Final report

Assessing the climate change impacts on species and habitats

Submitted by

ARJUN THAPA PH D

Practical Solution Consultancy Nepal Pvt. Ltd (PSPL)

Buddha Nagar, New Baneshwor, Nepal

Submitted to

Hariyo Ban Program

2020

This report is made possible by the support of the American People through the United States Agency for International Development (USAID.) The contents of this report are the sole responsibility of Practical Solution Consultancy Nepal Pvt. Ltd and do not necessarily reflect the views of USAID or the United States Government.

Executive summary

Chitwan-Annapurna landscape (CHAL), a part of central Himalaya, represents a rich biodiversity in N-S linkage constituting climatic and topographic heterogeneity. CHAL provides home for nationally and globally endangered fauna included One-horned rhinoceros, red panda and snow leopard those act as an indicator of healthily ecosystem at different ecological zone of the country. Such rich biodiversity of CHAL is under pressure of human driven climate change and land use land cover changes that forces these endangered species to highly sensitive and vulnerable to changing climate. Changing climate pattern and land use may affect the habitat of these keys species of CHAL. Understanding these gaps, this study assessed potential the impacts of climate change and land use and land cover change on the habitat of key species based on species occurrence records, and least correlated environmental variables using MaxEnt modelling in future climate scenarios (2050 and 2070). CA - Markov model was used to simulate and predict its temporal and spatial change of land use land cover in future projection (2050 and2070). Climatically potential suitable habitat is estimated about 1,192km^2, 2,417km^2, 4,080km^2 for rhinoceros, red panda and snow leopard respectively. Both snow leopard and red panda will be vulnerable in future climate change scenarios whereas rhinoceros will be exposed low vulnerable to future climate change. About 32.5% and 56% habitat of red panda and 36.3% and 41.8% of snow leopard will be loss in 2050 and 2070 respectively. Importantly, habitat of rhinoceros will be increased in future climate change. A total of 1,190km^2, 2,375km^2 and 1,052km^2 will act as the climate refugia in CHAL for rhinoceros, snow leopard and red panda respectively. Most of the land cover attributes are likely increased in the future projection, however snow cover is likely decreased (24%) in the simulation of future projection. Overall, results revealed that the suitable habitat of the snow leopard and red panda are likely to be affected by climate and land cover change in the future in CHAL. The study recommend that conservation concerned institutions should pay serious attention to the land use intervention activities in the future in order to mitigate the potential impact on these key species.

Contents

Tables and Figures

Chapter 1: Introduction

1.1. Background

Researchers have suggested that the climate of the world is alarmingly changing in unpredictable way since 1850. The IPCC report stated that the global surface temperature has abruptly risen since 1950 and compared to the last 100 years (1906-2005), the increase in the global temperature was noted to be 0.74°C +/- 0.18 °C due to the emission of greenhouse gases (GHGs) led largely from the anthropogenic activities like combustion of fossil fuels and land use changes (IPCC, 2007)The effect of this change is sooner or later perceived through rise in sea level, melting of glaciers, extreme weathers, floods and droughts thus bringing out the unequivocal changes in ecosystems, health, agricultural and economic sectors, while some places are already showing the signs of these impacts (Beaumont *et al.*, 2011).

Temperature rise projected due to climate change is to be stronger in the Himalayan highlands and is expected to lead to a higher intensity of extreme weather events in south Asia including Nepal. The warming rate is expected to be higher in the mountains and the middle hills of Nepal that may consequently affect various sectors like forestry, agriculture, livelihoods and many other resources thereby affecting the economy (NCP 2011). There is increasing evidence that global climatic change is affecting species physiology, phenology and distribution. Also, there is a growing trend of using phenological (life cycle events) response of plants for climate change assessment. Study conducted by Rawal on the germination and establishment potential of different tree species under projected climate change scenarios also depicts that some tree species are more vulnerable than others with the global environmental change and they tend to search for a more favorable environment (Rawal, 2014). Another study suggested that the tree line is expected to shift to higher altitudes as temperatures rise, and tree species in different vegetation zones will disperse if possible from hotter conditions to areas with a cooler and moist environment (Thapa *et al.*, 2016). This includes *Shorea robusta* which is currently a dominant species in the extensive lowland sal woodlands of the Terai. These changes in forest habitat and ecosystems are likely to have big impacts for faunal species, especially those with a narrow range of habitat requirements including temperature(Thapa *et al.*, 2016). Study from Himalaya already noted that there is upward shift of *A. spectabilis* at Manasulu Conservation area was

estimated to be 2.61 m yr−1 (Gaire *et al.*, 2011; Gaire *et al.*, 2014). .Snow leopards inhabit the alpine zone between snow line and tree line, which contracts and expands greatly during glacier-interglacial cycles (Li *et al.*, 2016). It is estimated that 30% of snow leopard habitat in the Himalayas may be lost due to tree line shift (Forrest et al 2012). Due to unique environmentally featured mountain in High Asia, there would be high possibility in existence of large refugia for snow leopard that maintain relatively constant arid or semi-arid climate (Li *et al.*, 2016). However, habitat loss leading to fragmentation in the Himalayas and Hengdu Mountain, along with increasing human activities, will present conservation challenges for snow leopards and other sympatric species (Li *et al.*, 2016). Also other studies illustrate that protected areas alone will not be able to conserve predators with large home ranges and conservationists and managers should not restrict their efforts to land sparing (Johansson *et al.*, 2016).

With variations in altitudinal ranges, climatic eco-regions, and topographic heterogeneity , the Himalayan region has provided habitats for many endangered species of flora and fauna (Liu et al., 2017; Nie et al., 2017). However changing climate and land cover have negatively impacted the habitats of many species (Thuiller, 2003; Jetz et al., 2007; Hofmeister et al., 2010). Higher annual temperature increase (increased by 0.13ºC/year) in other parts of the Himalayan region have been observed, particularly in Upper Mustang of the trans-Himalaya region (Aryal *et al.*, 2016). Consequence of climate changes resulted in snow/glacier melting, upward shifting of tree lines and rapid degrading of alpine grasslands have observed that could led to habitat range contractions of the snow leopard in the southern Himalayan ranges, although habitat expansion is predicted in the northern ranges (Forrest *et al.*, 2012; Farrington & Li, 2016). Increasing temperature has adversely impacted the habitat in the high altitude areas in Nepal, especially in the Himalayas (Shrestha & Aryal, 2011) where species habitat distributions had already been shifting upward in this area (Karki et al., 2009).

1.2. Deployed species distribution model approaches

Species distribution models (SDMs) have become the most well-known advance methods to predict distributions using species occurrence records (Sambrook & Russell, 2001; Elith & Leathwick, 2009).SMDs relate species presence records to different predictors, mainly environmental variables to predict the potential distribution of a species across an area of interest

(Pearson *et al.*, 2004; Elith *et al.*, 2005; Guisan & Thuiller, 2005; Elith *et al.*, 2006). SDMs are recognized as a good solution, and widely flourish among ecologists and conservation managers to applied in many areas of interest such as biodiversity exploration, species invasion (Härkönen, 2002; Tomkiewicz *et al.*, 2010), effects of climate changes, monitoring and restoration of declining populations in natural habitats (Peterson, 2011). Recent studies show, SDMs have been utilized in various biodiversity conservation projects, for instance managing biological invasion (Soberon *et al.*, 2001; Aryal *et al.*, 2016), identifying and protecting critical habitats (DEPI, 2013; Muscarella *et al.*, 2014), reserve selection and translocation (Johnson et al. 2007, NPS Seki 2011), and are widely followed by IUCN to build global species distribution range maps (Reid *et al.*, 1991; Wang, 1997). This model has vital functions in testing biogeographical, ecological and evolutionary hypothesis (Anderson *et al.*, 2003; Anderson & Martinez-Meyer, 2004; Graham *et al.*, 2004) for assessing species invasion and proliferation, and also epidemic disease outbursts. Selection of biologically meaningful predictors based on a species' eco-physiological tolerances or habitat requirements can affect the model prediction as well as performance (Austin, 2007; Aryal *et al.*, 2010). Out of various SDMs, five top models include MaxEnt, random forest, boosted regress trees, generalized additive models, and multivariate adaptive regression spines, these showed similar predictive performance despites difference in computational complexity (García-Callejas & Araújo, 2016). Due to unique features such as occurrence records, flexibility with sparse or noisy input information, limited occurrence data and good predictive performance, we selected MaxEnt: an easily implemented algorithm in the public domain. (Lande, 1988; Phillips *et al.*, 2006; Phillips & Dudik, 2008; Figueirido *et al.*, 2012; Fourcade *et al.*, 2014). Climate plays an important role in determining the species' distribution and evaluating influence of environmental variables (Bailey, 1985; Morelle and Lejeune, 2015), when model processes in large geographical area that provides information on suitable habitat for a species (Marino et al. 2011).

WWF Nepal undertook a study on "Climate change impacts on biodiversity in CHAL and TAL" in 2014 which combined two approaches; mapping projected vegetation distribution change through the coarser-scaled climate envelope modeling and adjusting it with projected micro-refugia resulting from local-level topography and aspect variation, to project changes in habitats of different species. That study has enlightened that most of the lower and mid-hill forests are

particularly vulnerable to climate change impacts, whereas the temperate Upper Mountain and subalpine forests are likely to be more resilient to climate change (Thapa *et al.*, 2016). But the latter analysis shows that areas of forest vegetation in climatically stable microrefugia, sheltered from regional influences of climate change by the highly dissected terrain of the Himalayan Mountains, mid-hills and Siwaliks, could remain relatively unaffected.

The majority of climate change vulnerability assessments have used Species Distribution Models (SDMs), which correlate data on species' contemporary distributions with observations of recent climates and then apply these correlations to climate projections to predict the location(s) of suitable climatic conditions for a species in the future (Phillips *et al.*, 2006). However, such SDMs take no account of the potential capacities of species to adapt to such changes by dispersal, behavioral change or evolutionary adaptation. This shortcoming has led to the development of next-generation, dynamic (or process-based) SDMs that include relevant biological traits such as dispersal ability, habitat requirements and other key parameters to assess the likelihood of population changes being realised over space and time (Conlisk *et al.*, 2013). However, to parameterize such models requires quantitative data for a species or system; something that is lacking for many species. An alternative approach, 'Trait-based Vulnerability Assessment' (TVA) considers the vulnerability of species to potential climate change based on the best available current knowledge of the species' ecology and life history (Willis *et al.*, 2015). Unlike process-based models, TVAs use composite indices to characterize the vulnerability of species to climate change.

1.3. Target Key Species and Ecological Zone Representation

Although the extent and specific nature of impacts on biodiversity are still unclear, shifts in vegetation, local species extinctions, and changes to ecosystem service delivery are expected. To develop a more detailed understanding of impacts on habitats and species, a rigorous research has become inevitable. In this study, the three charismatic globally threatened species that habitat specialized at different ecological zone; Greater One horned rhino, red panda, and snow leopard represent as the focal species to understand potential impacts of climate change in CHAL (Fig.1)

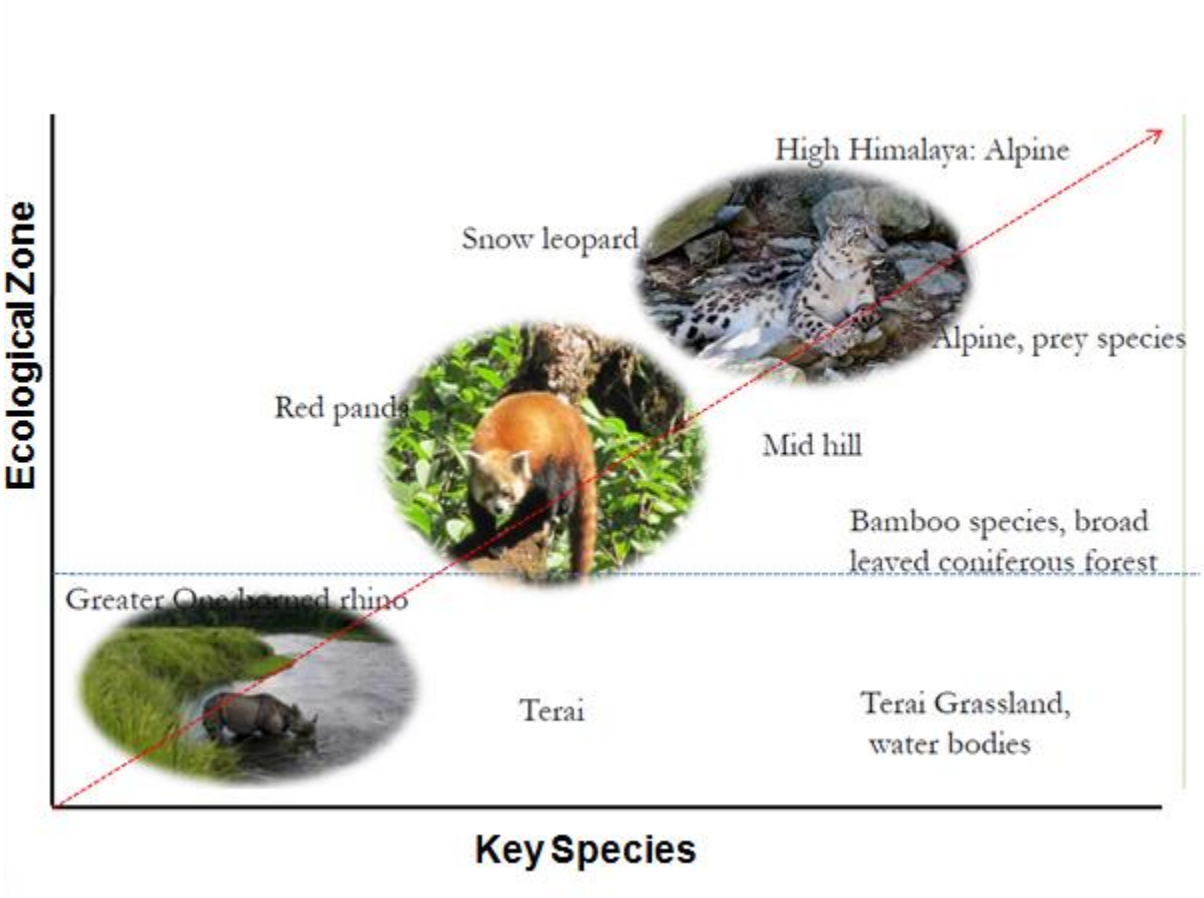


Figure 1 Key species and habitat features in different ecological zone

Changing climate pattern and land use may affect the habitat of wild flora and fauna in the Himalayas. Due to limited scientific information about effect of future environmental change on wildlife habitat, long-term species specific conservation plans are lacking to address effective action to cope such changes in particular areas of its distribution range.Scenarios of land use and land cover play an important role in exploring future developments and policy options for climate change, biodiversity, food security, ecosystem services, and sustainable development. Forecasts on Land use and Land cover change have become a focal point in managing natural resources and monitoring environmental changes in the ecosystem. Climate change and LUCC, poaching and human-wildlife conflicts, are the main threats leading to the decline of protected species populations within and outside the protected areas in the country and protective action is urgently needed (Jnawali *et al.*, 2011; Liu *et al.*, 2017). The snow leopard is the top predator and

