MODELLING CURRENT AND FUTURE SUITABLE HABITATS FOR MISHMI TAKIN AND BHUTAN TAKIN IN THE EASTERN HIMALAYAS

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June, 2021

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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
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ABSTRACT

The Mishmi takin (*Budorcas taxicolor taxicolor*) and the Bhutan takin (*Budorcas taxicolor whitei*) are endemic to the eastern Himalayas. They are the two least studied subspecies of the takin (*Budorcas taxicolor*) and listed as Vulnerable species by the IUCN Red List. Despite the fact that both subspecies are legally protected in their range, their population continues to decline due to poaching, habitat loss and fragmentation over the last few decades. In this study, I modelled current suitable habitats for both Mishmi takin and Bhutan takin in the Eastern Himalayas using ecological niche modelling, and identified the key environmental variables influencing their potential distribution. Furthermore, I tested the niche similarity between these two subspecies and also predicted the potential impact of future climate change on them. The results show that the current suitable habitat for Mishmi takin and Bhutan takin is 28,154 km^2 and 15,314 km^2, respectively. The key environmental variables determining the habitat suitability for the two subspecies are different. For Mishmi takin, precipitation seasonality and the standard deviation of NDVI are the two most important factors. In the case of Bhutan takin, the needleleaf forest and isothermality are the two major factors. The result also shows that the ecological niches of Mishmi takin and Bhutan takin are similar but not the same. The future climate change will have a significant negative impact on Mishmi takin and Bhutan takin in the Eastern Himalayas. The suitable habitat for the Bhutan takin is expected to disappear completely in the area, while the remaining suitable habitat for the Mishmi takin will also be very few. To the best of my knowledge, this is the first study that predicted the current and future suitable habitat for both Mishmi takin and Bhutan takin in the Eastern Himalayas. The findings of this study provide an important scientific basis for conservation planning of these two subspecies and its associated ecosystem in this region.

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I am still in awe of the grand support that I received from Wildlife Trust of India (WTI), Wildlife Conservation Society - Myanmar Program (WCS), Yunnan Normal University in China, and Nature Conservation Division (NCD), Wangchuck Centennial National Park (WCNP), and Jigme Dorji National Park (JDNP) under the Ministry of Agriculture and Forests of Bhutan. I am especially thankful to focal persons from these esteemed organizations who shared their immensely valuable takin data for this study, Dr. Rahul Kaul from WTI, Mr. Than Zaw from WCS, Prof. Jinliang Wang from Yunnan Normal University, Mr. Letro from NCD, Mr. Lungten Dorji from WCNP, and Mr. Yonten Jamtsho from JDNP. It would have been impossible even to start this study without their valuable contributions. I earnestly thank them and their organizations for putting their trust in the purpose of this study and me.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

AUC	Area under the receiver operating characteristic curve
BIOCLIM	Bioclimatic prediction and modelling system
BRT	Boosted regression tree
CBI	Continuous Boyce Index
DEM	Digital elevation model
GBIF	Global Biodiversity Information Facility
GCM	General circulation model
GIS	Geographic information system
GLM	Generalized linear model
H	Hinge
HDX	Humanitarian data exchange
IUCN	International Union for Conservation of Nature
L	Linear
MARS	Multivariate adaptive regression-splines
MESS	Multivariate environmental similarity surface analysis
NDVI	Normalized difference vegetation index
NIR	Near-infrared
P	Product
Q	Quadratic
RCP	Representative concentration pathway
ROC	Receiver operating characteristic
SEDAC	Socioeconomic Data and Applications Center
T	Threshold
TGS	Target Group Sampling
TSS	True skill statistic
VIF	Variance inflation factor

1. INTRODUCTION

1.1. Background

Global biodiversity is rapidly declining with an unprecedented extinction rate (IPBES, 2019). The current rate of extinction is greater than the anticipated rate from the fossil record (Barnosky et al., 2011). This rate of biodiversity decline is clearly indicated to trigger the sixth mass extinction that occurred only five times in about 540 million years. It is driven by increasing anthropogenic activities through poaching, exploitation of natural resources, fragmentation and degradation of suitable habitat, the introduction of non-native species, and climate change (Barnosky et al., 2011; Ceballos et al., 2015; Tollefson, 2019; Wilson, 1989). The loss of biodiversity alters the magnitude, pace, and temporal continuity of material and energy flow in an ecosystem, which threatens the ecosystem productivity and services, affecting human well-being (Cardinale et al., 2012; Díaz et al., 2006). Therefore, urgent action is needed to safeguard the biodiversity on planet Earth. An approach to conserve biodiversity is to identify the biodiversity hotspots for priority conservation and management (Myers et al., 2000).

Globally, a total of 34 biodiversity hotspots are recognized, among which three fall in the Eastern Himalayas (Chhetri et al., 2010). The Eastern Himalayas is a mountain ecosystem that stretches across Kali Gandaki valley in central Nepal to northwest Yunnan in China, including Bhutan, northeast states and north Bengal hills in India, southeast Tibet in China, and northern Myanmar (Sharma et al., 2009). It covers an area of approximately 525,000 km². The Eastern Himalayan mountain has a complex topography due to the rapid change in altitude over small distances. As a result, the region supports diverse bioclimatic zones. This diversity in the bioclimatic zone enables many globally significant flora and fauna to inhabit the region due to which the Eastern Himalayas is acknowledged as an important global conservation priority area with high biodiversity and endemism (Basnet et al., 2019; Brooks et al., 2006; Chhetri et al., 2010). For instance, the Eastern Himalayas is home to some of the vulnerable species like takin (*Budorcas taxicolor*), endangered species like Bengal tiger (*Panthera tigris*), and critically endangered species like Namdapha flying squirrel (*Biswamoyopterus biswasi*) (IUCN, 2020). At the same time, the region is vulnerable due to its geographic location and fragile ecosystem (Chhetri et al., 2010; Sharma et al., 2009). The Eastern Himalayas is located in between the densely populated countries that exert massive demand for natural resources to fuel people's livelihood and economic development (Chhetri et al., 2010). Mountains are one of the most fragile environments on Earth (Chettri et al., 2018). Many mountain ecosystems are greatly affected by land-use change and climate change, thereby experiencing a loss of biodiversity. The Eastern Himalayan mountain ecosystem is no exception. Therefore, the long-term viability of rich biodiversity in the Eastern Himalayas is in jeopardy due to poaching, land-use change, and climate change (Chhetri et al., 2010; Pandit et al., 2007; Sathyakumar & Bashir, 2010).

Poaching is rampant in the Eastern Himalayas (Sathyakumar & Bashir, 2010). Wild animals are illegally hunted for meat, medicine, and mainly for economic gain. For example, a study conducted in the Eastern Himalayan region in India revealed that animals like goral, serow, and takin are hunted and killed by people, which has led to local extinction or a decrease in the local population density of these animals (Dasgupta et al., 2010; Rawat & Sathyakumar, 2002). Likewise, poaching has reduced the number of tigers from 20,000 to 3000 despite significant efforts by conservationists to protect the wildlife (Anil et al., 2014). Mountain products have been traded for thousand years by the people in the border areas of the Himalayas (Oli, 2003). Access to modern infrastructure and economic activities have further increased the illegal trade of wild species and animal parts. The intruders are at an advantage because the law enforcement agencies are not based locally. Therefore, controlling the illegal hunting and trade of species at present is a difficult task.

Within the last few decades, the land-use change in Eastern Himalayas from forest to other types of usages is noticeable (Chhetri et al., 2010). The expansion of agriculture brings socio-economic development but at the cost of biodiversity and ecosystem services (Penjor et al., 2020). For example, at the current rate of deforestation caused by agricultural expansion and human settlement in the Indian Himalayas, it is projected to have only about 10% of the land under dense forest cover (>40% canopy cover) by 2100, a scenario capable to wipe out almost a quarter of endemic species (Pandit et al., 2007). The fuelwood consumption for cooking and space heating activities is dominant in the Eastern Himalayas, apart from the slash and burn agriculture practice (Bhatt et al., 2016). The estimated forest growth is not able to accommodate fast fuelwood consumption. So, the forest is degraded and needs restoration to support the energy requirement and maintain the ecosystem balance.

The impact of climate change is more pronounced in the Himalayas (Sharma et al., 2009). Over the last 100 years, the Eastern Himalayas temperature increased more than the 0.74°C global average. There is a relatively more increase in temperature and precipitation with increasing elevation in the area (Manish et al., 2016; Sharma et al., 2009). Such variation in physical factors like temperature and precipitation causes an alteration in the hydrological cycle and vegetation community, leading to permanent shifts in biomes (Bellard et al., 2012; Xu et al., 2009). Consequently, species respond by shifting or shrinking their ranges and niches, physiological adaptation, or become extinct (Bellard et al., 2012; Telwala et al., 2013). For instance, future climate change is projected to bring more than 20 to 80 m per decade theoretical shift in altitudinal vegetation belts in the higher elevation of Eastern Himalayas considering the current estimated temperature rise of about 0.01°C to 0.04°C per year (Tse-ring et al., 2010). As a result, it is assumed that apart from some of the species that can adapt or shift, the ability of other species to keep pace with changing climate is minimal.

Monitoring and conserving biodiversity under threat is challenging due to the limited resources. So, the alternative is chosen in the form of indicator, umbrella, and flagship species (Simberloff, 1998). Large mammals are considered as indicator species to inform the ecosystem health and diversity because of their large area requirement and essential ecological role (Ceballos & Ehrlich, 2002; Simberloff, 1998; Sinclair, 2003). Recently, Dorji et al. (2018) evaluated 255 terrestrial mammals to assess the efficiency of existing protected areas in the Eastern Himalayas. The mammals were considered as the key indicators of anthropogenic impacts on the ecosystem. The assessment identified the 50 most threatened mammals in the Eastern Himalayas. Of these 50 threatened mammals, takin is the only mammal endemic to the Eastern Himalayas, has a wide range, and falls under the vulnerable category of the International Union for Conservation of Nature (IUCN) Red List of Threatened Species (Dorji et al., 2018; Song et al., 2008).

Takin is an ungulate mountain mammal that is endemic to the Eastern Himalayas (Sharma et al., 2015). Taxonomically, takins are notable for being a species that is in between sheep and cattle (Zeng et al., 2003). They are shy animals that live in remote areas away from human habitation. They have a large body with thick and strong legs, a greatly convex face with a heavy mouth and a very thick neck. Takin's body is covered with a shaggy coat that varies in colour among the subspecies. They dwell in dense forests, mainly between 1,500 to 3,600 m in temperate and alpine forests. Takin is a herbivore and grazes on various plants and often gathers around the mineral lick sites (Schaller et al., 1986; Wangchuk et al., 2016). They exhibit seasonal migration which is influenced by plant phenology and temperature change (Guan et al., 2013, 2015; Wang et al., 2010; Zeng et al., 2008). There are four subspecies of takin (Neas & Hoffmann, 1987), namely Golden takin (*Budorcas taxicolor bedfordi*), Sichuan takin (*Budorcas taxicolor tibetana*), Mishmi takin (*Budorcas taxicolor taxicolor*), and Bhutan takin (*Budorcas taxicolor whitei*). They are legally protected throughout their distribution range in China, India, Myanmar, and Bhutan. In China, the takin is listed as a Class I species of the National Wildlife Law (1988) that forbids people from hunting them (Guan et al., 2013). In India, takin is protected as a Schedule I species of the Wildlife Protection Act of India, 1972 (Dasgupta et al., 2010). Likewise, in Myanmar, takin is protected under the Completely Protected Species category in the Protection of Wildlife and Wild Plants and Conservation of Natural Areas Law, Myanmar 2020 (Government of the Union of Myanmar, 1994). In Bhutan, takin is protected under the Schedule I category of the Forests and Nature Conservation Act of Bhutan 1995 (Royal Government of Bhutan, 1995). Despite their legal protection status, studies have confirmed that the population of takin is declining throughout their distribution range due to poaching, deforestation, habitat fragmentation, and climate change (Dasgupta et al., 2010; NCD, 2019; Sangay et al., 2016; Sharma et al., 2015; Song et al., 2008; Wei et al., 2017). Therefore, effective conservation measures are required to minimize further declines.

The collection of information and identifying information gaps is a necessary step in planning for biodiversity conservation (Groves et al., 2002). Previous literatures have reported takin to be a poorly studied species, partially due to the poor access to their remote habitat in the forests (Adkin et al., 2012; Dhendup et al., 2016; Groves, 1992; Guan et al., 2013; Sangay et al., 2016; Song et al., 2008; Zeng et al., 2008). Moreover, it is indicated that the focus was mainly on the two subspecies, namely Golden takin and Sichuan takin in China (Adkin et al., 2012; Guan et al., 2013, 2015; Hua et al., 2002; Schaller et al., 1986; Z.-G. Zeng et al., 2008, 2010). Mishmi takin and Bhutan takin are the least studied subspecies (NCD, 2019; Pan et al., 2019; Sangay et al., 2016; Song et al., 2008; Wangchuk et al., 2016).

Mishmi takin is distributed across southeast of Tibet and northwestern Yunnan in China, Kachin state in northern Myanmar, and Arunachal Pradesh in India (Song et al., 2008). It is estimated that there are 3,500 Mishmi takins in Tibet. The estimated population for Mishmi takin in the rest of the distribution range is not yet available. A few prior studies on Mishmi takin provides the partial preference of their habitat and information on threats in their distribution range. For example, the report on Mishmi takin distribution in India by Dasgupta et al. (2010) concluded that Mishmi takin prefers dense forests. The poaching and hydropower plant development is negatively affecting the population of Mishmi takin in India. They are still present in Arunachal Pradesh although it is extinct in Sikkim. Yang et al. (2019) selected Mishmi takin as one of the five flagship species in their study to identify the priority conservation areas that fall in the transboundary biodiversity hotspot of China and Myanmar. The result revealed that 80% of the identified priority conservation areas for the five flagship species were outside the existing protected area boundary. The studies in Myanmar reported that Mishmi takin is one of the most hunted wild animals for meat and commercial gain (Rao et al., 2010, 2011). In addition to these threats from poaching and land-use change, China, Myanmar, and India are reported to be highly vulnerable to future climate change (Gao et al., 2001; Gopalakrishnan et al., 2011; Rao et al., 2013).

Bhutan takin is an animal of national importance and cultural value in Bhutan (NCD, 2019). Bhutan takin was announced as the national animal of Bhutan in 1985 (Royal Government of Bhutan, 1995). Across its distribution range, Bhutan takin is mostly found in northern region of Bhutan (Sharma et al., 2015; NCD, 2019). It was last reported to be seen in Sikkim, India in 1999 (Sharma et al., 2015). The distribution in Tibet, China is not clear. Their estimated population is 500 to 700 individuals (Sharma et al., 2015). The partial habitat preference and information on threats within Bhutan is available based on previous studies. For instance, Wangchuk et al. (2016) assessed the Bhutan takin's habitat and diet during summer within Jigme Dorji National Park. They concluded that Bhutan takin prefers the area near mineral licks, and grazes on 68 different species of plants. Another study captured (through camera trap) the presence of Bhutan takin at an elevation of 4864 m in Wangchuck Centennial National Park, which is beyond the highest reported upper limit of 4200 m within Bhutan (Dhendup et al., 2016). NCD (2019) predicted Jigme Dorji National Park and Wangchuck Centennial National Park as the suitable winter habitat for Bhutan takin. Further, they reported a positive relationship with conifer forest and roughness, and a strong negative relationship with slope and road. Similarly, negative influence from road, power transmission lines, food resource competition, and the risk of zoonotic disease transmission from the domestic livestock was reported based on a questionnaire survey (Sangay et al., 2016). Apart from the previously reported threats to Bhutan takin, the impact of climate change is prominently felt with changing seasonal pattern and climate-induced disasters in Bhutan (Chhogyel & Kumar, 2018). Further, the vulnerability analysis of mammals to the impacts of land-use change and climate change predicted a reduced occurrence of species in future in Bhutan (Penjor et al., 2020).

