DISTRIBUTION OF THE RED PANDA *AILURUS FULGENS* (CUVIER, 1825) IN NEPAL BASED ON A PREDICTIVE MODEL

THESIS

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ACRONYMS

ASCII	American Standard Code for Information Interchange
AUC	Area under Curve
CA	Conservation Area
CITES	Convention on International Trade on Endangered Species
CSV	Comma separated value
DEM	Digital Elevation Model
ESRI	Earth System Resource Institute
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
GAM	Generalized Additive Model
GARP	Genetic Algorithm for Rule Set Production
GIS	Geographic Information System
GLCNMO	Global Land Cover by National Mapping Organizations
GLM	Generalized Linear Model
GPS	Global Positioning System
ISCGM	International Steering Committee for Global Mapping
IUCN	International Union for Conservation of Nature and Natural Resources (The World Conservation Union)
km	kilometer
LAI	Leaf-area Index
LPT	Lowest Presence Threshold
MaxEnt	Maximum Entropy
mm	millimeter
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index

NIR	Reflectance in near infra-red band
NP	National Park
ROC	Receiver Operator Curve
RPN	Red Panda Network, Nepal
RS	Remote Sensing
SPSS	Statistical Package for Social Survey
SRTM	Shuttle Radar Topography Mission
TXSTATE	Texas State University-San Marcos
VIF	Variance Inflation Factor
VIS	Reflectance in visible band

ABSTRACT

DISTRIBUTION OF THE RED PANDA *AILURUS FULGENS* (CUVIER, 1825) IN NEPAL BASED ON A PREDICTIVE MODEL

by

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The red panda (*Ailurus fulgens*), an endangered mammalian species endemic to the Eastern Himalaya, is protected from international trade from its presence on the International Union for Nature Conservation (IUCN) and the Convention of International Trade in Endangered Species (CITES) list for all member countries within its range. There is limited information on its distribution and status range-wide, mainly due to its elusive nature. Its rarity makes field studies exceptionally expensive and time consuming. To facilitate the time-efficiency and cost-effectiveness of field studies on red panda, a predictive local scale distribution model for the red panda was developed for

Nepal using maximum entropy (Maxent) species distribution modeling. In this method, 20 presence-only red panda occurrence points were used to train the model that used 10 uncorrelated environmental layers from various sources. A set of 86 independent points of red panda occurrences was used to evaluate the validity of the model. A probabilistic prediction for the red panda distribution was produced with a low omission rate and high accuracy (test AUC = 0.946). Elevation and temperature seasonality followed by tree cover were the most important environmental variables contributing to the red panda distribution model. The estimated suitable habitat for red panda in Nepal based on a 0.1 threshold of presence were areas of approximately 20,400 km^2. In Nepal 22.5 % of suitable habitat falls in nine montane protected areas. Regional classification of habitat demonstrated a larger proportion of suitable areas for red pandas occurred in the Eastern Region of Nepal which also had high probability areas for red pandas and one of the highest human population growth rates in Nepal. Amplification of the model to the global scale predicted about 425,700 km^2 of suitable areas for red pandas in six countries. The current Maxent model overestimated the modern distribution of the red panda in Asia. Despite the overestimation, this model can be used as an effective tool in planning future studies of the species and conservation efforts.

INTRODUCTION

Statement of Problem

The red panda (*Ailurus fulgens*, Cuvier 1825) is a rare species listed as "Vulnerable" in the International Union for Conservation of Nature (IUCN) Red List (IUCN 2010). It is protected against international trade by inclusion in the Convention on International Trade on Endangered Species (CITES) Appendix I. The red panda also has legal protection in all countries within its range across a network of protected areas (Choudhary 2001, Glatston 1994, Wei et al. 1999, Yonzon et al. 1997). However, whether these legal protections and the existing network of protected areas are enough to accommodate viable populations of red pandas remains a matter of debate. As with many other endangered species, habitat fragmentation following deforestation has been a major cause of population decline. This is evident, for example, in Langtang National Park in Nepal, where red pandas are now sub-divided into four sub-populations or metapopulation fragments (Yonzon and Hunter 1991). Such habitat fragmentation may lead to inbreeding and a consequent loss of genetic variation. It may also cause other effects, such as starvation in the giant panda, *Ailuropoda melanoleuca*, when fragments of habitat experience widespread senescence and decline of forage (Reid et al. 1991).

Other forms of anthropogenic impacts, such as livestock grazing in red panda habitat or simply the presence of herders and their dogs are additional sources of disturbances to red pandas (Mahato 2004b, Pradhan et al. 2001, Yonzon and Hunter 1991). During the mid 20th century, the demand for live harvest of red pandas from the wild for display in western zoos was an important cause of the decline of wild populations (Glatston 1994). Despite a lack of any real market value, red pandas are hunted locally for the pelt and for sport in some areas (Choudhary 2001, Glatston 1994, Wei et al. 1999, Yonzon et al. 1997).

The most pressing conservation problem for red pandas remains inadequate information regarding ecology and distribution. Its status in the wild is not sufficiently known nor its ecology documented. The extent of suitable habitat is also poorly understood, which has hindered the planning of protected areas and habitat connectivity.

Background Information on Red Panda

The red panda has interested scientists, in part, because of the ambiguity of its phylogenetic assignment. Classical systematists suggest the red panda along with the giant panda, should be placed in the sub-family Ailurinae within the family Procyonidae, instead of the sub-family Procyoninae which includes the New World procyonids (Walker 1968). However, serological (Leone and Wiens 1956) and DNA hybridization (O'Brien et al. 1985) studies alternatively suggested a closer relationship to the giant panda of the bear family (Ursidae). While the results of DNA hybridization support subsuming the red panda as a procyonid (Wayne et al. 1989), it was argued that placement of the red panda in the family Procyonidae was based on superficial similarities between the red panda and raccoons, such as face mask, ringed tails, etc. This argument was based on anatomical features (Decker and Wozencraft 1991) and cytogenesis (Wurster and Benirschke 1968), which suggested the red panda was a closer relative to bears. Based on these debates of its phylogeny and as suggested by Eisenberg (1981), placement of the red panda in a separate family – Ailuridae is currently widely accepted (Glatston 1994).

The red panda is endemic to the eastern Himalayan broad-leafed and coniferous forests (Olsen and Dinerstein 1998) extending from Nepal through India, Bhutan, China and Myanmar. The red panda distribution extends from Namlung Valley (Mugu District) and Rara Lake region in western Nepal eastward to the Min Valley in Western Sichuan (Glatston 1994, Roberts and Gittleman 1984). Two subspecies of red panda are known – *Ailurus fulgens fulgens* and *A. f. styani*. The later found in Myanmar and China is also known as Styan's or the Chinese red panda. The subspecies, *A. f. fulgens*, occurs in Nepal, India, Bhutan and certain parts of China (Glatston 1994). However, the actual distribution and isolation between these subspecies (if any) remain poorly understood.

The red panda inhabits fir-jhapra forests (fir with ringle bamboo in the understory) with an altitudinal preference between 2,400 and 3,900 m (Pradhan et al. 2001, Yonzon and Hunter 1991). In China red pandas share habitat with giant pandas (Wei et al. 2000). Despite the placement of red panda within the order Carnivora, it has a specialized herbivore diet. The major proportion (54-100%) of its food consists of leaves and shoots of bamboo (*Arundinaria maling* and *Arundinaria aristata)* followed by berries of *Sorbus microphylla and Sorbus cuspidata* (Yonzon and Hunter 1991). Behaviorally, the red panda is nocturnal and crepuscular (Roberts and Gittleman 1984). It is solitary outside the mating season, but females are seen with their cubs between parturition and the subsequent mating season (Pradhan et al. 2001, Yonzon and Hunter 1991). Red pandas are largely sedentary and have a small home range between 1.38 and 11.57 km^2. Females have a smaller home range (mean = 2.37 km^2) than males (mean = 5.12 km^2) (Yonzon 1989). Because of specialized feeding behavior and narrow and specialized habitat needs, the red panda is considered a habitat specialist.

Little was known about the ecology, status and distribution of this species in the wild until the late 1980s (e.g., Johnson et al. 1988, Yonzon 1989). Prior to this period most of the behavioral information on red pandas was from captive populations (e.g., Roberts 1981, Warnell 1988). A study in Langtang National Park in Nepal (Yonzon 1989) produced important information about habitat, feeding behavior, home range and habitat preference. Another long-term study in Singhalila National Park in India (Pradhan et al. 2001) provided additional ecological information. Some preliminary data came from Wolong Reserve in China (Johnson et al. 1988, Reid et al. 1991). Recent studies in Yele Nature Reserve (Wei et al. 2000) and Fengtongzhai Nature Reserve in China (Zhang et al. 2004) produced important information on microhabitat selection and separation between red and giant pandas. Recent surveys in Kanchenjunga Conservation Area (Mahato 2004a), Sagarmatha (Everest) National Park (Mahato 2004b), Ilam and Panchthar districts (RPN 2006-2009) supplied field-based confirmation of red panda occurrences. Red pandas were also reported in Sichuan and Yunnan provinces and Tibet in China (Wei et al. 1999), in Sikkim, Darjeeling District in West Bengal, and the northern part of Arunachal Pradhesh in India (Choudhary 2001).

Various techniques for modeling the distribution of species have been developed in recent years (Guisan and Thuiller 2005), and Geographic Information Systems (GIS) became a vital tool in this regard. In analyzing multivariate environments, GIS facilitates an understanding of the relation of environmental variables to species presence. This tool in combination with remotely sensed data has been successfully used to predict species distributions, e.g., wolf, *Canis lupus* (Corsi et al. 1999) and Asiatic black bear, *Ursus thibetanus japonicus* and Japanese serow, *Naemorhedus crispus* (Doko 2007). Species distribution models have been used to guide field survey efforts to successfully find populations (Guisan et al. 2006), support species conservation prioritization and reserve selection (Leathwick et al. 2005), predict species invasion (Thuiller et al. 2005), delimitation of species, and guide the reintroduction of endangered species (Pearce and Lindenmayer 1998).

Rationale of the Study

Understanding the spatial occurrence of a species is one of the first steps for its preservation or management. The most pressing problem in the conservation of the red panda is insufficient information regarding occurrence (Glatston 1994, Yonzon et al. 1997). Like all endangered or rare species, gathering such information for such an elusive species is both time and resource consuming. Therefore, predicting a species distribution is an important component of a conservation plan (Pearson 2007). Predicting distribution becomes more important for elusive species like the red panda for two reasons – firstly, detection is limited by its rarity and small body size, and secondly, limited accessibility to remote and rugged habitat makes field surveys exceptionally time consuming, expensive, and difficult, consequently hindering conservation efforts. Thus, modeling tools, which identify the environmental variables related to a species occurrence, have been developed to overcome these problems in conservation planning (Pearson 2007). In this effort, association among environmental variables and species occurrence are identified and environmental variables suitable for the species are extrapolated spatially across the area of concern.

Solving the issue of the red panda's status in the wild will require complementary investigations based on field studies combined with GIS. For example, Yonzon and Hunter (1991) suggested a population of 37 adult red pandas inhabited Langtang National Park, which provided 108 km^2 of suitable habitat for red pandas (ecological density = 1 panda per 2.9 km^2). Pradhan et al. (2001) indicated an estimated crude density of 1 panda per 1.67 km^2 existed in Singhalila National Park. A GIS based study (overlaying altitude – 3,000-4,000 m, forest cover – Fir-jhapra forest, and rainfall > 2,000 mm) using the ecological density observed in the Langtang National Park produced a population estimate of 314 red pandas in 912 km^2 of potential habitat in the Nepal Himalaya (Yonzon et al. 1997). This might have been either an overestimation or underestimation of habitat for two reasons – recent spatial data and the relationship between red panda occurrence and other environmental variables were not used in the study. Field studies in Wolong Reserve in China (Johnson et al. 1988, Reid et al. 1991) did not provide enough information regarding the abundance of red pandas. Therefore, I will use recent satellite data to estimate the present extent of red panda habitat and analyze the correlation between environmental variables and species occurrence, hence providing baseline information for planning habitat connectivity and a design for protected areas.

OBJECTIVES

The goals of my study were to understand and predict the red panda distribution by assessing the relationship between presence of the species and various environmental parameters. The specific objectives were:

1. To develop a landscape-level model for the red panda distribution for Nepal,

2. To use GIS analysis to test for correlations between the occurrence of red pandas and available ecological components (environmental factors) of habitat, and

3. To assess the conservation status of the red panda in Nepal based on the developed model.

STUDY AREA

Nepal lies between latitudes 26° 22′ and 30° 27′ N and longitudes 80° 04′ and 88° 12′ E between India and China in southern Asia (Fig.1). China is north of Nepal, while India encompasses the remaining border with Nepal. Nepal, with an area of 147,181 km^2, is divided into five development regions and 75 districts (Fig.2). The development regions of Nepal from east to west are: Eastern, Central, Western, Mid-western and Far-western.

Nepal is predominantly a mountainous country with an increasing elevational gradient from south to north. The elevational gradient changes from 63 m above sea level in the southern plains to 8,848 m on the top of the Mount Everest within an average north-south lateral distance of 150 km and causes variation in climatic conditions. In the southern area, there is a narrow belt of lowlands with a tropical climate. Smaller hills with a sub-tropical climate to the north supplant the lowlands and further north the mountains with a temperate climate replace the hills. The high mountains with sub-alpine and alpine environments occur in the northern part of the country.

The variation in the elevation gradient and the resulting varied bioclimatic circumstances support a highly diverse flora and fauna. Nepal is located at a transition of the Pale-arctic and Indomalayan biogeographic realms (Udvardy 1975). A combination of the flora and fauna of both realms contributes to the rich biodiversity of the country. A proportion of this rich biodiversity is protected by a network of 16 protected areas (Fig.3), which cover approximately 20% of Nepal's total land area (HMGN/MFSC 2002).

Figure 1. Relative location of Nepal within southern Asia.

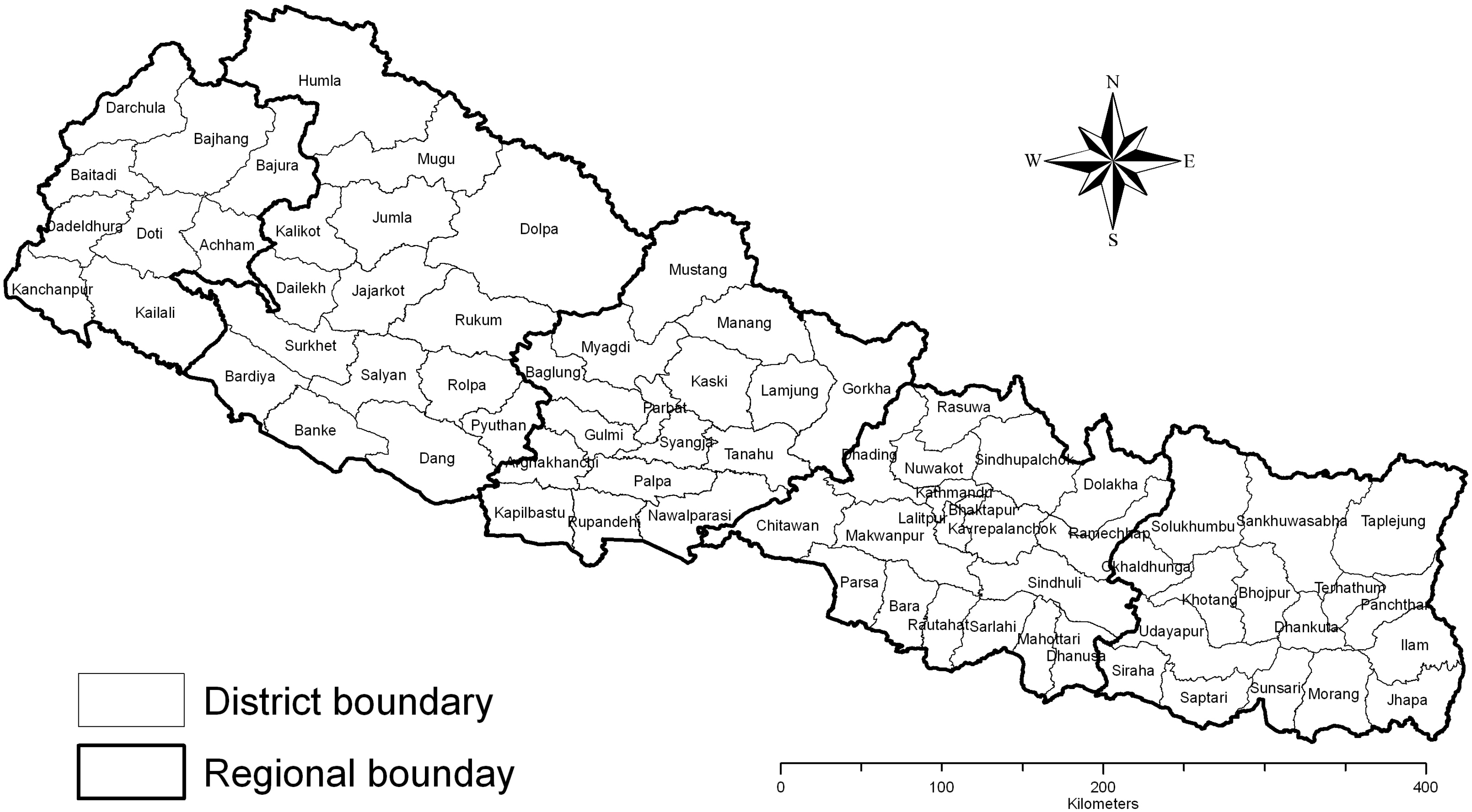

Figure 2. Regional and administrative boundaries of Nepal.

