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‘Geo-Spatial Analysis of Habitat Suitability for Common Leopard (*Panthera pardus*) in Shivapuri Nagarjun National Park, Nepal’

by

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Kathmandu, 12.01.2016

Science Pledge

By my signature below, I certify that my project report is entirely the result of my own work. I have cited all sources of information and data I have used in my project report and indicated their origin.

Kathmandu, 6.12.2015

Place and Date	Signature

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Abstract:

The predator like common leopard (*Panthera pardus*) are associated with high biodiversity, so the protection of their habitats is one of the most effective way to conserve biodiversity globally. Its population is threatened by habitat loss, fragmentation habitat. Unfortunately the distribution of this species have not been identified. Likewise, these habitat are separated by main road, settlement area, and research for the leopards also have not been conducted yet. Considering the facts above, the main objective of this research is to predict and map the possible habitat for Common Leopard in Shivapuri Nagarjun National Park by using remote sensing and GIS approach. In order to achieve that, Species Distribution Modelling (MaxEnt) was demonstrated to predict the Common Leopard's distribution and was applied to figure out possible suitable area in Shivapuri Nagarjun National Park. By using presence – only data of Common Leopard (*Panthera pardus*) occurrences, 138 observation points alongside several environmental variables which consist Distance from Settlement Area, Distance from Forest, Distance from Bush, Distance from road, distance from Sparse Forest and Distance from Agricultural Area were developed in to MaxEnt Programme. Remotely sensed imagery of Resource Sat II imagery for study area was used for Normalized Difference Vegetation Index (NDVI), land use and land cover. Image processing and feature extraction was done by Erdas Imagine 2011 and maximum likelihood supervised classification was done. The MaxEnt model based on Remotely sensed factors, habitat factors and Common Leopard presence locations resulted is much larger area classified as suitable for leopard. The contribution of variable "Distance from Settlement Area (52.4%)" was highest to impact the model. The model performance was accessed through using Receiver Operating Characterstics (ROC) plots and Jackknife tests.

The Area under Training data (ROC) curve (RUC) 0.828 and that of Test data ROC curve was 0.678 which is acceptable than the Random Prediction Model (AUC) of 0.5. From that

it is concluded that MaxEnt Modelling approach can be used to model the species geographic locations for assessing habitat suitability of the target wildlife with the help of presence only datasets. The suitability map resulted from the modelling was useful to delineate the sites that required specific planning and management interventions.

Abbreviations and Acronyms

SNNP	Shivapuri Nagarjun National Park
ASCII	American Standard Code for Information Interchange
CSV	Comma Separated Value
DNPWC	Department of National Parks and Wildlife Conservation
GPS	Global Positioning System
ESRI	Earth System Resource Institute
GIS	Geographical Information System
MaxEnt	Maximum Entropy
ROC	Receiver Operator Curve
IUCN	International Union for Conservation of Nature and Natural Resource
LISS	Linear Imaging Self Scanning sensor
AOI	Area of Interest
ISRO	Indian Space Research Organization
NPs	National Parks

GAM	Generalized Additive Model
GLM	Generalized Linear Model
BRT	Bossted Regression Tree

Table of Contents

List of Tables

List of Figures

List of Maps

Chapter-1: Introduction

1.1 Background

Leopards (*Panthera pardus*) are the most widely distributed wild cats, and occupy a broad variety of habitats, from rainforests to deserts and from the fringes of urban areas to remote mountain ranges **(Dickman & Marker, 2005)**. The leopard (*Panthera pardus*) is one of the most widely distributed felids across the forested landscapes of the Indian subcontinent **(Thapa et al., 2014)**. This spotted cat has short powerful limbs, heavy torso, thick neck, and long tail. Large black spots grouped into rosettes on the shoulders, upper arms, back, flanks and haunches, and smaller scattered spots on the lower limbs, head, throat and chest, and the belly has large black blotches **(Ghimirey, 2006)**. In the world, there are 36 species of wildcat exists **(Sunquist, 2002)**. Among them seven large wildcat species; *Panthera tigris* (Tigers), *Panthera leo* (Lions), *Panthera pardus* (Leopard), *Puma concolor* (Cougars/Puma), *Panthera onca* (Jaguars), *Acinonyx jubatus* (Cheetahs) and *Uncia uncia* (Snow Leopard), Common Leopard is the most common one which is not only restricted to forest or heavy cover but also thrive well in open country and this species is also known as forest leopard **(Ghimirey, 2006)**. In case of Nepal, Leopards are recorded throughout the country ranging from the Terai to the Himalayas. The leopard (*Panthera pardus*) is a widespread and relatively common large carnivore, but the species is declining in large parts of its range **(Swanepoel et al., 2015)**. Based on estimates of density and geographic range the leopard's total effective global population size has been estimated at greater than 50000 breeding individuals, and is listed as a species of least concern by the IUCN red list **(Edgaonkar, 2008)**. Prediction and mapping of potential suitable habitat for threatened and endangered species is critical for monitoring and restoration of their declining native populations in their natural habitat, artificial introductions, or selecting conservation sites, and conservation and management of their native habitat **(Kumar, 2015)**. Leopard is most common and widely distributed species among the wild cats of the world which are tolerant to habitat conversion, found in every habitat, ranging from subtropical to temperate region **(Gavashelishvili & Lukarevskiy,**