The accurate identification of target species' suitable habitat for protection is a crucial scientific intervention for well-organized conservation planning (Huang et al., 2020). The ecological niche model (ENM) or species distribution model (SDM) is a commonly used tool to predict the suitable habitat of a species (Elith & Leathwick, 2009; Rodríguez-Castañeda et al., 2012). ENMs are based on the concept that there is a close relation of a species to its environment (Grinnell, 1917). It is a numerical model that combines environmental variables with species' occurrence data to estimate the species-environment relationship. The earliest computer-based species distribution modelling began in the mid-1970s (Guisan & Thuiller, 2005). Since then, the subject has rapidly developed due to its applicability in fields other than predicting suitable habitats for species (Elith et al., 2011; Guisan & Thuiller, 2005). For instance, ENMs are used to predict the spread of disease (Peterson et al., 2002), for phylogeographic studies (Alvarado-Serrano & Knowles, 2014), for mapping the human ecological niche in the past glacial maximum in Europe (Banks et al., 2008), and to simulate the effects of frequent fire (Syphard et al., 2006). SDMs like the generalized linear model (GLM) has been in use since the early 1990s. It uses multiple-regression techniques to model complex ecological relationships. It is one of the stable models and uses presence-absence data for modelling. However, the collection of absence data is complicated, sparse, and unreliable (Mackenzie, 2005). In contrast, presence-only data are widely available with the development of digital databases like herbarium records and museum databases (Graham et al., 2004). Therefore, modelling techniques to use presence-only data like the maximum entropy method (Maxent) and BIOCLIM modelling method were developed (Elith et al., 2011; Pearce & Boyce, 2006; Phillips et al., 2006). Maxent is a statistical machine learning method (Phillips et al., 2006). It has been widely used since its availability in 2004 (Elith et al., 2011). More than 1000 studies have applied the Maxent method for species distribution modelling (Merow et al., 2013). For example, study to assess the human impacts on endangered red pandas living in the Himalaya (Panthi et al., 2019), the predicted negative affect of climate change and land-use change on the distribution of Rhododendrons in China (Yu et al., 2019), the assessment of threats and conservation priorities for Asian slow lorises (Thorn et al., 2009), and to evaluate the ecological indicator of climate change (Kou et al., 2020).

1.2. Problem Statement

The conservation of Mishmi takin and Bhutan takin cannot be achieved without knowing where they are. Effective conservation of these two species requires various information, at the very least, on their suitable habitats. However, knowledge on their suitable habitats is incomplete or unclear. For instance, the suitable habitat for Mishmi takin covering their distribution range is not yet available. Also, the prior habitat suitability study for Bhutan takin is focused on winter habitat only. The geographic boundary between Mishmi takin and Bhutan takin is uncertain (Song et al., 2008). Consequently, it limits the protection of their suitable habitat, thereby imposing a limit on drawing effective conservation, management, and monitoring plans.

The difference between Mishmi takin and Bhutan takin is still not well established. There are contradictions in the description of their pelage colour patterns. A study that carried out sequencing and characterization of the complete mitochondrial genome of Mishmi takin reported that Mishmi takin show close relationship with Sichuan takin than Golden takin (Kumar et al., 2019). However, comparison was not made with Bhutan takin although there are cases when both subspecies are thought to be of same genetic form. Thus far, there are no previous studies comparing their ecological niches, although assessing the similarity of ecological niches may help to mitigate the confusion between these subspecies.

The Himalayan mountain range is sensitive to climate change. There is strong evidence that the region is warming (Gautam et al., 2013). For example, for the period of 1901 to 2003, a 1°C rise in annual average maximum temperature was found in the whole of northeast India. Similarly, many studies report warmer trends for the eastern Himalayas in China. In the Himalayan regions of Bhutan, from 1985 to 2002 average temperature increased by 0.5°C in the non-monsoon season. Further, the large threatened and endemic species are expected to be the most vulnerable animals under the projected climate change scenarios in the Eastern Himalayas (Sharma et al., 2009). Yet, the potential impact of future climate change on Mishmi takin and Bhutan takin has not been explored in previous studies.

1.3. Research objectives

The overall objective of this study is to predict the current and future suitable habitats for Mishmi takin and Bhutan takin in the Eastern Himalayas. The specific objectives of this study are as follows:

1) To model the current suitable habitat for Mishmi takin and Bhutan takin in the Eastern Himalayas
2) To identify the key environmental variables that determine the habitat suitability of Mishmi takin and Bhutan takin
3) To test if the ecological niches of Mishmi takin and Bhutan takin are identical
4) To predict the impacts of future climate change on the habitat suitability of Mishmi takin and Bhutan takin in the Eastern Himalayas

1.4. Research questions

1) What is the area of suitable habitat currently available for Mishmi takin and Bhutan takin in the Eastern Himalayas?
2) What are the key environmental variables influencing the habitat suitability of Mishmi takin and Bhutan takin?
3) Are the ecological niches of Mishmi takin and Bhutan takin identical?
4) How will the suitable habitat for Mishmi takin and Bhutan takin change under future climate change?

1.5. Research hypotheses

Hypothesis 1

H_0: The key environmental variables affecting habitat suitability of Mishmi takin and Bhutan takin are the same

H_1: The key environmental variables affecting habitat suitability of Mishmi takin and Bhutan takin are different

Hypothesis 2
H_0: The ecological niches of Mishmi takin and Bhutan takin are identical
H_1: The ecological niches of Mishmi takin and Bhutan takin are not identical

Hypothesis 3
H_0: Suitable habitats for Mishmi takin and Bhutan takin are expected to increase under the future climate change scenario
H_1: Suitable habitats for Mishmi takin and Bhutan takin are expected to decline under the future climate change scenario

2. MATERIALS AND METHODS

2.1. Study area

The study area lies in the Eastern Himalayas (27°13' to 28°46' N, 88°10' to 98°27' E). It covers an area of 286,829 km² composed of parts of southwest China, northeast India, northern Myanmar, and Bhutan (Figure 1). The area is regarded as the current distribution range for Mishmi takin and Bhutan takin (Song et al., 2008).

The Eastern Himalayas is part of the youngest mountain range in the world. Apart from being the global biodiversity hotspot (Myers et al., 2000), the Eastern Himalayas is a glacier ice repository beyond the Poles. It is also called 'Water tower' or 'Third pole', a critical source of water for people living downstream (Sharma et al., 2009). The region's extreme altitudinal gradients range below 300 m in tropical lowlands to more than 8000 m in high mountains (Chhetri et al., 2010); the world's highest mountain peak, the Mount Everest stands there.

The forest and vegetation in the region are diverse due to the different bioclimatic zones and complex topography (Chhetri et al., 2010). Broadly, six different vegetation types are identified, namely tropical, sub-tropical, warm temperate, cool temperate, sub-alpine and alpine.

The climate in the region is characterized as tropical montane ecosystem type of climate, hot and humid in the foothills and cold and dry on higher elevations. It has about eight months of the active rainy season and hosts Cherrapunji, the wettest spot in the world (Shrestha & Devkota, 2010).

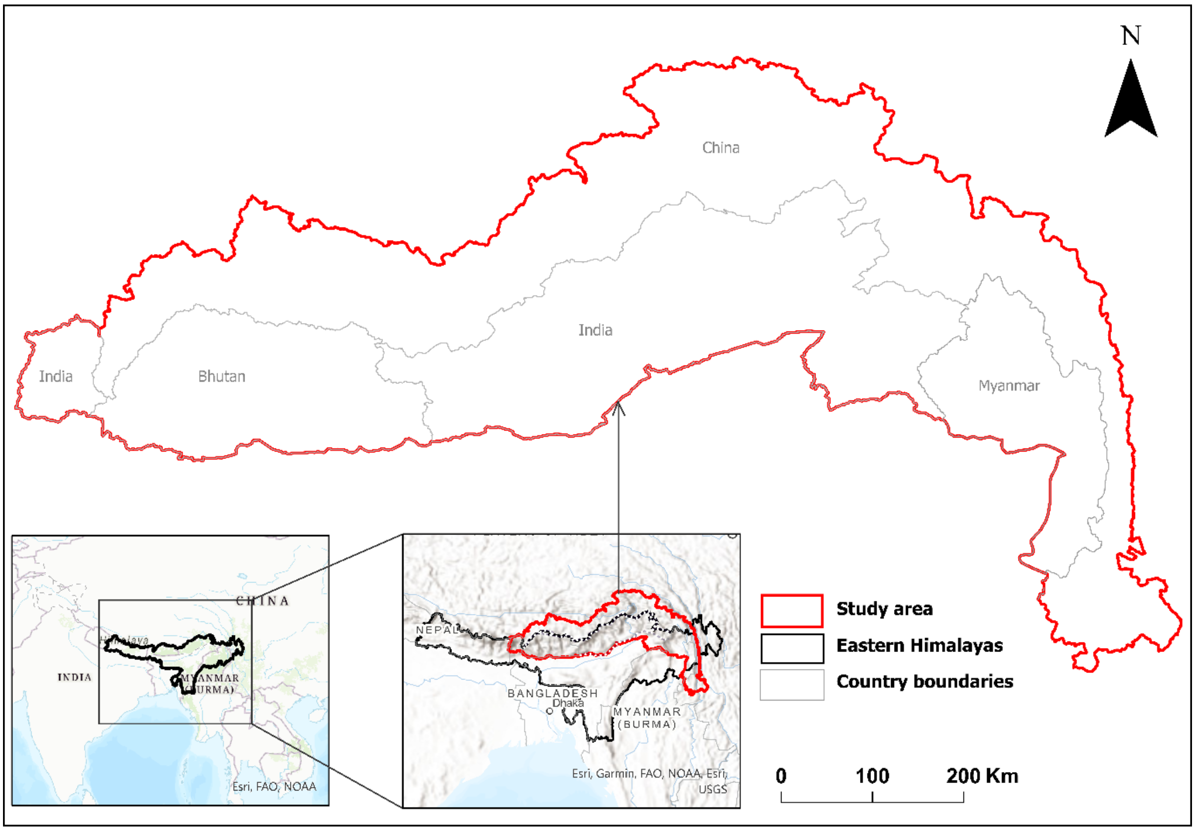


Figure 1: Geographical location of the study area in the Eastern Himalayas

2.2. Species data

The species occurrence data for Mishmi takin was shared by the Wildlife Trust of India, the Wildlife Conservation Society of Myanmar Program, and Yunnan Normal University in China. The data from India was collected from Sikkim and Arunachal Pradesh, northeastern states in India (Dasgupta et al., 2010). The surveys were sporadically conducted between August 2008 and May 2009. Two types of surveys, namely secondary survey and primary survey were conducted. The secondary survey involved interviews and consultation with forest personnel, knowledgeable people, and historical records of distribution to identify areas with the local presence of takin. Among the identified areas, suitable sites for the survey were recognized by selecting the areas between 1500 m and 3600 m and had dense forest cover. Within the identified sites, smaller priority plots for the survey were chosen based on recent sightings and in consultations with local hunters and forest personnel. The primary ground-based survey was conducted in these smaller priority plots by walking through the habitats. Both direct and indirect sightings of species were recorded. Additionally, some occurrence points were compiled from the published report of the Wildlife Trust of India collected in the period 1990 to 2007. The data received through the Wildlife Conservation Society was collected from northern Myanmar. The occurrence points were recorded using camera traps and opportunistic sightings, direct and indirect both. The data was collected in the year 2001 to 2005, 2014, and 2016. The data received from Yunnan Normal University was collected through field surveys, camera traps, and interviews with farmers in southwest China. The data was collected from 1992 to 2020.

The species occurrence data for Bhutan takin was provided by the Nature Conservation Division, Wangchuck Centennial National Park, and Jigme Dorji National Park, Royal Government of Bhutan. The data shared by Nature Conservation Division was collected during the takin national survey of Bhutan (NCD, 2019). The survey was conducted between February and March 2018 in the winter habitat of Bhutan takin. The study sites were selected based on the previous takin records. A grid of 5x5 km^2 was created on the selected study sites based on the estimated home range of Bhutan takin. The field survey combined a transect walk and camera trap method in the study sites. The laying of transects and placement of camera traps was guided by these grids. For the transect walk survey, a transect of 5 km (maximum) was set in accessible grids. They were laid to cover all representative habitat in each grid. Both direct and indirect sightings were recorded at locations 500 m apart in each grid. At every 500th meter, a 100 m circular buffer was virtually laid as the centre of the plot. The observers then searched for about 20 minutes in each plot. Each transect was visited once more in two weeks (minimum of 1 visit and maximum of 3 visits). For the camera trap survey, grids that were representative of habitat type but further enough to minimize spatial autocorrelation were chosen for unpaired camera trap installation. The camera traps were let to operate for 45 days before closure. The additional data shared by Wangchuck Centennial National Park and Jigme Dorji National Park cover the summer habitat of Bhutan takin. The data shared by Wangchuck Centennial National Park were collected between May and July 2015 through a transect walk. The data from Jigme Dorji National Park were collected between May and August 2020 through forest patrolling. The direct and indirect sightings were recorded from both the parks.

A total of 256 occurrence points for Mishmi takin was shared by data owners from India, Myanmar, and China. During the data exploration exercise, 58 duplicate points and 10 outliers were removed from the dataset. The outliers were determined based on the elevation extracted at each occurrence point in ArcGIS. Takins are generally known to dwell between 1500 m to 3000 m or above. Therefore, occurrence points with elevations lower than 1500 m were removed from the final set of data. The last set of data for Mishmi takin has 188 points (Figure 2). For Bhutan takin, 246 occurrence points were shared in total by data owners from Bhutan. 53 duplicate points were found and removed from the final set of data of 193 data points (Figure 2). No outliers were detected in the occurrence set of Bhutan takin.

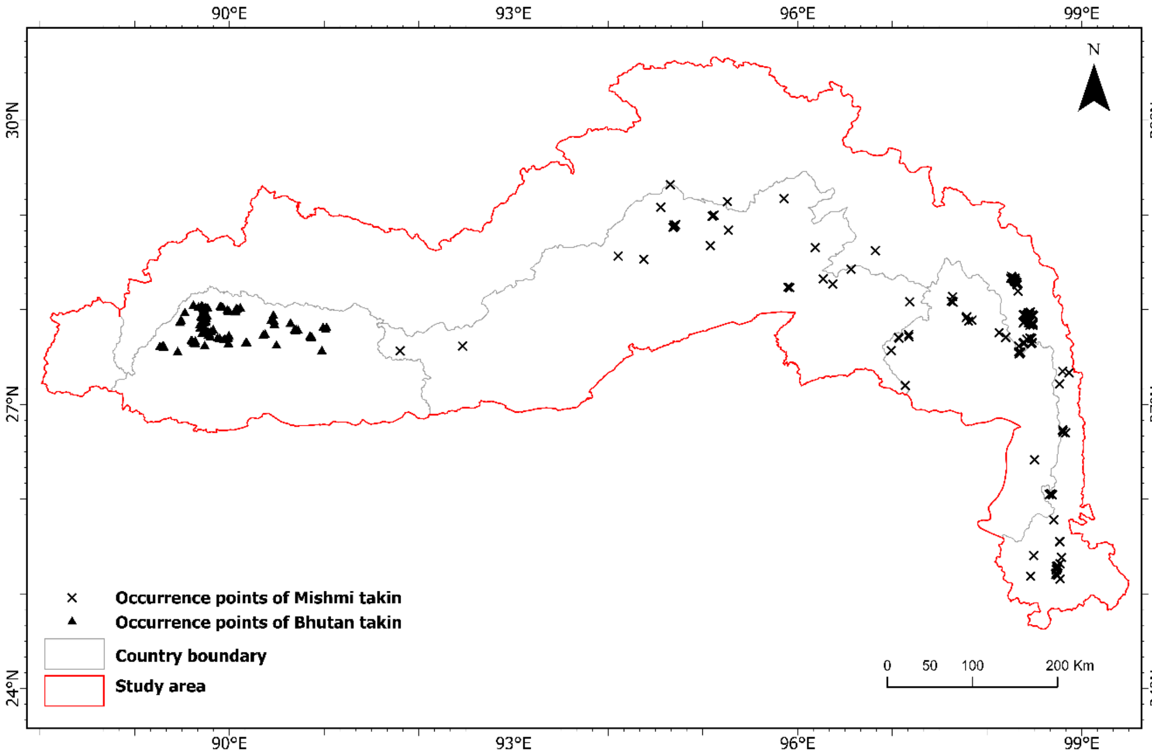


Figure 2: The geographical distribution of Mishmi takin and Bhutan takin occurrence points used for the study

2.3. Environmental variables

Modelling with appropriate environmental variables is critical to the performance of the model and its application in predicting suitable habitat of species (Williams et al., 2012). The appropriate environmental variables are direct or indirect factors that control the growth, reproduction, morphology, and behaviour of a species. In this study, the potential environmental variables were collected based on the information gathered on characteristics of takin's ecology through prior studies (Dasgupta et al., 2010; Dhendup et al., 2016; Groves, 1992; Guan et al., 2013; Kumar et al., 2019; NCD, 2019; Neas & Hoffmann, 1987; Sangay et al., 2016; Schaller et al., 1986; Sharma et al., 2015; Song et al., 2008; Wangchuk et al., 2016; Zeng et al., 2010) and in consultation with takin expert.