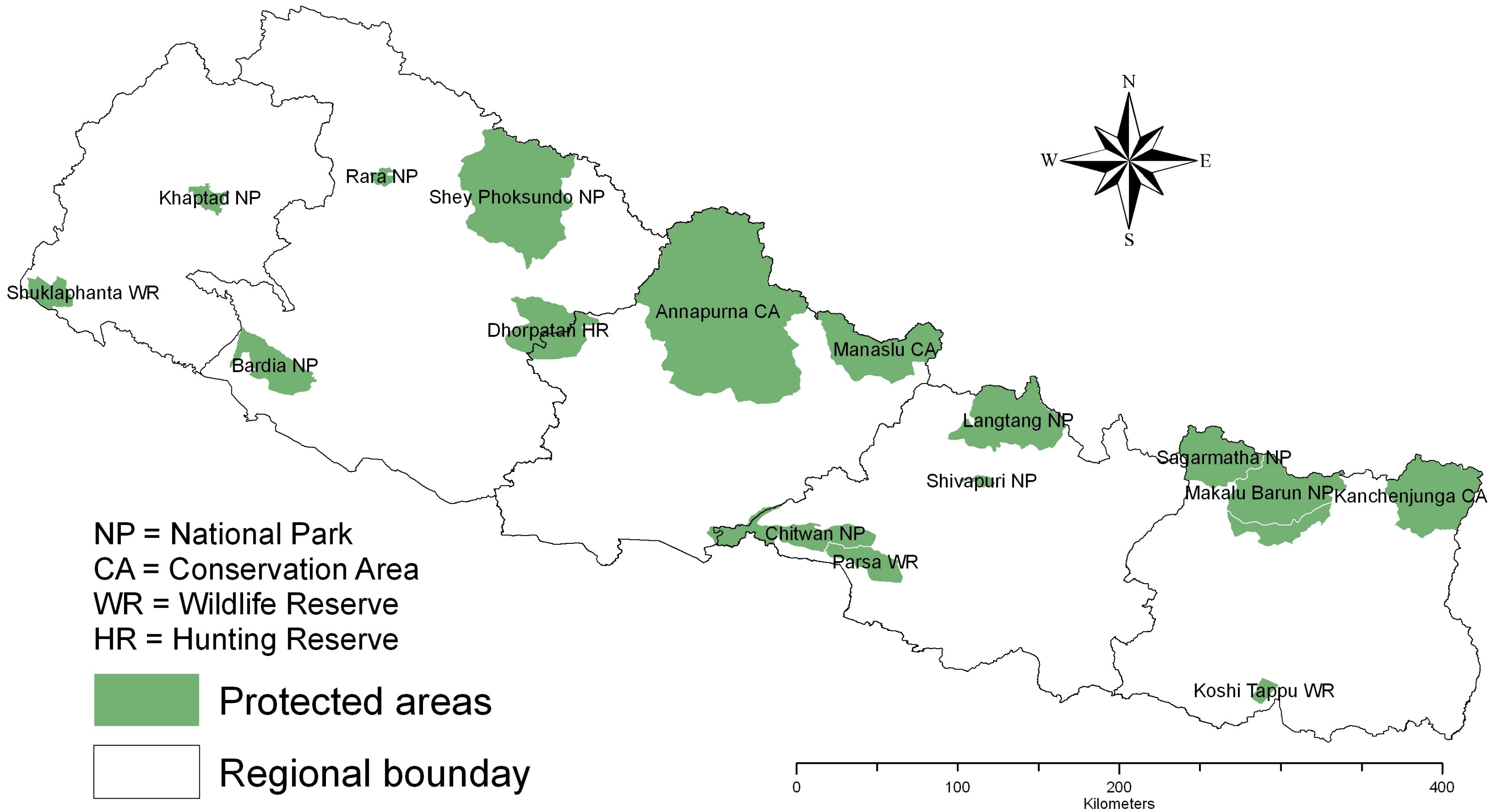

Figure 3. Distribution of protected areas in Nepal.

MATERIALS AND METHODS

Three components compose the statistical model of a species distribution – an ecological component (environmental variables), the presence dataset, and a predictive algorithm (statistical/ modeling tool) (Austin 2002).

Red Panda Occurrence Data

Species occurrence data is usually in two forms – presence and absence. Presence data are easy to obtain compared to the absence data. While use of both presence and absence data improve the performance of a model (Brotons et al. 2004), absence data are usually unavailable or may be unreliable in many cases, especially for rare and elusive species. This can lead to a false absence, which may become a serious bias in a distribution model (Hirzel et al. 2002). While locations with obvious red panda absence, e.g. the lowlands and higher elevations beyond red panda known range, can provide absence data, these were not used as well. Therefore, in this study only presence data were used.

Occurrence points for red pandas were based on presence data obtained from previous surveys. These data came from six areas occupied by red pandas in Nepal. These locations are listed in Table 1 and mapped in Figure 4. Though there were variations in how the different surveys were conducted, occurrence points were based on direct or indirect evidence with the location recorded using a handheld GPS unit. Most locations were based on indirect evidence of red panda presence, in most cases confirmation was based on fecal droppings.

More than 600 occurrence points in six habitat fragments were available. However, my analysis was at a resolution of 1 km; therefore, there were multiple points per pixel. I removed the multiple points per pixel in ArcMap 9.3 (ESRI Inc., Redlands CA) using Hawth's analysis tool (www.spatialecology.com). After correcting for multiple points per pixel, I obtained 107 unique points in each pixel.

Table 1. Red panda (*Ailurus fulgens*) presence points used in predictive GIS model.

Locations	Source
Dhorpatan Hunting Reserve	Sharma and Kandel (2009)
Kanchenjunga CA	Mahato (2004a)
Ilam and Panchthar districts	RPN (unpublished data)
Sagarmatha NP (Bufferzone)	Mahato (2004b)
Langtang NP	Stephens (2003), Regmi (2009)
Manang district	Stephens (2003)

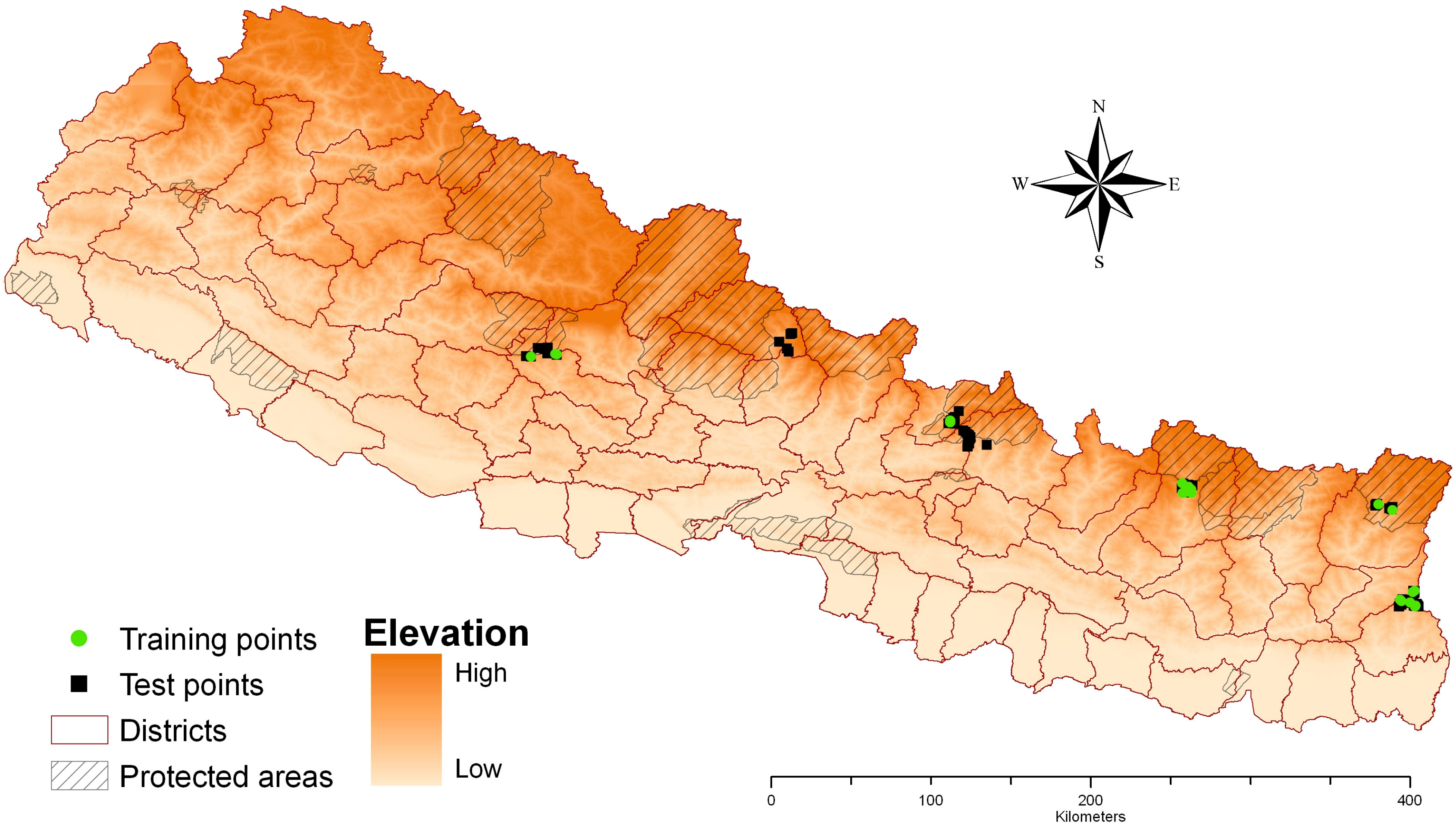

Figure 4. Locations of red panda (*Ailurus fulgens*) occurrences used in this study for distribution modeling in Nepal.

Environmental layers

Knowledge of the ecology of a species is helpful in deciding which biologically relevant environmental variables to use in distribution modeling. I collected and reviewed the available literature on red pandas and combined this information with my observations in the field in understanding the environmental variables potentially influencing the distribution of red pandas. I created spatial layers of the environmental variables at the landscape level and used ArcMap to sort the spatial layers. The environmental variables used in the model are listed in Table 1.

Table 2. Environmental layers used in modeling the distribution of red pandas (*Ailurus fulgens*) in Nepal.

Data layers	Sources
19 Bioclimatic layers	World Clim
Normalized difference vegetation index (NDVI)	Satellite data (3 seasons data)
Enhanced vegetation index (EVI)	Satellite data (3 seasons data)
Leaf area index (LAI)	Satellite data (3 seasons data)
Land cover Tree percent cover	Derived from satellite data
Altitude	World Clim

Bioclimatic Layers

Bioclimatic variables were downloaded as layers in ESRI grids format from free domain public global climate data – WorldClim (Hijmans et al. 2005). The bioclimatic layers were derivatives from monthly precipitation (mm) and temperature (Celsius) data. An additional 19 biologically meaningful variables were generated from these data (Table 3) representing annual trends (mean annual temperature and precipitation), seasonality (e.g., annual range in temperate and precipitation), and limiting environmental factors (e.g., temperate and precipitation of a certain quarter) (Hijmans et al. 2005). These climatic layers were generated through interpolation of average monthly climate data of 50 years from more than 47,000 weather stations throughout the world (e.g., Global Historical Climatology Network - GHCN, the Food and Agriculture Organization – FAO, International Center for Tropical Agriculture – CIAT, World Meteorological Organization – WMO, R-HYdronet).

Bioclimatic layers were available at a resolution of 30 arc sec which is approximately 1 km pixel size. The layers were masked from the global dataset in geographic coordinate system (WGS84) for the study area.

Elevation

The elevation layer was obtained in ESRI grids format from WorldClim which was generated from the Shuttle Radar Topography Mission (SRTM) elevation database. This layer was in the same spatial resolution as the bioclimatic layers (30 seconds arc) and the geographic coordinate system (WGS84).

Table 3. Nineteen bioclimatic layers obtained from WorldClim for use in a predictive GIS model for the red panda (*Ailurus fulgens*) in Nepal.

Environmental layers	Type
Annual Mean Temperature – P1	Continuous
Mean Diurnal Range – P2 (Mean of monthly (max temp - min temp))	Continuous
Isothermality [(P2/P7) ×100] – P3	Continuous
Temperature Seasonality (standard deviation ×100) – P4	Continuous
Max Temperature of Warmest Month – P5	Continuous
Min Temperature of Coldest Month – P6	Continuous
Temperature Annual Range (P5 – P6) – P7	Continuous
Mean Temperature of Wettest Quarter – P8	Continuous
Mean Temperature of Driest Quarter – P9	Continuous
Mean Temperature of Warmest Quarter – P10	Continuous
Mean Temperature of Coldest Quarter – P11	Continuous
Annual Precipitation – P12	Continuous
Precipitation of Wettest Month – P13	Continuous
Precipitation of Driest Month – P14	Continuous
Precipitation Seasonality (Coefficient of Variation) – P15	Continuous
Precipitation of Wettest Quarter – P16	Continuous
Precipitation of Driest Quarter – P17	Continuous
Precipitation of Warmest Quarter – P18	Continuous
Precipitation of Coldest Quarter – P19	Continuous

Satellite-derived Vegetation Indices

Three types of vegetation indices, normalized differential vegetation index (NDVI), enhanced vegetation index (EVI) and leaf-area index (LAI) derived from satellite data, were used as predictors of the red panda distribution. All three indices were obtained from MODIS (Moderate Resolution Imaging Spectroradiometer) Terra sensor. These MODIS products were obtained from Land Processes Distributed Active Archive Center (LPDAAC) located at U. S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (http://lpdaac.usgs.gov) in HDF-EOS data format (.hdf file format). NDVI and EVI were obtained as a 16-day mosaic at a spatial resolution of 1 km, while LAI was obtained as an eight-day mosaic at the same spatial resolution, all three in Sinusoidal projection system (LPDAAC 2008).

The vegetation indices obtained from various seasons were used to incorporate the seasonal variation in vegetation. For the purpose of this study, the annual cycle was arbitrarily divided into three seasons: pre-monsoon (January – June), monsoon (June – September) and post-monsoon (September – December). The products used in this study (based on the best available products) are listed in Table 4.

Table 4. List of Moderate Resolution Imaging Spectroradiometer (MODIS) products used in a predictive GIS model for the red panda (*Ailurus fulgens*) and the date the product was obtained. These data are distributed by the Land Processes Distributed Active Archive Center (LPDAAC), located at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (lpdaac.usgs.gov).

Vegetation index	Date acquired
Normalized Difference Vegetation Index (NDVI)	March 06, 2003
	September 30, 2003
	November 17, 2003
Enhanced Vegetation Index (EVI)	March 06, 2003
	September 30, 2003
	November 17, 2003
Leaf-Area Index (LAI)	March 06, 2003
	June 26, 2003
	November 26, 2003

Normalized Differential Vegetation Index (NDVI)

Normalized difference vegetation index, NDVI (Huete et al. 2002) provides an indication of vegetation health by quantifying biomass. NDVI is calculated from satellite images as:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$$

where, ρ_{red} and ρ_{NIR} are spectral reflectance measurements acquired in the red and near-infrared regions, respectively.

NDVI for a given pixel results in value ranging from -1 representing no vegetation to +1 representing the highest possible leaf density.

NDVI becomes insensitive to biomass in areas with dense canopies and is influenced mainly by soil reflectance in sparsely vegetated areas (Carlson and Ripley 1997, Huete et al. 2002, Pettorelli et al. 2005). Despite these limitations, NDVI is directly correlated to the biomass productivity and vegetative dynamics (Pettorelli et al. 2005, Reed et al. 1994) and is the most common form of satellite index used to monitor vegetation. However, to compensate for the limitations of NDVI, other forms of vegetation indices were used together with NDVI.