keystone species in terms of the food web and functioning ecosystems in the alpine, however people are experiencing a negative impact due to economic loss caused by the livestock depredation at high altitude areas. Though human-wildlife conflict has caused major issues in mountainous people those entirely depend on the natural resources because of habitat degradation. Still, studies concerning the potential impact of climate and land cover change in the future habitat impacts on species the is insufficiently assessed. Few studies in forecasting impact of climate changes on snow leopard has been carried out in large spatial scale covering entire range, however it not sufficiently documented at local scale. Yet, there has not assessed impact of climate change on red panda and One-horned rhinoceros at both local and large spatial scale. All these three species are highly conservation valued are the indicator species for healthy ecology system in different ecological zone Outcomes of this study is expected in addressing actions state in species action plan which is developed by the government:-"identify important snow leopard habitats with respect to climate and human-caused stressors" (Snow Leopard Conservation Action Plan 2017- 2021) (DNPWC, 2017); "initiate research on potential adverse impacts of climate change on rhinoceros and their habitats" (Rhino Conservation Action Plan 2017- 2021) (DNPWC, 2017); and "study climate change impact on red panda and its habitat:" (Red panda Conservation Action Plan 2019-2023) (DNPWC & DFSC,2018).

1.4. Objectives

The overall objective is to assess the climate change impacts on key species - snow leopard, red panda and Greater One horned rhino and their habitats. Specific objectives are

- To assess the impacts of climate change on key species and habitats
- To assess and verify the impacts and explore cases where these impacts are seen
- To recommend the possible strategies to cope with the impacts

1.5. Limitations

- Limited occurrence records were available for the red panda in CHAL
- Lack of open access occurrence database on prey species of snow leopard, eg. blue sheep, musk deer, which were excluded the modeling process.
- Lack of occurrence records of bamboo species which is staple food sources of red panda which also excluded in model

All of these information might have chances to hindered predicted model evaluation precisely

Chapter- 2: Approaches and Methodology

2.1 Study sites

Chitwan-Annapurna Landscape (CHAL) and the Terai Arc Landscape (TAL) consists three sub-basins (Seti, Marsyangdi and Daraudi) in CHAL and core areas (Chitwan, Banke, Bardia and Suklaphanta National Parks and their buffer zones) and critical forests corridors (Barandhabhar, Kamdi, Karnali and Brahmadev) in TAL that harbor heterogeneous landscape with diverse flora and fauna. With an area of 32090 km^2, which is almost 22% of Nepal's land area CHAL extends over 19 districts (Arghakhanchi, Gulmi, Palpa, Baglung, Parbat, Myagdi, Mustang, Syangja, Kaski, Tanahun, Lamjung, Gorkha, Manang, Rasuwa, Nuwakot, Dhading, Nawalparasi, Chitwan and Makwanpur). It covers all of the Gandaki Basin in Nepal and includes major rivers like Kali Gandaki, Seti, Marshyangdi, Daraundi, BudhiGandaki, Trishuli and Narayani/East Rapti. This landscape elevates from lowland Terai (200 m) to alpine high mountains and the cold and dry Trans-Himalayan region (above 4000 m). The landscape is most important habitat of Snow leopard, red panda, black bear and common leopard. The dispersals of these species in north and south indicates north and south linkage along the CHAL landscape (Fig 2).

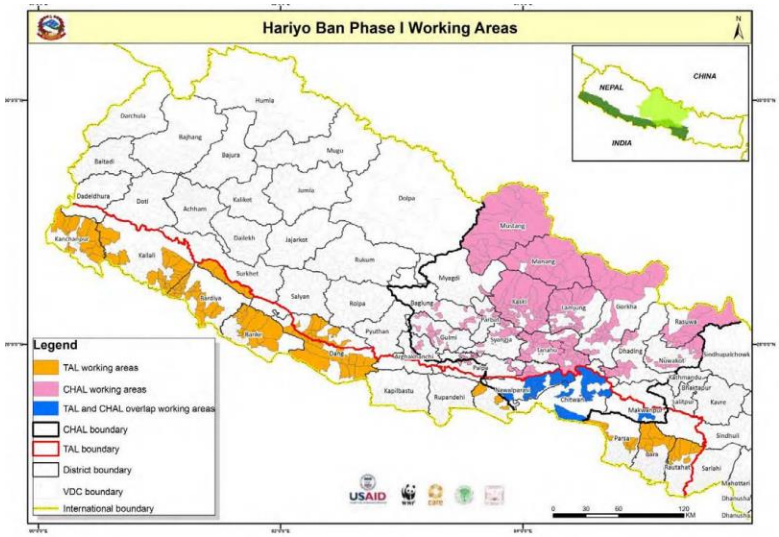


Figure 2 Study area (Sources: WWF Nepal 2017)

2.2 Methodological Framework

Integration of climate change projection model, habitat suitability model, mapping availability forage status (particularly vegetation and prey species) will be the important methodologies under this study. Detail research flow chart included different process in data sourcing, and modeling technique (Fig. 3.)

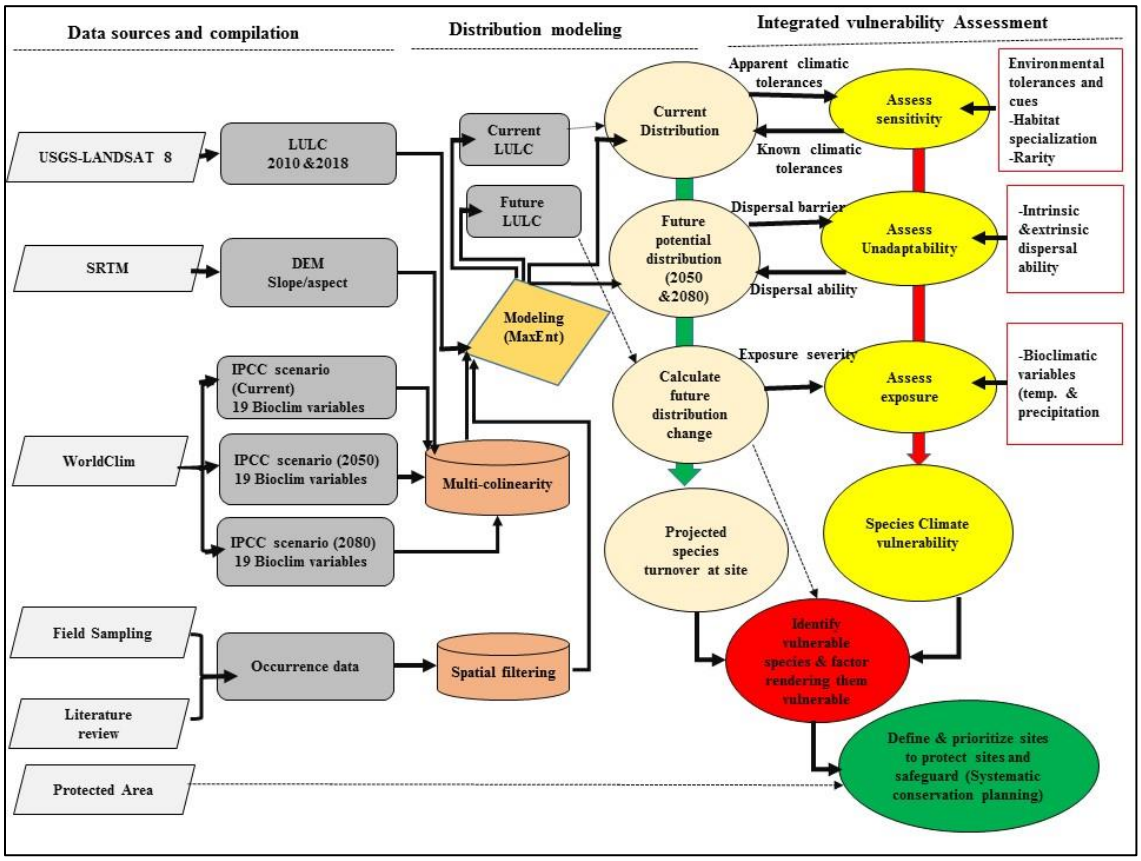


Figure 3 Detail research model flow chat (modified and adapted from Willis et al. 2015)

2.3 Methods

Following methods were deployed to achieve project's objectives.

2.2.1Desktop review

An intensive review of existing relevant sources of information were thoroughly reviewed. Published literature were extracted using Google search engine- Google, Google Scholar, and Web of Science using keywords relevant to the research topics: species, species + climate change, species + climate change + Nepal, SDM + species + Nepal, and land cover changes, land cover changes + future projection + Nepal, and trade based vulnerability analysis. Other reports, project reports, theses, documents and other relevant literatures on similar studies were accessed from libraries Tribbhuvan University (Central Library), Department of Forest and Soil Conservation, Department of National Parks and Wildlife Conservation, WWF, IUCN, NTNC and other relevant governmental and non-governmental organizations. Also, information were compiled through sending request from the project leaders that has submitted to their donors.

During review process, species occurrence records (latitude and longititude) were complied and other climates changes stress issued on the habitat were noted if variable in the literatures.(see Annex I).

2.2.2 Established species occurrence records and environment variables

All of these three species are distributed in the representative ecological zone of the country. Occurrences record of red panda, rhinoceros and snow leopard were collected from the secondary published literature and reports. Additionally, occurrence were also compiled from biologists those are involving in research of these target species. Records of species occurrence were both direct (sightings) and indirect evidences such as feces, dung, scats and pugmarks were recorded in field survey. Among these species, high species records were collected for the rhinoceros (N=411) in Chitwan National Park, red panda (N=104) and snow leopard (N=63). Occurrence records of snow leopard and red panda showed spatial distinct locations, however, rhinoceros was mostly clustered (Fig.4). To reduce autocorrelation, presence points were filtered by randomly selecting one point in each 1 km^2 grid (Aryal *et al.*, 2016; Thapa *et al.*, 2018).

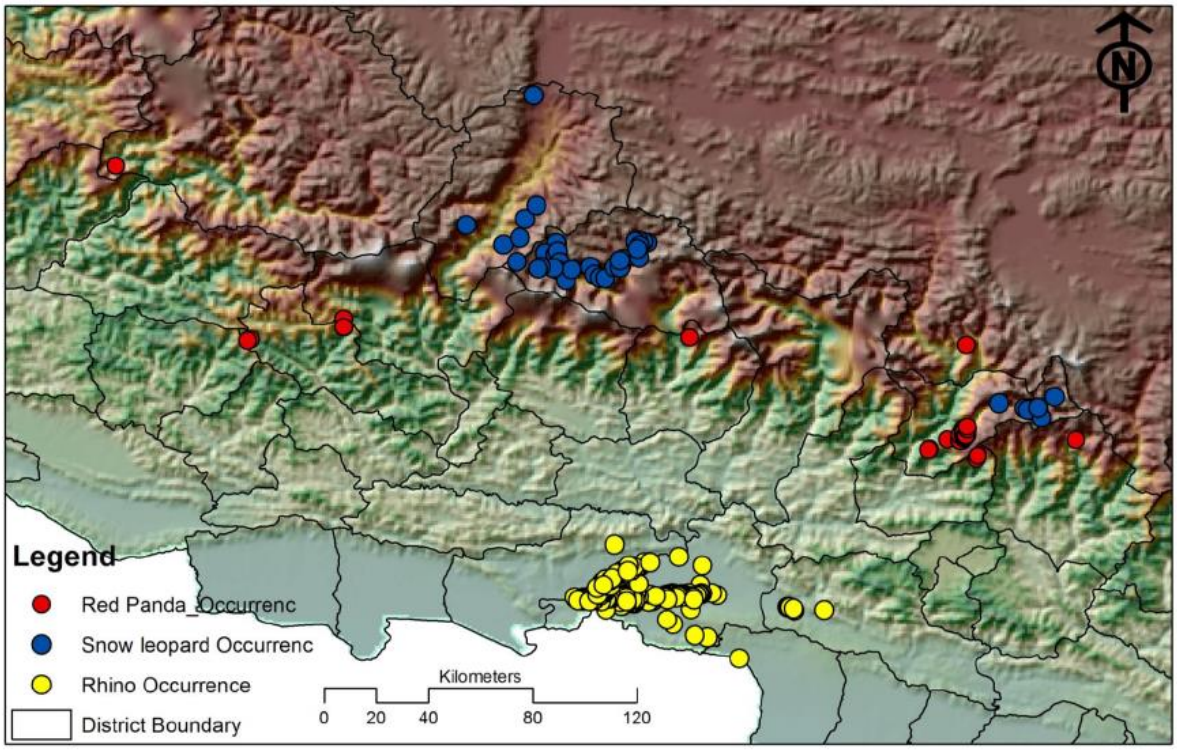


Figure 4 Distribution of species presence records of key species (snow leopard- blue dots, red panda -red dots, and rhinoceros-yellow dots

2.2.3.Species Distribution Model and evaluation

To model potential distribution, 19 bioclimatic variables (~1 km resolution) under current (average for 1950–2000) and future climatic conditions were extracted from the WorldClim database (http://www.world clim.org/version1) (Table 1). which were 30 arc sec 9 (~1 km) in spatial resolution (Hijmans et.al. 2005).These climatic layers represent annual trends (mean annual temperature and precipitation), seasonality (annual range in temperatures and precipitation), and limiting environmental factors (temperature and precipitation of a certain quarter) (Hijmans et al., 2005). Additionally, aspect and slope from elevation data of WorldClim have derived which have similar resolution with climate variables.