2008). Leopard are distributed across Africa to South Asia northwards to Central Asia and east to the Amur Valley in Russia **(Bailey, 1993)**. In Nepal, Leopard is widely distributed throughout the country **(Shah et al ., 2004)**. In the past, density and abundance of prey species were estimated using the line transect sampling method **(Karanth et al., 2004)**. Line transect sampling is one of the reliable method for abundance estimating approaches collectively known as distance sampling methods in a known area and boundary **(Karanth et al., 2002)**. The diets of cat species are known to reflect easy catch, with individual animals developing local and individual taste **(Kingdon, 2003)**. Leopard preferred to kill/prey on medium sizes prey (primary) species and also wide variety of small animals (sub-optimal) **(Bailey, 1993)**. Leopard forced to switch to more abundant sub optimal prey such as rodents in area with low densities of medium sized ungulates prey **(krishnan et al., 1999)** or secondary prey; livestock and dogs **(Heinen & Yonzon, 1994).** Diet of Leopard in Kruger National Park, South Africa, constitute medium-sized prey, mainly Impala and with wide variety of small animals including Hyrax, Civet and Mongoose **(Bailey, 1993)**. In the Kalahari Desert Leopard diet comprises small prey such as Bat-eared Foxes, Jackals, Genets, Hares, Duiker and Porcupines **(Hayward et al., 2006).** In Sambru community group ranches, Kenya, the Leopard's diet consists of both the domestic prey and wild ungulate. Wild prey contribute relatively higher than domestic in Leopard's diet **(Ogara et al., 2010)**. In Sarigol National Park Iran; Wild Sheep, Wild Pig, Wild Goat, Red Fox, Porcupine, and Pika constitute in Leopard diet along with domestic Prey **(Taghdisi et al., 2013)**. In Wilpattu National Park, Srilanka, Leopard's diet comprises Chital, Wild Pig, Sambar, Langur, Hare, Porcupine and domestic Buffalo calves **(Eisenberg & Thorington , 1973)**. In case of Nepal at Bandipur Tiger Reserve, Leopard diet composed of Sambar, Chital, Barking Deer, Four-Horned Antelope, Chevrotain, Wild Pig, Gaur, Langur, Hare, Cattle and other small prey species. Chital found to be most dominant followed by Wild Pig, Gaur, Langur. Medium size prey are dominant than large size prey and small prey species in the diet of Leopard **(Andheria et al ., 2007)**. In Bardia National Park high biomass of prey support dense Tiger population but due to low density of large prey Tiger force Leopard to switch to medium-sized prey and displaced to margin of protected are outside the home range of Tiger which caused increased interface of local with Leopard there by predation of livestock **(Deo, 2014)**. In mountainous region; Dhorpatan Hunting Reserve, Nepal, Leopard have been known to take medium as well as small mammal prey species in which small mammal becomes most significant part for the diet of Leopard **(Andheria et al., 2007)**. In the Chitwan National Park, Leopard diet consists of Chital, Sambar, Barking Deer, and livestock **(Thapa 2011).**

1.2 Conservation Status

The Leopard have low conservation priority because of their widespread distribution and ecological flexibility, however, global population status is still uncertain **(Henschel et al., 2009).** The Wild Cat Status Survey (IUCN/SSC Cat Specialist Group) has categorized Leopard as the Near Threatened species **(Henschel et al., 2008)**. Due to habitat conversion or fragmentation, trade of body parts, trend in decreasing number of Leopard, the International Union for Conservation of Nature (IUCN) listed its eight subspecies as endangered or critically among 14 sub species of Leopard **(Hayward, 2009)**. The Leopard is placed in Appendix I in the Convention on International Trade in Endangered Species (CITES) **(Nowell & Jackson, 1996)**. Under the CITES treaty, use of Leopard's pelts or body parts for commercial purposes is banned. But in the absence of effective public relation campaign, Leopard killing for commercial purposes could not be checked **(WWF 2007)**. In Nepal Leopard is not on the list protected species under the National park and wildlife conservation (NPWC) act 1973 **(Mehta & Kellert, 1998)**. There is no specific management strategy for its conservation where Leopard are surviving in considerable conflicts with people outside the protected areas **(Shrestha, 2015)**.

1.3 Objectives

The main objective of this research is to predict the possible suitable areas for Common Leopard (*Panthera Pardus*) in Shivapuri Nagurjun National Park by using remote sensing and GIS approach. More specific objectives are listed as follows.

- ❖ To identify the potential habitat parameter for Common Leopard (*Panthera Pardus*) in Shivapuri Nagarjun National Park.
- ❖ To prepare habitat suitability map of Common Leopard (*Panthera pardus*) in Shivapuri Nagarjun National Park.

1.4 Area of Focus

Leopard, an umbrella species, is top predator in the ecosystem of Shivapuri Nagarjun National Park which determines the condition of entire National Park. This study has assessed the abundance of Common Leopard which will be helpful in formulation of management plan for the conservation of predator as well as prey in and around the National Park **(Shrestha, 2015)**. Numerous researches on big cat species are available in Nepal. However, those researches are confined to Tiger and Snow Leopard which are enlisted as protected species by National Park and Wildlife Conservation Act, 1973. Studies on Leopard relating demography, diets, home range, and interaction with Tiger are available but are confined to low land **(Shrestha, 2015)**. While the similar study in mountainous region in Nepal is limited in spite of their prominent role in smooth functioning of the ecosystem in mountainous region of Nepal. Few study regarding on Leopard in the mountainous region of Nepal are available; status of Leopard (Deo, 2014), diet composition **(Wegge et al., 2009)**, Human-Leopard conflict **(Koirala et al., 2012)**. Furthermore, there are no specific management strategy for conservation and protection of Leopard. If Leopard have to conserve in natural habitat, it is necessary to carry study of

Leopard on remaining protected areas in order to maintain coexistence with people and viable populations of Leopard in ecosystems and landscape **(Swanepoel et al., 2015)**.

1.5 Limitation

The study of Common Leopard (*Panthera pardus*) was confined to forest area of Shivapuri-Nagarjun National Park. The finding stated in this study is based on data obtained during the field study. The estimation of prey density could not be performed because of inadequate time, financial resources as well as lower abundance of prey species. Due to inaccessibility in reach, the data from steep topography is excluded though animal trails were noticed revealing the presence of scats.

