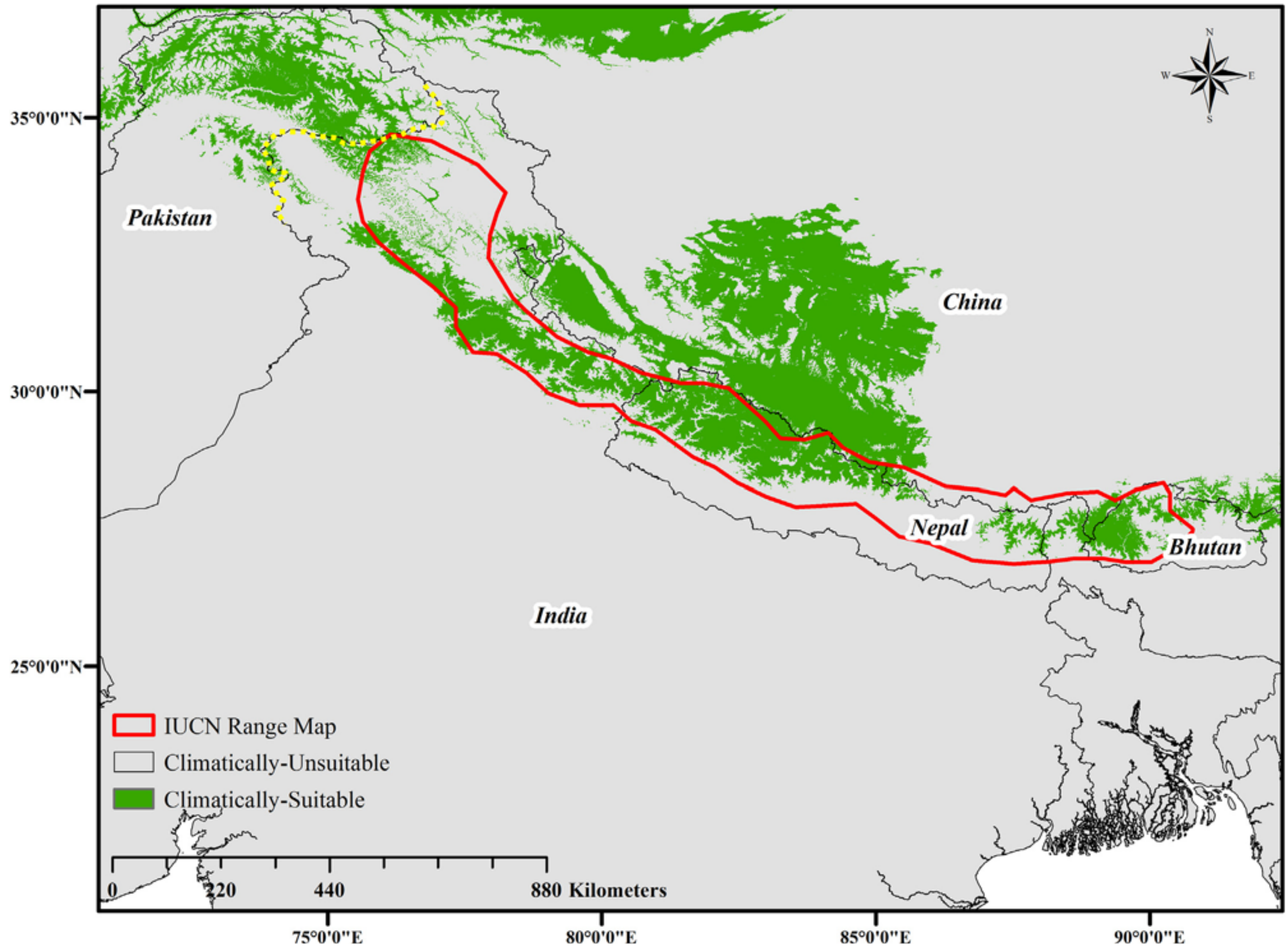

Fig. 5. Current climatically-suitable area for Himalayan musk deer as determined by the model. Yellow boundary line shows the geographical boundary of conflict. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