Excluding of highly correlated predictors performance better model, and removing multi-collinearity among predictors associated with occurrence of three species, Variance Inflation Factor (VIF) was used, and processed under R v2.15.0 (R Development Core Team, 2012), which was followed earlier studies of species distribution modeling procedures (Ranjitkar et al., 2014b; Ranjitkar et al., 2014a; Lauria et al., 2015; Aryal et al., 2016; Thapa et al., 2018). Here, those variables having VIF below 10 (vif>10) were used in model building process where VIF greater than 10 represents strong collinearity (Quinn and Keough, 2002) affects the model performance that were excluded in the modeling. At landscape scale, MaxEnt model often showed better performances, when a few number of environmental variable was used (Ficetola et al., 2014) ,which addressed the issues of limited occurrence record (eg., red panda in this study).

To predict the impacts of future climate conditions, Community Climate System Model (CCSM) representing three future greenhouse gases concentration trajectories, also known as representative concentration pathways (RCP2.6, RCP6.0 and RCP8.5) was selected for two different time periods (2050s and 2070s) as adopted by the International Panel on Climate Change (IPCC) in its fifth Assessment Report. The selected RCPs represent four possible greenhouse gas emission scenarios ranging from low (RCP2.6) to high (RCP8.5) corresponding to increases in global radiative forcing values in the year 2100 relative to preindustrial values (2.6, 4.5, 6.0 and 8.5 w/m2), respectively. Building on the RCPs, the impact of climate change over the species were studied through individual-species climate models. Field validated species occurrence and specie's ecologically significant variables were employed in a correlative

bioclimatic model using MaxEnt to determine the spatial vulnerability to climate change of a single species based on the different emissions scenarios (IPCC 2050 and 2070). In the modeling process, 75% of presence data of the species were used to build the model, with the remaining 25% used for model verification. predictive ability were tested within twenty- fold cross-validation and compared based the area under curve (AUC) of the receiver operator characteristics. MaxEnt regarded as the probability of species occurrence, with values ranging from 0 to 1. A threshold value was used to distinguish between suitable and unsuitable regions. The average logistic threshold value of maximum training sensitivity plus specificity (MTSPS) was recommended (Liu, et al. 2013). (Liu *et al.*, 2013), an inbuilt functionality in MaxEnt. Grids with probability values greater than the threshold were deemed suitable habitat Model . Training and test AUC above 0.75 indicated reasonable to high model discrimination ability, and are good model performance Final model results were included only RCP 6.2 for the 2050 and 2070 which has found satisfactory performance in constructing species distribution models under the future climate scenario

Table 1 The 19 bioclimatic variables from WorldClim (http://www.worldclim.org/bioclim)

Bioclimatic Variables (Bio_1-Bio_19	Variables sources
Annual Mean Temperature[BIO1]	http://www.worldclim.org
Mean Diurnal Range (Mean of monthly (max temp-min temp)) [BIO2]	http://www.worldclim.org
Isothermality (BIO2/BIO7)*(100)[BIO3]	http://www.worldclim.org
Temperature Seasonality (standard deviation*100) [BIO4]	http://www.worldclim.org
Max Temperature of Warmest Month[BIO5]	http://www.worldclim.org
Min Temperature of Coldest Month [BIO6]	http://www.worldclim.org
Temperature Annual Range (BIO5-BIO6)[BIO7]	http://www.worldclim.org
Mean Temperature of Wettest Quarter [BIO8]	http://www.worldclim.org
Mean Temperature of Direst Quarter[BIO9]	http://www.worldclim.org
Mean Temperature of Warmest Quarter[BIO10]	http://www.worldclim.org
Mean Temperature of Coldest Quarter [BIO11]	http://www.worldclim.org
Annual Precipitation[BIO12]	http://www.worldclim.org
Precipitation of Wettest Month[BIO13]	http://www.worldclim.org

Precipitation of Driest Month [BIO14]	http://www.worldclim.org
Precipitation Seasonality (Coefficient of Variation)[BIO15]	http://www.worldclim.org
Precipitation of Wettest Quarter[BIO16]	http://www.worldclim.org
Precipitation of Driest Quarter [BIO17]	http://www.worldclim.org
Precipitation of Warmest Quarter [BIO18]	http://www.worldclim.org
Precipitation of Coldest Quarter[BIO19]	http://www.worldclim.org

.

2.2.4 Land use and land cover projection

Anthropogenic activities and climate change could lead to land use and land cover changes. Mapping land-use change could also show how the potential habitat could be improving or degrading indicating where the species could thrive (existing micro- refugia/ stable habitat) and or disperse (new refugia/new habitat). Classified land cover database of 2002 and 2010 was downloaded from the International Centre for Integrated Mountain Development (ICIMOD) (http://rds.icimod.org/;Unddin et al. 2015) which is precise than other large scale global land cover database. Future land cover changes for 2050 and 2070 were projected based on land cover database of 2002 and 2010 using a cellular automata (CA) Markov model in TerraSet 18.21. Due to high predictive accuracy, Markov models have been used in numerous studies to predict land cover change scenarios (Kumar *et al.*, 2014; Huang *et al.*, 2015; Yuan *et al.*, 2015; Zhao *et al.*, 2017). Here, CA-Markov model equation is $S(t, t+1) = f(S(t), N)$ (Mondal *et al.*, 2016) in which S denotes the set of limited and discrete cellular states, N is the cellular field, t and $t+1$ denotes different times, and f is the transformation rule of cellular states in local space.

2.2.5 Vulnerability assessment

Changes in potential suitable habitat under the current and future climate scenarios were assessed by indentifying vulnerable habitat, increased suitable habitat and climate refugia.

a. Vulnerable habitat is an area of habitat currently suitable and predicted to be unsuitable under the future climate scenario.
b. Increased suitable habitat is an area of habitat currently unsuitable and predicted to be suitable under the future climate scenario.
c. Climate refugia is an area of habitat currently suitable and predicted to be suitable under the future climate scenario.

These three indicators were used to demonstrate the impacts of climate change on currently suitable habitat: (a) *AC*: suitable habitat change percentage; (b) SH_c: current suitable habitat loss percentage; and (c) SH_f: increased suitable habitat percentage under the future climate scenario (Duan *et al.*, 2016; Li *et al.*, 2017) Each indicator are expressed base this:

$$AC=(A_f-A_c)/A_c\times 100\%$$

$$SHc=(A_c-A_{cf})/A_c\times 100\%$$

$$SHf=(A_f-A_{cf})/A_f\times 100\%$$

Where A_c is the projected area of current suitable habitat; A_f is the projected area of future suitable habitat; and A_{cf} is the area of climate refugia.

Chapter-3 Results

3.1.Model performance and influencing variables

Potential habitat suitability models were build using least correlated bioclimatic variables and presence-only for three key species- snow leopard, red panda and rhinoceros in CHAL. In total, 410, 63, 30, occurrence records were used in modeling process for rhinoceros, snow leopard and red panda respectively. Occurrence records of snow leopard were spatial distinct, however occurrence records of red panda and rhinoceros were clustered spatially (Fig.4). To minimize multi-collinearity among predictor variables, the Variance Inflation Factor (VIF) was used separately for all three species with considering species' ecological zone. Out of 21variables, only five variables for snow leopard, five variables for red panda and six variables for rhinoceros were found least correlated (VIF<10), and were used in the modeling of potential habitat suitability.

For rhinoceros, the best models have a higher average test AUC (0.981) and training AUC (0.982) of 20 fold cross validation meaning that the model performed better than random when predicting habitat suitability (Fig.5). The MaxEnt model's Jackknife test of variable importance showed that Bio1 (annual mean temperature) was the variable with the highest gain when considering independently (Fig.6 and Fig.7). It indicated a strong contribution of Bio1 to the model development that has the most useful information among the variables. Furthermore, the percent contribution of model variables ranked from highest to lowest were as follows: annual mean temperature (Bio1; 90%), temperature seasonality (Bio 4; 5.4%), isothermality (Bio3; 2.1%), and other precipitation of direst quarter (Bio17), mean temperature of direst Quarter (Bio9), Annual precipitation (Bio12) have low contribution (Fig.7).

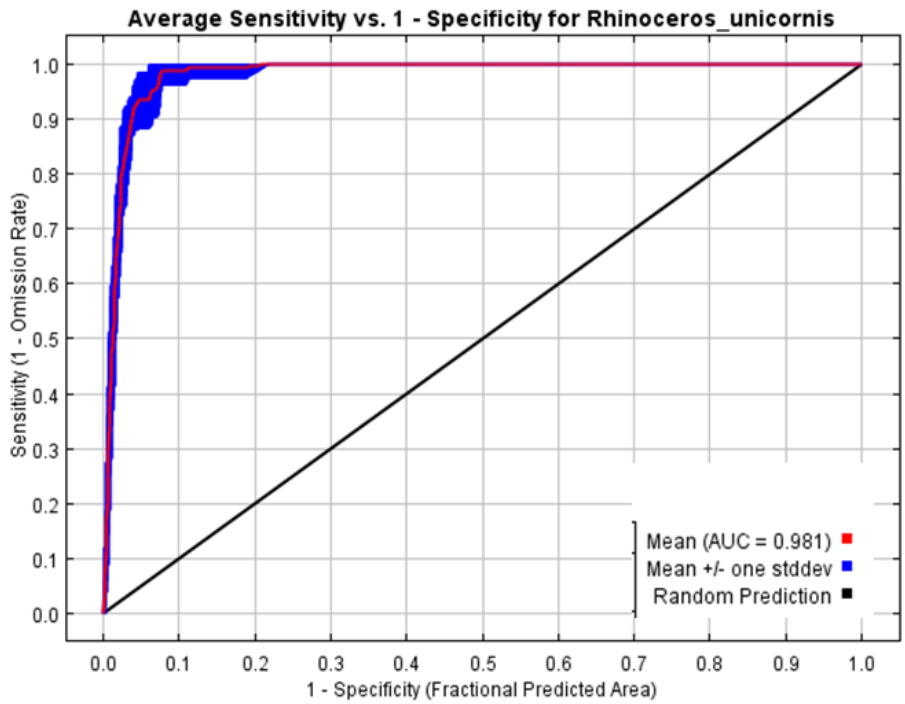


Figure 5 AUC values for the rhinoceros. The red line in each case represents the average and the blue bar denotes ±1 standard deviation

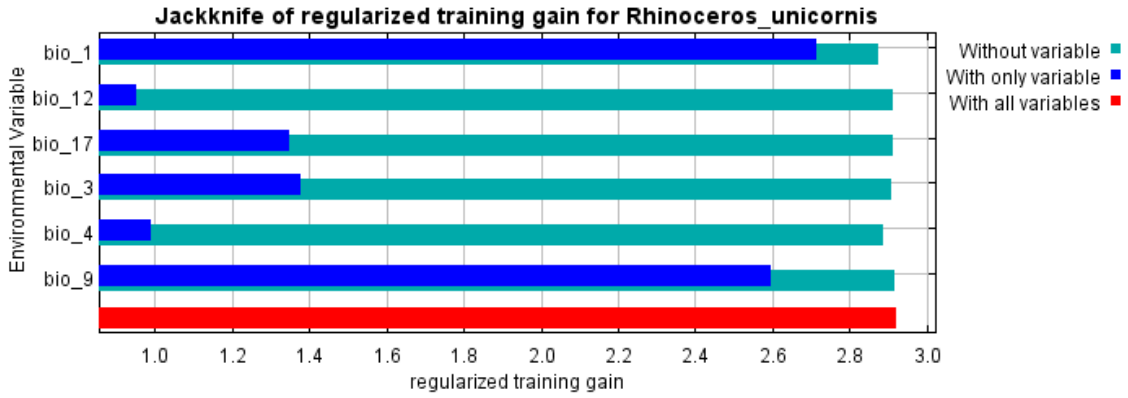


Figure 6 Jackknife test of environmental variables in training data for rhinoceros by MaxEnt

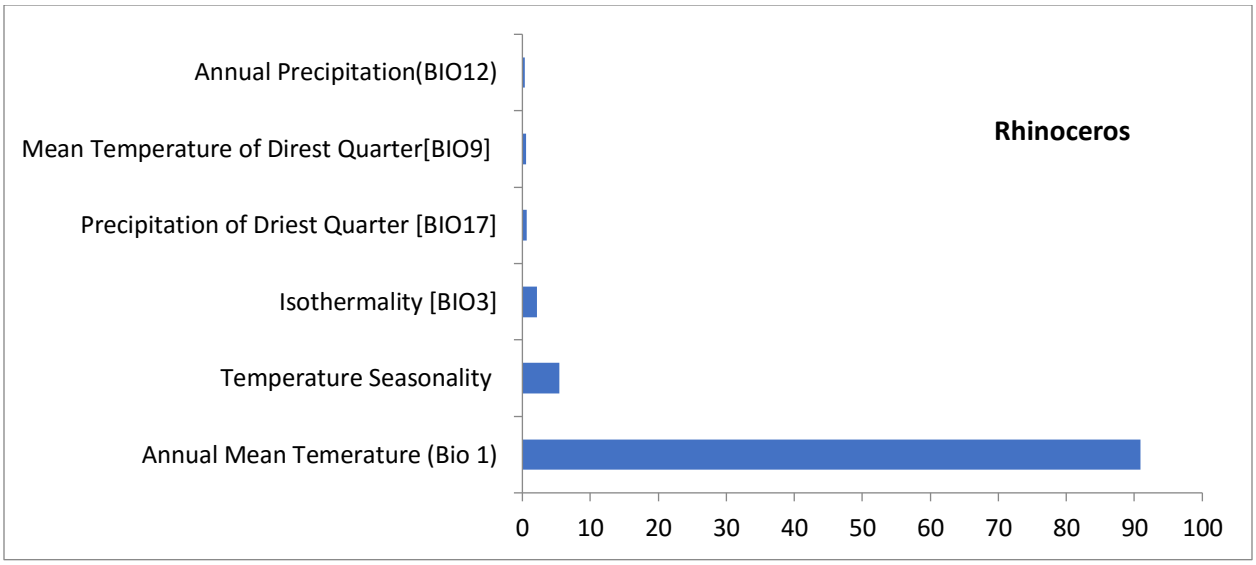


Figure 7 Relative importance of predictor variables in the predicted distributions of rhinoceros.