In the event of non-availability of actual home range for Mishmi takin and Bhutan takin, the i) past papers, ii) the availability of spatial resolution for potential environmental variables, and iii) the complex topography of the study area was used as the guide to determine the appropriate spatial resolution for environmental variables to be used in this study. The distribution and status of takin in India used 30 m forest cover satellite images and 90 m elevation data to extract good potential habitat for takin (Dasgupta et al., 2010). A spatial resolution of 90 m was used to predict the winter habitat of Bhutan takin (NCD, 2019), and 250 m vegetation data were analysed to examine the migration pattern of giant panda and golden takin (Wang et al., 2010). However, these studies did not use climatic variables. The climatic variables that influence takin migration are available at 1 km spatial resolution, the finest at present. Then, we could also use the estimated home range of Golden takin, which is 25 km^2 (Yan et al., 2017), but variations present in environmental conditions and surface features due to undulating terrain in the study region might not be captured. Therefore, the spatial resolution of 1 km was used to approximately balance all these aspects. Also, all the environmental variables were projected to Asia Lambert Conformal Conic

(EPSG: 102012) because it is one of the best for middle latitudes (ESRI, 2016) and is often recommended for studies in the Himalayan region. Finally, the potential environmental variables were downloaded from various sources (Table 1). They were grouped into five categories: bioclimatic variables, topographic variables, vegetation-related variables, land cover, and anthropogenic factors.

2.3.1. Bioclimatic variables

The search for optimum temperature condition is suggested as one of the drivers for seasonal migration in takin (Wang et al., 2010). The bioclimatic variables are biologically meaningful variables for species distribution derived from monthly temperature and precipitation (WorldClim, 2020). A set of 19 bioclimatic variables were downloaded from the WorldClim database (version 2.1) at a resolution of 1 km (Table 1). The database provides current (1970 - 2000) and projected climatic data for 2070 (2061 - 2080). The current data are averaged global climate layers over 30 years.

For future data, Intergovernmental Panel on Climate Change (IPCC) adopted greenhouse gas concentration trajectory called Representative Concentration Pathway (RCP) scenarios called RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. The RCPs indicate the possible future climate scenarios depending on the volume of greenhouse gas in the future (IPCC, 2014). The RCP 2.6 is a stringent mitigation scenario, RCP 4.5 and RCP 6.0 are intermediate scenarios, and RCP 8.5 is a very high emission scenario. The RCP 4.5 is desirable for future conservation. It is a stable scenario without exceeding the long-run radiative forcing target level. On the other hand, RCP 8.5 is the most outrageous scenario expected in future. It considers high greenhouse gas concentration levels with the increasing greenhouse gas emissions over time. Plus, they are often used scenarios for future climate change impact studies (Buras & Menzel, 2019; José et al., 2016; Rathore et al., 2019). Therefore, bioclimatic data of Community Climate System Model 4.0 (CCSM4) was downloaded for RCP 4.5 and RCP 8.5 scenarios. CCSM4 is one of the general circulation models (GCMs) from Coupled Model Intercomparison Project Phase 5 (CMIP5). It has been used for assessing the impact of future climate change on species distribution (Borzée et al., 2019; Qin et al., 2017) . Climate models make predictions on seasonal to decadal time scales and make projections of future climate over the coming centuries (Flato et al., 2013).

2.3.2. Topographic variables

The topographic variables are critical habitat factors that influence the microclimate, soil properties and species distribution (Wang et al., 2009). Variables like elevation, slope and aspect have often been used for species distribution modelling of various species. Also, takins are often sighted at a particular range of altitude, making these topographic variables a potential set of variables that most likely might influence their habitat preference. Such surface parameters are derived from Digital Elevation Model (DEM). So, 90 m DEM was downloaded to calculate the surface parameters using ArcGIS. The resulting slope, aspect, roughness, and elevation of 90 m were resampled to 1 km spatial resolution for further analysis. The 90 m resolution DEM was used for generating surface parameters because a test result concluded that we should calculate surface parameters from finer resolution DEM, and resample to coarser resolution (Grohmann, 2015). The reason being that the smoothing of topographical surface while resampling DEM from higher resolution to lower resolution will further affect the derived surface parameters. As a result, the calculated values of derivatives might be much smaller than real values.

2.3.3. Vegetation-related variables

Vegetation-related variables are essential in this study because takin is a herbivore by food habit. Also, plant phenology is one of the factors influencing seasonal migration of takin (Guan et al., 2013; Wang et al., 2010; Zeng et al., 2010). The normalized difference vegetation index (NDVI) is a commonly used vegetation index for monitoring vegetation phenology, animal migration, and modelling species distribution (Panthi et al., 2019; Pettorelli et al., 2005; Swanepoel et al., 2013; Wang et al., 2010). It is calculated using reflected red and near-infrared (NIR) radiation as NDVI = (NIR - RED) / (NIR + RED). The time series NDVI images are helpful in showing the spatial and temporal developments in vegetation productivity and distribution. Thus, it is representative of vegetation dynamics. Therefore, NDVI variables were used as a surrogate of plant phenology and food resources in this study. Takins live in remote parts of the study area so the major changes in the forest cover was not expected. Therefore, the time series NDVI images were collected between 2001 to 2005, falling in between the range of species data collection year (Section 2.2: Species data). The atmospherically corrected 10-day composite NDVI images were downloaded from SPOT-Vegetation at 1 km spatial resolution. These images were smoothened using a Savitzky-Golay filter to reduce noise caused by clouds using ENVI classic 5.6 software. The smoothened NDVI images were used for deriving NDVI statistical products (minimum, mean, maximum, and standard deviation) that were used as environmental variables for the study.

2.3.4. Land-cover

A dense forest cover was regarded as potential habitat for Mishmi takin in India (Dasgupta et al., 2010) and conifer forests was found to have a positive influence on habitat use by Bhutan takin (NCD, 2019). Therefore, forest canopy height and land cover variables were considered in this study. The global forest canopy height at 1 km spatial resolution was downloaded from the NASA/Earth data site. Global forest canopy height was collected using spaceborne light detection and ranging (lidar) for 2005 (Simard et al., 2011). The global 1 km consensus land cover for nine classes (Table 1) was downloaded from the EarthEnv repository. The datasets were generated by integrating land-cover products acquired from several global remote sensors (Tuanmu & Jetz, 2014). It provides the prevalence information on the land-cover classes.

2.3.5. Anthropogenic factors

Takin, a stout but shy mammal, is deemed to avoid proximity to human or human activities (Dasgupta et al., 2010; NCD, 2019). For instance, anthropogenic activities like construction of roads, use of grazing ground by domestic livestock, and human disturbances/settlements are seen to have a negative effect on the distribution of takin (Dasgupta et al., 2010; NCD, 2019; Sangay et al., 2016; Song et al., 2008). Therefore, anthropogenic factors like distance to road, distance to human settlement, human population density, and domestic animal density (cattle and sheep) were considered in this study. The road network was downloaded from Geofabrik, and human settlement points were downloaded from Humanitarian data exchange (HDX). The road networks and human settlement points were used to generate the distance to road and distance to settlement using the Euclidean distance tool in ArcGIS at 1 km resolution. The cattle and sheep density layers were acquired from the Livestock Geo-Wiki and human population density from the NASA Socioeconomic Data and Applications Center (SEDAC), both with 1 km spatial resolution.

Table 1: List of potential environmental variables for modelling the current suitable habitat of Mishmi takin and Bhutan takin

Category	Variables	Abbreviation	Unit
Bioclimatic	Annual mean temperature	bio1	°C
	Mean diurnal range (mean of monthly (max temp - min temp))	bio2	°C
	Isothermality (bio2/bio7)	bio3	Dimensionless
	Temperature seasonality (standard deviation)	bio4	°C

	Max temperature of warmest month	bio5	°C
	Min temperature of coldest month	bio6	°C
	Temperature annual range (bio5-bio6)	bio7	°C
	Mean temperature of wettest quarter	bio8	°C
	Mean temperature of driest quarter	bio9	°C
	Mean temperature of warmest quarter	bio10	°C
	Mean temperature of coldest quarter	bio11	°C
	Annual precipitation	bio12	mm
	Precipitation of wettest month	bio13	mm
	Precipitation of driest month	bio14	mm
	Precipitation seasonality (coefficient of variation)	bio15	Dimensionless
	Precipitation of wettest quarter	bio16	mm
	Precipitation of driest quarter	bio17	mm
	Precipitation of warmest quarter	bio18	mm
	Precipitation of coldest quarter	bio19	mm
Topographic	Elevation	elevation	m
	Aspect	aspect	Degree
	Slope	slope	Degree
	Roughness	roughness	Dimensionless
Vegetation-related	Annual minimum NDVI	ndvi min	Dimensionless
	Annual mean NDVI	ndvi mean	Dimensionless
	Annual maximum NDVI	ndvi max	Dimensionless
	Standard deviation NDVI	ndvi std	Dimensionless
Land-cover	Evergreen/Deciduous Needleleaf Trees	needleleaf forest	Dimensionless
	Evergreen Broadleaf Trees	evergreen broadleaf forest	Dimensionless
	Deciduous Broadleaf Trees	deciduous broadleaf forest	Dimensionless
	Mixed/Other Trees	mixed forests	Dimensionless
	Shrubs	shrublands	Dimensionless
	Herbaceous Vegetation	herbaceous	Dimensionless
	Cultivated and Managed Vegetation	croplands	Dimensionless
	Snow/Ice	snow and ice	Dimensionless
	Barren	barren	Dimensionless
	Forest canopy height	canopy height	Dimensionless

Anthropogenic	Road network	distance to road	km
	Human settlement points	distance to settlement	km
	Human population density	human population density	Population per square km
	Cattle density	cattle density	per square km
	Sheep density	sheep density	per square km

2.4. Collinearity analysis

Collinearity is the linear relationship between two or more environmental variables (Dormann et al., 2013). The most used statistical routines in ecology are sensitive to collinearity. It leads to unstable estimates of the parameter, inflated standard errors on coefficient estimates, and bias in the inference statistics. In species distribution models, collinearity among environmental variables was found to decrease the efficiency and increase the model uncertainty (De Marco & Nóbrega, 2018). Therefore, detection and removal of highly correlated environmental variables is a critical step prior to model building.

The Pearson correlation coefficient and variance inflation factor (VIF) are commonly used collinearity indices (Dormann et al., 2013). The Pearson correlation coefficient tests the strength of correlation between a pair of variables. As a rule of thumb, very highly correlated variable pairs are the ones with $|r|>0.7$. The multicollinearity among the variables can be tested using VIF. Again, as a rule of thumb, variables with VIF>10 indicate very high multicollinearity. The detected variables with very high collinearity and less important for species' ecology are removed.

Initially, 42 variables were listed as potential variables for predicting the habitat suitability for Mishmi takin and Bhutan takin (Table 1). These variables were tested for pairwise correlation and multicollinearity using the statistical software package R. The Pearson correlation coefficient test revealed that most of the bioclimatic variables were highly correlated ($|r|>0.7$) to each other and to elevation. Thus, only four of the bioclimatic variables that were not highly correlated and ecologically meaningful were retained for further analysis. They are annual mean diurnal range (bio2), isothermality (bio3), precipitation of the driest month (bio14), and precipitation seasonality (bio15). Similarly, ndvi mean, ndvi minimum, and ndvi maximum was removed for being highly correlated to elevation. A total of 19 variables were removed through the Pairwise correlation coefficient test leaving 23 variables (Figure 3). VIF was calculated for the remaining 23 variables. The result shows that VIF for all the variables was less than 10 (Table 2). Therefore, all 23 variables were retained for modelling the current suitable habitat for Mishmi takin and Bhutan takin (Table 3).

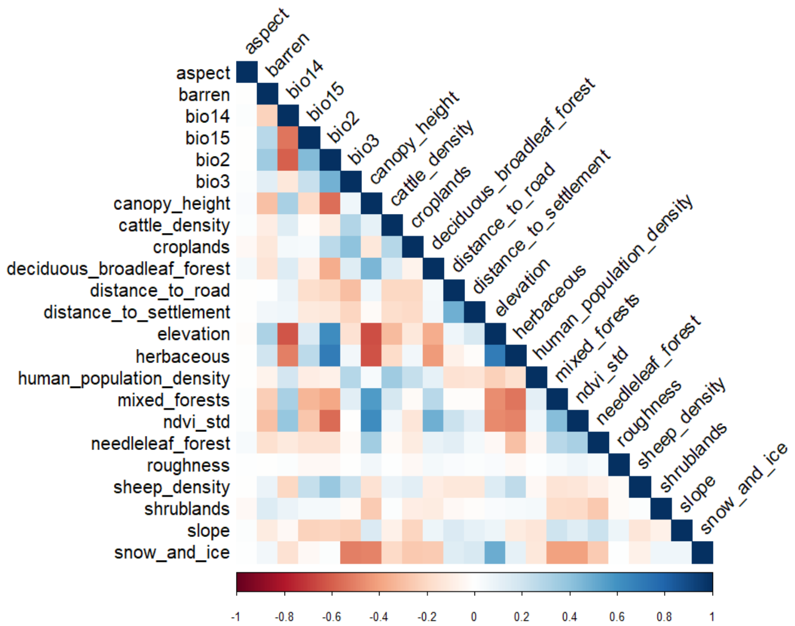


Figure 3: The correlation matrix of environmental variables after collinearity analysis. Red indicates negative correlation and blue indicates positive correlation. Darker the colour, stronger the relation and vice-versa.

Table 2: Multicollinearity analysis showing VIF < 10 for each variable

Variables	**VIF**
elevation	8.663
bio2	8.064
herbaceous	7.671
snow_and_ice	5.905
canopy_height	3.773
bio3	3.633
bio14	3.215
ndvi_std	2.665
needleleaf_forest	2.469
mixed_forests	2.379
bio15	2.115
croplands	1.908
barren	1.703
deciduous_broadleaf_forest	1.681
distance_to_road	1.496
distance_to_settlement	1.461
shrublands	1.449
cattle_density	1.433
human_population_density	1.322
slope	1.271
sheep_density	1.245
roughness	1.024
aspect	1.015

Table 3: Environmental variables used for modelling the current suitable habitat for Mishmi takin and Bhutan takin in this study

Category	Variables	Abbreviation	Unit
Bioclimatic	Mean diurnal range (mean of monthly (max temp - min temp))	bio2	°C
	Isothermality (bio2/bio7)	bio3	Dimensionless
	Precipitation of driest month	bio14	mm
	Precipitation seasonality (coefficient of variation)	bio15	Dimensionless
Topographic	Elevation	elevation	m
	Aspect	aspect	Degree
	Slope	slope	Degree
	Roughness	roughness	Dimensionless
Vegetation-related	Standard deviation NDVI	ndvi std	Dimensionless
Land-cover	Evergreen/Deciduous Needleleaf Trees	needleleaf forest	Dimensionless
	Deciduous Broadleaf Trees	deciduous broadleaf forest	Dimensionless
	Mixed/Other Trees	mixed forests	Dimensionless
	Shrubs	shrublands	Dimensionless
	Herbaceous Vegetation	herbaceous	Dimensionless
	Cultivated and Managed Vegetation	croplands	Dimensionless
	Snow/Ice	snow and ice	Dimensionless
	Barren	barren	Dimensionless
	Forest canopy height	canopy height	Dimensionless
Anthropogenic	Road network	distance to road	km
	Human settlement points	distance to settlement	km
	Human population density	human population density	Population per square km
	Cattle density	cattle density	per square km
	Sheep density	sheep density	per square km

2.5. Ecological niche modelling

2.5.1. Maximum entropy modelling (Maxent)

In a comprehensive model comparison study, Multivariate adaptive regression-splines (MARS), Boosted regression tree (BRT), and Maxent were the best performing models among the 16 commonly used models (Elith et al., 2006). The models like MARS and BRT need both presence and absence data, while Maxent was designed to work with presence-only data. Since presence-only data was provided for both subspecies, Maxent method was used for this study. Maxent uses the principle of maximum entropy to estimate the relationship between environmental variables and species presence (Phillips et al., 2006). It outputs an estimated probability of presence with logistic output format. Maxent can generate relatively higher predictive accuracy with small sample among other presence-only methods (Merow et al., 2013). In fact, it is considered as one of the best species distribution models for species with restricted range (Kramer-Schadt et al., 2013) as the target species of this study. It is also comparatively less demanding of the computational time when compared to the ensemble modelling method. Besides, a recent analysis of distribution maps produced by Maxent and ensemble methods concluded that Maxent results are comparable to the results from the ensemble method (Kaky et al., 2020). Maxent has been used for studies similar to this study (Aguilar et al., 2015; Du et al., 2021; Fuller et al., 2008; Gibson et al., 2010; Merow et al., 2013; Zhang et al., 2018). Furthermore, the method is easy to implement with a stand-alone Java application tool, Maxent 3.4.4 (latest at present), and has a user-friendly interface to change the settings when needed.

