Final report

Assessing the climate change impacts on species and habitats

Submitted by

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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.
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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 \textit{et al.}, 2011; Gaire \textit{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 \textit{et al.}, 2016). It is estimated that 30% of snow leopard habitat in the Himalayas may be lost due to tree line shift (Forrest \textit{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 \textit{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 \textit{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 \textit{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 \textit{et al.}, 2017; Nie \textit{et al.}, 2017). However changing climate and land cover have negatively impacted the habitats of many species (Thuiller, 2003; Jetz \textit{et al.}, 2007; Hofmeister \textit{et al.}, 2010). Higher annual temperature increase (increased by 0.13°C/year) in other parts of the Himalayan region have been observed, particularly in Upper Mustang of the trans-Himalaya region (Aryal \textit{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 \textit{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 \textit{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 despite 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)
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)](image)

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.)
2.3 Methods
Following methods were deployed to achieve project’s objectives.

2.2.1 Desktop 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 Tribhuvan 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.

Figure 3 Detail research model flow chat (modified and adapted from Willis et al. 2015)
During review process, species occurrence records (latitude and longitude) were compiled 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 km² 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.worldclim.org/version1) (Table 1), which were 30 arc sec (~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 (e.g., 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)

<table>
<thead>
<tr>
<th>Bioclimatic Variables (Bio_1-Bio_19)</th>
<th>Variables sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Diurnal Range (Mean of monthly (max temp-min temp)) [BIO2]</td>
<td><a href="http://www.worldclim.org">http://www.worldclim.org</a></td>
</tr>
<tr>
<td>Isothermality (BIO2/BIO7)*(100)[BIO3]</td>
<td><a href="http://www.worldclim.org">http://www.worldclim.org</a></td>
</tr>
<tr>
<td>Temperature Seasonality (standard deviation*100) [BIO4]</td>
<td><a href="http://www.worldclim.org">http://www.worldclim.org</a></td>
</tr>
</tbody>
</table>
Precipitation Seasonality (Coefficient of Variation)[BIO15]  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:

\[
AC = \frac{(A_f - A_c)}{A_c} \times 100\%
\]

\[
SH_c = \frac{(A_c - A_{cf})}{A_c} \times 100\%
\]

\[
SH_f = \frac{(A_f - A_{cf})}{A_f} \times 100\%
\]

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 21 variables, 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 1,192km², 2,417km², 4,080km² 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.

<table>
<thead>
<tr>
<th>Species</th>
<th>Current(km²)</th>
<th>Future scenarios (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2050 (RCP 2.6)</td>
</tr>
<tr>
<td>Rhinoceros</td>
<td>1,192</td>
<td>3,277</td>
</tr>
<tr>
<td>Red panda</td>
<td>2,417</td>
<td>1,141</td>
</tr>
<tr>
<td>Snow leopard</td>
<td>4,080</td>
<td>3,823</td>
</tr>
</tbody>
</table>

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 (17,190 km$^2$) of the country. Under the future climate scenario, the area of potential suitable habitat will be projected to be 3,483 km$^2$ and 3,934 km$^2$ 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 2,417 km$^2$ 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 1,674 km$^2$ and 1,108 km$^2$ 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).

![Figure 15. Density plot of the predicted habitat suitability values of red panda in different elevation range.](image)

Rhinoceros
The model of potential suitable habitat of rhinoceros occupied an area of 1,192 km². 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

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

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

$A_c$ =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, 1,190km², 2,375km² and 1,052km² 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

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Reference:
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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.