The MaxEnt model developed for red panda was performed well with average training AUC of 0.973 and a mean test AUC of 0.939 of 20-fold cross validation indicating the robust prediction of distribution of suitable areas by the selected variables (Fig 8). Precipitation-associated variables were dominant predictive performance for the red panda. Isothermality (Bio3) was the most important variable in the red panda model which has explained 71.1% (Fig.9 and 10); followed by precipitation of wettest quarter (bio16; 23%), slope (3.2%), precipitation of the quarter (Bio 19; 1.1%), and precipitation seasonality (Bio15; 1.13%) (Fig.10).

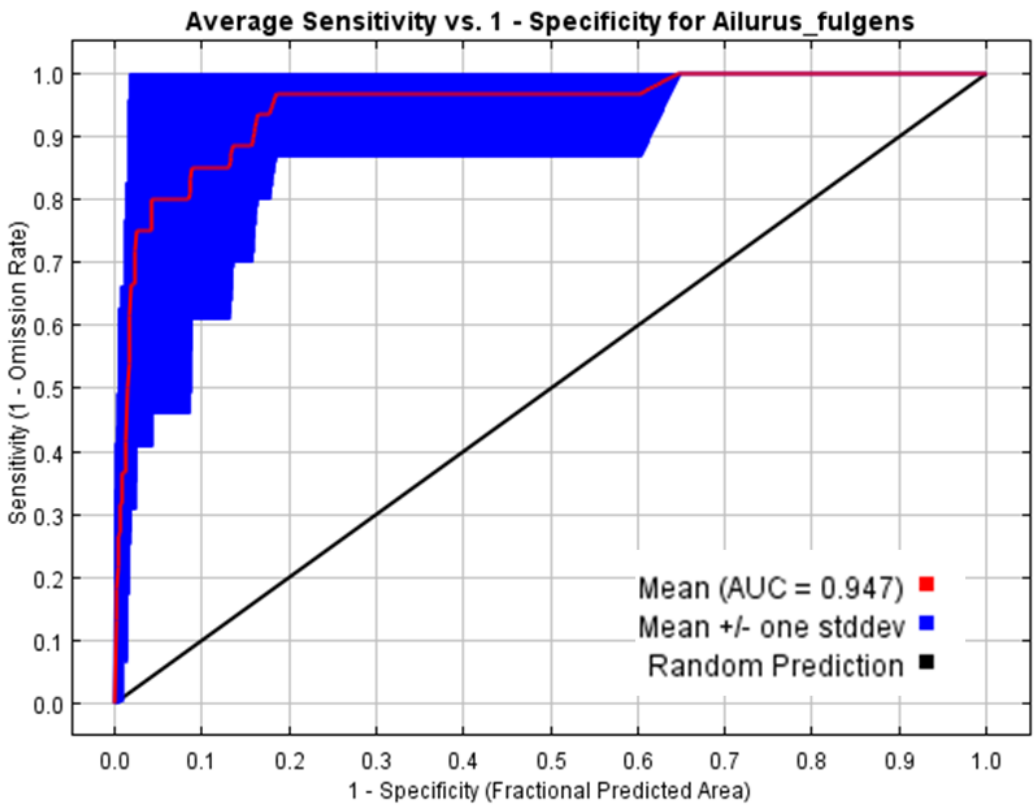


Figure 8 AUC values for the red panda. The red line in each case represents the average and the blue bar denotes ±1 standard deviation

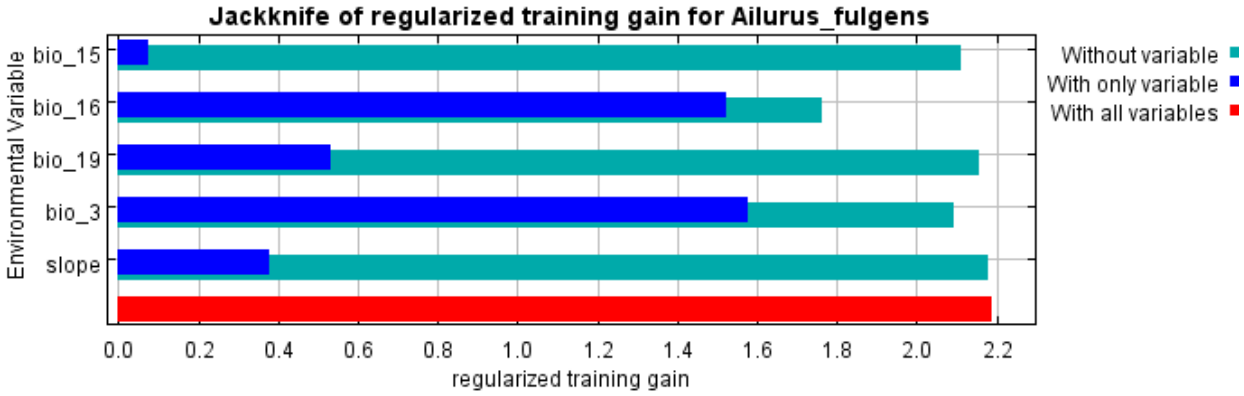


Figure 9 Jackknife test of environmental variables in training data for red panda by MaxEnt

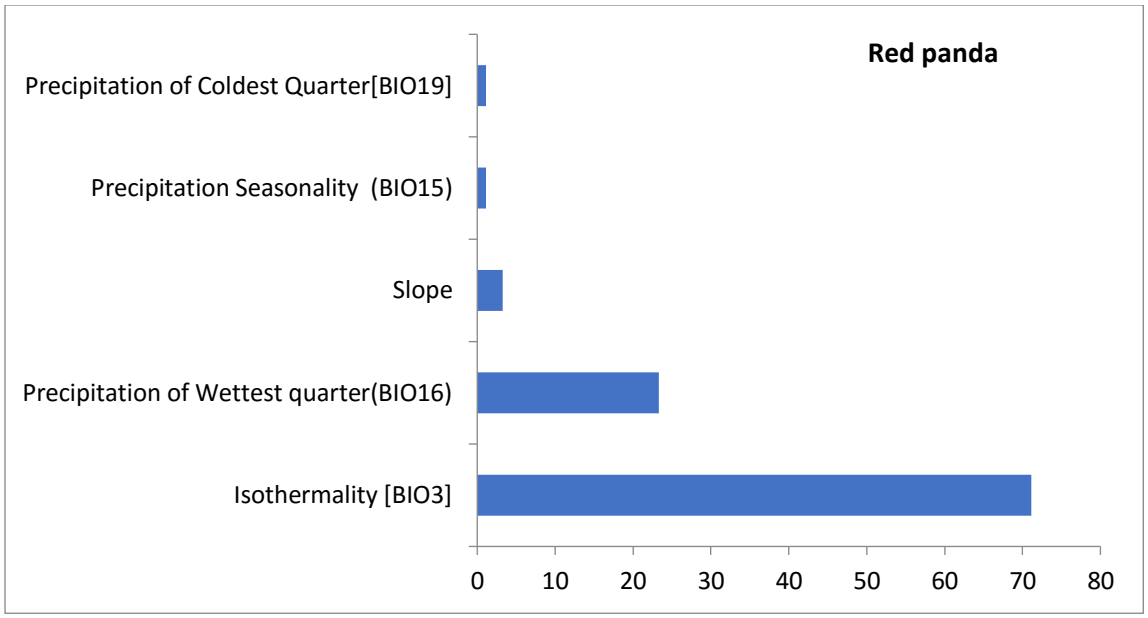


Figure 10 Relative importance of predictor variables in the predicted distributions of red panda

Snow leopard habitat distribution model was built, and used the 20-fold cross-validation procedure and the area under the ROC curve (AUC) to evaluate model performance. AUC of the training and test were 0.94±0.0028 (SD) and 0.92±0.0091 (SD) respectively indicating that this model performed well in the simulation of snow leopard habitat (Fig.11). The importance rates in the MaxEnt model prediction indicated that mean temperature of coldest quarter (Bio11) was the most influencing variable in predicting potential habitat suitability. Based on the jackknife estimator, mean temperature of coldest quarter (Bio11;92.7%), precipitation of wettest month (Bio13;3.94%), slope (2.26%) precipitation of direst month (Bio 14) and isothermality (Bio3) were the main factors contributing to predict potential habitat suitability(Fig.12 and Fig.13.).

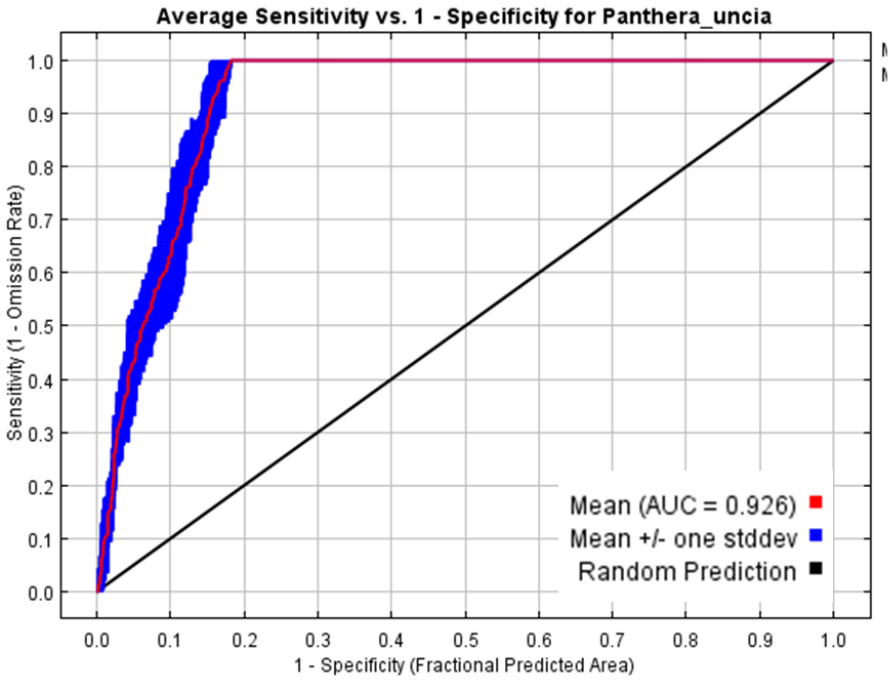


Figure 11 AUC values for the snow leopard. The red line in each case represents the average and the blue bar denotes ±1 standard deviation

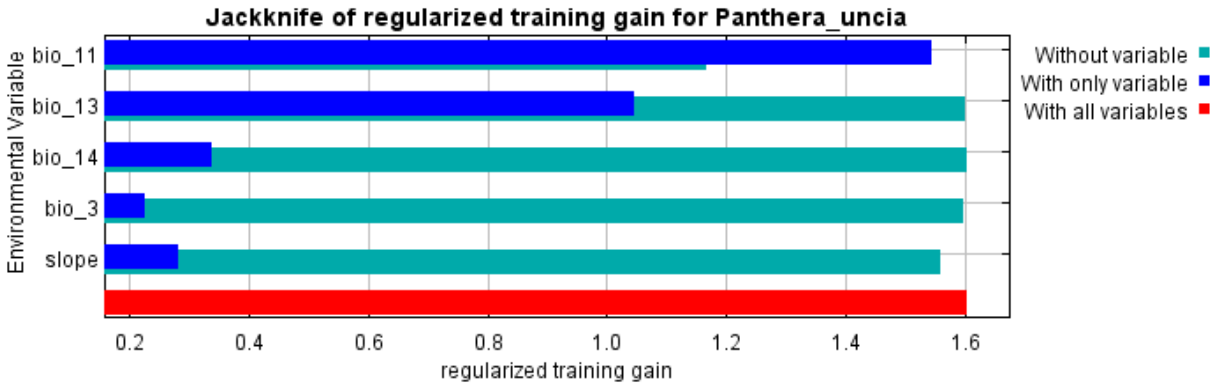


Figure 12 Jackknife test of environmental variables in training data for snow leopard by MaxEnt

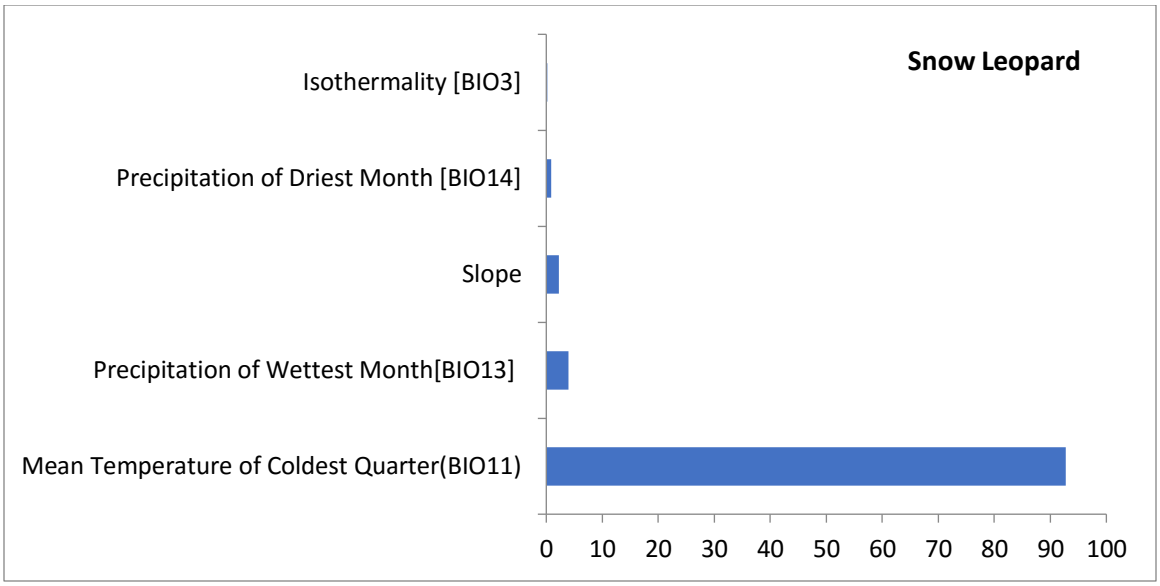


Figure 13 Relative importance of predictor variables in the predicted distributions of snow leopard

3.2. Current and future potential habitat

Predicted current potential habitat suitability were 1,192km^2, 2,417km^2, 4,080km^2 for rhinoceros, red panda and snow leopard respectively (Table 2). All of these current estimated areas were represented by 4%, 8%, and 13% area of the CHAL for rhinoceros, red panda and snow leopard respectively. Currently, almost entire habitat of snow leopard and rhinoceros encompassed within the protected areas (CNP, ACA and MCA), however most of the habitat of red panda lies outside protected areas.