Chapter-2: Literature Review

2.1 Species Distribution Model

With the rise of new powerful statistical techniques and GIS tools, the development of predictive habitat distribution models has rapidly increased in ecology **(Guisan & Zimmermann, 2000)**. Such models are static and probabilistic in nature, since they statistically relate the geographical distribution of species or communities to their present environment. The tool that can help us study habitat selection at the scale of the species range, and that has been particularly useful in the field of conservation, is habitat suitability modeling **(Thomasson, 2012)**. Recently, interest in species distribution modelling has increased following the development of new methods for the analysis of presence-only data and the deployment of these methods in user-friendly and powerful computer programs. However, reliable inference from these powerful tools requires that several assumptions be met, including the assumptions that observed presences are the consequence of random or representative sampling and that detectability during sampling does not vary with the covariates that determine occurrence probability **(Yackulic et al., 2013)**. Species distribution models (SDMs) estimate the relationship between species records at sites and the environmental and/or spatial characteristics of those sites **(Franklin, 2009)**. They are widely used for many purposes in biogeography, conservation biology and ecology **(Elith et al., 2011)**. Prediction and mapping of potential suitable habitat for threatened and endangered species is critical for monitoring and restoration of their declining native populations in their natural habitat, artificial introductions, or selecting conservation sites, and conservation and management of their native habitat **(Kumar & Thomas., 2009).** Species distribution modelling has a long tradition in ecology and is becoming increasingly important in applied ecology as researchers and managers seek to understand current species distribution patterns and to predict future distributions in the face of climate change, human-assisted invasions and many other ongoing environmental changes. Numerous methods exist to model species distributions when either repeated (i.e. multiple visits to a subset of specific sites) or single-visit ‘presence–absence’ data are available **(Yackulic et al., 2013)**. A wide array of models has been developed to cover aspects as diverse as biogeography, conservation biology, climate change research, and habitat or species management **(Guisan & Zimmermann, 2000)**. However distribution data on threatened and endangered species are often sparse and clustered making it difficult to model their suitable habitat distribution using commonly used modeling approaches **(Kumar, 2015).** Therefore, developing suitable management strategies outside protected areas could be a key factor in the future conservation of leopards, and more detailed knowledge is required of their ecology in such areas **(Dickman & Marker, 2005)**. Predictive geographical modelling has recently gained importance as a tool for estimating habitat suitability within a wide range of biodiversity and management studies, including studies in the marine environment **(Skov et al., 2008)**. Habitat suitability Model (HSM) models have been generally accepted in ecological management as a means to predict effects of pressures and restoration measures on habitats and populations. HSM-models estimate habitat suitability from relevant habitat variables **(Lee et al., 2006).** Habitat-suitability modelling is being increasingly used as a tool for conservation biology. Although studies at large spatial scales are more appropriate for reserve design and management, there is a scarcity of published work on local, high-resolution applications of such model **(Seoane et al., 2006)**.

2.2 Remote Sensing and GIS in Wildlife

Remote sensing (RS) is broadly understood as the science, art and technology in acquiring information about an object, phenomenon and scene by device (technology based) without performing any contact under investigation **(Lillesand et al., 2004)**. It is divided into two main processes consist of data acquisition and data analysis. The first process covers energy sources from the sun to the earth and retransmitted through the atmosphere as electromagnetic energy. It will be captured by sensing system in pictorial or digital type and processed in data analysis phase. Sensing products, combined with reference and experience data about particular area, are then interpreted and analyzed to produce information in the form of maps and files. Finally, the product of remote sensing can be further processed through Gegoraphical Information System (GIS) and used for the decision – making process **(Lillesand et al., 2004)**.

Meanwhile, GIS is a computer – Based system which progicient in collecting spatial data (remotely sensed imageries are being one of them), relating, performing and displaying spatial data and tabular data into a map **(Huisman & de, 2009)**. There are six component parts of GIS which consist of software, data, procedures, hardware, people and network **(Pettorelli, Safi, & Turner, 2014).** GIS software is provided in wide range starting from a simple package to a major industrial – strength. Data which represent an object of interest on Earth's surface digitally will be processed to some specific purposes. The component of software, hardware, database and network need organization and procedures to run the system. Over the whole element mentioned above, people are considered as the vital component to perform the entire process. Recently, the application of RS and GIS has been broadly recognized. **(Lillesand et al., 2014)** explained that wildlife management notably habitat enormously needs RS and GIS to provide up to date and accurate information related particular site.

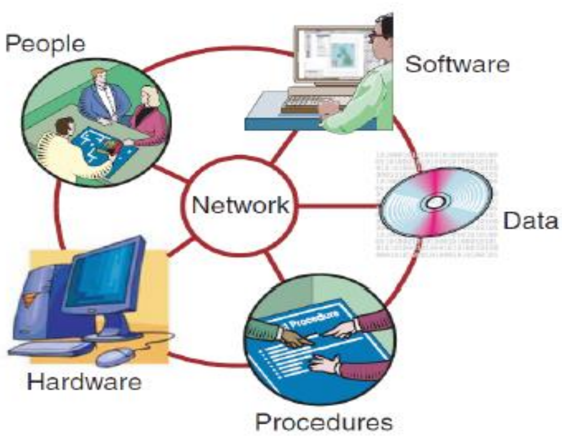


*Figure 1 Six Part of GIS (Source : **Goodchild et al., 2005**)*

By applying RS technology and GIS data processing as a tool, specific feature of wildlife like habitat can be figured out sufficiently as well as its possible threats **(Goodchild et al.,**

2005). The use of remotely sensed imageries has become prominent as its products which similar to the original from **(Pettorelli et al., 2014)** and let the scientists to analyze the objects or phenomenon without performing any contact to the object of interest.