Enhanced Vegetation Index (EVI)

Enhanced vegetation index, EVI (Huete et al. 2002) is an improved form of vegetation index which provides complementary information about variation in vegetation minimizing the insensitivity of NDVI to dense canopy and the residual influence of atmospheric aerosols (Huete et al. 2002, Pettorelli et al. 2005). The adjustment factor used in EVI makes it sensitive to topography (Matsushita et al. 2007). EVI is calculated from satellite images as:

$$EVI = G\frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + L}$$

where, ρ_{red}, ρ_{NIR} and ρ_{blue} are spectral reflectance measurements acquired in the red, near-infrared and blue regions, respectively; L (= 1) is canopy background adjustment, G (= 2.5) is gain factor, C_1 (= 6) and C_2 (= 7.5) are coefficient of aerosol resistance.

Leaf-Area Index (LAI)

Leaf-area index, LAI (sometimes also known as plant-area index – PAI) is the total area of leaves per unit area of the ground (Curran and Steven 1983) and indicates an index of canopy density.

Land Cover

Land cover data were obtained from Global V.1 of the Global Land Cover by National Mapping Organizations (GLCNMO) from the Secretariat of International Steering Committee for Global Mapping (ISCGM). GLCNMO was created by using a

16-day composite of MODIS data (Terra Satellite) acquired in 2003. These data are available at a resolution of 30 arc sec (~ 1 km) and has 20 land cover classes (Table 5) at a global scale based on the land cover classification system developed by the Food and Agriculture Organization (FAO). However, four land cover classes did not occur in Nepal; resulting in only 16 classes. The land cover map was obtained in geographic coordinate system WGS84.

Tree Cover

Tree cover data were also obtained from a global version of a vegetation /percent tree cover map produced by ISCGM. The tree cover data were derived from a 16-day composite MODIS (Terra Satellite) image acquired in 2003 at a resolution of 30 arc sec (~ 1 km). The global percent tree cover represents the density of trees on the ground. The percent tree cover was derived from the most photosynthetic period of the year to account for leaf drop from deciduous trees during dry seasons.

Percent tree cover ranges from 0 to 100 % cover. However, the 8-bit raster layer may contain value between 0 and 255. Therefore, pixel value in this layer ranges between 0 and 100 for tree cover, and 255 for the pixels with "no-data". The percent tree cover map was obtained in geographic coordinate system WGS84.

Multicolinearity Analysis Between Environmental Layers

Intercorrelation among environmental predictors may cause a bias, such as multicollinearity, in prediction (Graham 2003). Multicollinearity occurs primarily when predictor variables are more significantly correlated with each other than they are with a

Table 5. Sixteen coded land cover classes used in a predictive GIS model for the red panda (*Ailurus fulgens*) distribution in Nepal. Land cover classes coded 9, 14, 15 and 19 do not occur in Nepal at 1 km^2 pixel size.

Code	Land cover class
1	Broadleaf evergreen forest
2	Broadleaf deciduous forest
3	Needle-leaf evergreen forest
4	Needle-leaf deciduous forest
5	Mixed forest
6	Tree open
7	Shrub
8	Herbaceous
10	Sparse vegetation
11	Cropland
12	Paddy field
13	Cropland / other vegetation mosaic
16	Bare area, consolidated (gravel, rock)
18	Urban
19	Snow / ice
20	Water bodies

dependent variable. Multicollinearity among predictors in statistical approaches to species distribution modeling has been detected by using cross correlations (e.g., Kumar and Stohlgren 2009), cross correlation in combination to other tools (e.g., Doko 2007), and variance inflation factor (VIF) (e.g., Lai 2009, Negga 2007). In this study, multicollinearity was examined by calculating VIF for each predictor.

VIR indicates inflation in the variance of each regression coefficient compared with a situation of orthogonality. As a rule of thumb, predictors, those with a VIF > 10, are considered under the influence of multicollinearity. A VIF was calculated as:

$$VIF = \frac{1}{1 - R^2}$$

where R^2 is a coefficient of determination.

I generated 200 random points throughout Nepal using Hawth's analysis tool in ArcMap and added these to the 107 red panda occurrence points to calculate a VIF. VIF for all non-categorical environmental predictors was calculated against these 307 points using the linear regression tool in the statistical software SPSS 18.0 (SPSS Inc., Chicago, IL). The variable with the highest VIF was removed and a VIF for the remaining variables was re-calculated. Removal of any one variable significantly changed the VIF of the remaining variables; therefore, the process was reiterated until all the variables had a VIF < 10.

All pre-selected variables excluding tree cover and land cover were subjected to VIF analysis. Land cover was excluded from the VIF analysis because it is a categorical (discrete) variable. Tree cover is an important variable in determining red panda distribution; therefore, it was selected deliberately without testing for correlation with other variables excluding it from the VIF analyses.

MaxEnt Distribution Modeling

A wide range of approaches is available for species distribution modeling which uses both presence-only and presence-and-absence datasets. Common approaches include the generalized linear model (GLM) and generalized additive model (GAM), which use both presence and absence datasets (Guisan et al. 2002, Pearce and Ferrier 2000). Several other approaches are available which involve ecological niche factor analysis (ENFA), e.g., Genetic Algorithm for Rule-set Production – GARP (Stockwell and Peters 1999) and Maximum Entropy – MaxEnt (Phillips et al. 2006). MaxEnt was used in this study because of its better performance and availability of presence-only data.

Maximum Entropy is a general-purpose machine learning method in niche modeling of species using presence-only data (Phillips et al. 2006). This approach uses environmental (ecological) factors as constraints in estimating the probability of a species distribution. Since presence-only points are the most common form of data available in niche modeling, it is an advantage to have a framework based on presence-only data. Predicting a species distribution in MaxEnt is accomplished using the software Maxent version 3.2.1 (http://www.cs.princeton.edu/~schapire/maxent/).

Maxent modeling has been used to predict distribution of a wide range of species (e.g., Asiatic black bear (*Ursus thibetanus japonicus*) and Japanese serow (*Naemorhedus crispus*) (Doko 2007); freshwater diatoms (*Didymosphenia geminate*) (Kumar et al. 2009); *Canacomyrica monticola* (Kumar and Stohlgren 2009); various amphibian species

(Negga 2007); various geckos' species (Pearson et al. 2007). While the advantage of using the Maxent modeling over other techniques is explained by the use of presence-only data; it also gives the best result (Kumar et al. 2009) and performs well with a small number of presence data (Pearson et al. 2007, Kumar and Stohlgren 2009).

MaxEnt uses environmental factors in ASCII formats and the binary species occurrence points in CSV file format. Two files with red panda occurrence points – training file (20 points) and test file (87 points) were entered along with the ASCII environmental layers. The user-specified parameters – regularized multiplier was set to 1, convergence threshold was set to 10^{-5}, and maximum iterations were set to 500. In addition to 21 presence points, additional 10,000 background points were used to determine the MaxEnt distribution. As output, a logistic output format was selected. In addition, response curves and jackknife test of variable importance were also selected.

Processing of Environmental Layers

MaxEnt requires all environmental layers to be in the same coordinate system and spatial resolution and cover the same geographic extent. The environmental layers were obtained from various sources in different coordinate systems and spatial resolutions (pixel size). The layers were processed to a single coordinate system, pixel size and the same geographic extent. Since most of the layers were in geographic coordinate system WGS84 and had a spatial resolution of 1 km, all the other layers were re-projected to geographic coordinate system WGS84 and re-sampled at a pixel size of 1 km. All layers were masked with the boundary of Nepal to ensure the same geographic extent. Preprocessing of spatial layers was carried out in ArcMap 9.3 and Imagine 9.2 (ERDAS Inc., Norcross, GA).

All pre-processed environmental layers were converted into ASCII file format using ArcMap 9.3 for analysis. The presence points were imported in ArcMap and processed in a shapefile format (.shp file). This layer was also re-projected into the same coordinate system as the environmental layers. Then the red panda occurrence points were exported into CSV table format. MaxEnt reads environmental layers in ASCII format (.asc file extension) and occurrence points in CSV table format (.csv file).

Layer Reduction

After removal of auto-correlated predictor variables, the remaining 14 predictor variables were initially used to run the model. Variables with the lowest contribution to the model were removed in a step by step process until a significant loss in test AUC was observed in the ROC curve. A goodness of fit analysis tested whether the final model with the fewest variables differed from the model with all variables. The logistic prediction values were classified into habitat suitability classes and 261 points were generated randomly representing all classes. These points were used to run a goodness of fit test between the two models

The sample error matrix (Story and Congalton 1986) was used to estimate the agreement between the final model and the model with all 14 predictors. In the sample error matrix, the proportion of sample pixel that falls in the same category in both models provides an estimate of overall agreement between the two models.

Threshold of Presence

Following the recommendations of Liu et al. (2005) and Pearson (2007), four thresholds of presence were considered that used presence-only species occurrence data.

1. A fixed threshold value was chosen based on careful observation of probability value of all the presence points for the red panda (Manel et al. 1999, Robertson et al. 2001). I also evaluated a commonly used threshold of 0.5 (Jimenez-Valverde and Lobo 2007).

2. A fixed sensitivity (Pearson et al. 2004) of 90% was chosen which corresponded to a 10% omission rate.

3. The lowest presence threshold (LPT) (Pearson et al. 2006, Philips et al. 2006) was the lowest probability value at a known presence point of the red panda.

4. The threshold of presence was determined at the point where sensitivity and specificity are equal (Pearson et al. 2004).

Model Evaluation

Testing or validation is required to assess the predictive performance of a distribution model. A subset of randomly selected set of 86 points (80% of total presence points) was split from the entire 107 red panda occurrence points to evaluate the model (Fielding and Bell 1997). Both threshold-dependent and threshold-independent methods were used in model evaluation. In the threshold-dependent method, model performance was investigated using extrinsic omission rate (Phillips et al. 2006). The omission rate is a fraction of test localities that fall into pixels not predicted as suitable for red pandas. In the threshold-independent method, the model was evaluated using a ROC (receiver operating characteristics) curve.

Receiver Operating Characteristics (ROC) Curve

A receiver operating characteristics (ROC) curve is a threshold independent method widely used in evaluating species distribution models (Fielding and Bell 1997), which relates to the relative proportion of correctly and incorrectly classified predictions over a wide and continuous rage of threshold levels. A ROC is a graphical plot of "sensitivity" and "1 – specificity" for all possible thresholds. Sensitivity is a measure of the proportion of actual positives identified correctly, while specificity is a measure of the proportion of negatives which are correctly identified.

ROC has proved to be highly correlated with other test statistics, e.g., Cohen's Kappa Coefficient (Cohen 1960), used in evaluating species distribution models (Manel et al. 2001). Both presence and absence data are needed to calculate a ROC. However, presence-only data are used in MaxEnt. In order to overcome this gap, MaxEnt has a built-in function which uses random background points (pseudo-absence) against presence points (Phillips et al. 2006). An area under the curve (AUC) value indicates the efficacy of the model. AUC values ranges between 0 and 1. In the case of a random prediction, the AUC value is 0.5.

Relative Importance of Environmental Variables

MaxEnt assesses the importance of variables to the distribution model. MaxEnt keeps track of the contribution (gain) of each environmental variable to the model output. The relative contribution of each variable is converted into a percent at the end of the training process. However, the percent contributions are only heuristically defined, and especially when there are highly correlated variables, they should be cautiously interpreted.

MaxEnt assesses the relative importance of a predictor variable running jackknife operations. Jackknife operates by sequentially excluding one variable at a time out of the model and running a new model using the remaining variables. It then runs the model using only the excluded variables in isolation.

Conservation Status of Red Panda in Nepal

The protected areas with predicted suitable red panda habitat were identified and the extent of suitable habitat protected in the country was estimated by clipping the predicted area by the protected area boundary. Considering the regions as a unit of comparison, predicted red panda suitable areas were compared with human population growth in the districts with predicted red panda habitat within the last three decades.

Red Panda Habitat Projection at Global Scale

The red panda suitability model derived for Nepal was used to project potential suitable habitat for the red panda throughout its range. The projection was carried out at the same resolution as the model (30 arc sec, i.e., approx. 1 km) and at the geographic extent encompassed by north-east Pakistan, northern India, southern part of Mongolia, the entire area of China, Nepal, Bhutan, Myanmar, Laos, Vietnam, Bangladesh, and part of Taiwan and Thailand.

RESULTS

Multicolinearity Analysis between Environmental Layers

The intercorrelation analysis for 29 environmental predictor variables resulted in 17 layers that were highly correlated and were dropped stepwise. Only 12 layers were obtained with a VIF value < 10 (Table 6).

Layer Reduction

The initial model used all 14 remaining variables, 12 after removing the autocorrelated variables, tree cover and the land cover. The step by step removal of predictor variables resulted in a final model with only 10 variables. Spring EVI, monsoon NDVI, winter NDVI and monsoon EVI were removed respectively in each step based on their minimal contributions to the model. Other variables made significant contributions to the model, and therefore, were not removed.

My decision of selecting a model with only 10 predictor variables was based on two factors. First, goodness of fit showed no significant deviation between the two models ($\chi^2 = 4.385$, $P = 0.223$, df = 3). Second, the sample error matrix showed an overall agreement between the two models of 88.12%.

Table 6. Twelve variables in decreasing variance inflation factor (VIF) order selected for use in a predictive GIS model for the red panda (*Ailurus fulgens*) distribution in Nepal.

Predictor variables	VIF
Spring NDVI	8.056679
Monsoon NDVI	10.73685
Winter NDVI	8.469501
Spring EVI	8.868479
Monsoon EVI	7.298795
Winter EVI	5.330023
Temperature Seasonality	3.726506
Precipitation Seasonality	5.849006
Precipitation of Warmest Quarter	2.983946
Precipitation of Coldest Quarter	2.842485
Elevation	3.396977
Winter LAI	2.671713

Red Panda Distribution Model

The probabilistic distribution model produced a red panda potential distribution map which was close to the known distribution of the red panda in Nepal (Mahato 2004a, Mahato 2004b, Yonzon et al. 1997, Yonzon and Hunter 1989, Regmi, 2009, Subedi 2009, Stephens 2003, RPN 2006-2009). A narrow irregular belt of suitable habitat for the red panda was predicted in a west to east direction mainly along the northern districts of the country. The probability of distribution of red panda was predicted as higher in the eastern part of the country while tending to decrease towards the west (Fig.5). The total area predicted as suitable habitat for the red panda was dependent on the threshold of presence selected.

Threshold of Presence

A threshold of 0.5 yielded a high omission rate of 57% (Fig.6). A fixed sensitivity of 90% corresponded to the logistic threshold value of 0.08 (Fig.6). The lowest presence threshold, LPT was observed at a logistic value of 0.23 (Fig.7), which yielded an omission rate of 29% (Fig.7). Sensitivity and specificity were equal at a logistic threshold of 0.094.

Based on a careful observation of logistic probability of presence, a fixed threshold of 0.1 was determined. At this threshold, the omission rate was estimated at 11.6% (Fig.6). The fixed threshold of 0.1 is very close to the threshold at which both specificity and sensitivity are equal, and it also gave an omission rate closer to the fixed sensitivity of 90%. Therefore, this threshold was used to calculate the predicted presence area for red pandas.