Table 2. Predicted current and future habitat of three key species in CHAL.

Species	**Current(km^2)**	**Future scenarios (km^2)**		
		2050 (RCP 2.6)	2050 (RCP 6.0)	2070 (RCP 6.0)
Rhinoceros	1,192	3,277	4,157	2,884
Red panda	2,417	1,141	1,674	1,108
Snow leopard	4,080	3,823	3,483	3,934

Snow leopard

The model of potential suitable habitat of snow leopard occupied an area of 4,080 km^2 that represents 23.73% of predicted current suitable habitat (17,190km^2) of the country. Under the future climate scenario, the area of potential suitable habitat will projected to be 3,483km^2 and 3,934km^2 in 2050 and 2070 respectively (Table 2 and Fig. 17). Suitable habitat of snow leopard will be decreased by 15% and 4% in 2050 and 2070 respectively. Habitat reduction primarily occurred in the Langtang Manang, Mustang, and Manasulu in CHAL. Elevation of current predicted habitat ranged between 3,600m and 5,100m with an average at 4400m. However, in future climate change prediction scenario, elevation will be ranged between 4100m to 5600m with an average at 4900m. Density plots showed that mostly predicted habitat peaked 4800m in current as well as future projection scenarios which indicated habitat contraction and stable at this elevation range (Fig.14).

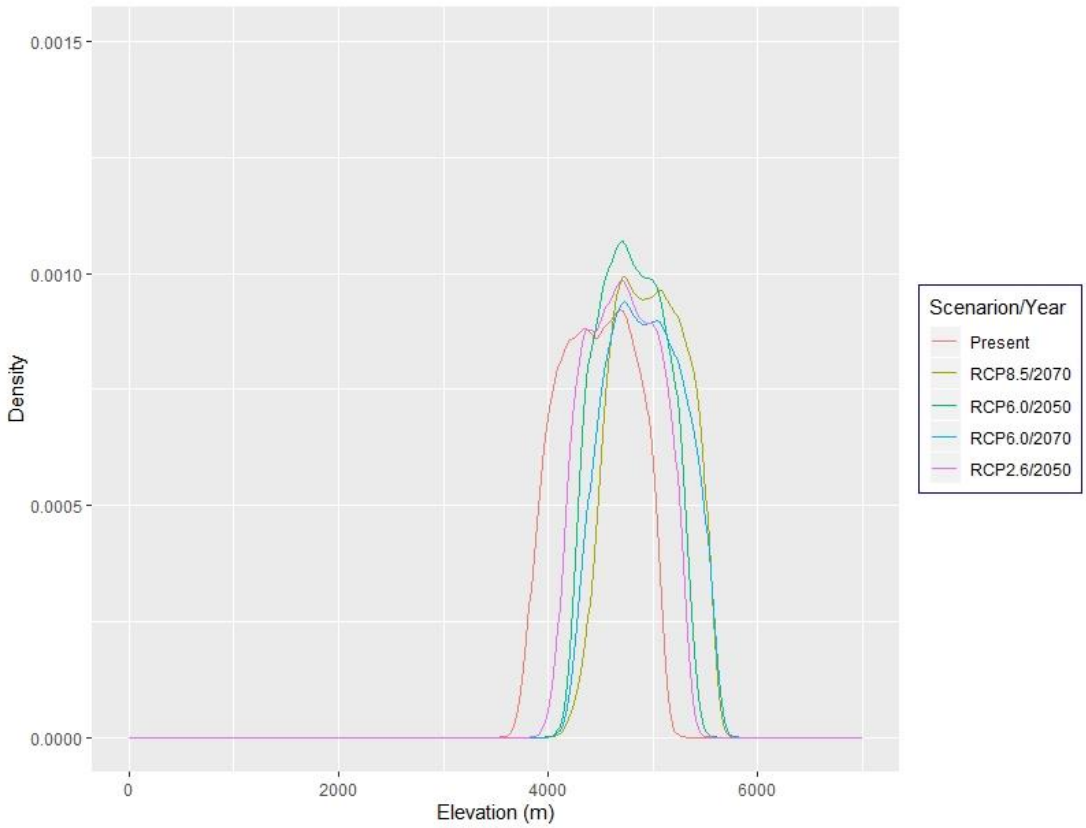


Figure 14 Density plot of the predicted habitat suitability values of snow leopard in different elevation range

Red panda

The total potential climatically suitable habitat for red panda was estimated to be 2,417km^2 which represents 11.14% of the current predicted habitat (21,680 km^2) of the country (Table 2 and Fig.17). In the future climate projection, potential habitat will be 1,674km^2 and 1,108km^2 in 2050 and 2070 respectively. Suitable habitat of red pandas will be decreased by 7% and 13% in 2050 and 2070 respectively due to climate change. Habitat reduction primarily occurred in the middle part of predicted habitat and which further seen habitat contraction toward in the eastern (Rasuwa) and western (Mygadi) area in CHAL. Current predicted habitat of red panda lies between 2000m to 4100m with average 3000m but in the future prediction slightly increased elevation up 5300 with an average 3200m. Density plot showed that maximum predicted suitable habitat peaked closer to 3000 m in the current as well as future scenarios which indicated most of the stable suitable habitat. Furthermore, predicted habitat suitability peaks are slightly shifting from current to future scenarios which could seen from relation between predicted pixel and elevation in the density plot (Fig.15).

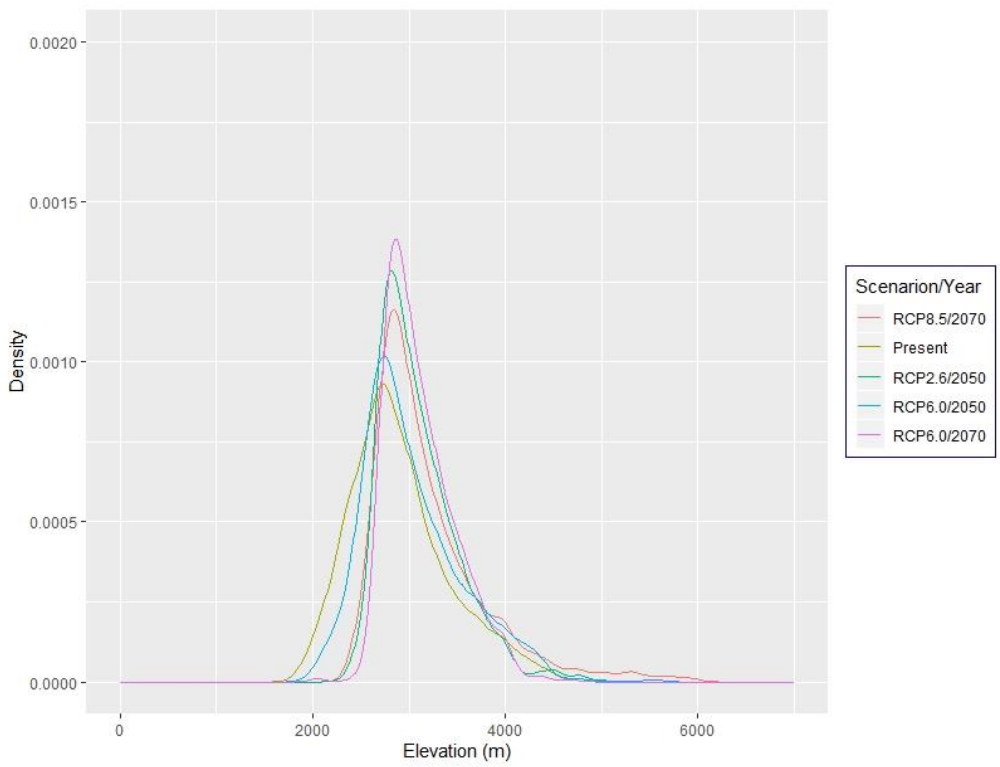


Figure15. Density plot of the predicted habitat suitability values of red panda in different elevation range.

Rhinoceros

The model of potential suitable habitat of rhinoceros occupied an area of 1,192 km^2. area of Potential suitable habitat of rhinoceros was projected to be increased in RCP 6.0 in 2050 and 2070 (Table 2 and Fig 17). Habitat increase primarily occurred in north and north-western of current projected habitat following to inner river valleys. Current predicted habitat range of rhinoceros were laid in between 120m to 320m elevation, which will be projected to be increased up to 700m with an average at 200m in the future scenario (Fig.16.). This result indicated upward expansion of suitable habitat of rhinoceros in the future climate. Density plot showed that maximum predicted suitable habitat peaked below 200 m in the current as well as future scenarios which indicated stable suitable habitat (Fig.16).

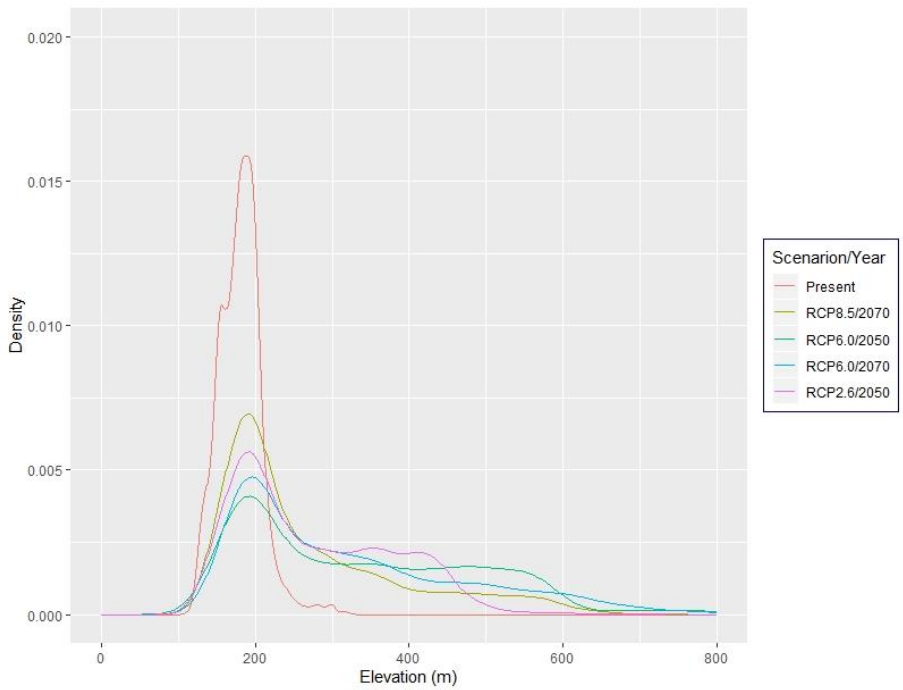
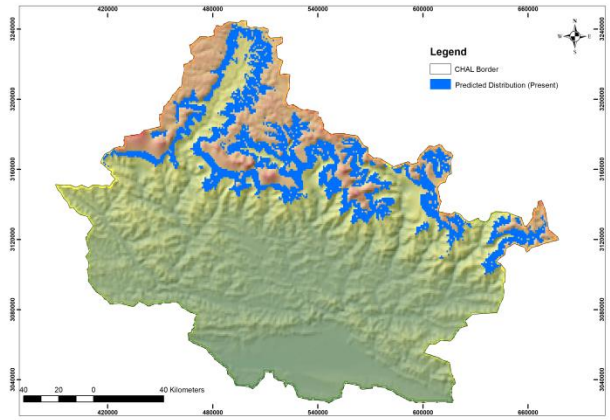
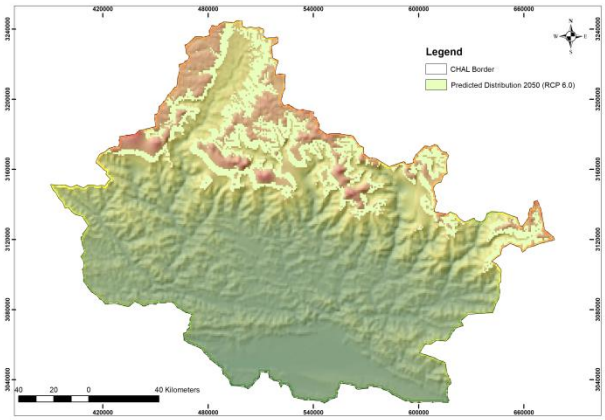


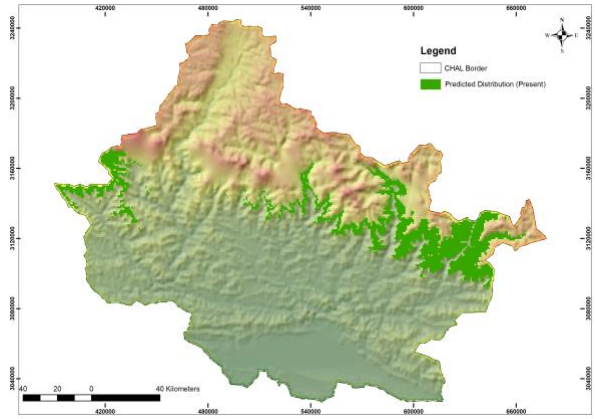
Figure 16. Density plot of the predicted habitat suitability values of rhinoceros in different elevation rang

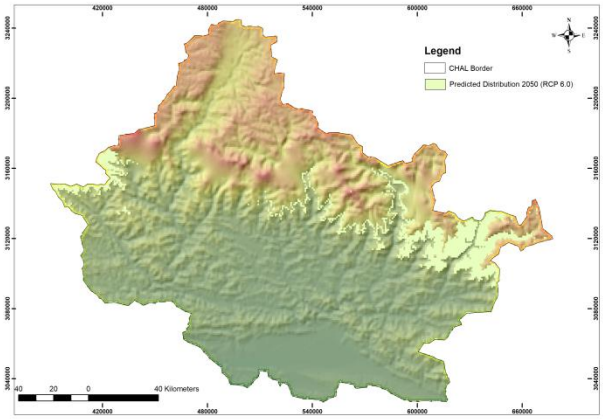
Current potential suitable habitat | *Current potential suitable habitat*