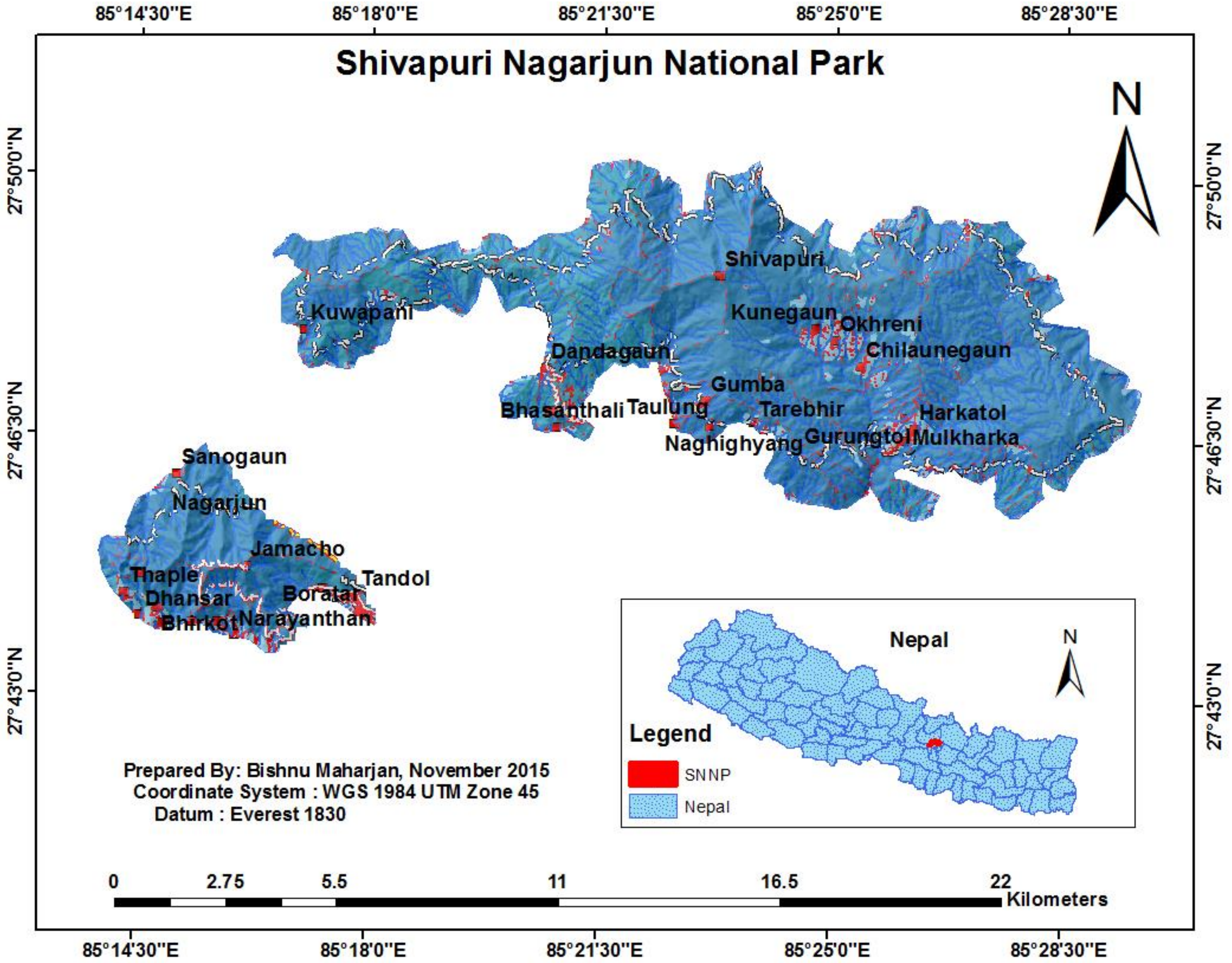
2.3 MaxEnt Distribution Modelling

Recently, interest in species distribution modelling has increased following the development of new methods for the analysis of presence-only data and the deployment of these methods in user-friendly and powerful computer programs **(Yackulic et al., 2013)**. Maxent is a recently introduced modeling technique, achieving high predictive accuracy and enjoying several additional attractive properties. The MaxEnt software package is one of the most popular tools for species distribution and environmental niche modeling, with over 1000 published applications since 2006. Its popularity is likely for two reasons: 1) *MaxEnt typically outperforms other methods based on predictive accuracy and* 2) *the software is particularly easy to use* **(Merow et al., 2013)**. The performance of Maxent is influenced by a moderate number of parameters **(Phillips, Anderson, & Schapire, 2006)**. Maxent is a general-purpose method for making predictions or inferences from incomplete information **(Phillips & Dudík, 2008)**. The idea of Maxent is to estimate a target probability distribution by finding the probability distribution of maximum entropy (i.e., that is most spread out, or closest to uniform), subject to a set of constraints that represent our incomplete information about the target distribution **(Evangelista et al., 2008)**. When Maxent is applied to presence-only species distribution modeling, the pixels of the study area make up the space on which the Maxent probability distribution is defined, pixels with known species occurrence records constitute the sample points, and the features are climatic variables, elevation, soil category, vegetation type or other environmental variables, and functions thereof **(Ward, 2007)**.

We used Maxent version 3.2.1 (http://www.cs.princeton.edu/~schapire/maxent/) to generate the models. The Maxent algorithm estimates habitat suitability by finding the distribution with maximum entropy under constraints given the relationship of environmental data with species presence data. Maxent model parameters used were regularization multiplier = 1, maximum iterations = 500 and a convergence threshold =1. Initially, Maxent models were run using a single environmental layer as input, to test for the fit of the validation points to individual layers. This was assessed using the AUC (area under the receiver operating characteristic curve) to select those layers that best explained the distribution of each taxon **(Yesson et al., 2012)**. The AUC is a threshold independent measure of model performance ranging from 0 to 1. An AUC value of 0.5 represents a model that performs no better than random, whilst 1 is maximally predictive **(Howell et al., 2011)**. Map outputs were based on models using all occurrence data for training, and saved as logistic scores (0 – 1), which represent the probability of presence of the modelled data **(Elith & Leathwick, 2009)**.

Chapter-3: Research Methodology

3.1 Study Area



Map 1 Location Map of Shivapuri Nagarjun National Park

Shivapuri Nagarjun National Park is the nearest National Park from Kathmandu covering an area of 159 sq. Km. It encompasses two separate forest patches viz. Shivapuri and Nagarjun. Shivapuri forest covers an area of 144km^2 while Nagarjun forest covers 15km^2. Further information of the study area such as geographic location, study area location, watershed value, history, management and flora and fauna are briefly described below.