The Maxent software has often been utilized with the default settings, but many scientists do not recommend the default set-up (Anderson & Gonzalez, 2011; Cao et al., 2013; Merow et al., 2013; Morales et al., 2017; Warren & Seifert, 2011). The default setting was found to either produce overfitting or underfitting models. The scientists have emphasized on the model settings and their importance while building a model through Maxent. Therefore, the default model setting is not necessarily the optimal configuration especially, when the sample size is small and when a single species is being modelled. Both conditions are valid in this study. Therefore, parameter tuning is deemed as a critical step before running the Maxent model. The three crucial model settings explored in this study are i) selecting appropriate number of background points for model building, ii) selecting appropriate number of model replicates, and iii) Selection of optimal feature types and regularization coefficient value.

2.5.1.1. Selection of background points

In Maxent, the occurrence points will be contrasted against the background points selected from the given background or study area (Merow et al., 2013). It assumes that each pixel in the background has an equal probability of being picked for modelling. It means that defining a bigger extent of background will accordingly include higher variation in values of environmental variables producing unimodal response curves, and a smaller extent of background might not capture all the environmental variability offered by the landscape producing monotonic response curves. Neither unimodal nor monotonic response curve is more correct than the other. However, background's influence on the feature selected for modelling is apparent. Therefore, a careful selection of background that is ecologically justified is more appropriate.

Accordingly, the background or the extent of the study area for this study was chosen with reference to prior studies conducted on takin, currently occupied areas, areas with the historical record of spotting a takin (Mishmi takin or Bhutan takin), potential distribution range, and in consultation with the takin expert. Proceeding further, models were built using 10000 and 15000 background points for both subspecies to conduct a simple comparative analysis of models based on Area under the receiver operating characteristic curve (AUC). The result shows a slightly lower AUC for models with 15000 background points than models with 10000 background points (Table 4). It implies that increasing background points from 10000 to 15000 will not necessarily improve the model's predictive accuracy for the given set of data and background. Therefore, 10000 background points are considered appropriate for modelling current habitat suitability in this study.

Table 4: Comparative analysis of model performance based on AUC with different number of background points

	Mishmi takin	Bhutan takin
10000 background points	0.929 (AUC)	0.979 (AUC)
15000 background points	0.922 (AUC)	0.978 (AUC)

2.5.1.2. Selection of model replications

Since Maxent is a machine learning method, it is necessary to repeatedly run the model and evaluate model stability across sample models for a robust result (Sillero & Barbosa, 2021). Maxent offers functionality under the basic setting to run the model repeatedly called Replicates. It allows using the result that is averaged over the number of replicates specified by the user. Most often, users use 10 replicates (Abdelaal et al., 2019; Khanum et al., 2013; Wei et al., 2018), but it is to be noted that when specifying the number of replicates in Maxent, it also defines the number of k-folds when cross-validation is chosen as the data partitioning method for the training and testing datasets. Cross-validation method is selected for partitioning the dataset while building the models in this thesis. The cross-validation method is advantageous because all the data is used for validation without replacement, thereby making better use of a small dataset (Phillips, 2017). This method is also the recommended choice when using Maxent for modelling as it helps obtain a generalized model that does not overfit or underfit (Merow et al., 2013). Consequently, selecting the appropriate number of replicates is essential. To select the appropriate number of replicates, Maxent model was run with five and ten replicates consecutively. A simple comparative analysis of models based on AUC was conducted. The analysis outcome for both subspecies shows slightly lower AUC with a higher number of replicates (Table 5). It is concluded that increasing replicates will not necessarily increase the model's predictive accuracy for the given data set. Also, the difference in between the AUCs is not abruptly changing indicating that the model is stable. Therefore, five model replicates are considered appropriate for modelling the current habitat suitability of Mishmi takin and Bhutan takin.

Table 5: Comparative analysis of model performance based on AUC with different number of replicates

	Mishmi takin	Bhutan takin
5 replicates	0.931 (AUC)	0.980 (AUC)
10 replicates	0.929 (AUC)	0.978 (AUC)

2.5.1.3. Selection of optimal feature types and regularization multiplier:

Ecological niche models rely on the species' response to the given predictors for model building (Elith et al., 2011). Since the response of the species tends to be complex, fitting a non-linear function is preferred. In machine learning programs like Maxent, it is achieved by applying a transformation to the predictors called features. Maxent offers five feature types, namely linear (L), quadratic (Q), hinge (H), product (P), and threshold (T). The default setting of Maxent allows usage of all features when the number of occurrence is higher than 80, thereby creating a complex model (Merow et al., 2013). A complex model can easily overfit the model to the training dataset, which reduces the generalization capacity of the model. Therefore, a subset of available features can be used to build a simplified model with similar performance. Regularization is used by Maxent to select useful features that contribute most to the model fit (Merow et al., 2013). It reduces model overfit by i) ensuring that the empirical constraints do not fit the data too precisely, and by ii) penalizing the model in relation to the magnitude of the coefficients. The default regularization multiplier value of one in Maxent often retains many correlated features, but it is more useful to obtain a simpler model when biological interpretation is essential (Merow et al., 2013).

Muscarella et al. (2014) developed an R package called ENMeval that can estimate the optimal set of feature types and regularization multiplier value for given set of occurrence data and predictors. A total of 48 different model settings were explored using the ENMeval R package by combining eight different regularization values ranging from 0.5 to 4 (0.5, 1, 1.5, 2, 2.5, 3, 3.5, and 4) with L, LQ, H, LQH, LQHP, LQHPT feature set each. The output provides evaluation metrics for each model combination to characterize the model performance (Muscarella et al., 2014). A corrected Akaike information criteria (AICc) selected models were reported to perform better than other evaluation metrics especially when the sample size are small (Warren & Seifert, (2011). Therefore, AICc was used to select the optimal model combination. The model combination having lowest AICc value (Table 6) among the 48 models was selected for final model construction.

Table 6: Feature type and regularization multiplier value for modelling the current suitable habitat of Mishmi takin and Bhutan takin in the study area

	Feature type	Regularization multiplier	AICc
Mishmi takin	LQH (Linear, Quadratic, Hinge)	4	3842
Bhutan takin	LQ (Linear, Quadratic)	4	3449

2.6. Model performance assessment

The assessment of the model's predictive accuracy is an important indicator to understand the model performance (Allouche et al., 2006). The predictive accuracy of the model can be measured in two complementary ways, namely, discrimination and calibration (Pearce & Ferrier, 2000; Phillips & Elith, 2010). Discrimination is the ability of the model to differentiate between occupied and unoccupied sites. Calibration is the extent of agreement between the predicted probability of occurrence and observed occurrence. In this study, both approaches are used to evaluate the accuracy of the models. The discrimination metrics such as AUC, true skill statistic (TSS), and a calibration metric, Continuous Boyce Index (CBI) are used.

2.6.1. Area under the receiver operating characteristic curve (AUC)

AUC is a threshold independent accuracy measure (Fielding & Bell, 1997). It is a popular measure to evaluate the model performance (Pecchi et al., 2019). AUC is the area under receiver operating characteristic (ROC) curve. ROC plots sensitivity (true positive) against 1-specificity (false positive). An AUC value of 0.5 represents a random model, AUC > 0.7 denotes a useful model, and 1 indicates the perfect model (Phillips & Dudík, 2008). The AUC reported in this study is Maxent generated average AUC for all model replicates.

2.6.2. True Skill Statistic (TSS)

The predicted habitat suitability or species distribution information are often used in identifying biodiversity hotspot, and delineating areas for conservation based on binary maps (Allouche et al., 2006). Hence, the selection of a threshold is inevitable. Liu et al. (2016) concluded that maximizing the sum of sensitivity and specificity (maxSSS) threshold selection method is not affected by the ratio of known presences to random points. It generates similar result with presence/absence and presence-only datasets. As such, the threshold determined by the maxSSS method will be used to create binary maps in this study.

Consequently, a threshold dependent model evaluation measure like TSS is required. It is a threshold dependent and prevalence independent measure of accuracy for models (Allouche et al., 2006). TSS considers both omission and commission errors and success from random guessing. It is a recommended statistical accuracy measure that retains the advantages of kappa statistics but eliminates the drawback. The value of TSS ranges from -1 to +1, where a value of 0 or less denotes a random model, TSS > 0.7 represents a useful model and, 1 indicates a perfect model. The TSS for each model replicates were calculated using PresenceAbsence R package and the average TSS is reported in this study.

2.6.3. Continuous Boyce Index (CBI)

CBI is a reliable presence-only model evaluation measurement (Hirzel et al., 2006). It is a threshold independent evaluator and varies between -1 and +1. CBI values closer to 0 indicate a random model, positive CBI values represent a model that is consistent with the evaluation dataset, and negative CBI values denote counter predictions. The CBI value for each model replicates were calculated using Ecospat R package and the average CBI is reported in this study.

2.7. Jackknife test

Identifying which environmental conditions are most important for a species is one of the applications of environmental niche modelling (Harisena et al., 2021). The Jackknife test was used to assess the importance of different environmental variables for Mishmi takin and Bhutan takin. It is one of the key analyses that can be conducted using Maxent. It indicates which variables matter the most for the species being modelled (Phillips, 2017). The result of the Jackknife test is a bar chart showing the model's information gain or loss in three different variable-use aspects. First, a model is built using all variables. Second, a model is created by using an individual variable in isolation. Third, a model that excludes one variable at a time while creating the model with the remaining variables. The models from the first and second aspects show the information gain from the variables being used, while the third aspect shows the information loss when a particular variable is excluded. As such, the result from the second type of modelling aspect is critical in explaining which variable by itself has the most useful information in predicting the habitat suitability of the species being modelled. The result of the third type of modelling aspect is crucial in identifying the variable that has the most information, which isn't present in the rest of the variables used for modelling. Therefore, the most contributing variable from second and third type of modelling is reported as the two most important variables for each of the subspecies. Further, subspecies' ecological response to these variables are presented through response curves built in Maxent. Response curves indicate a species' respond to changes in environmental conditions (Harisena et al., 2021). It can also show conditions that are most preferred by a species along environmental gradients.

2.8. Ecological niche similarity analysis

The ecological niche similarity analysis is conducted in this study to assess the ecological niche distinction between Mishmi takin and Bhutan takin. The ecological niche similarity analysis is a comparative analysis of ecological niches of different species. It is widely being used for conservation planning, niche evolution, speciation and to understand the ecological diversity within clades (Aguirre-Gutiérrez et al., 2015; Warren et al., 2008, 2010). The basis of such comparative analyses is quantifying species' environmental requirements and assessing the differences among them or how they change over time (Broennimann et al., 2012). The useful approaches for such analyses are ecological niche equivalency and niche similarity test. The niche equivalency test aims to analyse if the ecological niches are identical (Warren et al., 2010). While the niche similarity test determines if the ecological niches are more similar or divergent than expected by chance. However, both tests start by calculating the niche overlap between the niches of species being compared. The niche overlap is measured using Schoener's *D* and Warren's *I* statistics. The value for niche overlap ranges from 0 to 1 for both statistics. A value of 0 indicate no niche overlap at all, and a value of 1 represents the niches that completely overlap. In this study, both tests were executed using ENMTools. It is a software that facilitates quantitative comparisons of ecological niche generated using Maxent (Warren et al., 2021). ENMTools test hypothesis using nonparametric tests based on Monte

Carlo methods. Initially, the empirical niche overlap between the two ecological niches of species is measured using *D* and *I*. Then, for each hypothesis testing, null distribution is generated from simulations. The simulations are a bunch of replicate realizations of null hypothesis. Finally, the empirical observation is compared to observations from null distribution to either reject or accept the null hypothesis.

The niche identity test or niche equivalency test conducted in ENMTools examine the hypothesis if the ecological niches of two subspecies are identical (Warren et al., 2010). The empirical *D* and *I* niche overlap between the ecological niche of Mishmi takin and Bhutan takin was calculated. Then, *D* and *I* value of niche overlap for null distribution is generated. To create the null distribution, the ENMTools randomizes the population identities of sample points that were pooled from the two subspecies. Then, a new population sample is extracted for each subspecies, which is further used to produce the ENM for each subspecies. This process was repeated 100 times, recommended, to get the distribution of *D* and *I* scores, assuming that the two subspecies can interchangeably use their niche spaces. Finally, the empirical observation is compared to the percentiles of null distribution in one-tailed test, critical observation, calculated at 95% confidence interval. If the empirical value is higher than critical value, then the ecological niches of Mishmi takin and Bhutan takin are concluded to be identical. On the contrary, if the empirical value is lower than critical value, then the ecological niches of two subspecies are not identical.

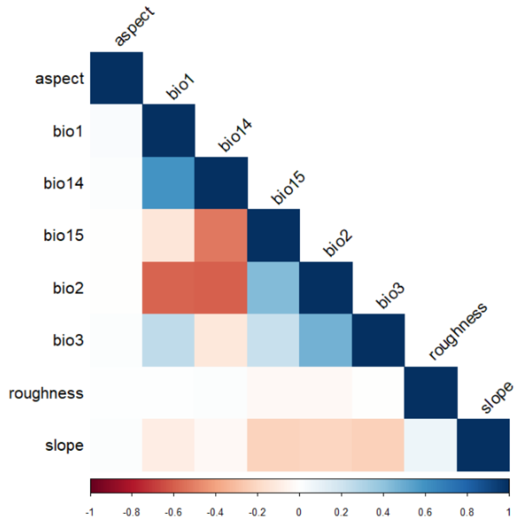
The background test or ecological niche similarity test is conducted to test whether the ecological niches of target species are more different than expected given the underlying differences in environmental conditions between the areas in which they occur (Warren et al., 2008). The test is particularly important to analyse ecological niche similarity between allopatric populations (Warren et al., 2010). Since Mishmi takin and Bhutan takin are mostly sighted in different regions of the study area (Dasgupta et al., 2010; NCD, 2019; Sharma et al., 2015), the background test was included in this study. The empirical niche overlap value was already calculated before running ecological niche identity test, so it need not be calculated again. The background test generates a null distribution by placing occurrences of Mishmi takin within the range of Bhutan takin and vice versa. It was repeated 100 times, as recommended, in both directions: Mishmi takin occurrence within the range of Bhutan takin and Bhutan takin occurrence within the range of Mishmi takin. The range in this context is user-specified area including the areas of species occurrence. For this study, the predicted current suitable habitats (Section 2.5) for both subspecies were used as range. Finally, if the empirical scores fall outside of the 95% confidence limits of the null distribution, critical value, then the null hypothesis is rejected. Accordingly, if empirical values are lower or higher than the critical values, then the species being compared are more divergent or more similar than expected by chance respectively.

2.9. Future climate change impact analysis

2.9.1. Habitat suitability modelling under climate change projections

The predicted future suitable habitat for Mishmi takin and Bhutan takin was modelled using Maxent. It is a frequently used tool for modelling the impact of future climate change on various species (Abdelaal et al., 2019; Lamsal et al., 2018; Qin et al., 2017; Xu et al., 2019). The environmental variables representing different aspect of takin's ecology (Section 2.3) is desirable but not available for future climate change projections. Therefore, bioclimatic variables available for RCP 4.5 and RCP 8.5 scenarios (Section 2.3.1), and topographical variables that are not likely to change were listed as potential environmental variables. The data download, exploration, processing, modelling, and validation followed the procedures described in previous sections of this thesis (Section 2.3, 2.4, 2.5, 2.6).