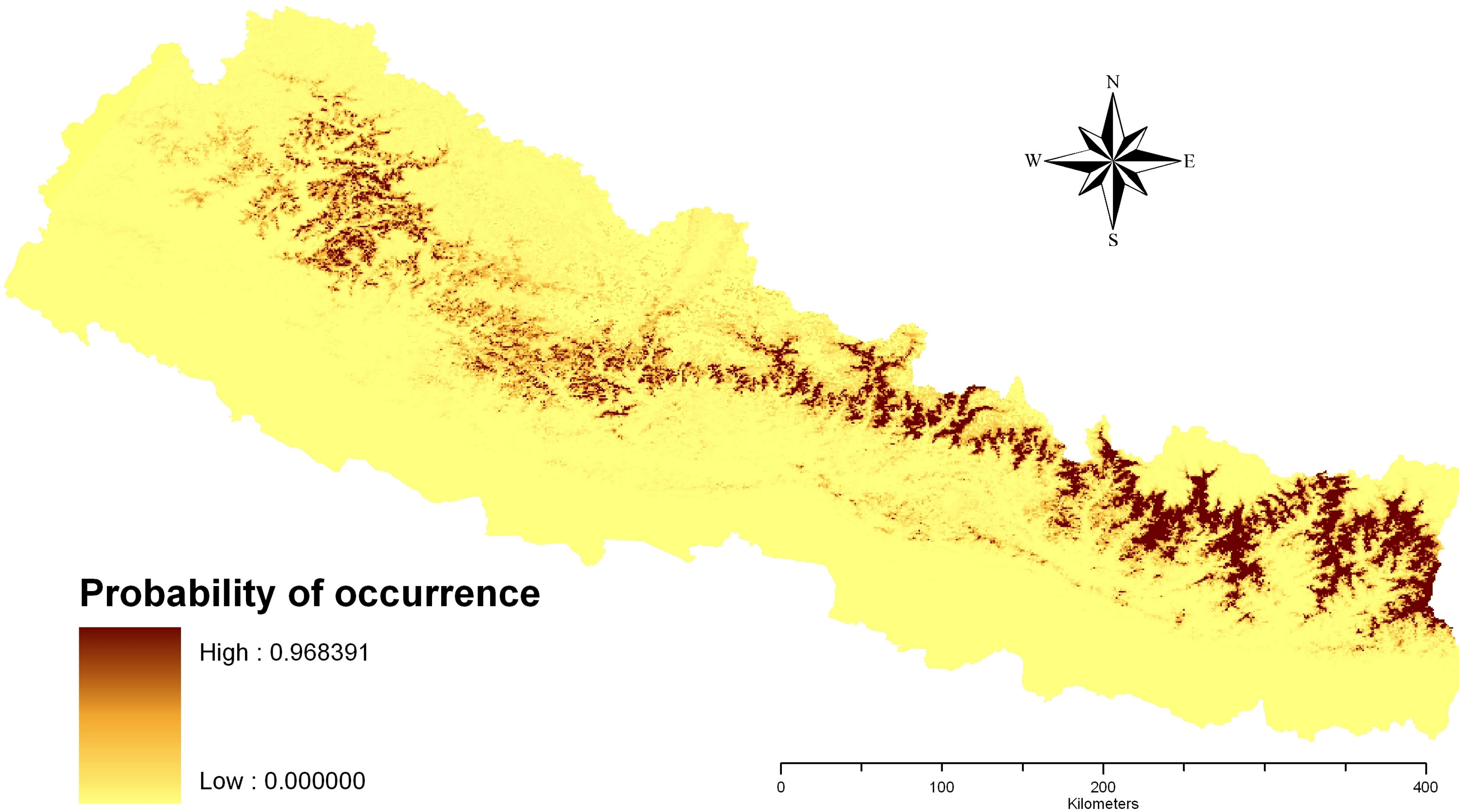

Figure 5. Predicted logistic probability for red panda (A*ilurus fulgens*) occurrence in Nepal.

Habitat Suitability Classes

After a threshold of red panda presence was determined, three arbitrary probability classes were defined based on careful observation of the predicted probability of all presence points corresponding with habitat suitability types (Table 7). The part of area with a probability of < 0.1 was classified as an unsuitable area for the red panda. The extent of high suitability area (probability > 0.7) was estimated to be 1,387 km^2 while moderately suitable area was estimated at 10,117 km^2 (Table 8, Fig.8). The total extent of area estimated at a threshold of 0.1 was approximately 20,400 km^2 (Table 8).

At the 0.5 threshold, the extent of suitable area for red panda was estimated to be 3,612 km^2 (Fig.9). However, due to a very high omission rate of 57% (Fig.6), this threshold was not used.

Model Evaluation

The red panda distribution model (Fig.8, Fig.10) predicted potential suitable habitat for the red panda at a high success rate with a low omission rate of 11.6%. The ROC curve also indicated higher accuracy yielded by the model. The AUC on the training data was 0.9823, while the AUC on the test data was 0.9458 (Fig.12) with a standard deviation of 0.0115. The AUC values ranged between 0.5 and 1, where an AUC of 0.5 was equal to a random prediction.

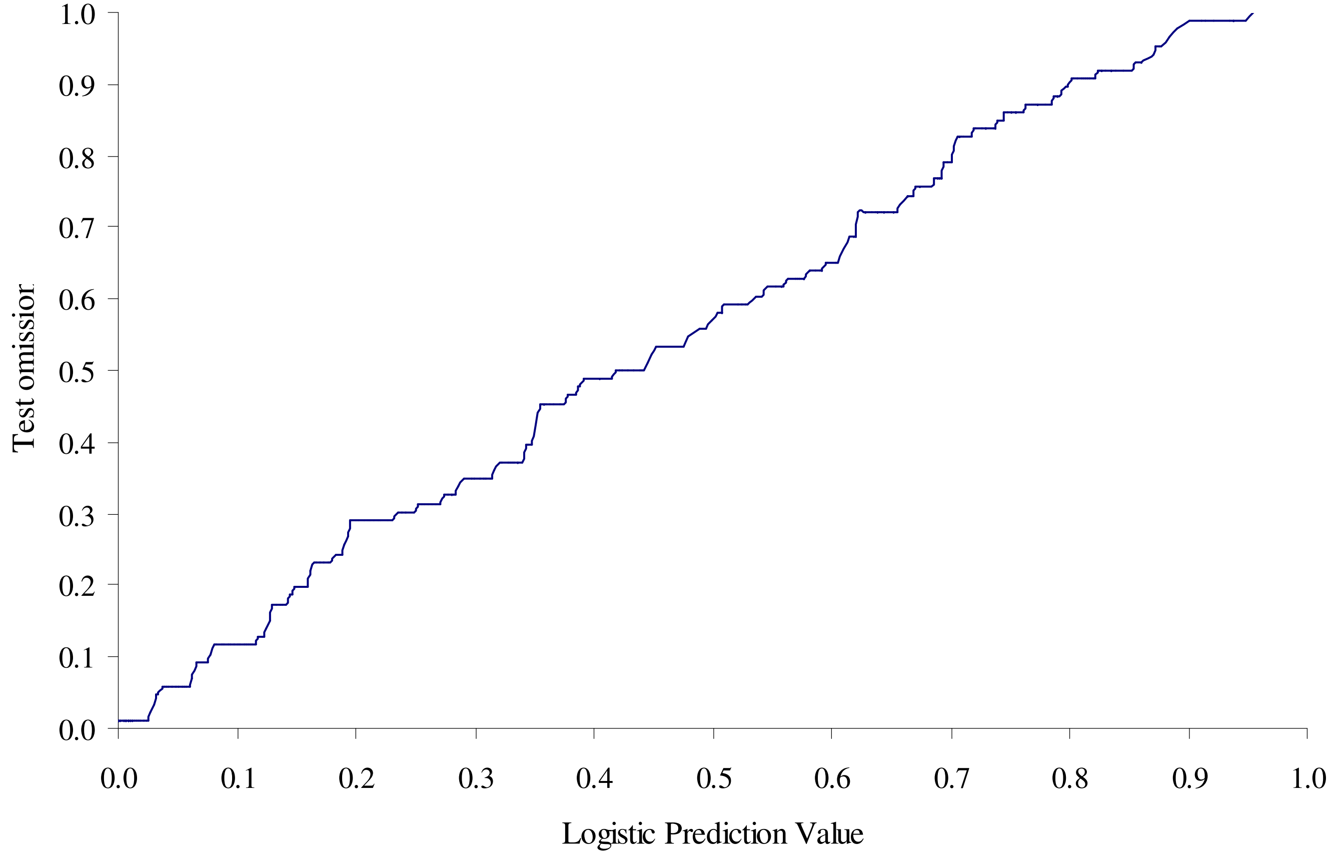

Figure 6. Omission rate at various logistic thresholds for the red panda (*Ailurus fulgens*) occurrence test points.

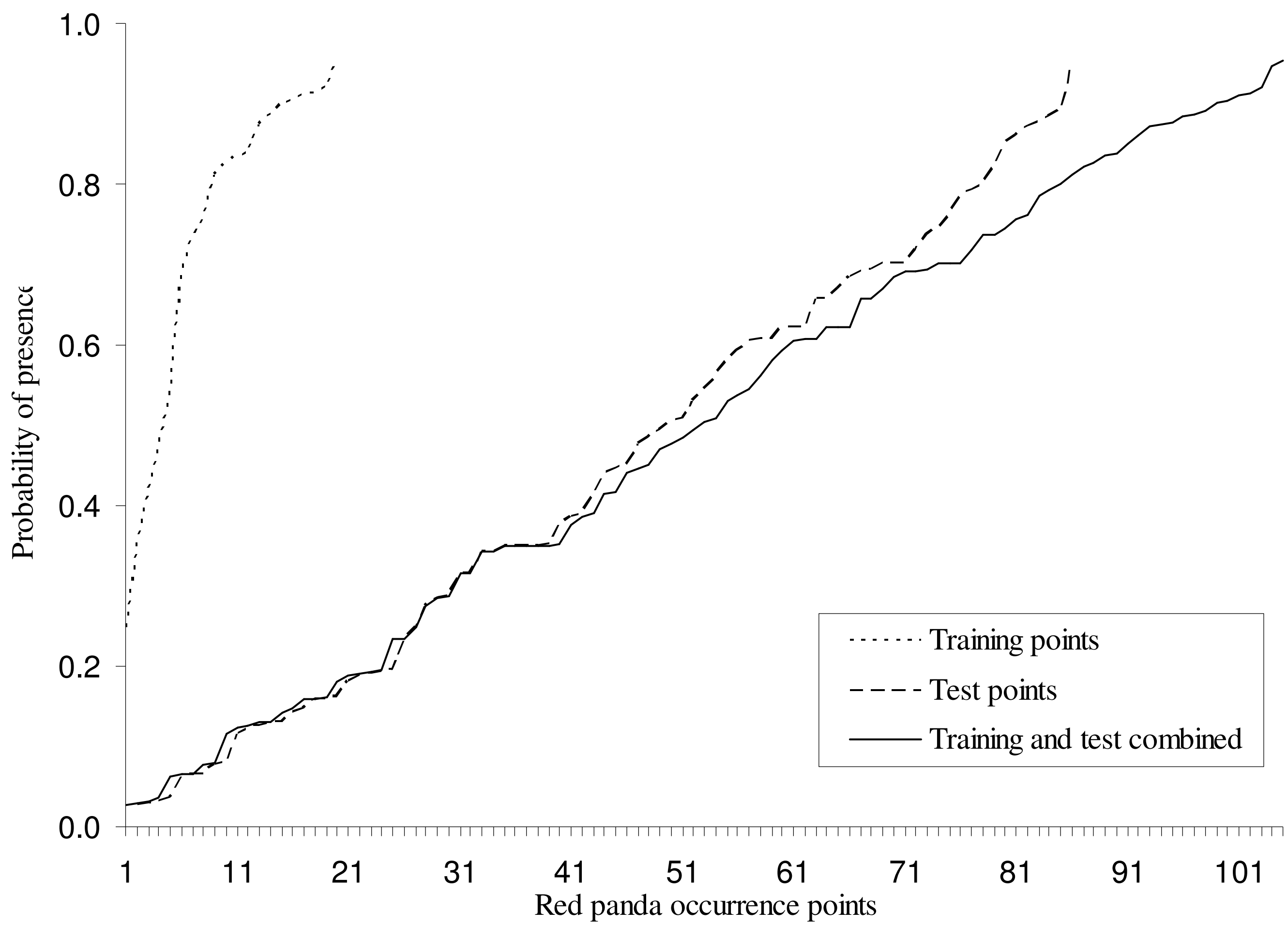

Figure 7. Predicted probability value for red panda (*Ailurus fulgens*) occurrence points.

Table 7. Thresholds used to group the predicted logistic output into classes.

Habitat class	Probability value
No habitat (Extremely low suitability)	< 0.1
Less suitable habitat (Low suitability)	0.1 – 0.2
Moderately suitable habitat (Medium suitability)	0.2 – 0.7
Suitable habitat (High suitability)	> 0.7

Table 8. Predicted size of suitable areas for the red panda (*Ailurus fulgens*) in Nepal based on different classes of suitability.

Habitat class	Area (km^2)
Suitable habitat	1,387
Moderately suitable habitat	10,117
Less suitable habitat	8,893
Total predicted area	20,397

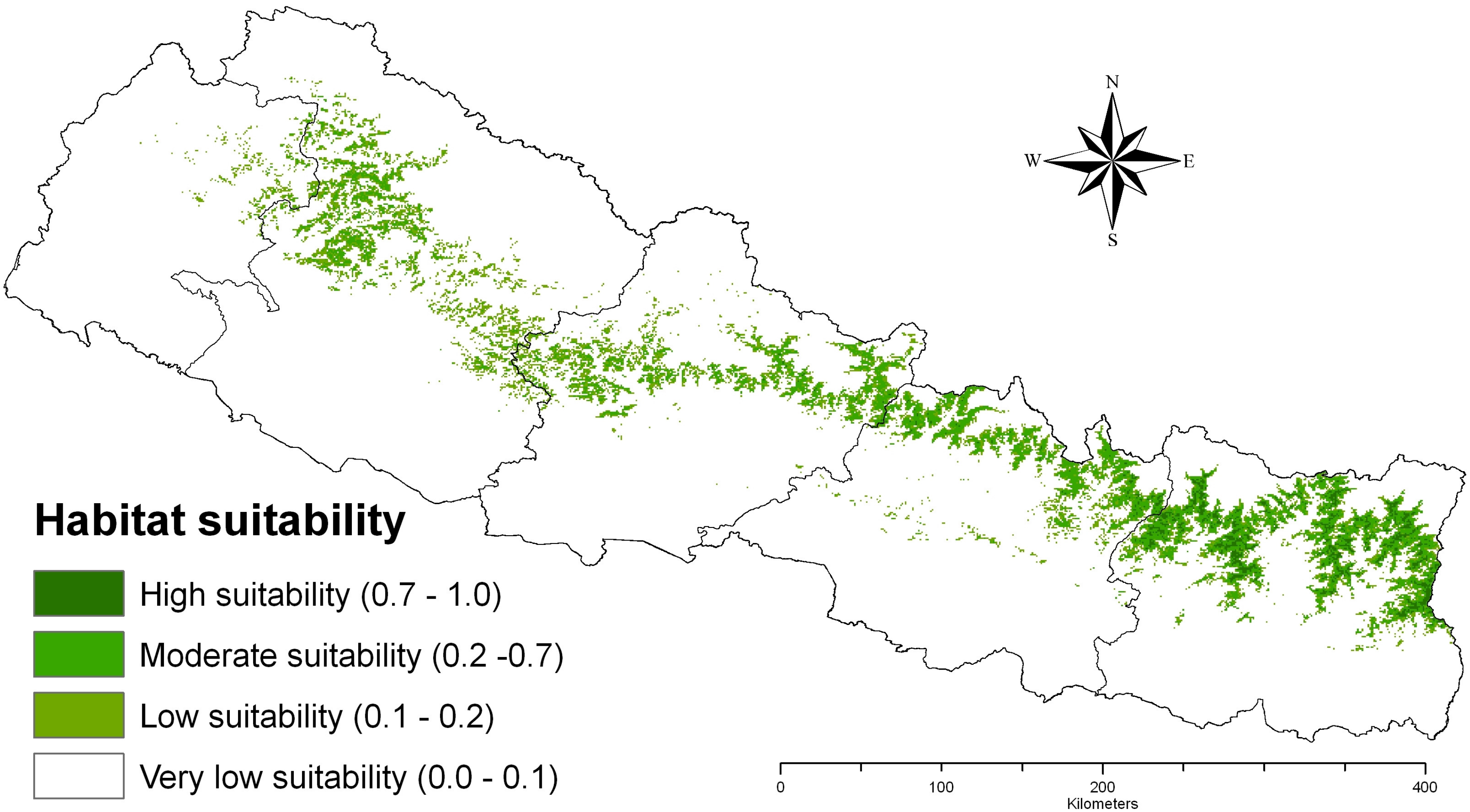

Figure 8. Predicted potential suitable habitat for the red panda (*Ailurus fulgens*) in Nepal (with regional boundaries included).