3.2 Location

The research was conducted in Shivapuri Nagarjun National Park, which is the only protected area lying entirely within the Nepal’s mid hills ecosystem. It is spread over Kathmandu, Nuwakot, Dhading and Sindhupalchwok districts of central Nepal. The elevation ranges from 1350m to 2732m and its boundary is demarcated by a 111 km long boundary wall and 95 km long ring road. It is the true representation of the mid hills in the protected area system of Nepal. It is located on the northern fringe of Kathmandu valley and lies about 12 km away from the capital city between 27º45' to 27° 52' northern latitude and 85° 15' to 85º 30' eastern longitude. The park gazette as the country’s ninth national park in 2002, covers an area of 159km^2. The highest point is the Shivapuri peak is 2732m above mean sea level, and represent the second highest peak around the Kathmandu valley. The lowest parts are at altitude of approximately 1360m above mean sea level. The upper slopes are covered with forest **(Birch et al., 2012).** The Shivapuri Nagarjun National Park is situated in the north of Kathmandu which is one of the primary sources of freshwater for Kathmandu valley. The park is bestowed with an abundance of streams/streamlets. The park provides over 40 percent of the drinking water to the Kathmandu valley. SNNP has been managed by the Department of National Park and Wildlife conservation (DNPCW)/ Ministry of Forests and Soil Conservation (MFSC), with the support of army, who has 6 military posts around the park **(Shrestha, 2012)**.

3.2.1 Climate

The climate is of the monsoon type. The rainy season stars in June and last four months. The other months are relatively dry. However, just before the rainy season occasional thunderstorms with hail occur. The maximum temperature recorded in December/January 0.3° c. In the foothills, the temperature seldom drops below 0° C. During winter, morning fogs cover the surrounding valleys. The hilltops and sometimes the high-altitude zone of the northern aspect are covered with snow during the winter. The average rainfall recorded in Kakani is 2,727 mm **(Shrestha, 2015)**. Of the total rainfall, 84% occurs from June to September.

3.2.2 Geology

Geologically the Shivapuri area occupies the inner Himalayan region and dominant rocks of the area contain metamorphic rocks such as phyllite, limestone and dolomite and gneiss which are loamy on the northern aspect and sandy on the southern aspect **(Shrestha, 2012)**. Eo-cambrian bands of quartzite and limestone are also present in this area **(Koirala & Chalise, 2012)**. Shivapuri area has steep mountainous topography more than half of the land has slopes greater than 30 degree **(Sigdel et al., 2015)**. The Shivapuri Nagarjun National Park is drained by many smaller rivers and rivulets. Important rivers are Bagmati, Bishnumati, Sangla and Syalmati.

3.2.3 Soils

Soils of the study area contain metamorphic rocks such as phyllite, limestone and dolomite, gneiss and ingratiate 12 which are loamy on the northern aspect and sandy on the southern aspect. Due to the dense vegetation covers, in most of the park area, the run off rate is relatively low and the nutrient content in the soils is high **(Sigdel et al., 2015)**. The nutrients in the soil are very high and the runoff rate is relatively slow because of dense vegetation and high humus deposits in the Shivapuri forest but the runoff rate was very fast in the degraded forest **(Shrestha, 2015)**.

3.2.4 Flora and Fauna

The park lies in the transit zone between sub-tropical and temperate regions. There are more than 1250 species of floras. About 129 species of mushrooms have been described from the park. Schima-Castanopsis, Pines, Oaks, and Rhododendron are the dominant vegetation in the park **(Koirala & Chalise, 2012)**. The vegetation in the park can be categorized into four types: (i) Lower mixed hardwood forests (*Schima - Castanopsis*) between 1350m and 1500m, (ii) Chirpine forests between 1350m and 1600m, (iii Oak forests between 2300 and 2732 m, and (iv) Upper mixed hardwood forests between 1500 and 2732 m. The major tree species are *Schima walichii*, *Castanopsis indica*, *Alnus nepalensis, Pinus roxburghii*, *Myrica esculanta*, *Pyrus pasia, Quescus semicarpifolia, Rhododendron arboreum*, *Juglan regea* etc **(Jha & Tripathi, 2012)**.

3.2 Methods

In order to develop modelling for Common Leopard's distribution alongside its habitat connectivity, several activities and processed – data as environmental layers need to be prepared beforehand. Basic needs for habitat as it has been initiated before (spatial area, shelter, forest etc.) become the main consideration in predicting the preference habitat for Common Leopard. Nonetheless, the impede factors for their moving will determine the possible habitat structure which determine their suitability.

3.2.1 Maximum Entropy

As a machine learning method which requires presence only data in modelling, Maximum Entropy (MaxEnt) has high accuracy in predicting species geographic distribution **(Phillips, 2005)**. Basically, according to **(Philips et al., 2006)** maximum entropy can be applied to solve the problem in any constraints. The principle of maximum – entropy in species distribution exposes unknown probability of species occurrence over the set of pixel in the study area. An individual element as pixel will be regarded as points and defined a non – negative probability to each point. **(Phillips et al., 2006)** also clarified the process of prediction distribution of species by record 1 if the species is present and 0 for absent in every pixel over the study area. The value will be 0 or 1 for plants and range from 0 to 1 to animals which depicts the probability of species every pixel. The aim behind that idea lies on the incapability of determining species prevalence only by occurrence data.

3.2.2 Presence Point

The presence point of Common Leopard were collected through village survey, interview, direct and indirect evidences, in Shivapuri Nagarjun National Park. The device etrex 30 channel Global Positioning System (GPS) was used to take the Coordinate of respective Leopard presence point. Then GPS location of total leopard and other points were converted to UTM WGS 84 zone 45N projection for subsequent GIS integration. The study area, the Shivapuri Nagarjun National Park is all hilly, so it was not feasible to mark and monitor straight line transects. Therefore relative abundance of leopards was estimated by walking on forest trails, fire line and grassland The location of leopard presence was taken through indirect method i.e. scats, pugmark, scraps and opportunistic search method. The combination of these kinds of data was applied in the modelling process by using MaxEnt Program.