A highly correlated but less important variables (r > 0.7 and VIF > 10) were removed before modelling (Figure 4). The final set of variables that were used for modelling the future suitable habitat of both subspeceis are annual mean temperature (bio1), annual mean diurnal range (bio2), isothermality (bio3), precipitation of driest month (bio14), precipitation seasonality (bio15), aspect, slope, and roughness.



Variables	VIF
bio2	4.946
bio1	4.481
bio3	3.013
bio14	2.509
bio15	1.777
slope	1.196
roughness	1.009
aspect	1.001

Figure 4: Result of collinearity analysis showing correlation matrix for variables used for modelling the future suitable habitat of Mishmi takin and Bhutan takin (left), and result of multicollinearity test showing VIF values for each of the variables (right)

Other parameters like number of background points, number of model replication, feature types and regularization coefficient values were tuned for both subspecies (procedure given in Section 2.5). So, specific model settings were used for modelling (Table 7).

Table 7: Model settings estimated for modelling the current and future suitable habitats of Mishmi takin and Bhutan takin under the future climate change scenarios

	Number of background points	Number of replicates	Feature types	Regularization coefficient
Mishmi takin	20000	5	LQHP	2
Bhutan takin	10000	5	LQHPT	2.5

One of the challenges of using Maxent is projecting future species distribution because it needs extrapolating models to novel environmental conditions (Merow et al., 2013). Predicting to novel environmental conditions of future bioclimatic variables are contentious applications because it usually requires predicting to conditions that was not sampled by the training data. Therefore, clamping and multivariate environmental similarity surface analysis (MESS) was implemented for extrapolation. The clamping handles the novel environmental conditions outside the training range as though they were at the limit of the training range (Phillips, 2017). MESS measures the similarity of any given point to a set of reference points based on chosen predictor variables (Elith et al., 2010). It indicates the closeness of a point to the distribution of reference points.

2.9.2. Distribution changes analyses

To quantify the distributional changes between two time periods (current and 2070), firstly, the distribution changes between current and future suitable habitat was calculated to output an area of no change, range contraction, and range expansion in km². Secondly, the core distributional shift between current and future suitable habitat was calculated to show direction of change through time. This analysis considers the central point of species' distribution to generate a vector, an arrow, showing the direction of change. The analyses were conducted in ArcGIS using SDMtoolbox 2.0. SDMtoolbox is a free python-based geographic information system (GIS) toolkit (Brown, 2014). The toolkit works well with Maxent generated outputs. It simplifies GIS analyses required for environmental distribution modelling.

3. RESULTS

3.1. Model performance and predicted current suitable habitat for Mishmi takin and Bhutan takin

An area of 28,154 km² is currently available as suitable habitat for Mishmi takin in the Eastern Himalayas (Figure 5). The suitable habitat was predicted with high-performing environmental niche model. The model's predictive accuracy is 0.916, 0.729, and 0.912 for AUC, TSS, and CBI respectively.

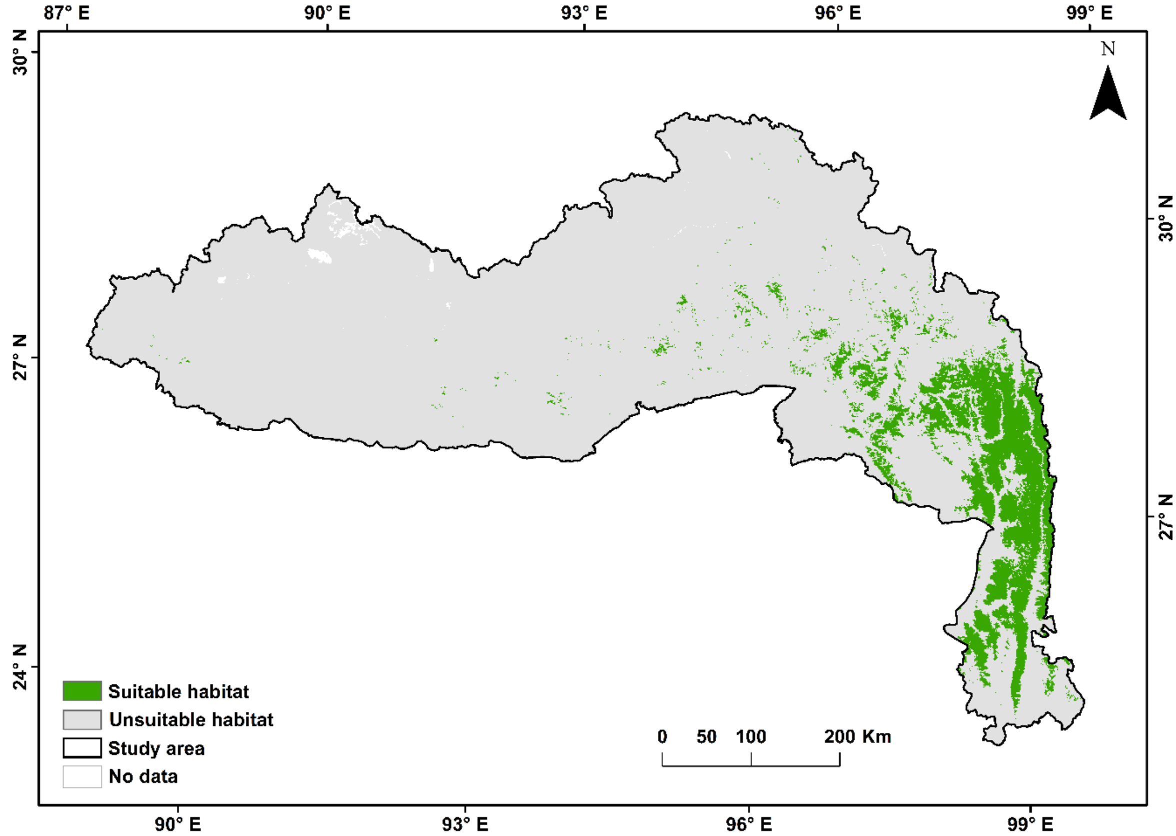


Figure 5: Map showing the current suitable and unsuitable habitat for Mishmi takin in the Eastern Himalayas

The current habitat suitability for Mishmi takin in the Eastern Himalayas is shown in Figure 6.

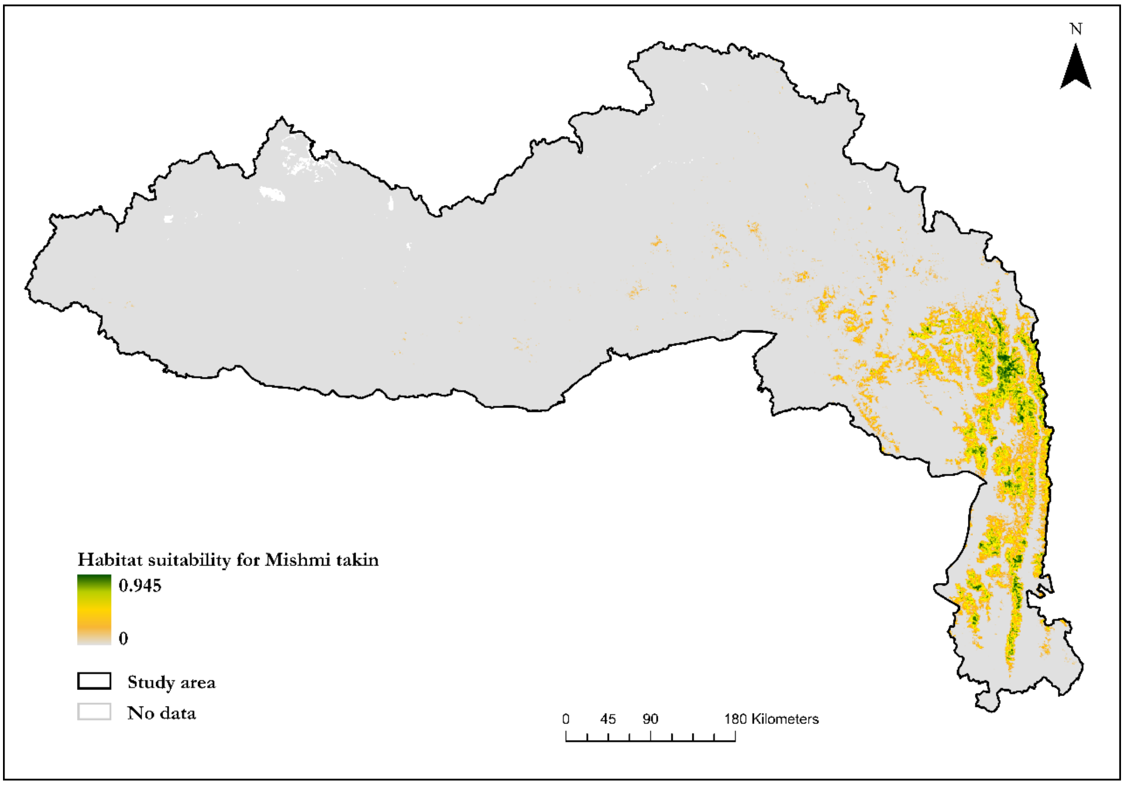


Figure 6: Map showing the current habitat suitability for Mishmi takin in the Eastern Himalayas

An area of 15,314 km² is currently available as suitable habitat for Bhutan takin in the Eastern Himalayas (Figure 7). The suitable habitats were predicted with high-performing environmental niche model. The model has predictive accuracy of 0.970, 0.876, and 0.933 for AUC, TSS, and CBI respectively.

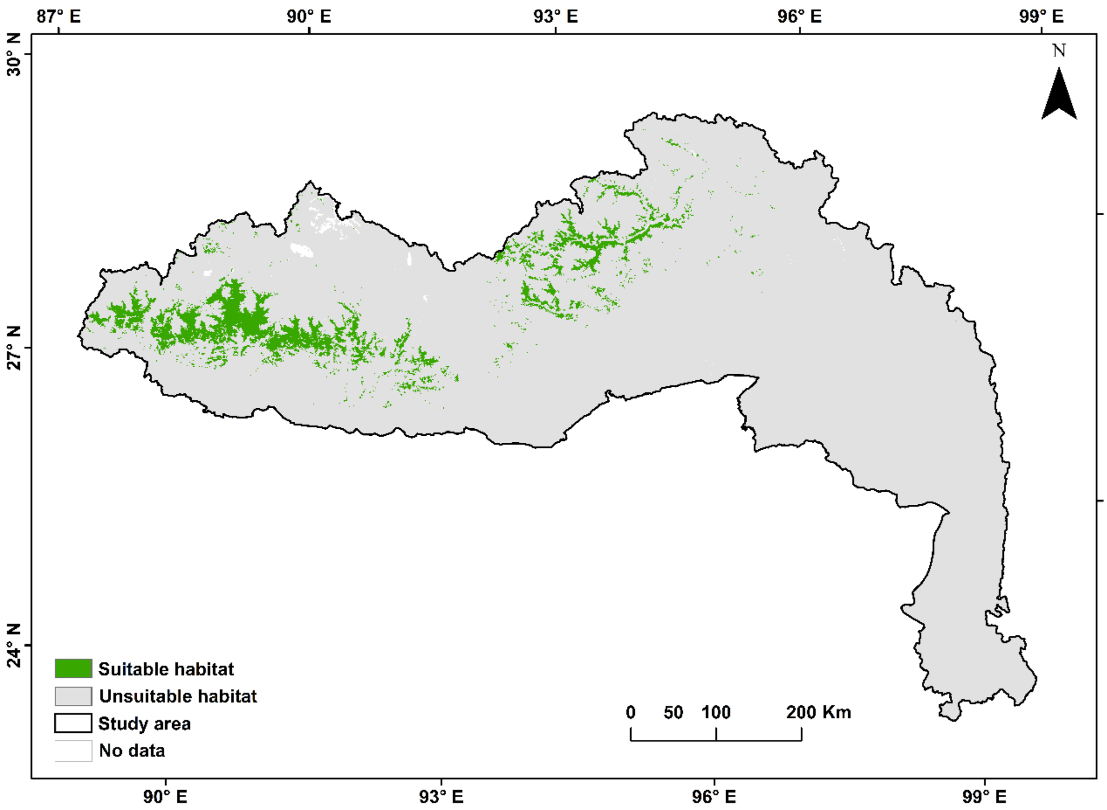


Figure 7: Map showing the current suitable and unsuitable habitat for Bhutan takin in the Eastern Himalayas

The current habitat suitability for Bhutan takin in the Eastern Himalayas is shown in Figure 8.

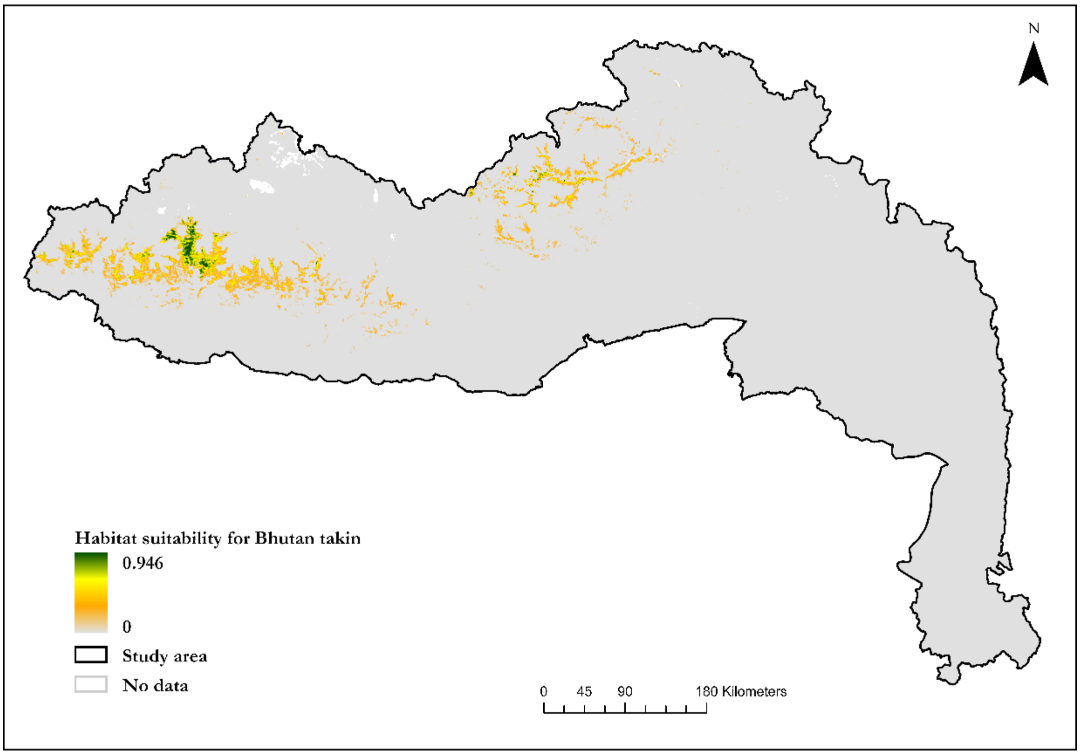


Figure 8: Map showing the current habitat suitability for Bhutan takin in the Eastern Himalayas

3.2. Key environmental variables determining habitat suitability of Mishmi takin and Bhutan takin

Bioclimatic and vegetation-related environmental variables play role in determining the habitat suitability of Mishmi takin. The importance of variables to predict the suitable habitat of Mishmi takin is shown in Figure 9. The precipitation seasonality (bio15) and standard deviation NDVI (ndvi std) are the two key environmental variables determining the habitat suitability of Mishmi takin. The precipitation seasonality generated the highest gain when modelled in isolation, indicating that it contains the most useful information for predicting the habitat suitability by itself. The withdrawal of NDVI standard deviation reduced the model gain the most, meaning, it holds important information which is not found in the rest of the variables.