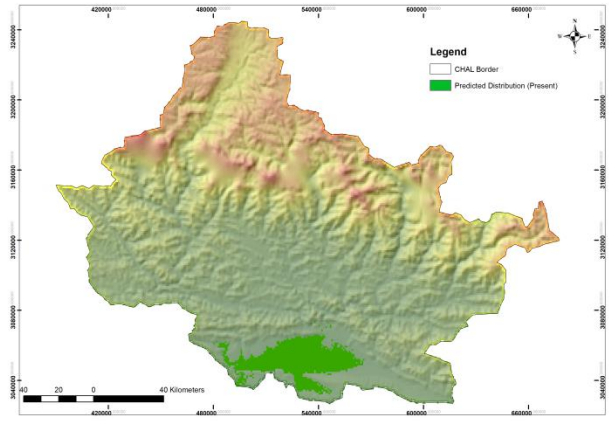


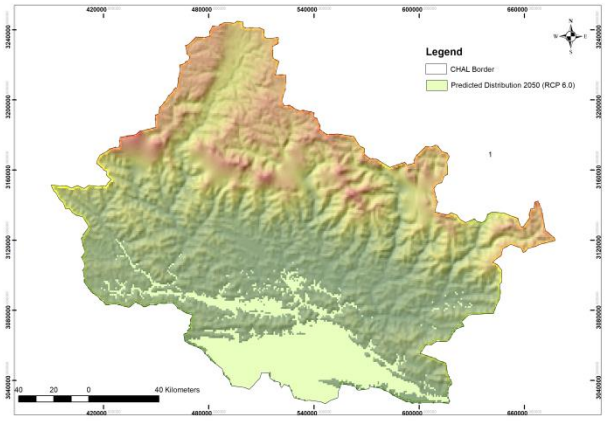
Snow leopard(left current and right future projection)





Red panda(left current and right future projection)





Rhinoceros (left current and right future projection)

Figure 17 Predicted current and future habitat of key species

3.4. Vulnerability assessment and geographic feature of climate refugia

Due to climate change, both snow leopard and red panda will be vulnerable in the future. In comparing to these two species, rhinoceros will be exposed low vulnerable to future climate change based on this study. Current potential habitat of snow leopard will be loss by 36.3% and 41.8% in 2050 and 2070 respectively (Table 3). Similarly, 2,600km^2 and 2375km^2 area will act as climate refugia for snow leopard and were mainly distributed in the area of Lomanthang, Neshyang, Narphu,Noshong, Chum Nurbi, Rubi valley, Darche and Langtang (Fig.18.). Climate refugia of snow leopard habitat ranged in altitude from 3755m to 5630m with an average 4705m.

Similarly, in 2050 and 2070, 32.5% and 56% habitat of red panda will be loss in the future indicating highly vulnerable to climate change in the CHAL. A total area of 1,632km^2 and 1,052km^2 will be found as climate refugia in 2050 and 2070 which were distributed in the areas of Dhulagiri range, Rubi valley, Gosaikunda and Helambu of Langtang National Park (Table 3 and Fig.19). Climate refugia of red panda habitat ranged in altitude from 2005m to 4781m with an average 3129m.

An area of 1,192km^2 (SHc= 0.1 % and 19.6%) of current suitable rhinoceros habitat was projected to be low vulnerable to future climate . Most of current predicted habitat will be stable and act climate refugia for the rhinoceros in the future climate. Areas of potential suitable habitat under the future climate scenario covered 1,190km^2 and 959km^2 in 2050 and 2070 respectively (Table 3 and Fig 20). Mostly climate refugia of rhinoceros habitat ranged in altitude from 120m to 337m with an average 182m.

Table 3 Predicted changes of potential suitable habitat for species in CHAL

Species	Scenarios (RCP6.0)	A_c (km^2)	A_f (km^2)	A_{cf} (km^2)	A_c (%)	SH_c (%)	SH_f (%)
Snow leopard	2050	4,080	3,483	2,600	-14.6	36.3	25.4
	2070	4,080	3,934	2,375	-3.6	41.8	39.6
Red panda	2050	2,417	1,674	1,632	-30.7	32.5	2.5
	2070	2,417	1,108	1,052	-54.2	56.5	5.0
Rhinoceros	2050	1,192	4,157	1,190	248.8	0.1	71.4
	2070	1,192	2,884	958	142.0	19.6	66.8

A_c =projected area of current suitable habitat;A_f = projected area of future suitable habitat; and A_{cf} =the area of climate refugia

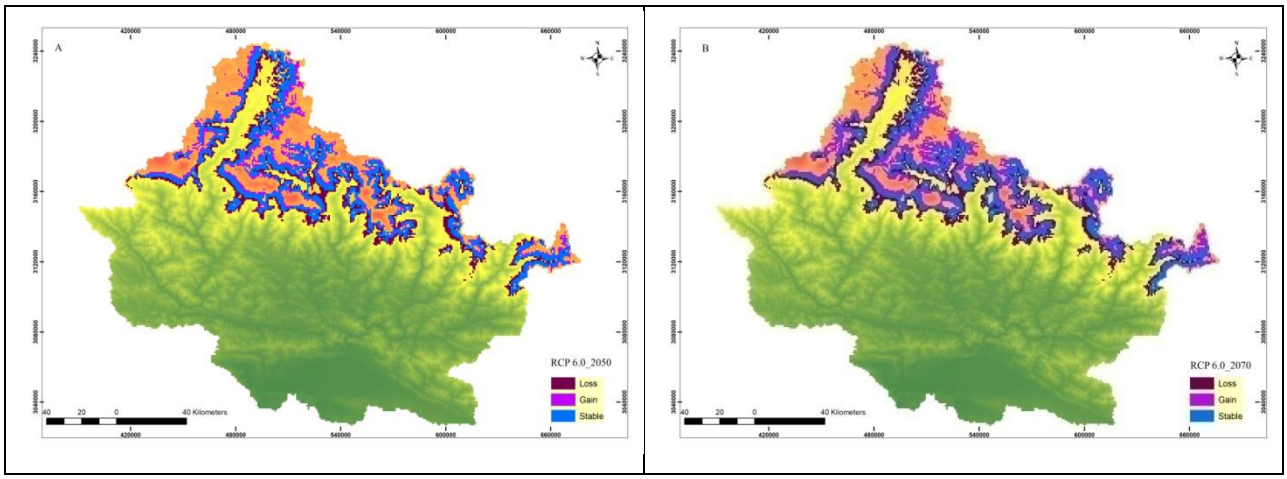


Figure 18. Predicted habitat changes of snow leopard in 2050 and 2060

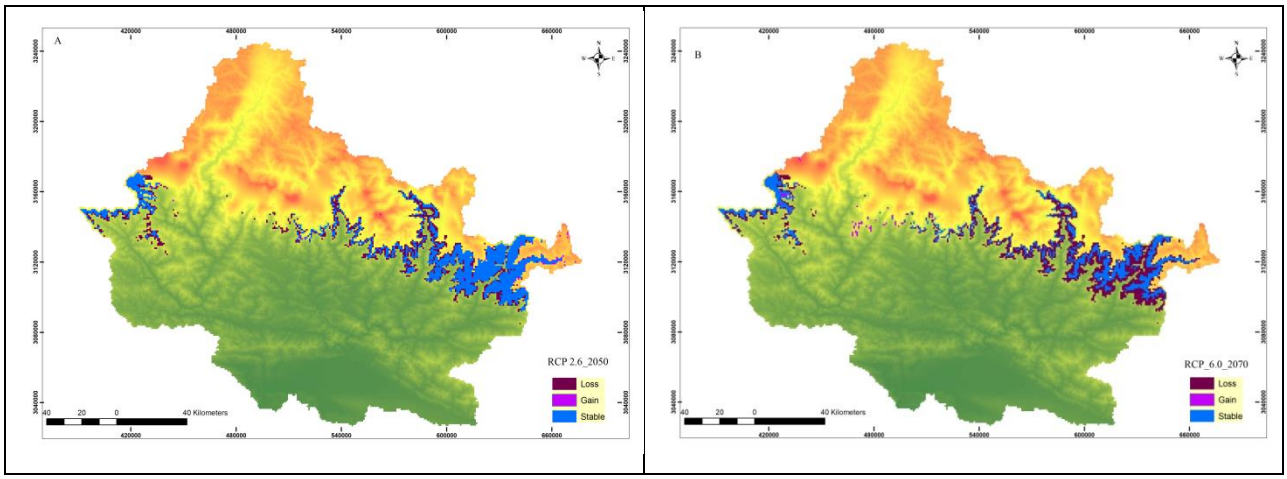


Figure 19. Predicted habitat changes of red panda in 2050 and 2060

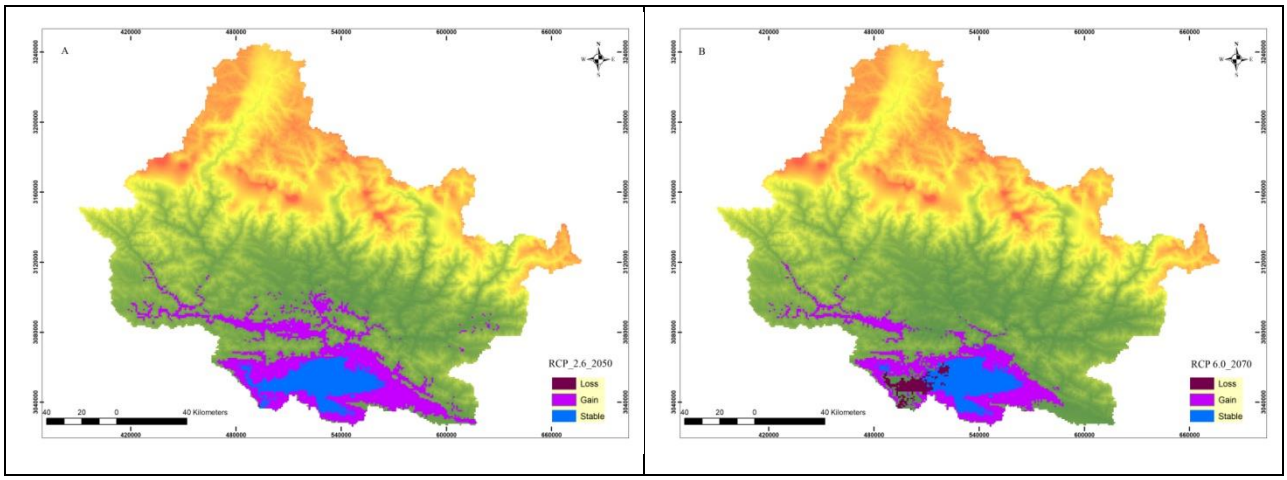


Figure 20. Predicted habitat changes of rhinoceros in 2050 and 2060

3.5 Predicted land use and cover changes

The result showed that most of the land cover attributes are likely increased in the future projection, however snow cover is likely decreased in the simulation analysis of future projection. This simulation was relied basically mathematical model that depends on input baseline land cover of 2002 and 2010. Snow cover area is likely to be decreased by 24% in 2050 which will be impacted due to climate changes in future (Fig 21. and Fig.22). However other land cover features such as urban area is likely increased 20% in 2050 followed by shrub (8.8%), agriculture (3.6%), and forest (3.5%) in CHAL. Importantly, other remaining land cover attributes including snow cover (24%), water (4.7%) and barren area (4.3%) are likely decreased in 2050 (Fig.. and Fig.). Similarly, urban area will be increased 37% in 2070 followed by shrub (15%), grassland(8.9%), forest (8.3%), barren land (7.5%) and water bodies (4.7%) where as snow cover is likely to be decreased in high percentages.

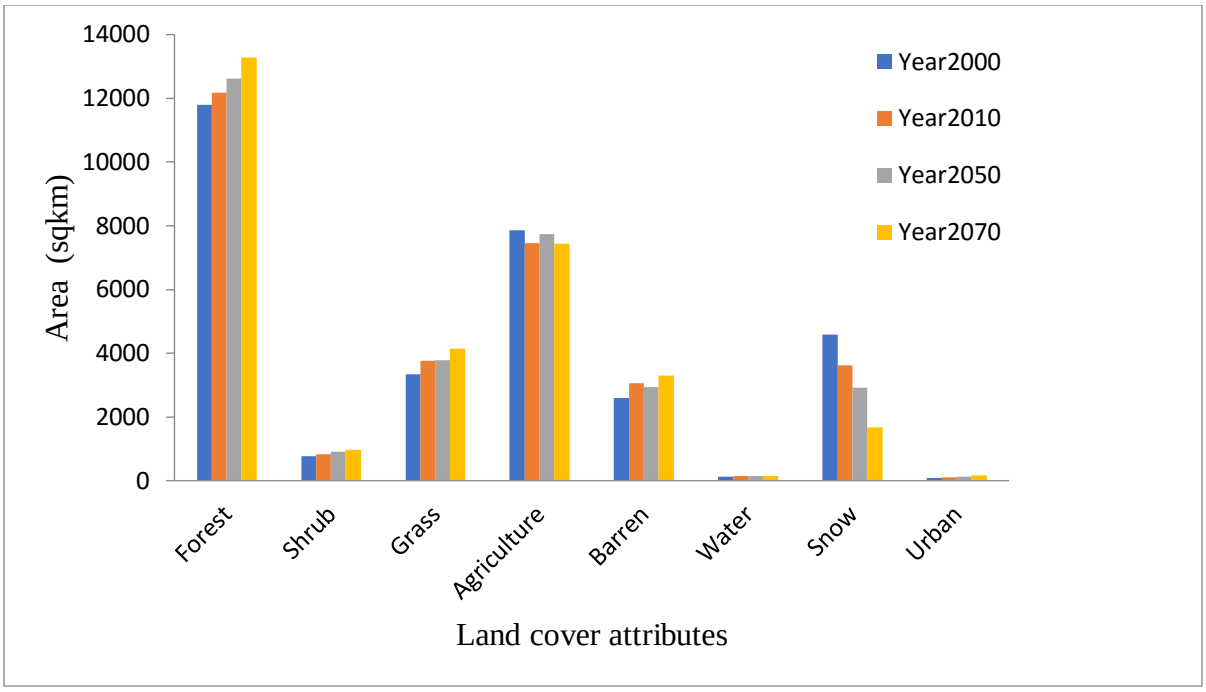


Figure 21 Area of land use land cover attributes in current and future projection