3.2.3 Land Cover

I used the ResourceSat-2 image from ISRO (Indian Space Research Organization) LISS-4. The spatial and spectral resolution of LISS-4 imagery provides high resolution image (spatial resolution 5m Swath Width: 70km) information of the Earth's surface which is appropriate for vegetation monitoring in heterogeneous landscape. The data used were a 3 x 12,288 MS mode product which was geometrically (systematically) corrected. The ISRO (LISS-4) images contain three multispectral bands B2: 0.52-0.59, (green), B3: 0.62-0.68, (red) and B4: 0.77-0.86 (NIR). As this is the latest satellite imagery captured at 25th January 2015 and there was no any cloud cover. In this scenario, a standard procedure for creating Supervised Classification on Resource Sat II image, the following six objects were considered for creating training areas,

i. Dense Forest
ii. Sparse Forest
iii. Road
iv. Agricultural Land
v. Settlement Areas
vi. Bushes/Shrub/Grassland

To create training areas in ERDAS 2011, the Resource Sat II image was loaded in the viewer and Supervised > Signature Editor Tool was selected. Then multiple polygons representing each object class were drawn as AOI layer. Mainly, multiple training sites were collected for the same class that has different spectral characteristics. To ensure the quality of training site, the histogram of each of the signature class was checked. The training area was also verified by cross checking the same area in Google Earth.

Then supervised classification was performed again after re-editing and deleting some of the signature classes. Also supervised classification was performed by merging multiple training areas per class. The results were compared, and it was found that the signature classes with unmerged training areas gave better result.

3.2.4 Performing Accuracy Assessment

Accuracy assessment of land-cover classifications derived from remote sensing data has been recognized as a valuable tool in judging the fitness of these data for a particular application. Recent research initiatives in the area of spatial data accuracy and integration of remote sensing data in geographic information systems have revived the discussion on accuracy assessment **(Janssen & Vanderwel, 1994)**. **(Foody et al., 2003)** describes that “Classification of remotely sensed data is being used increasingly to produce thematic land cover maps”. These maps are used in various applications, for example: to describe the spatial distribution and pattern of land cover; to estimate areal extent of various cover categories; as input parameters to various environmental models; as a source of regionally extensive environmental data; or as basis of policy analysis **(Stehman & Czaplewski, 1998)**. Accuracy assessment is important to determine the quality of the information derived from remotely sensed data in classified maps **(Congalton, 1991)**. Evaluation was done using both the standard error matrix and the Kappa statistics for both overall and class specific results. Therefore, overall accuracy indicates accuracy of all classes, whereas user's and producer's accuracy measure the accuracy of individual classes.The result of supervised classification was opened using Accuracy Assessment tool. File>Open. Then 100 Random points were generated. Edit/Create-Add Random Points (**Error! Reference source not found.**).

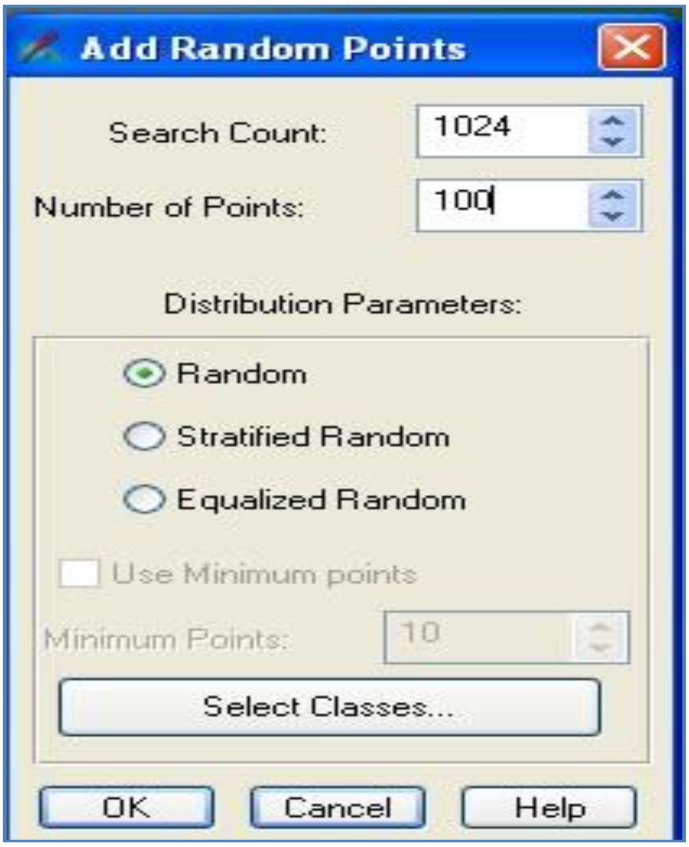


Figure 2 Adding Random Points for Accuracy Assessment

Two viewers were opened in ERDAS; in the first one, the original Resource Sat II was loaded and in the second one, the classified image was loaded as reference image. Both the views were linked as well as synced. Then 100 random points generated were loaded in the viewer. The class values of these points were displayed in "Class" column in the Accuracy Assessment table. The actual value of each point was then determined by looking in the corresponding location of reference image and entered in the "Reference" column of the accuracy table.

3.2.5 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is the most popular vegetation index **(Xu, Guo, 2014)** which can be applied to figure out the greenness on a patch of land and vegetation canopy biophysical properties **(Weier & Herring, 2001)**. Its development is broadly used to depict forest condition as a basic for further management **(Franklin, 2001)**. As the principal of sunlight exposes to an object, particular wavelengths are absorbed and other are reflected in a certain degree of intensity. On one hand, plant leaves contains chlorophyll absorb visible light (wavelength 0.4 – 0.7µm) in the photosynthesis process and on the other hand, its cell structure reflect near infrared spectrum in (0.7 – 1.1) µm. The more leaves immensely reflect these wavelengths of light and vice versa **(Weier & Herring, 2001)**. In this study Resource Sat II image of spectral bands 3 and 4 of the Red and Near Infrared bands ratio imagery with a spatial resolution of 5.8m having wavelengths of (0.62 – 0.68)µm and (0.77 – 0.86) µm have been used for the generation of NDVI. This index is defined as:

NDVI = NIR – RED/NIR + RED,

Where NIR is near – infrared wavelength and RED is red wavelength. Its calculation result has range value spread from (-1) to (+1) which indicate no green leaves (no vegetation) to high density of leaves, respectively. The low value of NDVI below 0.1 considered as bare land, sand or rock, moderate value range from 0.2 to 0.5 correspond to sparse vegetation such as grass land and shrub or senescing crop and the high value 0.6 – 0.8 indicate dense vegetation as that can be found in tropical rain forest or crops in their uttermost growth phase **(Weier & Herring, 2001)**. Normalized Difference Vegetation Index value on this study was derived from Resource Sat II which has been processed in ArcGIS 10.2 software.