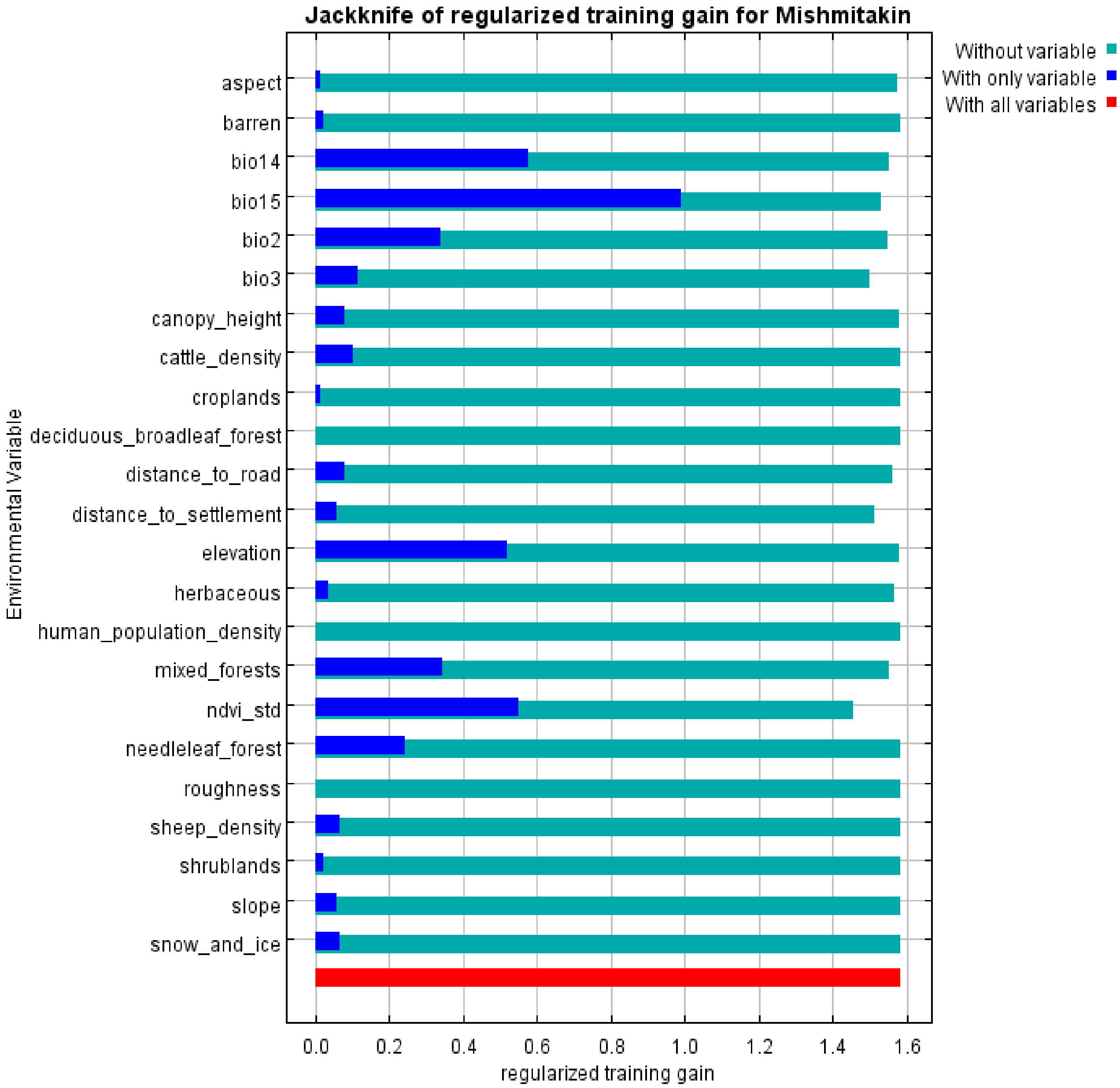
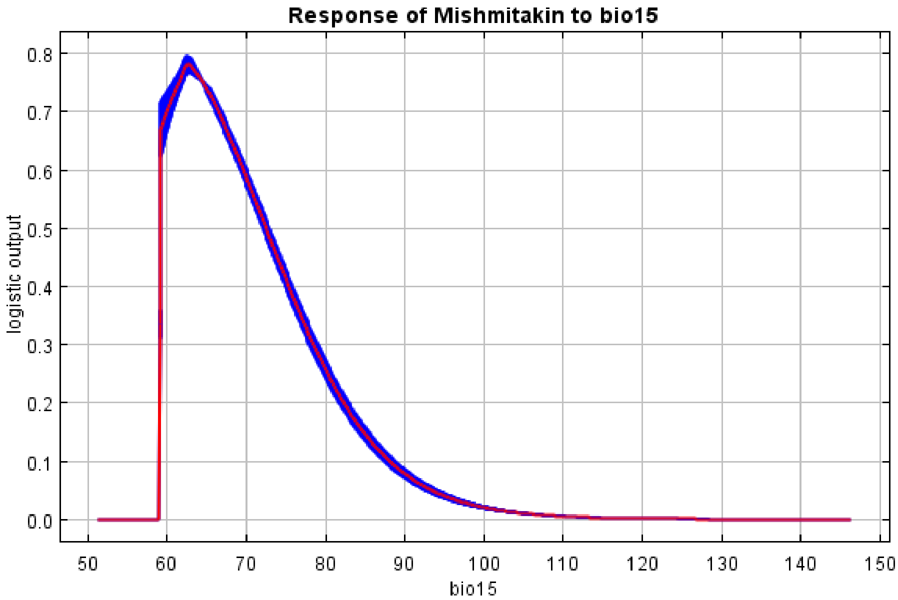


Figure 9: Importance of environmental variables in modelling the habitat suitability for Mishmi takin in Eastern Himalayas. The "With only variable" shows the result of model when a single variable is used in isolation. The "Without variable" shows the effect of removing a particular variable from the full model.

The response curve is important in understanding the limiting environmental conditions of suitable habitat for Mishmi takin. The response curves for precipitation seasonality and NDVI standard deviation were obtained while building the ENM of Mishmi takin (Figure 10). It is observed that Mishmi takin's habitat is suitable at lower range, ~ 59% to 64%, of precipitation variability. The habitat suitability for Mishmi takin is increasing with an increasing value of NDVI standard deviation. It reveals that higher vegetation is preferred by Mishmi takin.



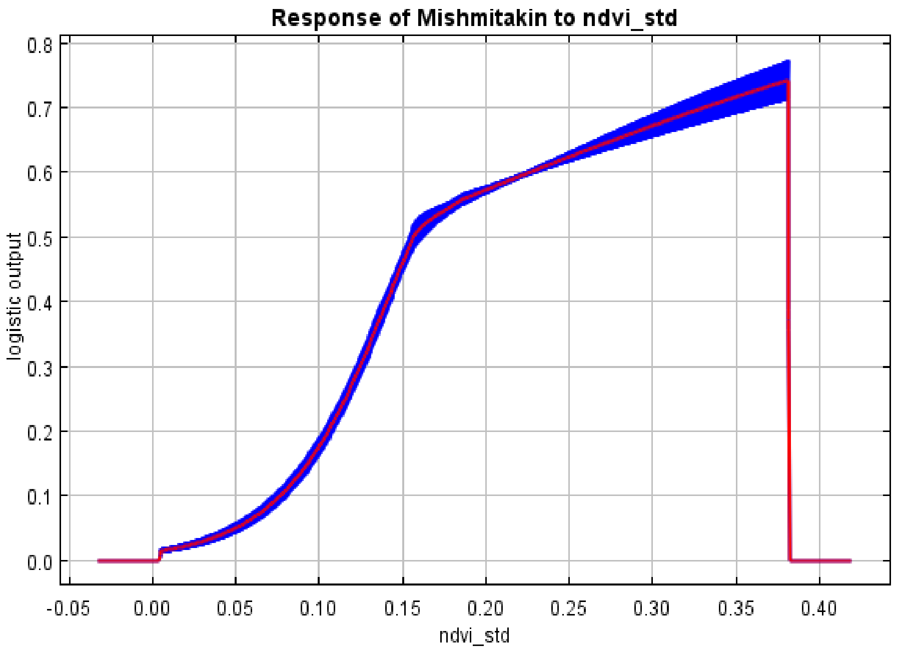


Figure 10: Response curves show the relationship between habitat suitability of Mishmi takin and an environmental variable. These curves show how the response changes for a particular variable used in isolation.

Bioclimatic and vegetation-related environmental variables play role in determining the habitat suitability of Bhutan takin. The importance of variables to predict the suitable habitat of Bhutan takin is shown in Figure 11. The needleleaf forest cover (needleleaf forest) and isothermality (bio3) are the two most important environmental variables for predicting the suitable habitat of Bhutan takin (Figure 11). The needleleaf forest cover produced highest gain when modelled in isolation and removal of isothermality from the set of variables brought the highest decrease in model gain.

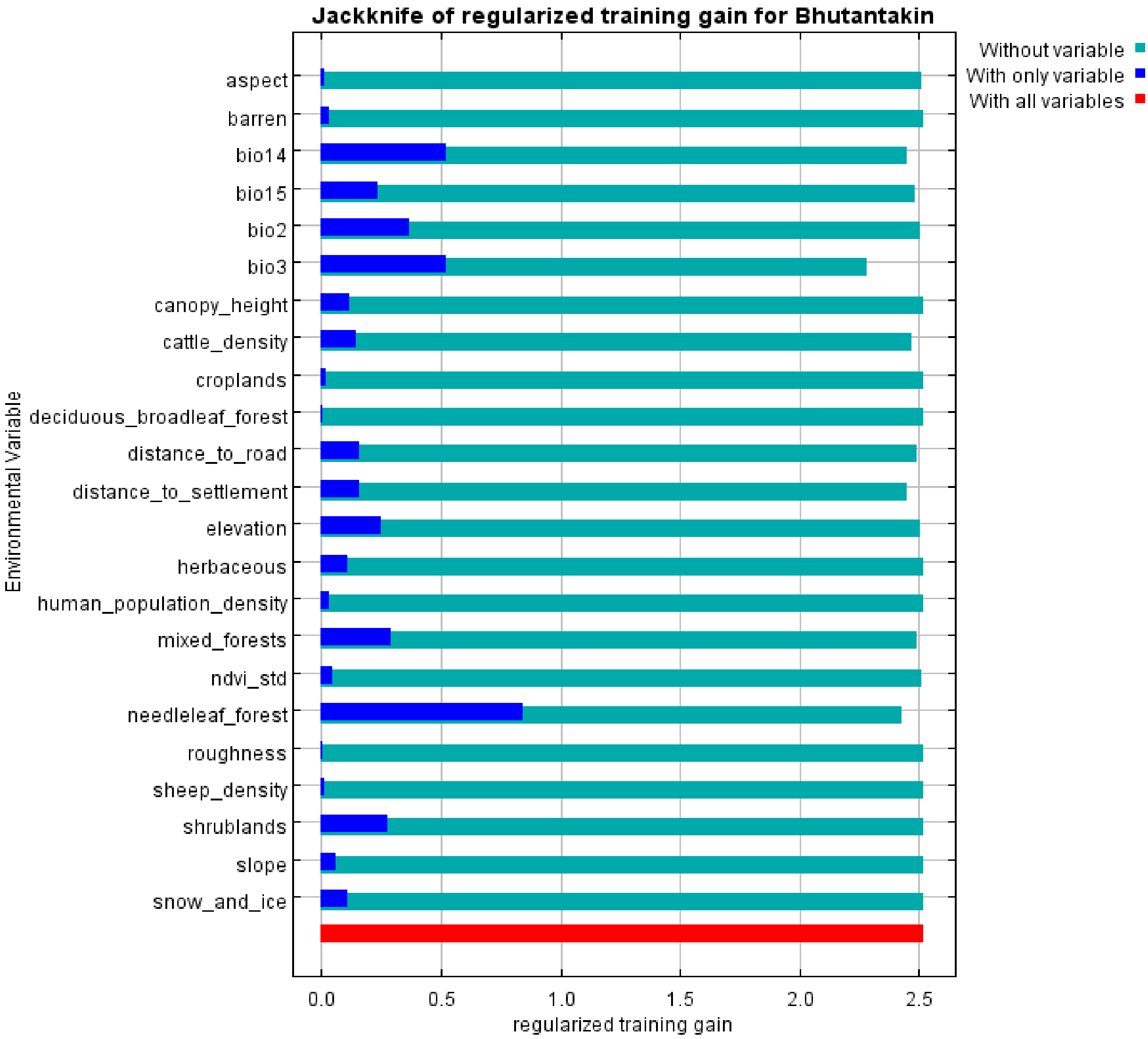


Figure 11: Importance of environmental variables in modelling the habitat suitability for Bhutan takin in Eastern Himalayas. The "With only variable" shows the result of model when a single variable is used in isolation. The "Without variable" shows the effect of removing a particular variable from the full model.

The response curves for needleleaf forest cover and isothermality were obtained while building the ENM of Bhutan takin (Figure 12). Bhutan takin is responding to the changing needleleaf forest cover in unimodal fashion. The suitability of an area increases with increasing prevalence until ~ 60; beyond this the suitability gradually decreases with an increasing prevalence. An increase in isothermality increases the habitat suitability of an area for Bhutan takin.

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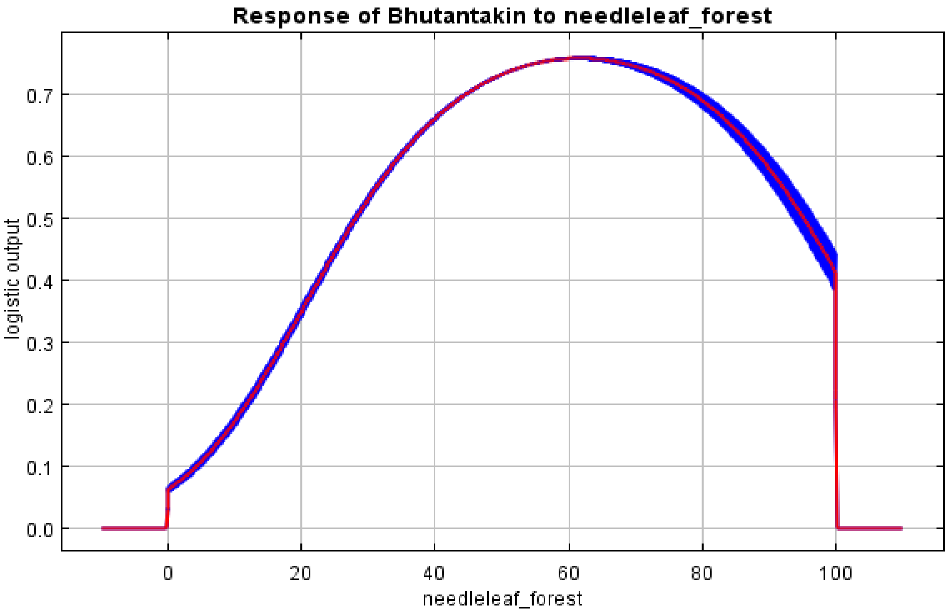

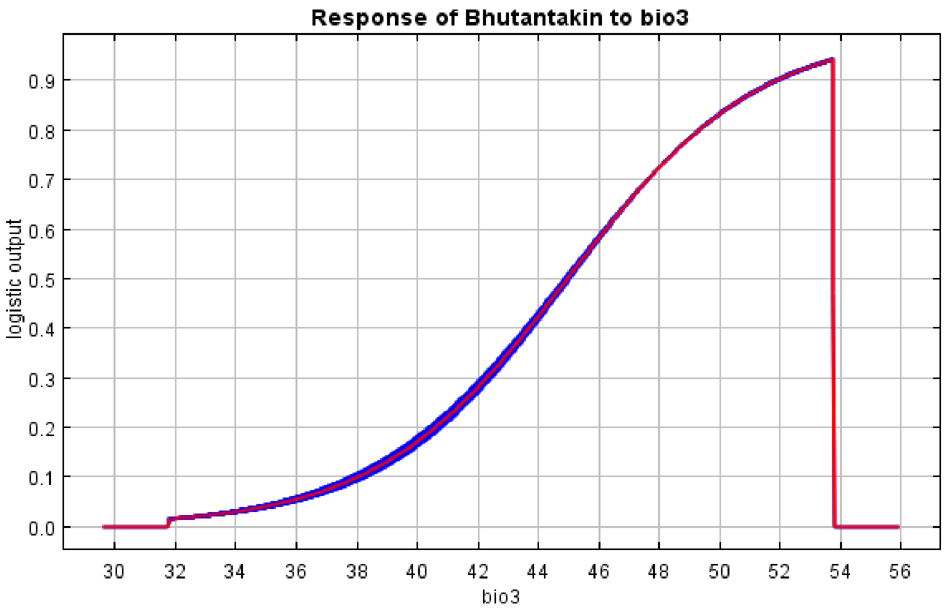

Figure 12: Response curves show the relationship between habitat suitability of Bhutan takin and an environmental variable. These curves show how the response changes for a particular variable used in isolation.