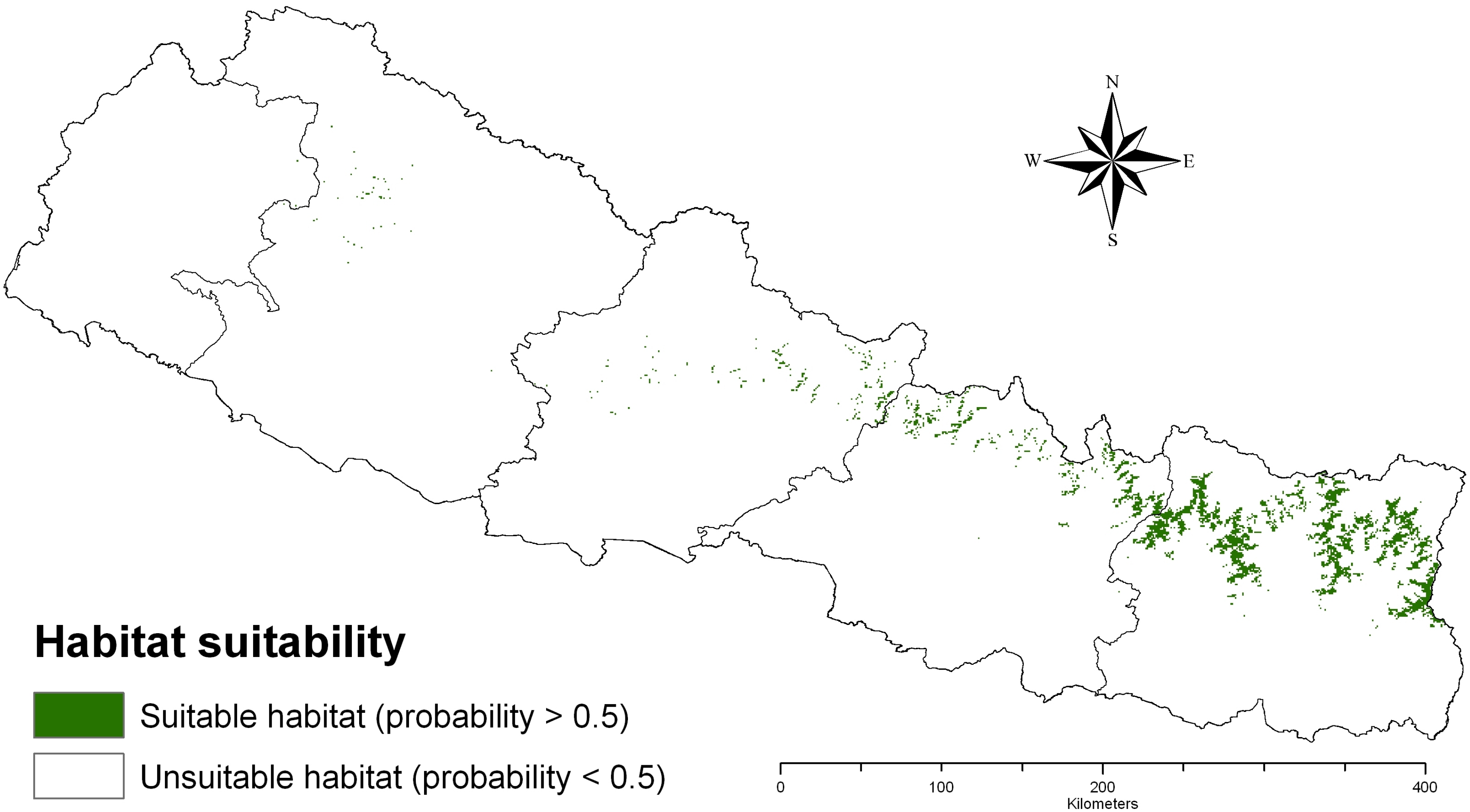

Figure 9. Predicted potential suitable habitat at 0.5 threshold for red panda (*Ailurus fulgens*) in Nepal (with regional boundaries included).

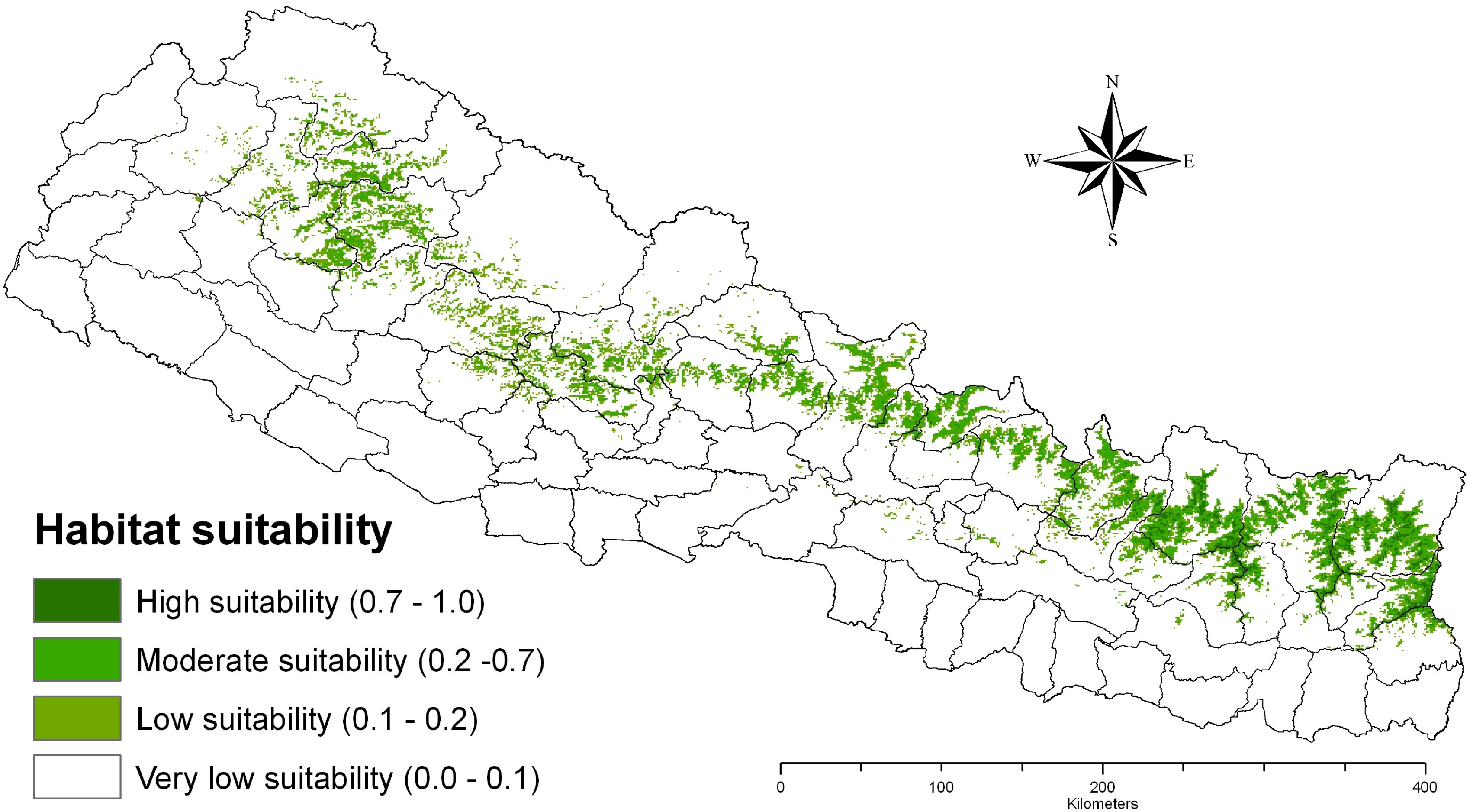

Figure 10. Predicted potential suitable habitat for the red panda (*Ailurus fulgens*) in Nepal (with political district boundaries depicted).

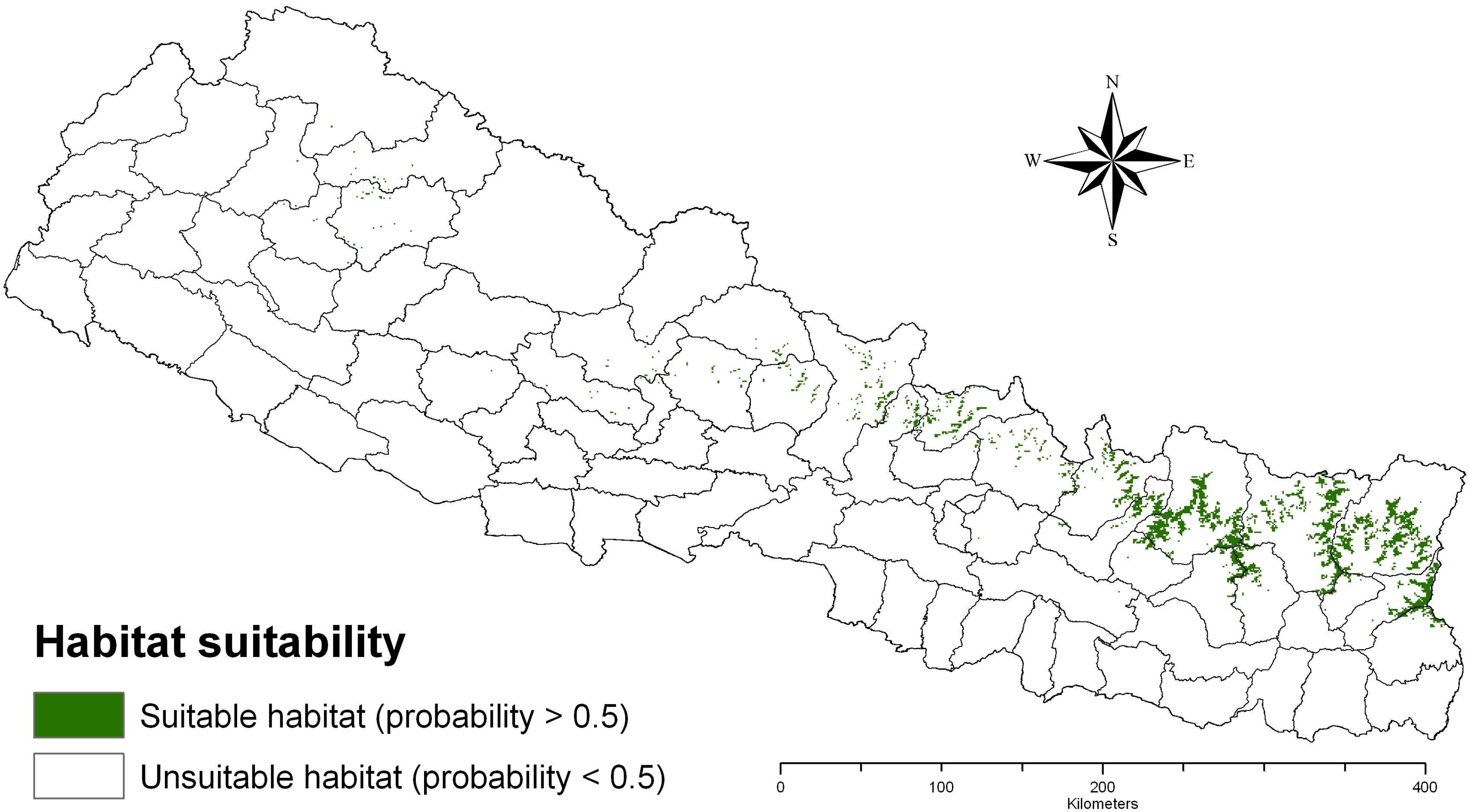

Figure 11. Predicted potential suitable habitat at a 0.5 threshold for the red panda (*Ailurus fulgens*) in Nepal (with political district boundaries depicted).

Relative Importance of Environmental Variables

Elevation was the most important predictor of the red panda distribution (Table 9) with a total contribution of 37.3% followed by temperature seasonality (20.2%) and tree cover (12.7%).

Jackknife Test

The jackknife evaluation of relative importance of environmental variables indicated elevation made the highest contribution to the red panda distribution followed by temperature seasonality (Fig.13). Elevation had the highest AUC gain when run in isolation (> 0.91) and the relative loss in AUC was highest when the model was run without it. AUC gain was the lowest when elevation was removed compared to the removal of any other single variable. A similar pattern was observed for temperature seasonality but with a lower magnitude after elevation. Although the AUC loss was small after removing temperature seasonality, it had the highest gain after elevation when run in isolation. Precipitation in the coldest quarter followed by precipitation seasonality was the most important factors after elevation and temperature seasonality. These two variables had the highest AUC gain (both > 0.72) in isolation after elevation and temperature seasonality and AUC losses were also significant after removal of these variables.

Table 9. Relative percent contribution of 10 environmental variables (layers) to the red panda (*Ailurus fulgens*) distribution in Nepal.

Layers	Contribution (%)
Elevation	36.4
Temperature seasonality	21.2
Tree cover	12.8
Winter EVI	6.1
Land cover	5.8
Winter LAI	5.8
Precipitation of coldest quarter	4.3
Precipitation of warmest quarter	3.6
Precipitation seasonality	3.1
Spring NDVI	1.1

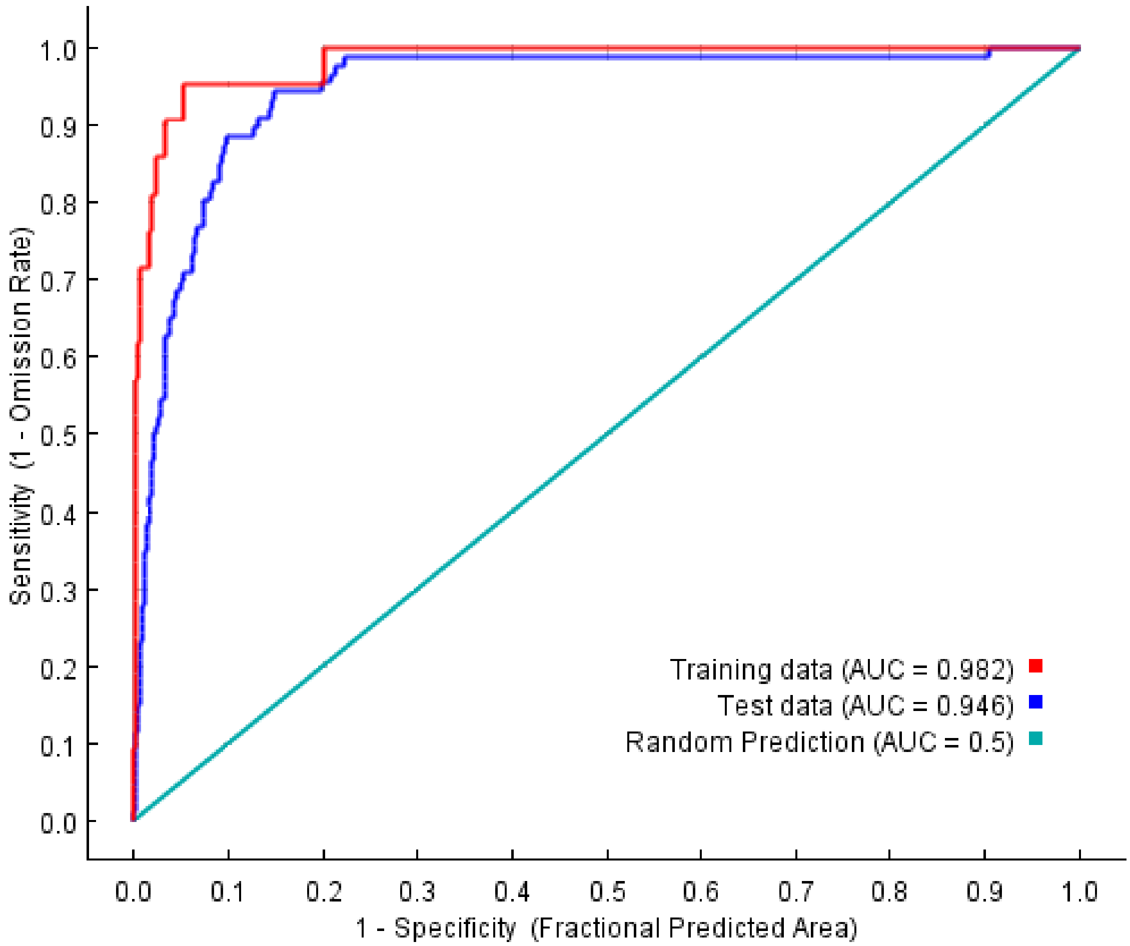

Figure 12. Receiver operating characteristic curve (Sensitivity vs. 1 – Specificity) on red panda occurrence training and test data for a predictive model in red panda.