3.2.6 Distance from Road/Settlement/Bush/Forest/Agricultural Land

Based on research about corridor for tiger in India by **(Rathore et al., 2012),** the existence of roads or paths has been affected the tiger's movement activity. Despite of Leopards' characteristics as the most adaptable big cat species, this creature will always attempt to avoid humans and noises naturally. By using raster map, Euclidean distance was calculated in ArcGIS 10.2. Similar to road/path distance, **(Gunawan et al., 2012)** described that Leopard tend to keep the distance from settlement approximately more than half a kilometer. As the consequences of settlement proximity to protected areas, human wildlife conflicts are inevitable **(Naughton-Treves, 1997)**. In order to provide distance from settlement area as an environmental layer, image classification was calculated its distance by applying Euclidean distance in ArcGIS. The same method in calculating distance above, distance from agricultural land, bushes, forest, sparse forest etc.

3.2.7 Preparing Environmental Layers for MaxEnt

Maximum Entropy program needs environmental layers in ASCII raster grid format on its execution. Therefore, all processed variables converted in ASCII format in the exactly same cell, bond and coordinate system. First of all, the boundary of the study area was created by considering the extent which covers SNNP land scape. The focus areas are SNNP's and landscape in between whilst considering the crowdedness of settlements and agricultural areas neighboring the parks. The boundary was used as layer mask (raster based with pixel value 5) in environmental setting under Geoprocessing tool in ArcGIS. Output coordinate was set in WGS_1984_UTM_Zone_45N. For processing extent was set the same to layer mas (top extent 3080264.657586, Left =325748.264320, right =351638.264320, bottom = 3068059.657586). Before executed the process, cell size under raster analysis menu was defined as 5.8m.

To finalize the process, clipping and resampling were applied to make all the layers matching by using raster calculator. All the layers were multiplied by mask layer and the final products resulted in the same cell size and number (column 5178, rows 2441), cell alignment, projection system and extent as the mask. The origin value of each layer do not change since the multiplying factor (mask layer) has the value of 5. The last step is preparing the layers was converting all files into ASCII format and saving into an environmental layers folder.

3.2.8 Running MaxEnt Model

MaxEnt programme requires samples and environmental layers in its process. For common leopard distribution modelling, a csv file of common leopard was put as sample and environmental layers folder which contains all variables in ASCII format was employed in MaxEnt's environmental layers menu. After that, the data of each variable has been changed either categorical or continuous. The box of create response curves, make pictures of predictions and do jackknife to measure variable importance have been ticked in MaxEnt menu. In order to determine random test percentage, basic setting of MaxEnt has been set into 25 in 1 replicates. On replicated run type menu, bootstrap was choosen in relatively few observation data, finally, equal training sensitivity and specificity was chosen as threshold rule in advanced setting while write background predictions was ticked to obtain pseudo background data of AUC and TSS calculation process.

3.2.8 Model Evaluation

Model evaluation forms an important part in model building. Testing or validation is required to assess the predictive performance. Both threshold – dependent and threshold independent methods were used in model validation. Starting from conceptual formulation, statistical formulation, model calibration and will be finished in model evaluation, modelling holds a certain degree of validity. In threshold dependent model, model performance was investigated using extrinsic omission rate. The omission rate is a fractional of test localities that fall into pixels not predicted as suitable for Common Leopard (*Panthera pardus*). Meanwhile, model validity can be assessed by calculating AUC. The area under receiver operating curve (ROC) is the probability of a presence site which chosen randomly will be ordered from a randomly absence site. In threshold independent method, the model was evaluated through using a ROC (Receiver operating characteristics) curve.

3.2.9 Response Curve

Maxent creates two sets of response curves for the environmental variables. The first set of curves are called marginal curves and they demonstrate how the model prediction changes as the values of each environmental variable changes slightly while the rest of the variables remain at their average values **(Peterson & Nakazawa, 2008)** warn that the marginal curves may be difficult to interpret if the environmental variables are correlated. The second set of response curves shows that the Maxent prediction reaches a peak and then decreases as the values go up for each environmental variable. Likewise Maxent uses two different methods to estimate variable importance. The first method implemented by Maxent creates a table using data gathered during the training of the model that summarizes the environmental variable contribution to the model and the permutation importance, or stability, of the variable. Variable contribution is determined by the amount of increase or decrease of the model fit, called gain, caused by an environmental variable for each iteration of the Maxent algorithm. The permutation importance is calculated by randomly changing the value of an environmental variable among the model training points. The lower this value is the more stable the variable's contribution to the model. The value of the decrease in the training AUC is normalized so that the data can be represented as percentages for both the percent contribution and the permutation importance **(Boubli & Lima, 2009)**. Another method that MaxEnt uses to determine variable importance is the jack-knife test. The jack-knife test trains the model removing each environmental variable to calculate which variable causes the largest decrease in the model's gain. This variable contains the most information not found in the other environmental variables. The second part of the jack-knife test is training the model using each environmental variable by itself. The environmental variable with the highest gain is considered to have the most useful information by itself.

3.3 Model Performance

The receiver operating characteristic (ROC) analysis, a threshold independent method, is also a widely-used method for evaluating the accuracy of classification models **(Tuanmu et al., 2010)**. The ROC curve is generated by plotting sensitivity values (i.e., fraction of true positive) against 1-specificity values (i.e., fraction of false positive) for every possible threshold **(Esselman & Allan, 2011)**. The AUC is a comparison of the true positive rate and the false positive rate, or how well the model is able to predict presence and absence. Maxent uses presence-only data. The AUC created for Maxent models shows how well the model is able to distinguish presence from random **(Merow et al., 2013)**.