3.3. Ecological niche similarity between Mishmi takin and Bhutan takin

The ecological niches of Mishmi takin and Bhutan takin are similar, but not same. The empirical *D* and *I* values were higher than the critical *D* and *I* values obtained from background test, in both directions (Table 8). This shows that the ecological niches of Mishmi takin and Bhutan takin are more similar than merely expected by chance. It means that there is something common between these two subspecies in their use of ecological niche space. However, the empirical *D* and *I* values were lower compared to the critical *D* and *I* values obtained from identity test (Table 9). This indicates that their niches are not equivalent. Thus, Mishmi takin and Bhutan takin do not completely overlap in their use of ecological niche space.

Table 8: The critical *D* and *I* niche overlap values obtained from the similarity score for ENMs built from known occurrences of two species, and empirical *D* and *I* niche overlap values obtained from similarity scores for ENMs constructed using points drawn at random from the region defined as background range for one of the species.

	Mishmi takin ⟶ Bhutan takin		Bhutan takin ⟶ Mishmi takin	
	D	I	D	I
Critical value	0.101	0.274	0.041	0.144
Empirical value	0.119	0.310	0.119	0.310

Table 9: The critical *D* and *I* niche overlap values obtained from the similarity score for ENMs built from known occurrences of two species, and empirical *D* and *I* niche overlap values obtained from similarity scores between ENMs built from occurrences drawn randomly from the pooled occurrences for the two subspecies

	D	I
Critical value	0.670	0.891
Empirical value	0.119	0.310

3.4. Impact of future climate change on habitat suitability of Mishmi takin and Bhutan takin

To predict the suitable habitat for Mishmi takin and Bhutan takin in future, the species occurrence data and eight environmental variables, namely annual mean temperature (bio1), annual mean diurnal range (bio2), isothermality (bio3), precipitation of driest month (bio14), precipitation seasonality (bio15), aspect, slope, and roughness (Section 2.9.1), were used. The impact was assessed under RCP 4.5 and RCP 8.5 scenarios (Section 2.3.1). The predicted impact of future climate change on suitable habitat of Mishmi takin and Bhutan takin is atrocious.

The predicted current and future suitable habitat for Mishmi takin is shown in Figure 13. It is seen that there is drastic decrease in the availability of suitable habitat in future as compared to the current suitable habitat (48,129 km^2). There is very less area (587 km^2) available as suitable habitat for Mishmi takin under RCP 4.5 scenario. The availability of suitable habitat is least (150 km^2) under the RCP 8.5 scenario. The ENM for current habitat suitability has good predictive accuracy of 0.926 for AUC, 0.699 for TSS, and 0.939 for CBI.

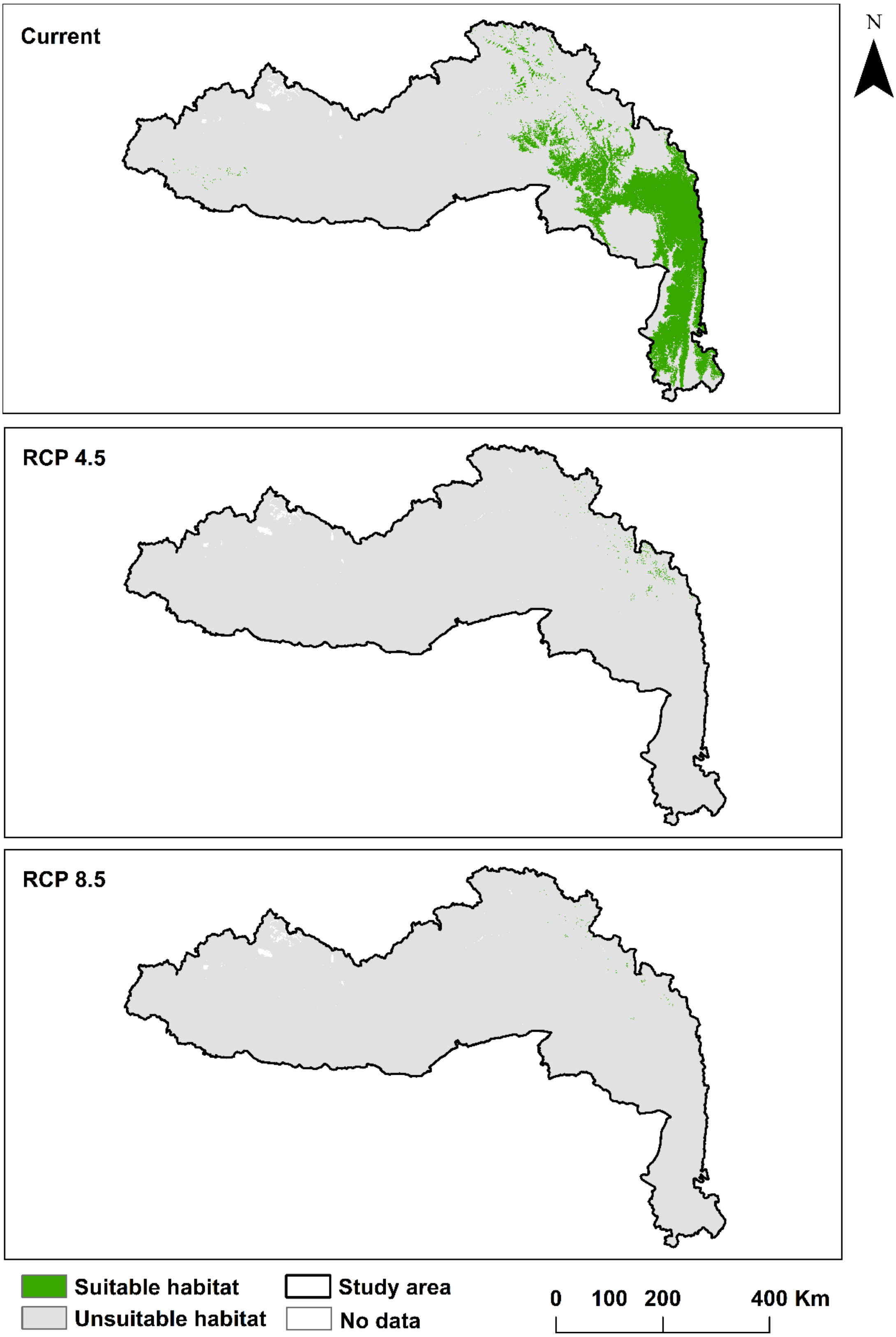

Figure 13: Map showing the suitable and unsuitable habitat for Mishmi takin in the Eastern Himalayas for current and future (RCP 4.5, and RCP 8.5 in 2070)

The distribution range is predicted to contract by 47,009 km² and expand by 544 km² under RCP 4.5 scenario. Similarly, the distribution range is predicted to contract by 47,023 km² and expand by 148 km². An area of 13 km² remains unchanged under RCP 4.5 scenario but there is no area that remains unchanged under RCP 8.5 scenario. There is significant contraction in their distribution range as compared to the expansion (Figure 14). Therefore, Mishmi takin is likely to face extinction in future due to climate change in the Eastern Himalayas.

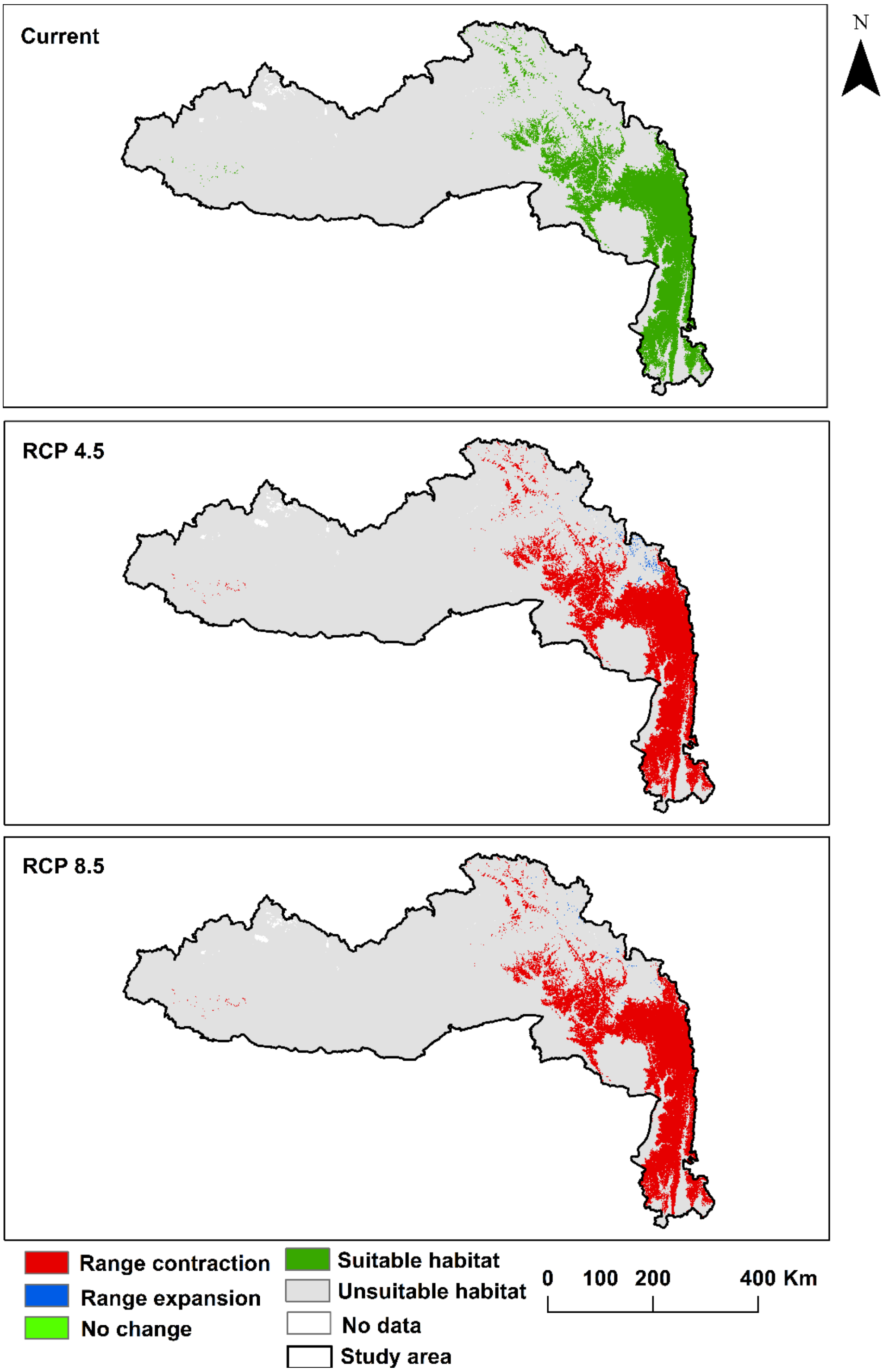

Figure 14: Map showing the suitable and unsuitable habitat for Mishmi takin in the Eastern Himalayas for current, and showing the distribution range contraction, range expansion and area of no change under future climate change scenarios (RCP 4.5, and RCP 8.5 in 2070)

The core range shift showed that there would be shift in north direction under RCP 4.5 and RCP 8.5 scenarios (Figure 15). It is an indication of range shift in suitable habitat, regardless of the available size of the suitable habitat.

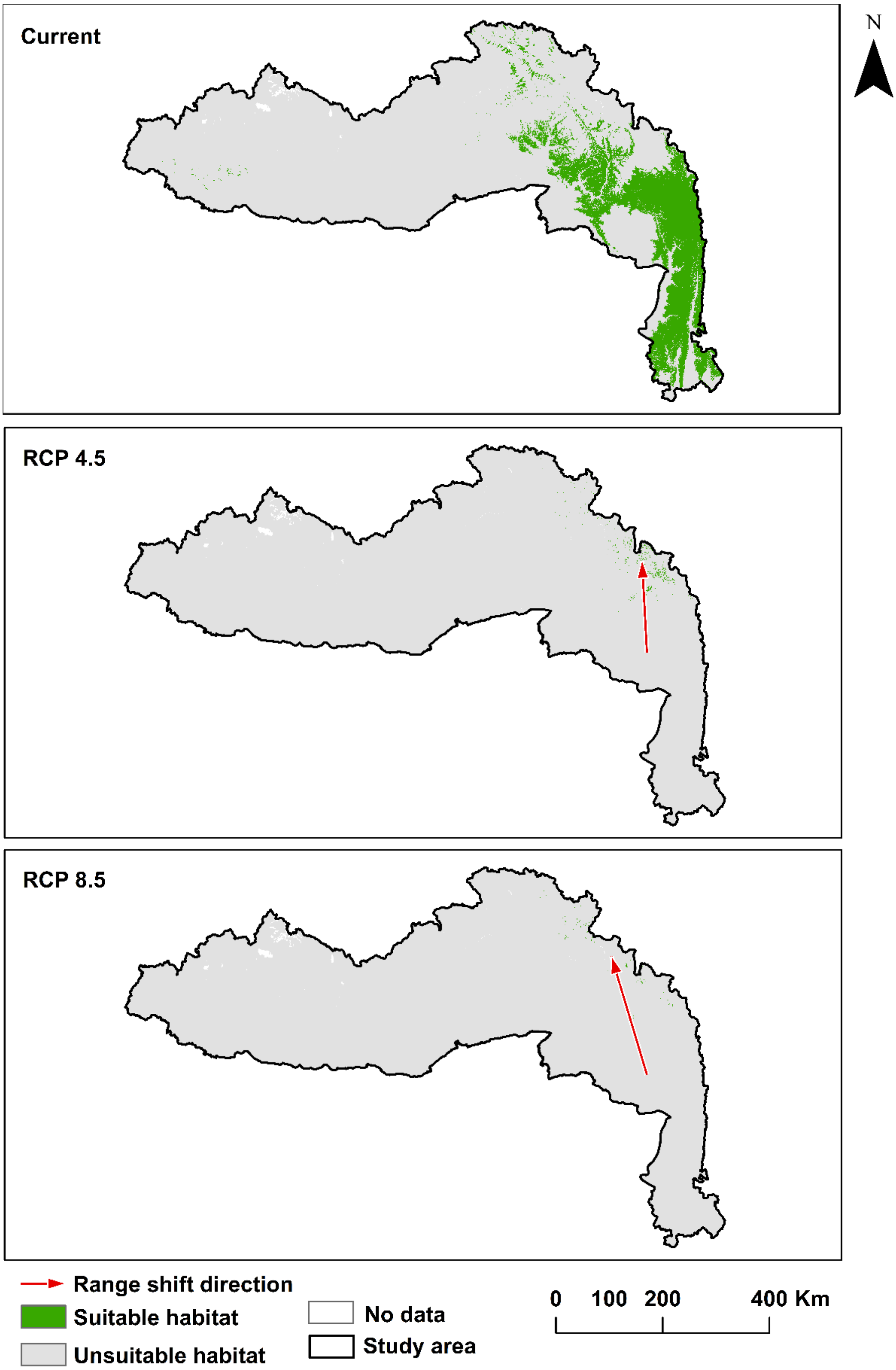

Figure 15: Map showing the core range shift for Mishmi takin in the Eastern Himalayas under future climate change scenarios (RCP 4.5, and RCP 8.5 in 2070)

The predicted current and future suitable habitat for Bhutan takin is shown in Figure 16. It is seen that there is no suitable habitat available in future for Bhutan takin under both RCP scenarios. The ENM for current habitat suitability has good predictive accuracy of 0.969, 0.858, and 0.938 for AUC, TSS, and CBI, respectively. The predicted impact of future climate change suggests that the entire population of Bhutan takin in the Eastern Himalayas can be wiped out due to none availability of suitable habitat.