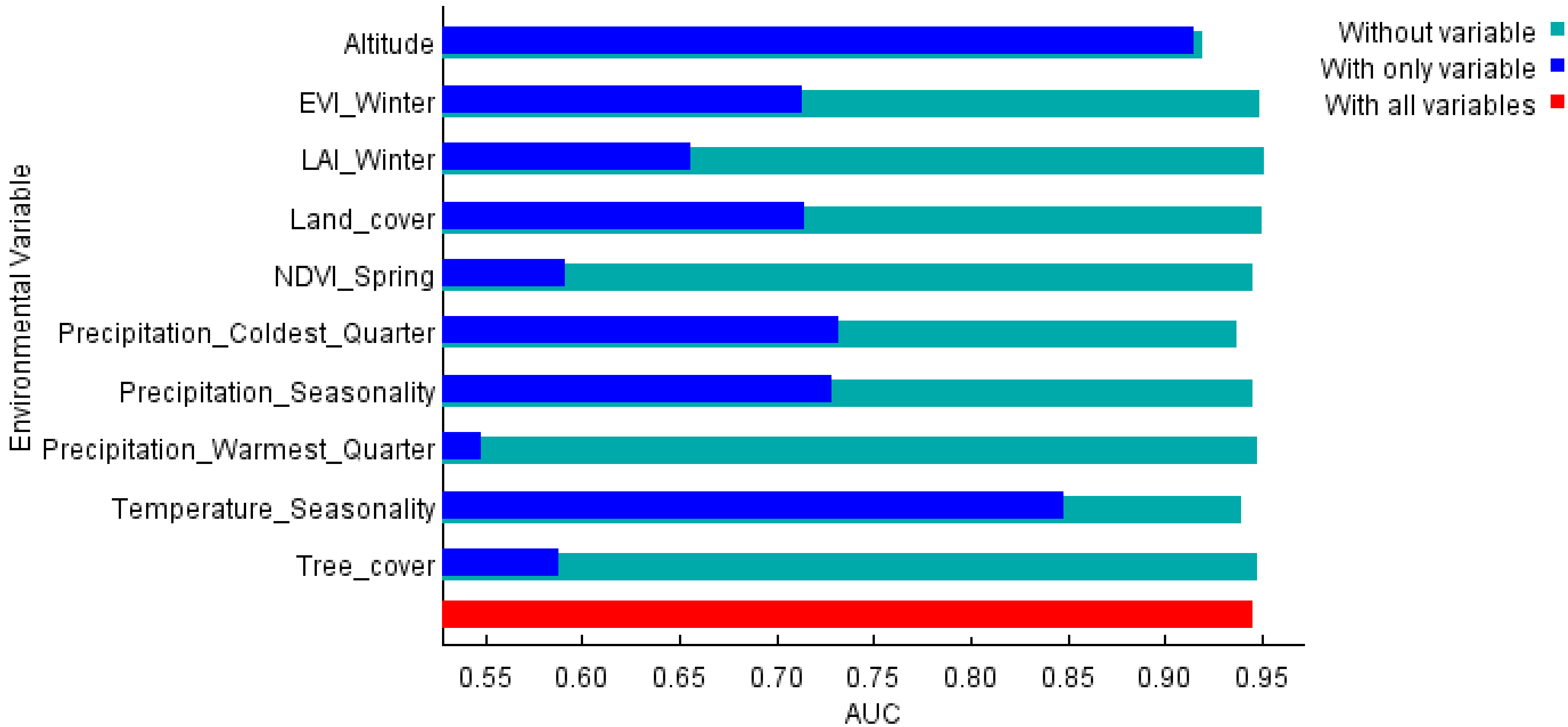

Figure 13. Result of jackknife test for relative importance of environmental variables using area under the curve (AUC) on test data for predictive GIS model for the red panda (*Ailurus fulgens*) distribution in Nepal.

Response of Environmental Factors to Red Panda Distribution

Elevation, the variable with highest relative importance to the MaxEnt model, had the highest response at a value of 3,000 m (Fig.14). The response of tree cover was directly proportional to its magnitude, though its response saturated around 75% cover (Fig.15). The response to the EVI in the winter season was observed between positive and negative 0.4 with its highest response around an EVI value of 0 (Fig.16). Only four categories of land cover types since land cover is a categorical variable, showed a response to the model. Broadleaf deciduous forest had the highest response followed by needle-leaf evergreen forest and mixed forest, both with a similar magnitude of response, and shrub with the lowest response (Table 5, Fig.17). The response of winter LAI was observed between 0 and 40, with the highest response near a value of 10 (Fig.18). The response of precipitation in the coldest quarter was the highest close to 50 and the response decreased for higher precipitation and saturated at 160 (Fig.19). The highest response of precipitation, 1100, was during the warmest quarter (Fig.20). The response of spring NDVI gradually increased up to a value of 0.5 and then sharply decreased (Fig.21).

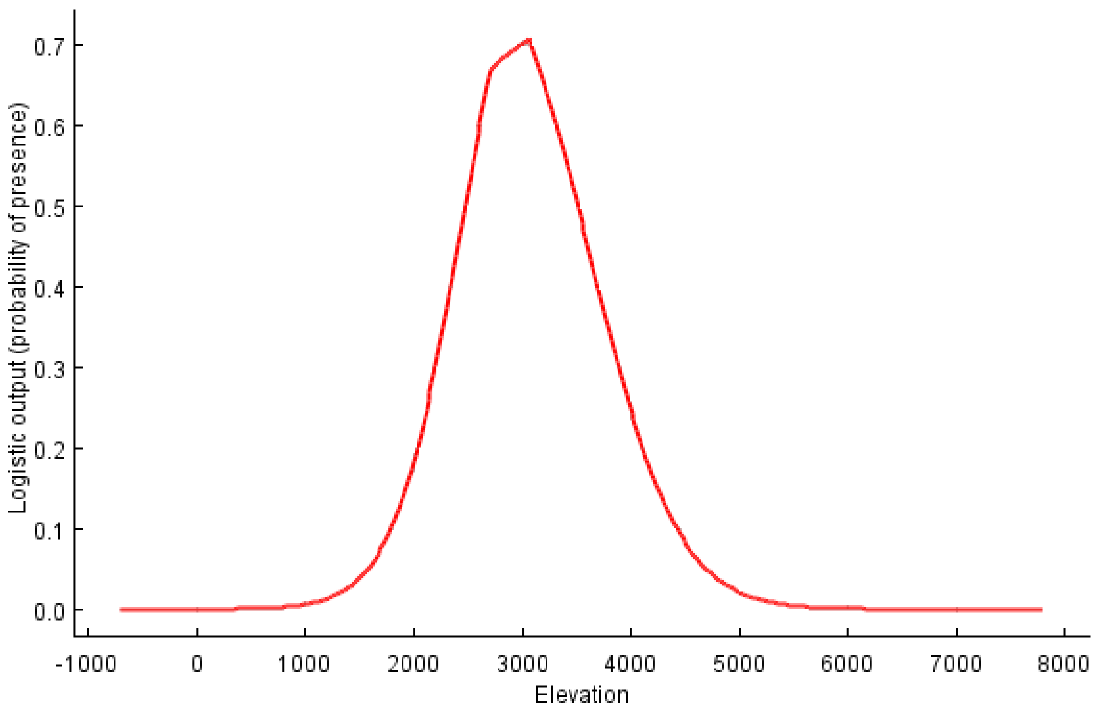

Figure 14. Response of the red panda (*Ailurus fulgens*) presence to elevation (in meters).

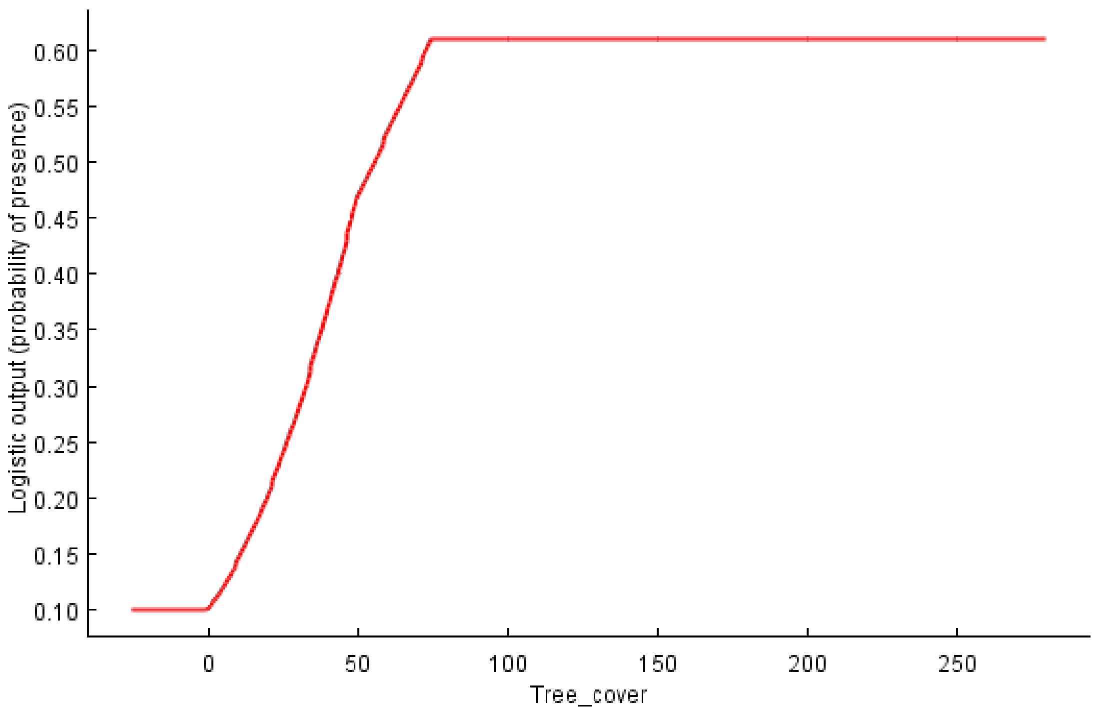

Figure 15. Response of the red panda (*Ailurus fulgens*) presence to tree cover.

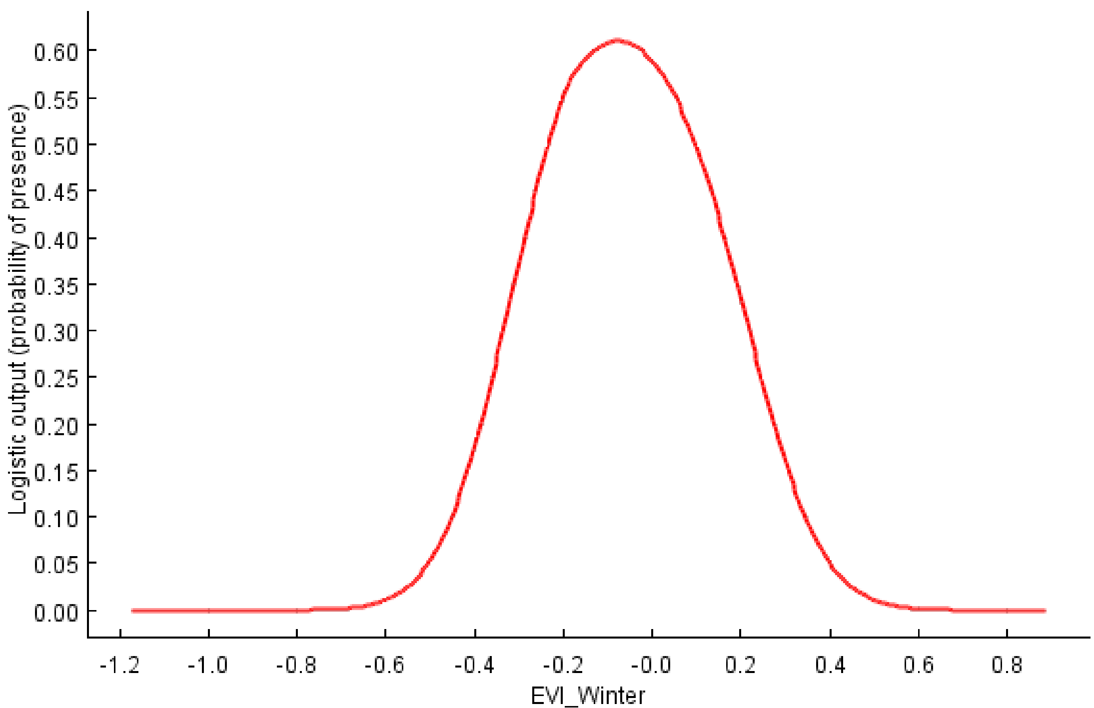

Figure 16. Response of the red panda (*Ailurus fulgens*) presence to winter enhanced vegetation index (EVI).

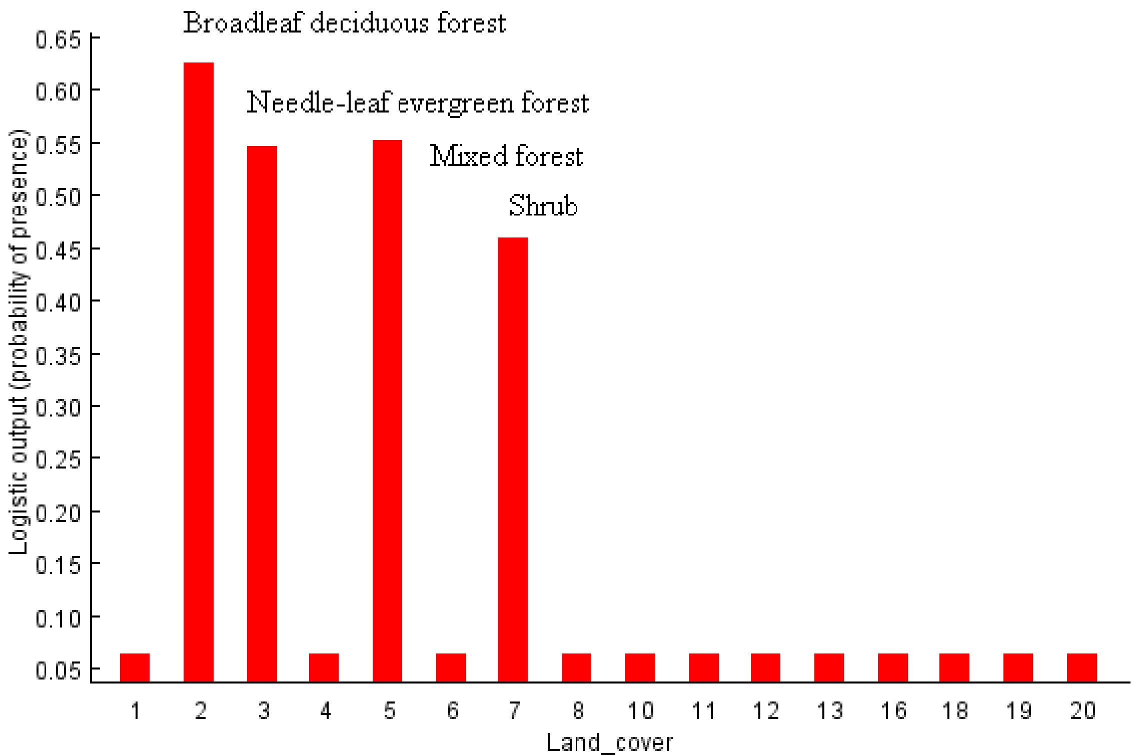

Figure 17. Response of the red panda (*Ailurus fulgens*) presence to land cover (land cover code: 2–broadleaf deciduous forest, 3–needle-leaf evergreen forest, 5–mixed forest, 7–shrub).

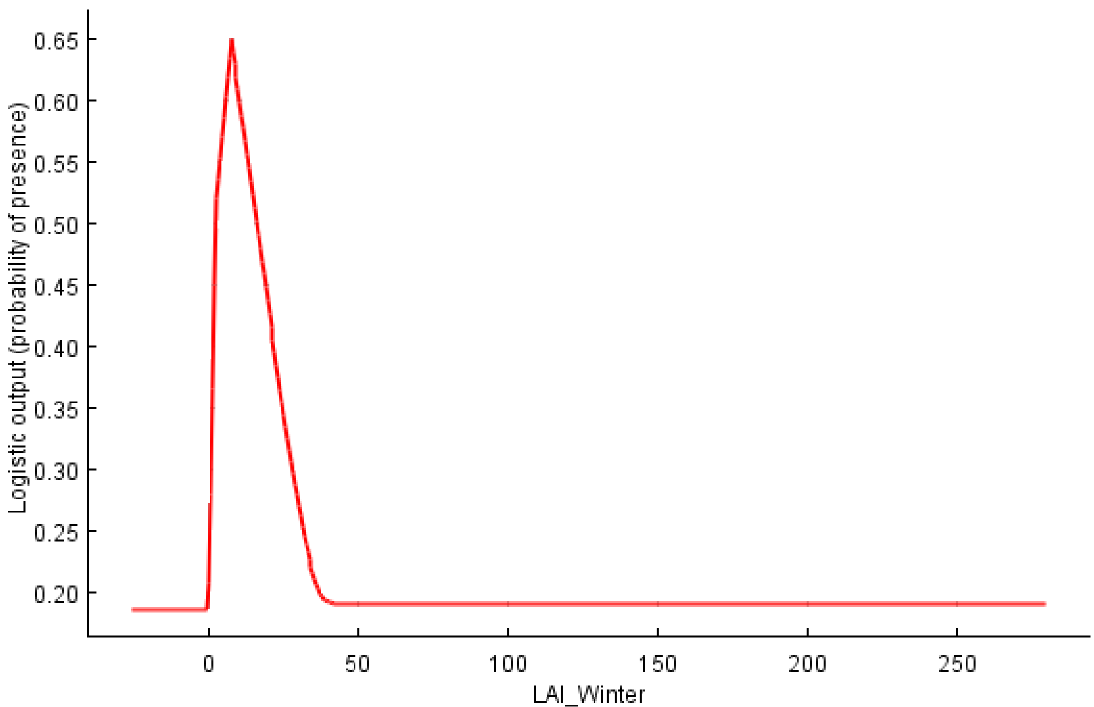

Figure 18. Response of the red panda (*Ailurus fulgens*) presence to winter leaf-area index (LAI).