temperate areas), where the magnitude of climate change effects is predicted to be greater (Parmesan, 2007), because of projected relatively high rise in temperature and variation in precipitation patterns at those latitudes and altitudes (IPCC, 1996; Hughes, 2000) (for maps showing the evolution of climatic conditions between the current state and 2050 in the study area, see Appendix). Therefore, effects of climate change on the species are inevitable, since a narrow range of annual mean temperature, low precipitation seasonality, and low annual precipitation appear to be the major determinants to its habitat distribution. As for other taxa, temperature has been found to be a major component structuring distribution of Himalayan species (Elsen et al., 2017). However, how and to what extent these climatic changes will affect the species cannot be explained with certainty primarily because of knowledge gap and incomplete information about the ecology of the species. Yet we can hypothesize that the effects would be direct via physiological/phenological effects and indirect via cascading effects on resource bases or both. Since evidences suggest that temperate species have relatively broader thermal tolerance (Chan et al., 2016; but see Elsen et al., 2017), the latter hypothesis however would be more reasonable to test in the future studies to better understand the effects of climate change. Nevertheless, design of new conservation areas and expansion of existing conservation areas towards the predicted potentially suitable geographic area could aid in conservation of the species.

It is noteworthy that climatic variables are not the sole factors driving species distribution over space, although their crucial role in determining the geographic range of many species is undisputable (Andrewartha and Birch, 1954; IPCC, 1996; Venier et al., 1999). Other ecological factors like dispersal pattern and capacity, resource distribution and availability, ecological interactions, habitat selection etc. deserve well considerations, and better integrations within SDMs to predict a better picture of their distribution over space (Guisan and Thuiller, 2005; Elith and Leathwick, 2009). Incomplete availabilities of such data, to fully integrate the ecological theories of species into modeling process, have in part added some limitations to this study. Other factors that contribute to the uncertainties and limitations of SDMs are; sample size, sampling bias, spatial resolution of predictors including their choices, multi-collinearity; that deserve well considerations during modeling process (Stockwell and Peterson, 2002; Kadmon et al., 2004; Segurado et al., 2006). Maxent, however, has been invoked to perform considerably well with small sample sizes as well with optimal predictive power (see Wisz et al., 2008). Although we tried to deal with issues of multi-collinearity (by dropping highly correlated variables) and background sampling bias (by picking the background samples from the area of occurrences records only), yet we acknowledge the possible uncertainties in our findings, due in part to other potential issues (for example, biotic interactions, dispersal capacity, phenology) that could not be dealt and/or integrated into the modeling process. Inclusion of biologically relevant factors in modeling process in future would further refine the predicted distribution map of environmentally suitable habitat for the species. Yet, the predicted suitable area from the study is climatically-conducive to the survival of the species; hence the