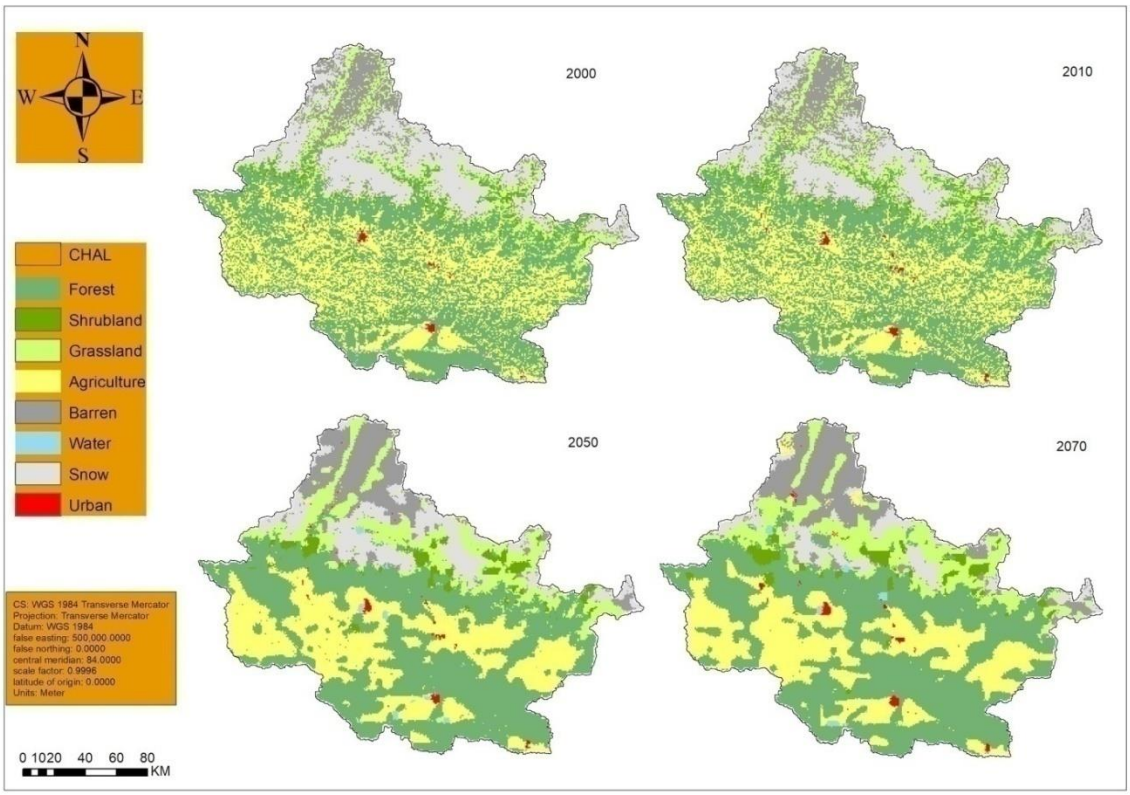


Figure 22 Projected land use and land cover changes of CHAL in 2050 and 2070.

Chapter 4. Conclusion and recommendations

Current potential habitat suitability covered 4%, 8%, and 13% area of the CHAL for rhinoceros, red panda and snow leopard respectively. Almost entire habitat of snow leopard and rhinoceros encompassed within the protected areas (CNP, ACA and MCA), and habitat of red panda lies outside protected areas. Both snow leopard and red panda will be vulnerable in future climate change scenarios due to decreased habitat area but rhinoceros will be exposed low vulnerable future climate change with increased habitat. Habitat of rhinoceros will be increased in future climate change. In future climate change, 1,190km^2, 2,375km^2 and 1,052km^2 will act as the climate refugia in CHAL for rhinoceros, snow leopard and red panda respectively. Most of the land cover attributes are likely increased in the future projection, however snow cover is likely decreased in the simulation of future projection. The study recommend that conservation concerned institutions should pay serious attention to the land use planning in the future in order to mitigate the potential in these key species. Future studies should focused in the areas where micro-refugia were aggregated and isolated.

Acknowledgment

This study is financially supported by WWF- Nepal Hariyoban Program-II (Agreement #IBA75). We would like thanks to Department of National Park and Wildlife Conservation (DNPWC) for granting permission to conduct activities in CNP, LNP and ACA. We also thankful to Mr. Hari Basnet and Mr. Suraj Baral for data generating and support during project duration. Thanks to all those were participated in interaction phase for the project activities.

Reference:

Beaumont, L.J., Pitman, A., Perkins, S., Zimmermann, N.E., Yoccoz, N.G., Thuiller, W., 2011. Impacts of climate change on the world's most exceptional ecoregions. Proceedings of the National Academy of Science 108, 2306–2311.

IPCC, 2007. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the International Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. pp-36

Wikramanayake, E., Thapa, GJ, Khanal, K. 2015: Selecting Tree Species for Climate Change-Integrated Forest Restoration and Management in the Chitwan-Annapurna Landscape, Nepal 2015, Hariyo Ban Program, WWF Nepal

Rawal, DS., 2014. Vulnerability Assessment of Hill Sal and Subtropical/Tropical Broad Leaf

Forest Trees of CHAL Region, Nepal: An Implication to Climate Change. Final Report submitted to Hariyo Ban Program, WWF Nepal.

Forrest, JL., Wikramanayake, E., Shrestha, R., Areendran, G., Gyeltshen, K., Maheshwari, A.,Mazumdar, S., Naidoo, R., Thapa, GJ., Thapa, K., Conservation and climate change: Assessing the vulnerability of snow leopard habitat to treeline shift in the Himalaya, Biological Conservation 150 (2012) 129–135

Anderson, R.P. & Martinez-Meyer, E. (2004) Modeling species' geographic distributions for preliminary conservation assessments: an implementation with the spiny pocket mice (Heteromys) of Ecuador. *Biological Conservation*, **116**, 167-179.

Anderson, R.P., Lew, D. & Peterson, A.T. (2003) Evaluating predictive models of species' distributions: criteria for selecting optimal models. *Ecological Modelling*, **162**, 211-232.

Aryal, A., Raubenheimer, D., Subedi, S. & Kattel, B. (2010) Spatial habitat overlap and habitat preference of Himalayan Musk Deer (" Moschus chrysogaster") in Sagarmatha (Mt. Everest) National Park, Nepal. *Current Research Journal of Biological Sciences*, **2**, 217-225.

Aryal, A., Shrestha, U.B., Ji, W., Ale, S.B., Shrestha, S., Ingty, T., Maraseni, T., Cockfield, G. & Raubenheimer, D. (2016) Predicting the distributions of predator (snow leopard) and prey (blue sheep) under climate change in the Himalaya. *Ecology and Evolution*, **6**, 4065-4075.

Austin, M. (2007) Species distribution models and ecological theory: A critical assessment and some possible new approaches. *Ecological Modelling*, **200**, 1-19.

Beaumont, L.J., Pitman, A., Perkins, S., Zimmermann, N.E., Yoccoz, N.G. & Thuiller, W. (2011) Impacts of climate change on the world's most exceptional ecoregions. *Proceedings of the National Academy of Sciences*, **108**, 2306-2311.

Conlisk, E., Syphard, A.D., Franklin, J., Flint, L., Flint, A. & Regan, H. (2013) Uncertainty in assessing the impacts of global change with coupled dynamic species distribution and population models. *Global change biology*, **19**, 858-869.

DEPI (2013) Biodiversity information tools for use in native vegetation decisions. The State of Victoria Department of Environment and Primary Industries, Department of Environment and Primary Industries, Melbourne, Australia. In, The State of Victoria Department of Environment and Primary Industries, Department of Environment and Primary Industries, Melbourne, Australia.

Duan, R.-Y., Kong, X.-Q., Huang, M.-Y., Varela, S. & Ji, X. (2016) The potential effects of climate change on amphibian distribution, range fragmentation and turnover in China. *PeerJ*, **4**, e2185.

Elith, J. & Leathwick, J.R. (2009) Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, **40**, 677-697.

Elith, J., Ferrier, S., Huettmann, F. & Leathwick, J. (2005) The evaluation strip: A new and robust method for plotting predicted responses from species distribution models. *Ecological Modelling*, **186**, 280-289.

Elith, J., Graham, C.H., Anderson, R.P., Dudik, M., Ferrier, S., Guisan, A., Hijmans, R.J., Huettmann, F., Leathwick, J.R., Lehmann, A., Li, J., Lohmann, L.G., Loiselle, B.A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J.M., Peterson, A.T., Phillips, S.J., Richardson, K., Scachetti-Pereira, R., Schapire, R.E., Soberon, J., Williams, S., Wisz, M.S. & Zimmermann, N.E. (2006) Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, **29**, 129-151.

Farrington, J.D. & Li, J. (2016) Climate change impacts on snow leopard range. *Snow Leopards*, pp. 85-95. Elsevier.

Ficetola, G.F., Bonardi, A., Mucher, C.A., Gilissen, N.L.M. & Padoa-Schioppa, E. (2014) How many predictors in species distribution models at the landscape scale? Land use versus LiDAR-derived canopy height. *International Journal of Geographical Information Science*, **28**, 1723-1739.

Figueirido, B., Serrano-Alarcon, F.J. & Palmqvist, P. (2012) Geometric morphometrics shows differences and similarities in skull shape between the red and giant pandas. *Journal of Zoology*, **286**, 293-302.

Forrest, J.L., Wikramanayake, E., Shrestha, R., Areendran, G., Gyeltshen, K., Maheshwari, A., Mazumdar, S., Naidoo, R., Thapa, G.J. & Thapa, K. (2012) Conservation and climate change: Assessing the vulnerability of snow leopard habitat to treeline shift in the Himalaya. *Biological Conservation*, **150**, 129-135.

Fourcade, Y., Engler, J.O., Rodder, D. & Secondi, J. (2014) Mapping species distributions with MAXENT using a geographically biased sample of presence data: a performance assessment of methods for correcting sampling bias. *PLoS One*, **9**, e97122.

Gaire, N., Koirala, M., Bhuju, D. & Borgaonkar, H. (2014) Treeline dynamics with climate change at the central Nepal Himalaya. *Climate of the Past*, **10**, 1277-1290.

Gaire, N.P., Dhakal, Y.R., Lekhak, H.C., Bhuju, D.R. & Shah, S.K. (2011) Dynamics of Abies spectabilis in relation to climate change at the treeline ecotone in Langtang National Park. *Nepal Journal of Science and Technology*, **12**, 220-229.

García-Callejas, D. & Araújo, M.B. (2016) The effects of model and data complexity on predictions from species distributions models. *Ecological Modelling*, **326**, 4-12.

Graham, C.H., Ron, S.R., Santos, J.C., Schneider, C.J. & Moritz, C. (2004) Integrating phylogenetics and environmental niche models to explore speciation mechanisms in dendrobatid frogs. *Evolution*, **58**, 1781-1793.

Guisan, A. & Thuiller, W. (2005) Predicting species distribution: offering more than simple habitat models. *Ecology Letters*, **8**, 993-1009.

Härkönen, E. (2002) 1999 Inventory of Nepal's Forest Resources. *Mountain Research and Development*, **22**, 85-87.

Hofmeister, E., Rogall, G.M., Wesenberg, K., Abbott, R., Work, T., Schuler, K., Sleeman, J. & Winton, J. (2010) Climate change and wildlife health: direct and indirect effects. In. US Geological Survey

Huang, J., Wu, Y., Gao, T., Zhan, Y. & Cui, W. (2015) An integrated approach based on Markov Chain and cellular automata to simulation of urban land use changes. *Applied Mathematics & Information Sciences*, **9**, 769.

IPCC, C.C. (2007) The physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. *Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA*, **996**, 2007.

Jetz, W., Wilcove, D.S. & Dobson, A.P. (2007) Projected impacts of climate and land-use change on the global diversity of birds. *PLoS biology*, **5**, 1211-1219.

Jnawali, S., Baral, H., Lee, S., Acharya, K., Upadhyay, G., Pandey, M., Shrestha, R., Joshi, D., Laminchhane, B. & Griffiths, J. (2011) The Status of Nepal Mammals: The National Red List Series, Department of National Parks and Wildlife Conservation Kathmandu, Nepal. *Preface by Simon M. Stuart Chair IUCN Species Survival Commission The Status of Nepal's Mammals: The National Red List Series*, 4.

Johansson, Ö., Rauset, G.R., Samelius, G., McCarthy, T., Andrén, H., Tumursukh, L. & Mishra, C. (2016) Land sharing is essential for snow leopard conservation. *Biological Conservation*, **203**, 1-7.

Karki, M., Mool, P. & Shrestha, A. (2009) Climate Change and its Increasing Impacts in Nepal. *The Initiation*, **3**, 30-37.

Kumar, S., Radhakrishnan, N. & Mathew, S. (2014) Land use change modelling using a Markov model and remote sensing. *Geomatics, Natural Hazards and Risk*, **5**, 145-156.

Lande, R. (1988) Genetics and demography in biological conservation. *Science*, **241**, 1455-1460.

Lauria, V., Gristina, M., Attrill, M.J., Fiorentino, F. & Garofalo, G. (2015) Predictive habitat suitability models to aid conservation of elasmobranch diversity in the central Mediterranean Sea. *Sci Rep*, **5**, 13245.

Li, J., Liu, F., Xue, Y., Zhang, Y. & Li, D. (2017) Assessing vulnerability of giant pandas to climate change in the Qinling Mountains of China. *Ecology and evolution*, **7**, 4003-4015.

Li, J., McCarthy, T.M., Wang, H., Weckworth, B.V., Schaller, G.B., Mishra, C., Lu, Z. & Beissinger, S.R. (2016) Climate refugia of snow leopards in High Asia. *Biological Conservation*, **203**, 188-196.

Liu, C.R., White, M. & Newell, G. (2013) Selecting thresholds for the prediction of species occurrence with presence-only data. *Journal of Biogeography*, **40**, 778-789.