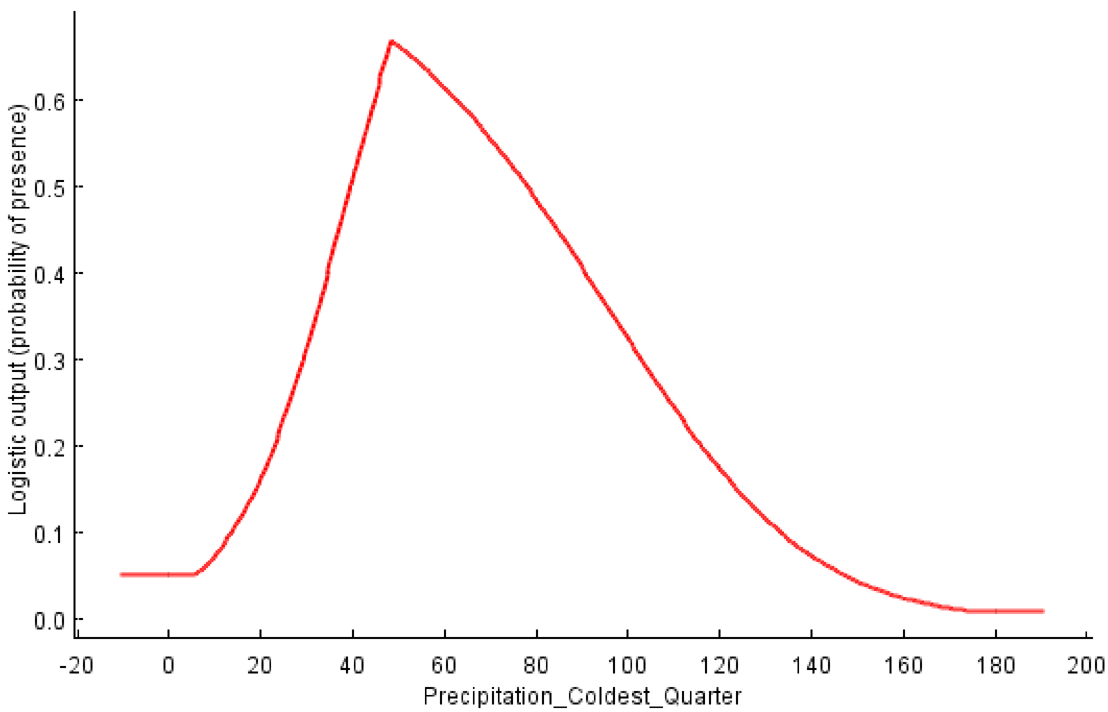

Figure 19. Response of the red panda (*Ailurus fulgens*) presence to precipitation (in mm) in the coldest quarter.

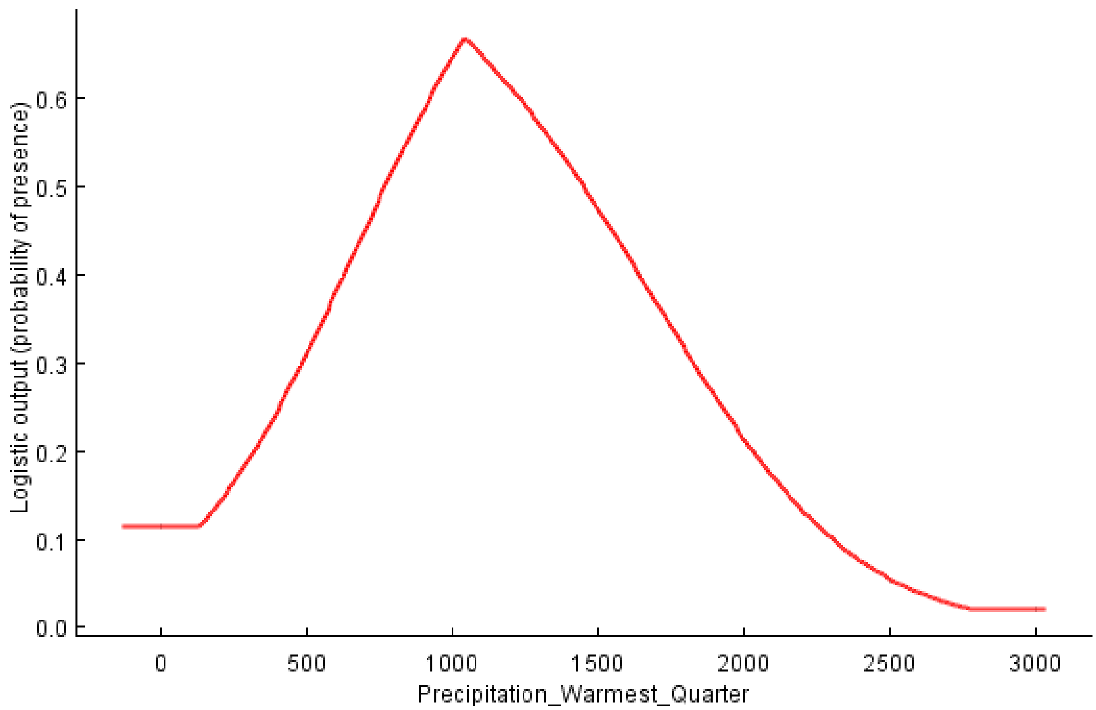

Figure 20. Response of the red panda (*Ailurus fulgens*) presence to precipitation (in mm) in warmest quarter.

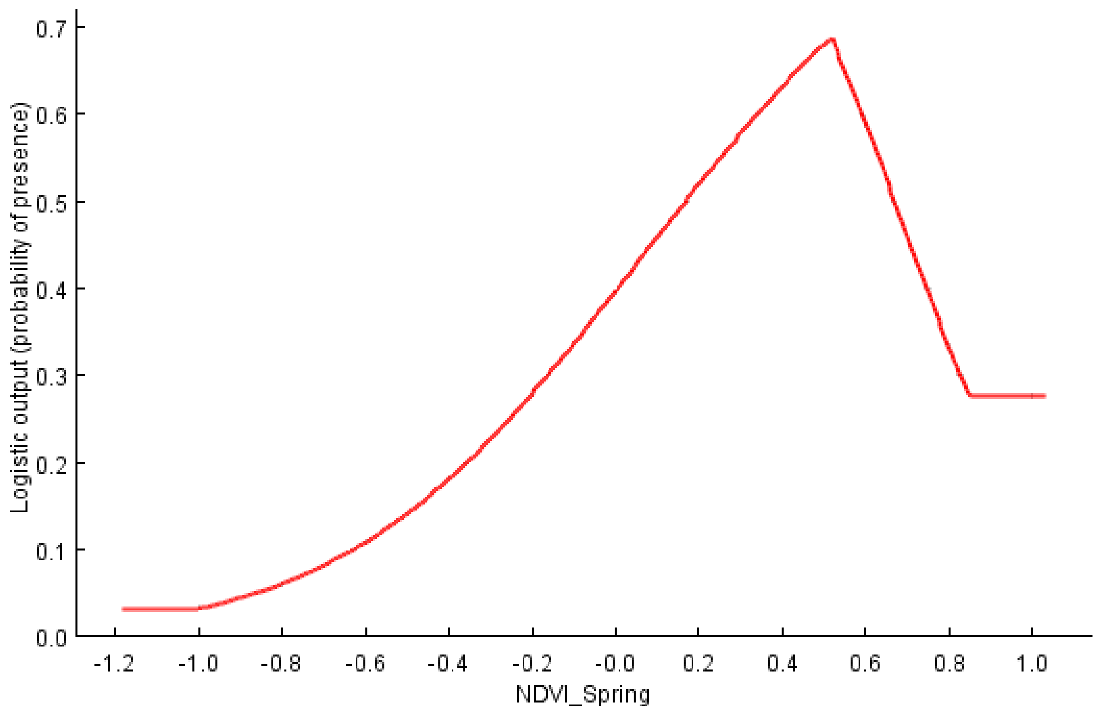

Figure 21. Response of the red panda (*Ailurus fulgens*) presence to spring normalized differential vegetation index (NDVI).

Conservation Status of Red Panda in Nepal

The model (Fig.22) predicted suitable habitat for the red panda in nine (Kanchenjunga Conservation Area, Makalu Barun National Park, Sagarmatha National Park, Langtang National Park, Manaslu Conservation Area, Annapurna Conservation Area, Dhorpatan Hunting Reserve, Rara National Park, and Khaptad National Park) of Nepal's 11 protected montane areas. However, at a 0.5 threshold, suitable habitat for red pandas would only be predicted in 7 protected areas (excluding Dhorpatan Hunting Reserve and Khaptad National Park). Less than a quarter (4,602 km^2 area) of the total predicted area of suitable habitat is protected (Table 10, Fig.23).

Table 10. Size and percent of predicted red panda (*Ailurus fulgens*) habitat under protected areas based on habitat classes.

Habitat class	Area (km^2)	Protected
Suitable habitat	298	21.5 %
Moderately suitable habitat	2,405	24 %
Less suitable habitat	1,899	21 %
Total predicted area	4,602	22.5 %

The proportions of suitable red panda habitat predicted by the model in different regions are summarized in Table 11. The western region has the largest proportion (40.5%) of red panda habitat protected while the far-western and mid-western regions had the lowest. However, the western (36.5 %) and eastern (36.2 %) regions had the largest proportion of protected red panda habitat in the country.

A higher human population growth occurred between 1971 and 2001 in districts with suitable red panda habitat in all five regions (Table 11). The most extreme growth in human population density was in the central region which has relatively less red panda habitat. However, the red panda habitat in the eastern region is under threat due to high human population growth (67%).

While the eastern region has the largest area (36.4 %) of predicted suitable habitat for red pandas, only 22.5 % of the suitable red panda habitat in the region is protected areas. Hence a large proportion of the suitable red panda habitat is still unprotected in this region. However, a greater proportion of high probability red panda distribution areas fall within this region, indicating highly suitable red panda habitat exists in this region. This region also has one of the highest human population growth rates (67% growth since 1971, Table 11) and it continues to grow. The increasing human population in the region, hence, exerts high anthropogenic pressure on the unprotected, highly suitable red panda habitats in eastern Nepal.

Table 11. Percents of red panda (*Ailurus fulgens*) suitable habitat, protected habitat and human population change with size and number of protected areas in five regions of Nepal. (* The Dhorpatan Hunting Reserve falls into two regions).

	Eastern	Central	Western	Mid-western	Far-western
Population growth (1971 – 2001)	67 %	75 %	34 %	30 %	51%
Population growth (1991 – 2001)	12 %	18 %	25 %	19 %	19 %
Suitable habitat (> 0.2)	47.6 %	20 %	17.5 %	13.9%	1.0 %
Suitable habitat (0.1 – 0.2)	21.7 %	16.6 %	24.2 %	32.8 %	4.7 %
Total suitable habitat area	7,416 km^2	3,777 km^2	4,162 km^2	4,510 km^2	535 km^2
Proportion of total red panda habitat	36.4 %	18.5 %	20.4 %	22.1 %	2.6 %
Number of protected area	3	1	3*	3*	1
Proportion protected in the region	22.5 %	22.2 %	40.5 %	8.9 %	3.8 %
Proportion of protected	36.2 %	18.2%	36.5 %	8.7 %	0.4 %

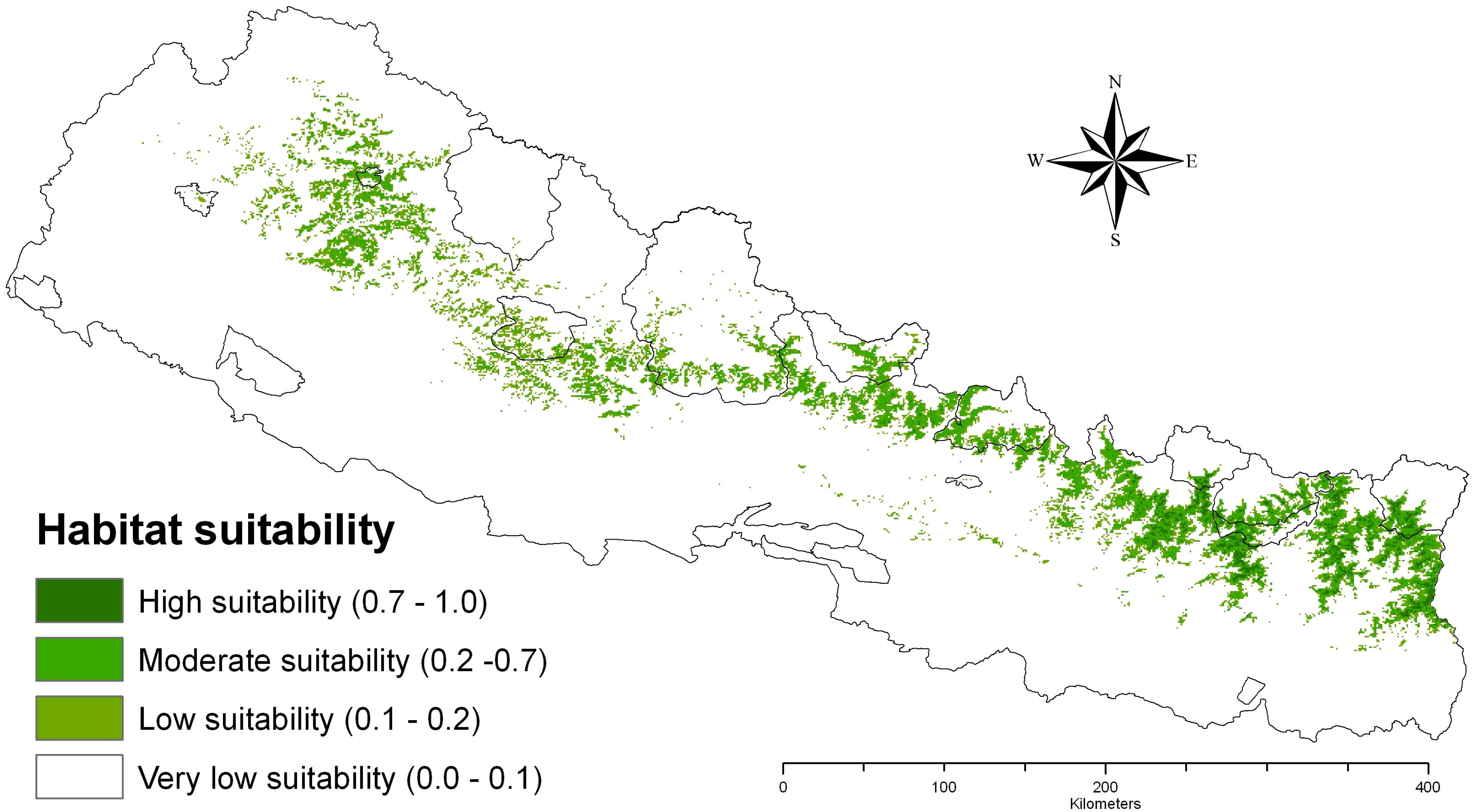

Figure 22. Predicted potential suitable habitat for the red panda (*Ailurus fulgens*) within protected areas in Nepal.