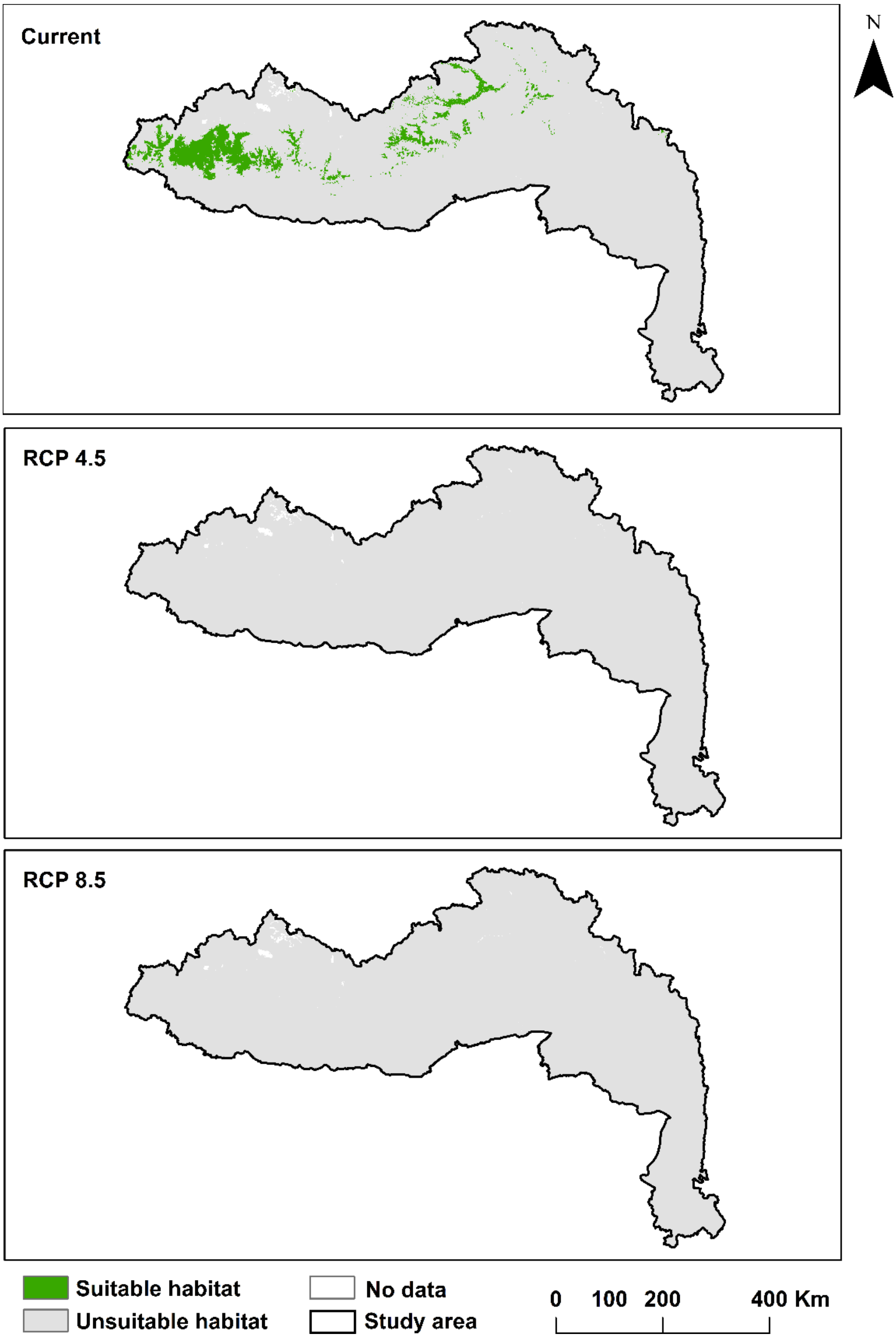

Figure 16: Map showing the suitable and unsuitable habitat for Bhutan takin in the Eastern Himalayas for current and future (RCP 4.5, and RCP 8.5 in 2070)

4. DISCUSSION

4.1. Currently available suitable habitat for Mishmi takin and Bhuntan takin

To the best of my knowledge, a clear or complete suitable habitat map for Mishmi takin and Bhutan takin is not yet available. Therefore, this is the first study to produce the current suitable habitat map for Mishmi takin and Bhutan takin including i) their potential distribution range in the Eastern Himalayas, ii) covering both summer and winter habitat use, and iii) modelling the response of Mishmi takin and Bhutan takin to five different categories of variables. The result of this study shows that an area of 28,154 km^2 is currently available as suitable habitat for Mishmi takin. The area is distributed across southeast Tibet and northwest Yunnan in southwest China, Kachin state in northern Myanmar, and northeast state of Arunachal Pradesh in India. The areas identified in this study are consistent with previous studies that indicate the presence of Mishmi takin in Cibagou Nature Reserve of southeast of Tibet (Pengju & Endi, 2006) and Mt. Gaoligong in northwest Yunnan (Pan et al., 2019) in China, Hponkanrazi Wildlife Sanctuary and Hkakaborazi National Park in Kachin, northern Myanmar (Rao et al., 2010, 2011), and Arunachal Pradesh in India (Dasgupta et al., 2010). However, Dasgupta et al. (2010) reported Mishmi takin's distribution across all districts of Arunachal Pradesh, which partly contradicts the result of this study. They modelled the distribution of takin using dense forest cover and altitudinal range of 1500 m to 3600 m. Whereas, this study used bioclimatic variables, topographic variables, vegetation-related variables, land cover, and anthropogenic factors. This difference in predictor variables could have potentially influenced the difference in result of predicted suitable habitat for Mishmi takin. However, takin is sensitive to anthropogenic activities and exhibit migration in response to food and temperature optimality. Therefore, the result of this study is more robust to such affects. The predicted current suitable habitat for Bhutan takin is 15,314 km^2. The area is distributed in northern Bhutan, northeast state of Sikkim and Arunachal Pradesh in India, and southeast Tibet in southwest China. The result is in coherence with Bhutan takin's winter habitat identified by NCD (2019) within Bhutan. Although takins are currently reported to be extinct in Sikkim (Dasgupta et al., 2010), it is worth noting that suitable habitat has been identified in Sikkim and Tibet. Historically, people have reported sighting Bhutan takin in Sikkim (Sharma et al., 2015). For instance, Bhutan takin was seen in Sikkim in 1976, again in 1984, and the last record in 1999 was seen and photographed by C. Lachungpa in Sikkim. Further, the distribution of Bhutan takin in Tibet is unclear but theory that takin moved through Tibet to Bhutan and Sikkim (Sharma et al., 2015) favours the finding of this study.

An underlying assumption of Maxent is that the entire study area has been systematically sampled (Kramer-Schadt et al., 2013; Merow et al., 2013; Phillips et al., 2009). However, a systematic primary data collection was not feasible in this study mainly since the target species is distributed in four different countries, Bhutan, India, Myanmar, and China, which entail resource-intensive data collection exercises. Therefore, given the limited time and resources provided for the completion of this study, secondary data was collected from data owners of specific countries. Most of the data collected did not explicitly follow a sampling design rather, opportunistic sightings were recorded. Therefore, sampling bias is likely to occur. The most straightforward method to deal with sampling bias is to manipulate the presence data by removing the data from an over-sampled area using spatial filtering (Phillips et al., 2009). The occurrence records for target species of this study are already limited for deleting any valuable records from the set, but basic spatial filtering of keeping only one record per pixel was applied by enabling the "Remove duplicate presence record" option in the Maxent setting. The alternate suggested by Merow et al. (2013) when explicit information on survey effort is not known is based on Target Group Sampling (TGS). TGS uses the similarly collected occurrence points of taxonomically related species under the assumption that the surveyors would have documented the presence of focal species if it occurred there. It is incorporated in Maxent by either creating a bias file with nonuniform weighing assigned to background points or a bias file that modifies the selection of background points within the study area. To acquire TGS for this study, Global Biodiversity Information Facility (GBIF) database (https://www.gbif.org/) was explored. A total of only 650 occurrence points were available for Mammalia taxa in the study area between 1990 to current year. These occurrence points were not covering the spatial extent of the study area and were not sufficient. Hence, this method of bias correction was not possible. Therefore, the results of this study could possibly be subjected to sampling bias. Nonetheless, given the facts, i) wildlife sighting locations are sensitive information that are not easily shared, ii) takins generally use remote area which limits both systematic or opportunistic data collection, and iii) Himalaya is a data deficient region, the data shared by respective data owners is the best available data to conduct this study.

Most of the suitable habitat for both subspecies falls within the conservation areas in respective countries. However, their population is in decreasing trend according to IUCN assessment (Song et al., 2008). Many prior studies have shown images (Dasgupta et al., 2010) and statistics (Rao et al., 2011) of takins being hunted for various purpose throughout their distribution range. Therefore, existing efforts of conservation don't seem rigorous enough in their defence. Hence, the suitable habitat maps produced in this study can further be used to device strict monitoring plans and identification of priority area for conservation of both subspecies. It is also recommended to establish transboundary collaboration since the suitable habitats are stretching across international boundaries.

4.2. The key environmental variables affecting habitat suitability of Mishmi takin and Bhutan takin are different

The result shows that the critical environmental variables which influence the habitat suitability of Mishmi takin are precipitation seasonality (bio15) and NDVI standard deviation. In the case of Bhutan takin, needleleaf forest and isothermality were found to be important. These variables are vegetation-related variables and bioclimatic variables. NDVI standard deviation and needleleaf forest cover are proxies for food resources that are available to both subspecies. The variation in rainfall fluctuates soil water content that considerably affects plant phenology, leaf and fruit development (Zeppel et al., 2013). Similarly, temperature fluctuations within a month relative to the year might have impacts on takin's seasonal routine. It is a reasonable finding which is validated by the ecological behaviour of takins, that is, the movement of takin is attributed to seasonal temperature changes and plant phenology (Guan et al., 2013; Wang et al., 2010; Zeng et al., 2008, 2010).

Apart from the given set of variables, the habitat suitability of both subspecies is also affected by other factors such as predations and competition for resources like food and water that are not considered in this study. However, the responses of species to environmental conditions are hardly a result of a single ecological process (Harisena et al., 2021). So, the inclusion of all potential factors is complicated in many aspects. Additionally, the computation of variable importance assumes no spatial autocorrelation exists in the sample data. Therefore, spatial filtering of one sample per pixel (1 km) was applied. However, detailed spatial autocorrelation analysis was not conducted in this study. Furthermore, these results are limited to 1 km spatial resolution.

4.3. The ecological niches of Mishmi takin and Bhutan takin are not identical

The result of the identity test shows that the ecological niches of Mishmi takin and Bhutan takin are not identical. It is backed by the different set of key environmental variables that constrain their habitat suitability which was identified in objective 2 of this study. The finding tells that characterizing the niche of Mishmi takin based on Bhutan takin's niche characteristics is not accurate and vice versa. Similar conclusions were drawn by researchers that conducted the similar test (Aguirre-Gutiérrez et al., 2015;

Zhao et al., 2019). Subsequently, the background test found the two subspecies to be more similar than expected. In other words, Mishmi takin and Bhutan takin share more characteristics of their environmental niches as compared to random expectation. In conclusion, the result of the identity test and background test highlights that although they are similar, they are not the same. Therefore, Mishmi takin and Bhutan takin are two distinct subspecies under takin species, but not two different species in themselves. Previous studies have supported the same based on their morphology (Neas & Hoffmann, 1987; Sharma et al., 2015).

According to Warren et al. (2010), bias in identity tests can be introduced due to bias in sampling effort, sampling bias, and differences in the habitat available to the focal species in their spatially separated habitat. Hence, the result of equivalency is subjected to sampling bias in this study. Similarly, the result of background test is sensitive to the background range (Section 2.8) from which the species is believed to be selecting habitat. However, the background range selected for the background test was modelled with the best available species occurrence data, various predictor variables (Section 2.3) and species-specific model setting (Section 2.5) in this study. Therefore, the background range selected for the background test in this study is expected to be ecologically meaningful.

4.4. Impact of future climate change impact on Mishmi takin and Bhutan takin

Our results show that Mishmi takin and Bhutan takin will be negatively affected by climate change in future. The results revealed that the suitable habitats for both subspecies are likely to disappear in the Eastern Himalayas due to climate change. The future climate change impact in Eastern Himalayas is expected to be challenging (Sharma et al., 2009; Tse-ring et al., 2010), which backs these findings that the threat posed by changing climate to vulnerable species like takin is strong. Also, given the already limited geographic distribution of these subspecies, the loss of all its suitable habitat is largely possible.

However, the result is limited to eight variables and its uncertainties inherited from general circulation model (GCM). Uncertainty is a critical concern for all climate change assessment (Tang et al., 2018). Ignoring it can adversely affect the usefulness of climate change assessment outcomes for making conservation related decisions. Especially, such uncertainties are issues for evaluating future distribution of species given the multiple other sources of uncertainties in existence. Other sources of uncertainties are quality of species information/data, methodology used, predictor variables used, thresholds used for converting the continuous map to binary map, and model settings used. Therefore, the result of future prediction is likely to be associated these uncertainites. However, famous George Box, one of the great statistical minds of the 20th century said, “all models are wrong, but some are useful”. Likewise, although these variables alone are not adequate enough to precisely predict what will happen to takin’s habitat in future but, it can still make an important contribution especially when the current distribution of both subspecies are found to be constrained by bioclimatic factors like precipitation seasonality (bio15) and isothermality (bio3). Thus, the result of this impact analysis can help us understand the possibility of extremes entailed with future climate change.

Montane species are moving their distributions upslope in search of optimal climate due to climate change (Freeman et al., 2018). This indicates that species inhabiting higher-elevation have no more areas left to shift upslope when species living at lower-elevation encroach their space. These mountaintop species gradually face extinction over time. Although takins are not on the topmost elevation of the Eastern Himalayan mountains, a new record of Bhutan takin was confirmed by a camera trap at 4864 m in Bhutan recently (Dhendup et al., 2016). This possibly suggests that upslope movement in takins might have already begun even though human observation is limited in their remote habitat. Hence, adopting climate change mitigation and adaptation strategies at a local and global level is important. More immediately, it is urgent to maintain protected habitat corridors across elevation gradient to avoid limiting the species movement in the face of on-going climate change.

5. CONCLUSIONS

This study predicted current suitable habitats for both Mishmi takin and Bhutan takin in the Eastern Himalayas, and identified the key environmental variables influencing their potential distribution using ecological niche modelling. In addition to it, this study tested the niche similarity between the subspecies. Furthermore, this study also predicted the impact of future climate change on Mishmi takin and Bhutan takin. Based on the results I conclude that:

1. Approximately 28,154 km^2 of suitable habitat is currently available for Mishmi takin, which is widely distributed across southeast Tibet and northwest Yunnan in southwest China, Kachin state in northern Myanmar, and northeast state of Arunachal Pradesh in India. While about 15,314 km^2 of suitable habitat is currently available for Bhutan takin, which is sparsely distributed across northern Bhutan, northeast state of Sikkim and Arunachal Pradesh in India, and southeast Tibet in China.
2. The key environmental factors influencing the current habitat suitability of Mishmi takin are the precipitation seasonality and the standard deviation of NDVI. While the most important environmental factors influencing the current habitat suitability of Bhutan takin are the needleleaf forests and isothermality. Thus, the important environmental variables that determine the habitat suitability for both subspecies are different.
3. The ecological niches of Mishmi takin and Bhutan takin are similar but not the same. Thus, Mishmi takin and Bhutan takin are two distinct subspecies under takin species, but not two different species in themselves from an ecological perspective.
4. The future climate change will have a significant negative impact on the availability of suitable habitats for both Mishmi takin and Bhutan takin in the Eastern Himalayas. The suitable habitat for Bhutan takin is likely to be completely disappeared in this region under future climate change scenario. While only few suitable habitats are expected to remain due to future climate change.

The predicted current suitable habitats from this study are critical for the long-term survival of Mishmi takin and Bhutan takin. The suitable habitat for Mishmi takin can be treated as the baseline in initiating a transboundary conservation strategy and management plan. Similarly, the predicted suitable habitat for Bhutan takin can be used in conjunction with the prior findings to strengthen the conservation activities. Further, the impacts of projected future climate change on both subspecies are found to be disastrous. Therefore, conservation priority should also be given to these two subspecies with other prioritized wildlife in the region.

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