Liu, L., Zhao, Z., Zhang, Y. & Wu, X. (2017) Using MaxEnt Model to Predict Suitable Habitat Changes for Key Protected Species in Koshi Basin, Central Himalayas. *Journal of Resources and Ecology*, **8**, 77-87.

Mondal, M.S., Sharma, N., Garg, P. & Kappas, M. (2016) Statistical independence test and validation of CA Markov land use land cover (LULC) prediction results. *The Egyptian Journal of Remote Sensing and Space Science*, **19**, 259-272.

Muscarella, R., Galante, P.J., Soley-Guardia, M., Boria, R.A., Kass, J.M., Uriarte, M. & Anderson, R.P. (2014) ENMeval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. *Methods in Ecology and Evolution*, **5**, 1198-1205.

Nie, Y., Sheng, Y., Liu, Q., Liu, L., Liu, S., Zhang, Y. & Song, C. (2017) A regional-scale assessment of Himalayan glacial lake changes using satellite observations from 1990 to 2015. *Remote Sensing of Environment*, **189**, 1-13.

Pearson, R.G., Dawson, T.P. & Liu, C. (2004) Modelling species distributions in Britain: a hierarchical integration of climate and land-cover data. *Ecography*, **27**, 285-298.

Peterson, A.T. (2011) Ecological niche conservatism: a time-structured review of evidence. *Journal of Biogeography*, **38**, 817-827.

Phillips, S.J. & Dudik, M. (2008) Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography*, **31**, 161-175.

Phillips, S.J., Anderson, R.P. & Schapire, R.E. (2006) Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, **190**, 231-259.

Ranjitkar, S., Xu, J., Shrestha, K.K. & Kindt, R. (2014a) Ensemble forecast of climate suitability for the Trans-Himalayan Nyctaginaceae species. *Ecological Modelling*, **282**, 18-24.

Ranjitkar, S., Kindt, R., Sujakhu, N.M., Hart, R., Guo, W., Yang, X., Shrestha, K.K., Xu, J. & Luedeling, E. (2014b) Separation of the bioclimatic spaces of Himalayan tree rhododendron species predicted by ensemble suitability models. *Global Ecology and Conservation*, **1**, 2-12.

Reid, D.G., Hu, J.C. & Yan, H. (1991) Ecology of the red panda Ailurus fulgens in the Wolong Reserve, China. *Journal of Zoology*, **225**, 347-364.

Sambrook, J. & Russell, D. (2001) Molecular Cloning: A Laboratory Manual. 3rd Cold Spring Harbor Laboratory Press. *New York*,

Shrestha, A.B. & Aryal, R. (2011) Climate change in Nepal and its impact on Himalayan glaciers. *Regional Environmental Change*, **11**, 65-77.

Soberon, J., Golubov, J. & Sarukhan, J. (2001) The importance of Opuntia in Mexico and routes of invasion and impact of Cactoblastis cactorum (Lepidoptera : Pyralidae). . *Fla. Entomol*, **84, 486–492.**

Thapa, A., Wu, R., Hu, Y., Nie, Y., Singh, P.B., Khatiwada, J.R., Yan, L., Gu, X. & Wei, F. (2018) Predicting the potential distribution of the endangered red panda across its entire range using MaxEnt modeling. *Ecology and Evolution*, **8**, 10542-10554.

Thapa, G.J., Wikramanayake, E., Jnawali, S.R., Oglethorpe, J. & Adhikari, R. (2016) Assessing climate change impacts on forest ecosystems for landscape-scale spatial planning in Nepal. *Current Science*, **110**, 345-352.

Thuiller, W. (2003) BIOMOD–optimizing predictions of species distributions and projecting potential future shifts under global change. *Global change biology*, **9**, 1353-1362.

Tomkiewicz, S.M., Fuller, M.R., Kie, J.G. & Bates, K.K. (2010) Global positioning system and associated technologies in animal behaviour and ecological research. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, **365**, 2163-2176.

Wang, X.M. (1997) New cranial material of Simocyon from China, and its implications for phylogenetic relationship to the red panda (Ailurus). *Journal of Vertebrate Paleontology*, **17**, 184-198.

Willis, S., Foden, W., Baker, D., Belle, E., Burgess, N., Carr, J., Doswald, N., Garcia, R., Hartley, A. & Hof, C. (2015) Integrating climate change vulnerability assessments from species distribution models and trait-based approaches. *Biological Conservation*, **190**, 167-178.

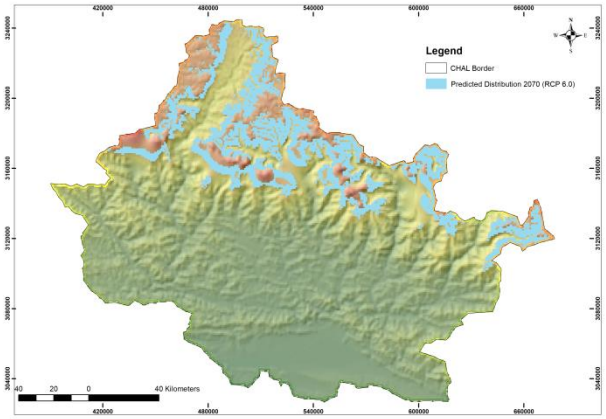
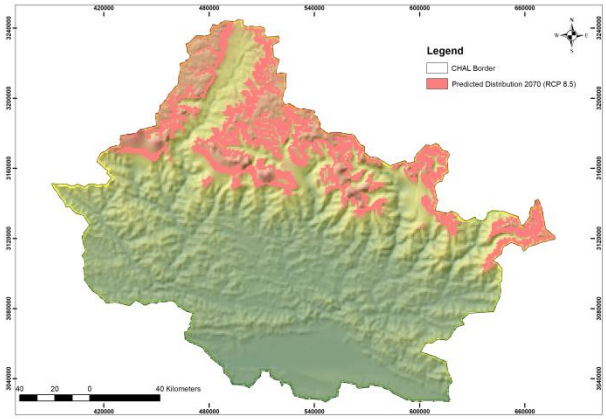
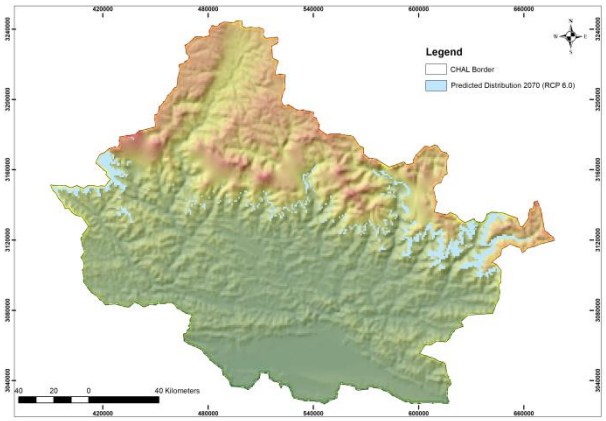
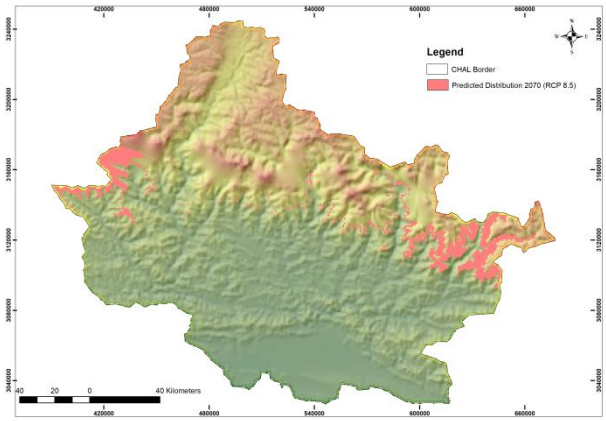
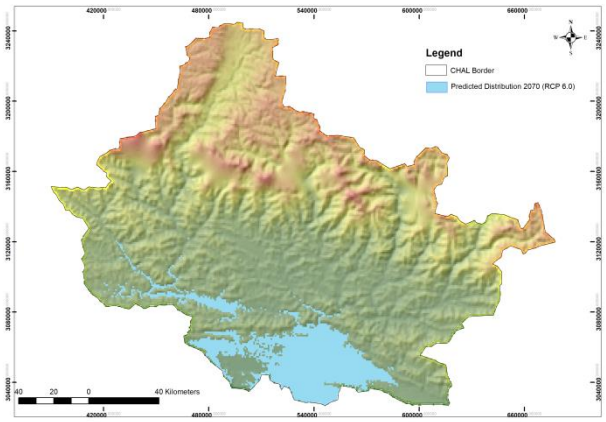
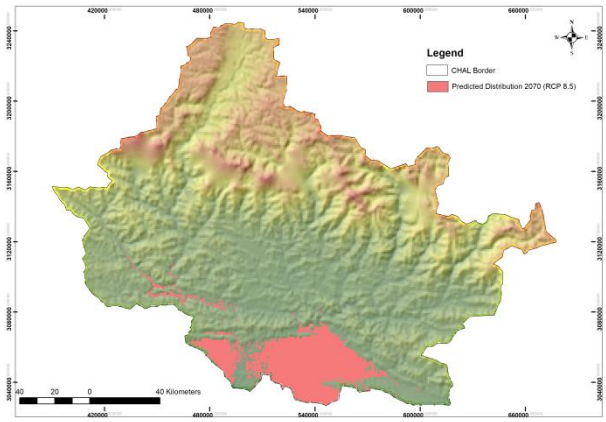
Yuan, T., Yiping, X., Lei, Z. & Danqing, L. (2015) Land use and cover change simulation and prediction in Hangzhou city based on CA-Markov model. *International Proceedings of Chemical. Biological and Environmental Engineering*, **90**, 108-113.

Zhao, Z., Wu, X., Zhang, Y. & Gao, J. (2017) Assessment of changes in the value of ecosystem services in the Koshi River Basin, central high Himalayas based on land cover changes and the CA-Markov model. *Journal of Resources and Ecology*, **8**, 67-76.

NPC, 2011. Climate-Resilient Planning. [Working Document], Government of Nepal, National Planning Commission, Kathmandu, Nepal.

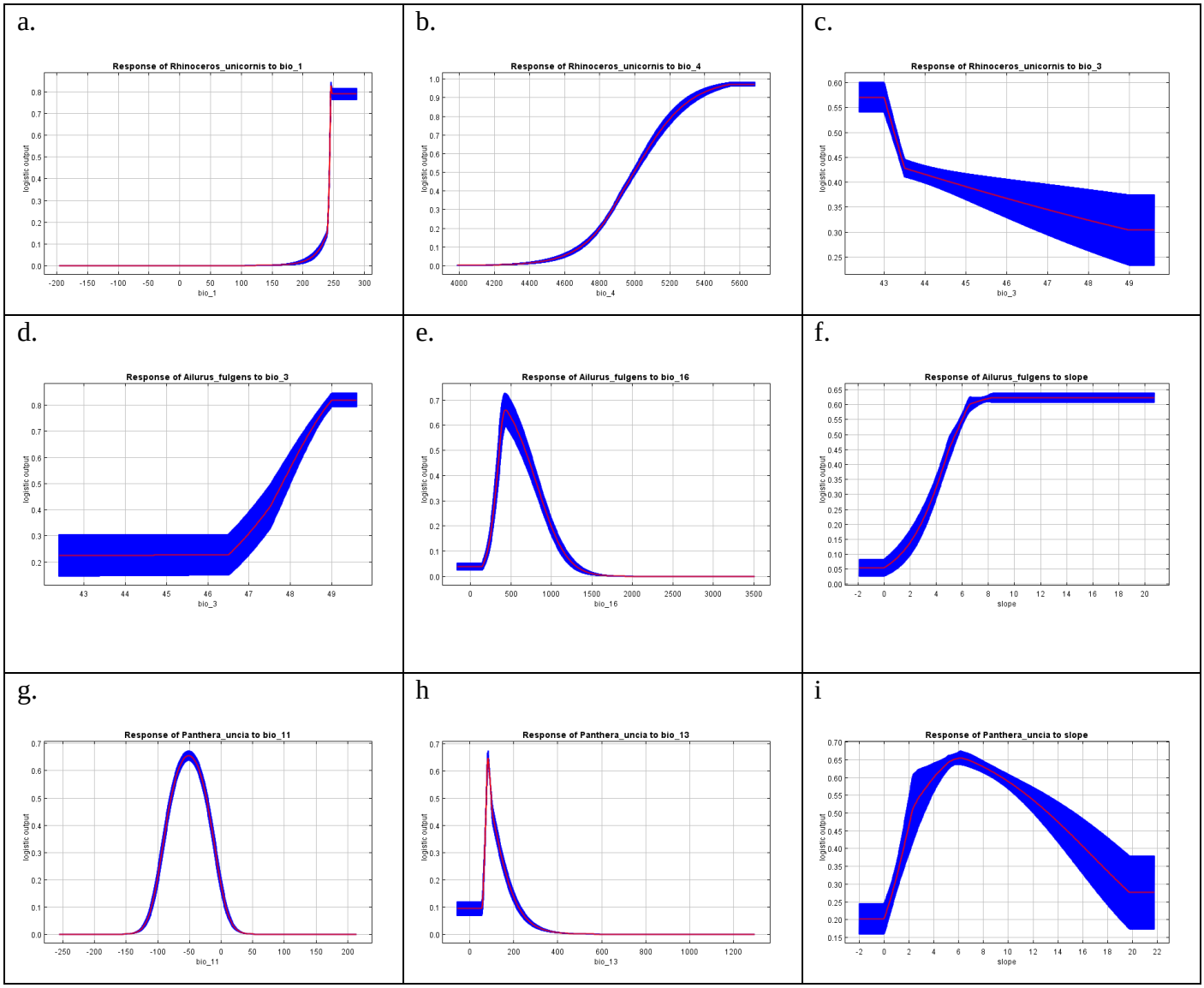
WWF Nepal. 2017. Biodiversity, People and Climate Change: Final Technical Report of the Hariyo Ban Program, First Phase. WWF Nepal, Hariyo Ban Program, Kathmandu, Nepal.

Appendix- Supplementary figures

Projected future habitat 2070 (RCP6.0)	Projected future habitat 2070 (RCP 8.5)
	
Snow leopard	
	
Red panda	
	
Rhinoceros	

S. Figure. 1. Projected future habitat in 2070

Response curve



S. Figure 2.