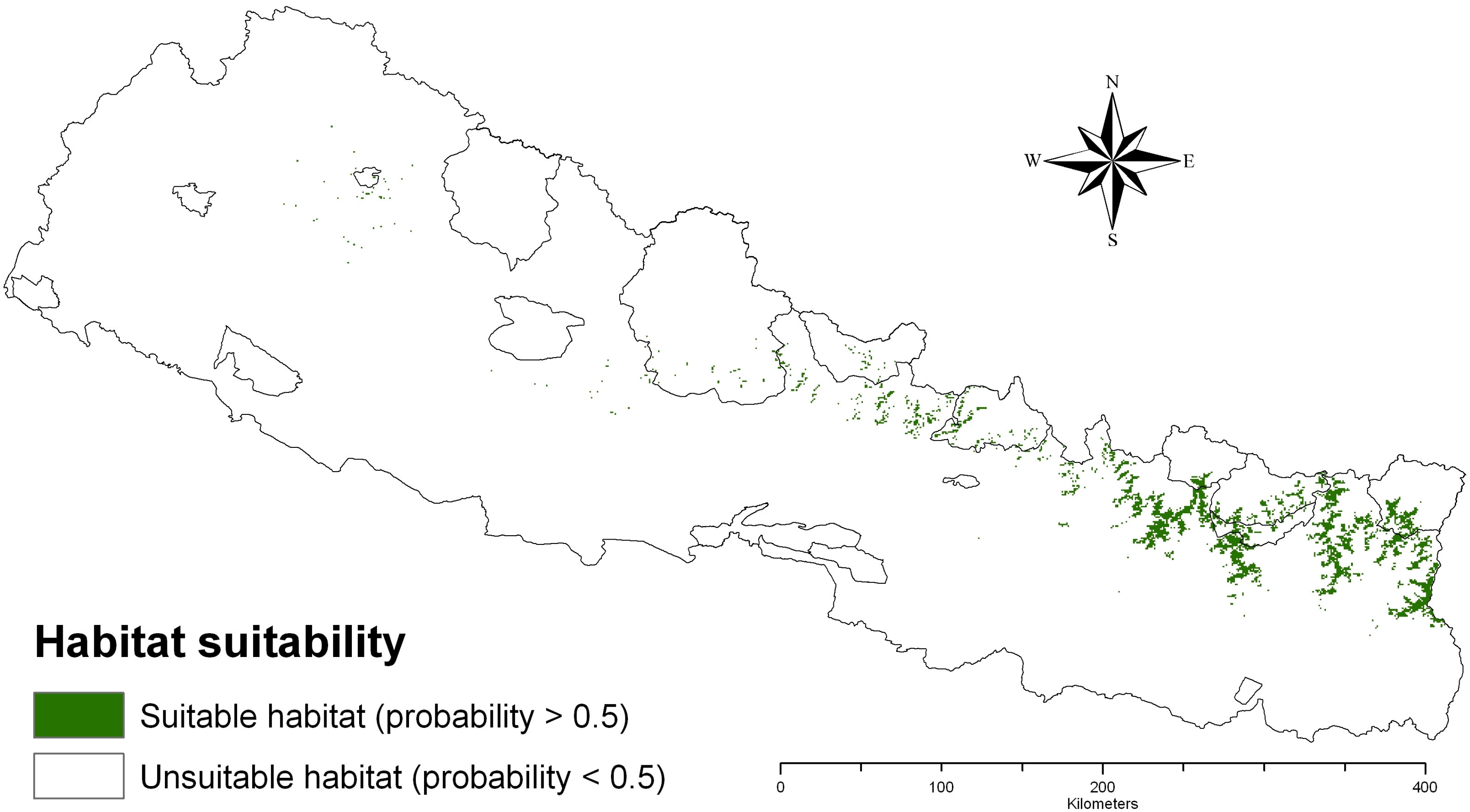

Figure 23. Predicted potential suitable habitat at 0.5 threshold within protected areas for the red panda (*Ailurus fulgens*) in Nepal.

Red Panda Habitat Projection at Global Scale

I also projected the distribution model to an area larger than Nepal to predict the red panda distribution throughout Asia. A total area of 425,700 km^2 (Table 12) was predicted as suitable red panda habitat in seven countries: Nepal, India, Bhutan, China, Myanmar (Burma), Laos and Vietnam (Fig.24). The projected model predicted a global distribution of the red panda as far west as western Nepal and as far east as northwestern Vietnam. Based on a commonly used threshold of 0.5, predicted suitable habitat occurs in approximately 34,380 km^2 mostly in Nepal and China with smaller areas in Bhutan, India, Myanmar and Vietnam (Fig.25).

I projected the prediction of the red panda potential distribution to other countries based on the red panda occurrence in Nepal. This may lead to inaccurate and bias predictions in the other countries. Therefore, I used two classes to roughly estimate the extent of the red panda distribution in these countries (Table 12). I also estimated the proportion of red panda habitat in the different countries. China had the largest proportion of red panda habitat (72%) followed by India (9.5%). Nepal had only 5.5% of the total suitable area for the red panda. Laos had a smallest proportion of predicted red panda habitat (0.5%, Table 13).

Table 12. Proportion of potential suitable habitat for the red panda (*Ailurus fulgens*) throughout Asia.

Class of habitat	Area (sq km)
Suitable habitat (probability 0.2 – 1.0)	199,674
Marginal habitat (probability 0.1 – 0.2)	226,032
Total predicted area	425,706

Table 13. Proportion of predicted red panda (*Ailurus fulgens*) habitat in Asian countries.

Country	Proportion
China	72 %
India	9.5 %
Burma	6.5 %
Nepal	5.5 %
Bhutan	5 %
Vietnam	1%
Laos	0.5 %

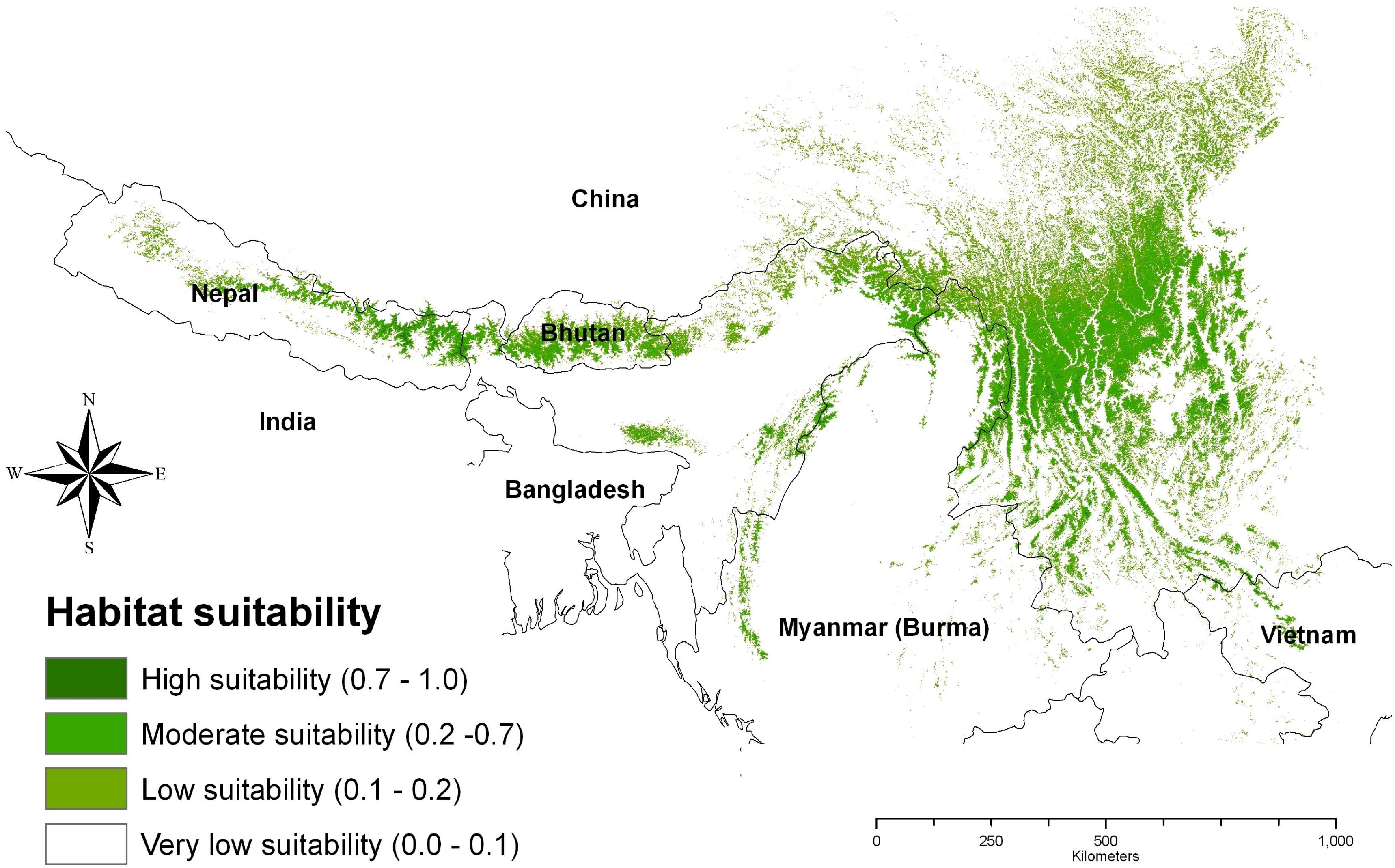

Figure 24. Predicted potential suitable habitat for the red panda (*Ailurus fulgens*) in Asia.

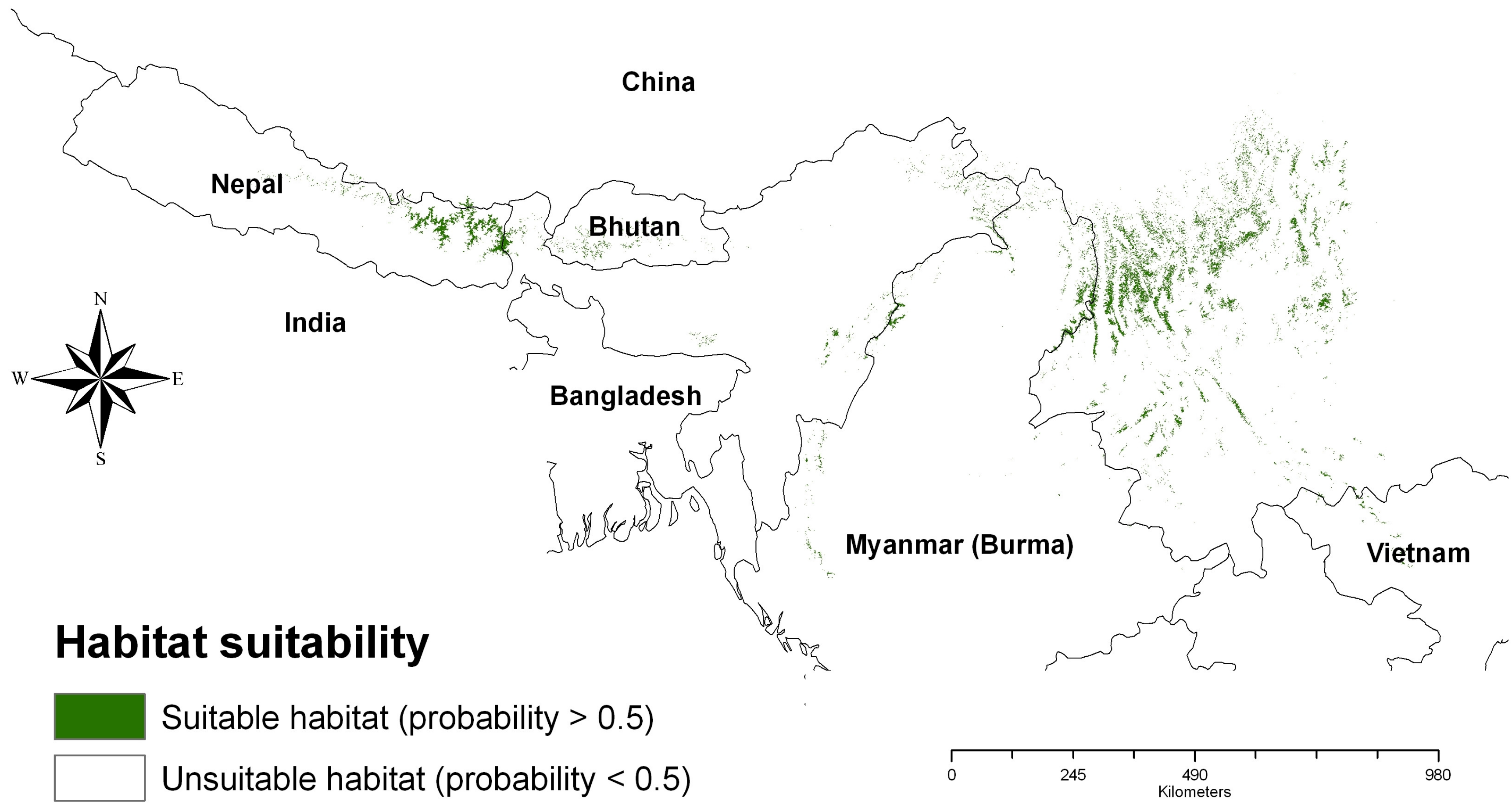

Figure 25. Predicted potential suitable habitat at 0.5 threshold for the red panda (*Ailurus fulgens*) in Asia.

DISCUSSION

The MaxEnt species distribution modeling basically maps the fundamental niche of a species which is different from an occupied niche and usually larger than the fundamental niche (Pearson 2007). Such models usually over-predict the species distribution because the area predicted as suitable habitat is the fundamental niche of a species even though the species may not occur in that area due to other factors, e.g., anthropogenic factors. Though these models have higher sensitivity, they may have less specificity.

The MaxEnt model of the red panda distribution in Nepal predicted suitable red panda habitat at a higher success rate with as low an omission rate as 11.6 %. The predicted red panda distribution approximates the anecdotally known and even the systematically confirmed distribution of the red panda in Nepal (Glatston 1994, Yonzon et al. 1997). The model predicted the western limit of the red panda distribution in the far-west region of Nepal in Bajura and Bajhang districts located close to the western known limit of the red panda distribution in Mugu District (Glatston 1994). Just east of these districts, the red panda has been reported from Jumla District (Yonzon et al. 1997) and from Rara National Park in Mugu District (Sharma 2009). Therefore, at this extent, it is equally likely that the red panda distribution may have been over-predicted or the red panda is simply yet unreported from the area west of Mugu District. However, the omission rate of 11.6 % and the careful observation of predicted logistic value for all 106 red panda occurrence points (Fig.7) also indicates slight under-prediction of red panda suitable habitat in Nepal.

The red panda distribution has also been over-predicted in the central lower mountains in small patches. These areas may be suitable as the fundamental niche of the red panda; however, these small and fragmented patches are probably unsuitable due to a lack of connectivity. Alternately, these areas have very dense human populations, and hence at a finer scale may be unsuitable for red pandas. While resolution of analysis has little influence on the model (Guisan et al. 2007), the resolution of this study (1 km) at the national scale cannot capture settlements and defragmentation in forest cover within a pixel, and hence the model may over-predict the suitable areas. However, overlaying of a finer resolution forest cover for smaller scale analysis will reduce the total suitable area. A GIS-based overlay analysis at a resolution of 0.25 km^2 (Yonzon et al. 1997), estimated only 912 km^2 of area suitable for the red panda in Nepal. This analysis used only three parameters – area with fir forest within an elevational range of 3,000 – 4,000 m with annual precipitation > 2,000 mm. However, the red panda has been recorded beyond this elevation range, e.g., at 2,800 m in the Kanchenjunga region (Mahato 2004a) and as low as 2,400 m in Ilam and Panchthar districts (pers. obs. 2007) and in Sinhalila National Park in India (Pradhan et al. 2001). Likewise, the red panda has been recorded in other forest types, e.g., pine forest in the Everest region (Mahato 2004b), *Rhododendron* forest and mixed broadleaf forest in eastern Nepal (pers. obs. 2006, 2007) and in Singhalila National Park (Pradhan et al. 2001). Therefore, Yonzon et al. (1997) may have underestimated the red panda distribution.

Despite a reasonable probability of over-prediction and slight under-prediction in suitable red panda area and a coarse grain size, this model provides a baseline for further investigation. It provides an understanding of the red panda distribution at a landscape level on a national scale. Furthermore, projection of the model to other countries provides a better understanding of the global red panda distribution. The model is helpful in conservation planning (Rodriguez et al. 2007) and in the identification and prioritization of sites for further ground-truth investigation. With the help of this model, a fine-scale distribution map can also be prepared to determine the red panda distribution more precisely. The fact that most of the known locations of the red panda were confirmed in the recent decade (Mahato 2004a, Mahato 2004b, Regmi 2009, Sharma and Kandel 2007, Sharma 2009, Subedi 2009) is evidence that ground-truth information on the red panda distribution is not well understood in Nepal. Therefore, this model can be used as a tool in identifying potential areas and planning for ground-truthing surveys of the red panda distribution at a reduced cost in both time and money. This is particularly important for rare and elusive species like the red panda.

The predictor variables used to build this model were selected based on the available ecological information on the red panda. The selection of variables was also based on the resolution of analysis. For instance, there are other variables which are important predictors of the red panda distribution, e.g., aspect, slope. However, I could not incorporate these variables at the coarse resolution necessitated by the available habitat and ecological layers. However, these and several additional variables, e.g., distance to water, distance from settlement etc., may be important variables to consider in the future construction of a finer resolution distribution map.

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