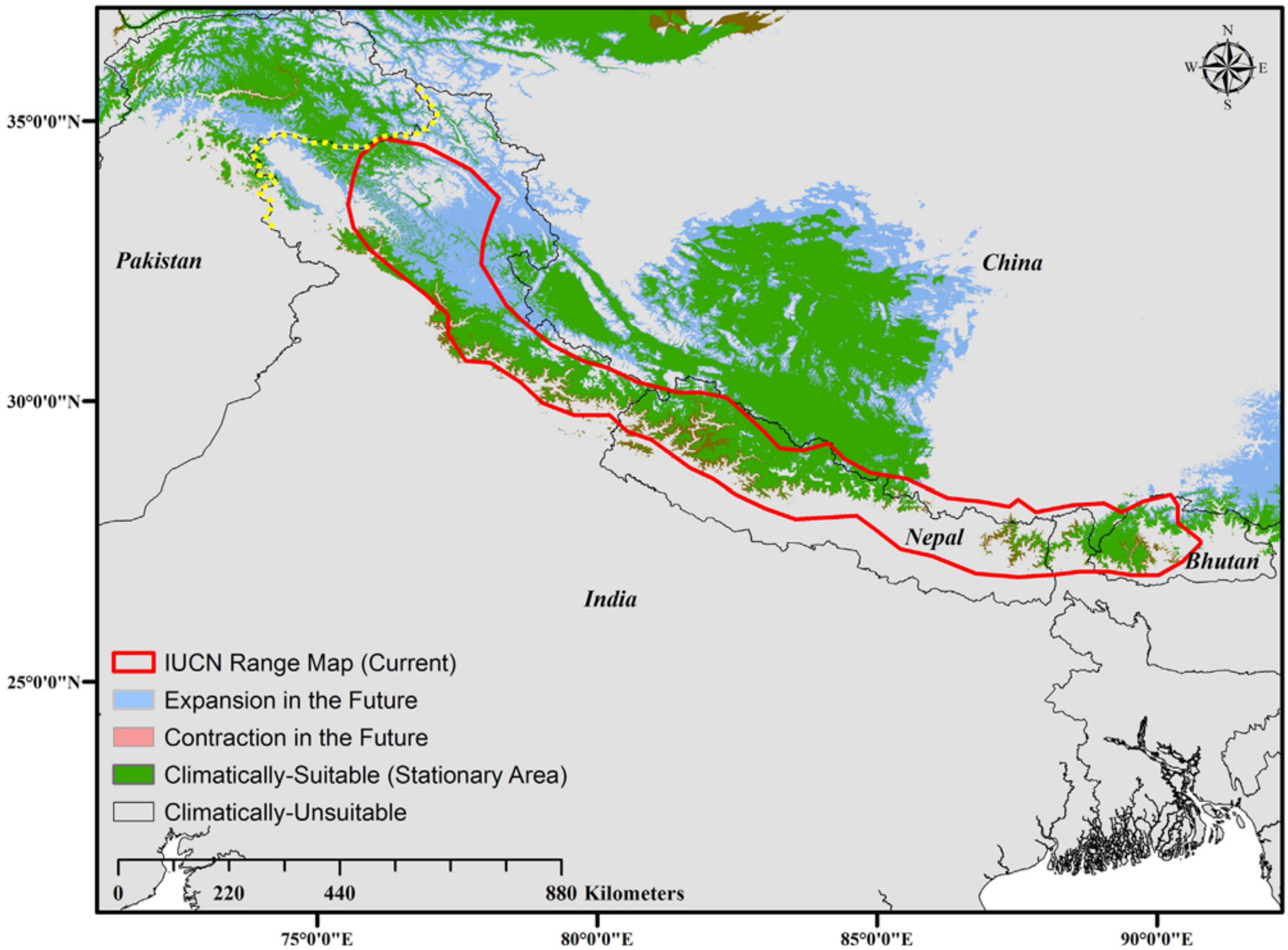

Fig. 6. Future climatically-suitable area for Himalayan musk deer as predicted by the model along with the expansion and contraction of area under projected climate change.

area deserves considerable concern for conservation of the species in the context of climate change.

SDMs are increasingly and diversely used in conservation biogeography with relatively good success (Austin et al., 1990; Elith and Burgman, 2002; Ferrier, 2002). Of notable beauty of these techniques is an easily understandable and interpretable output, in the form of binary maps (i.e. habitat-suitability maps), required by wildlife managers for conservation actions and risk analyses. Although interpreting habitat and its suitability from patterns of occurrence can sometimes be misleading (van Horne, 1983), which is usually the case with high population size; yet for a small population size of Himalayan musk deer, it is unlikely to misinform the suitability of habitat by the occurrence points of the species used here. This, however, requires exploration of musk deer populations in the predicted geographical space for validity. It is expected that the findings of the current study could assist wildlife managers and other stakeholders in conservation planning and sound management decisions of, declining and threatened, Himalayan musk deer in the context of climate change.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.mambio.2017.02.007.

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