The value for the AUC ranges from 0 to 1, the closer the value of the AUC is to 1 the better the fit of the model. An AUC value of 0.5 equals random prediction **(Phillips & Dudík, 2008)**. The area under the ROC curve (AUC) provides a single-value measurement of model performance. Since omission errors reduce sensitivity and commission errors reduce specificity, both types of errors equally reduce the AUC value. While an AUC value of 1 indicates a perfect model, a value of 0.5 indicates a random model. A standard for judging model performance based on AUC values **(Jennings et al.,**

2013). Likewise the Receiver Operating Curve (ROC) is a threshold independent model widely used in evaluating species distribution models **(Elith et al., 2011).** A ROC is a graphical plot of “Sensitivity” and “1- Specificity” for all possible thresholds. Sensitivity is a measure of proportion of the actual positive identified correctly while Specificity is a measure of the proportion of negatives which are correctly identified. In this case presence only data is used so the model is tested against a random model **(Phillips et al., 2006).** A good model is defined through a curve that maximizes sensitivity for low values of the false – positive fraction **(Edrén et al., 2010)**. MaxEnt has built function which has random background points (Pseudo – absence) against presence points **(Boubli & Lima, 2009)**. The AUC is a ranked approach for assessing model fit that determines the probability that a presence location will be ranked higher than a random background **(Wilting et al., 2010)**. AUC is determined through plotting the sensitivity values against 1 – Specificity. AUC gives a measures of overall for and ranges from 0.5 – 1, which values close to 0.5 indicate a fit no better than random, 1.0 indicates perfect fit **(Araújo 2007)**.

3.4 Methodological Flowchart

The resume of methodological sequence can be seen in (Figure 4).

3.5 Raw Data

Below is the list of data materials used in this research:

Table 1 Data used in Research

Data	Description	Source
Base Map	Shivapuri Nagarjun National Park	DNPWC
Leopard’s Presence Data	Presence Point	Fieldwork at SNNP
Resource Sat II Image	Landcover, NDVI	ISRO

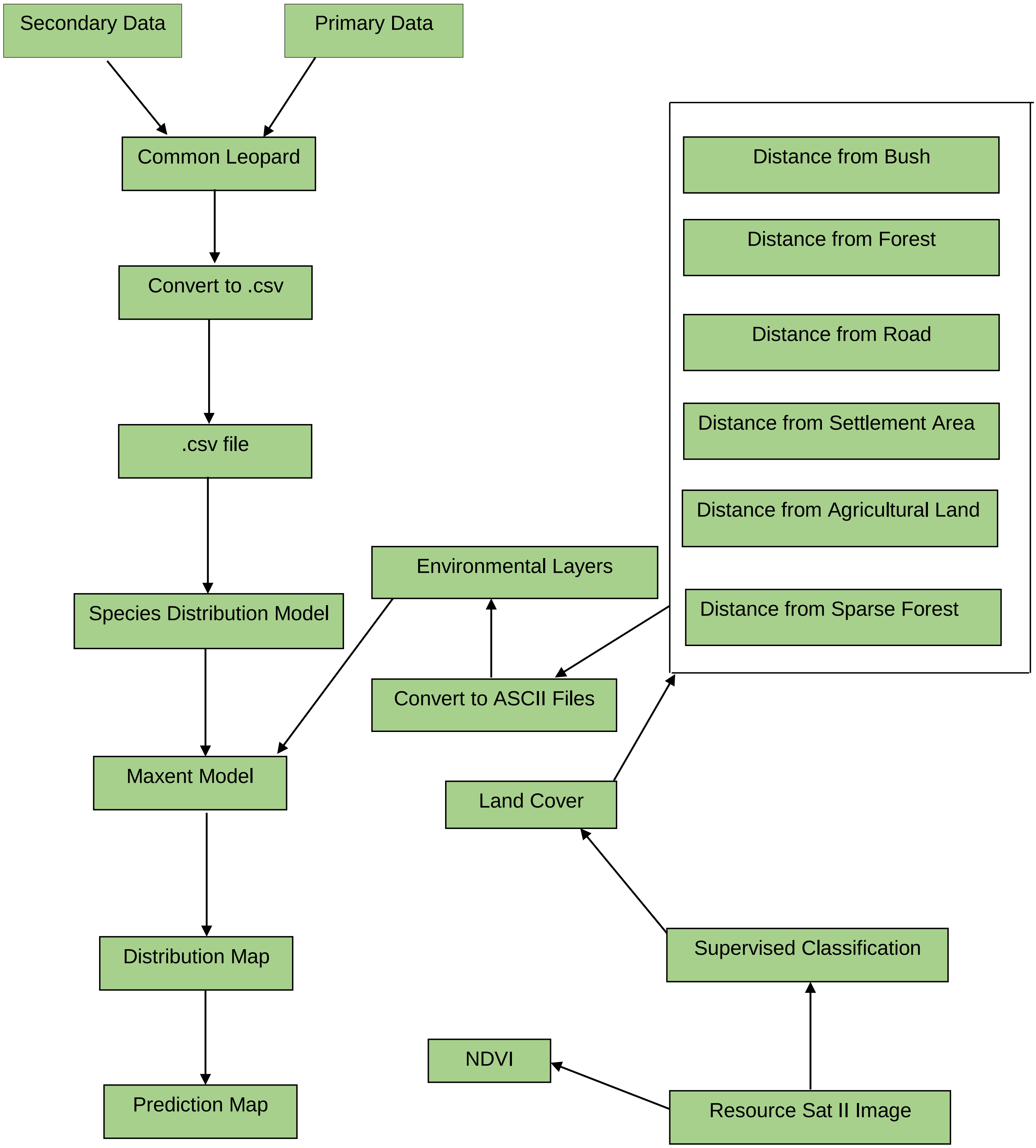


Figure 3 Methodological Flowchart

Chapter-4: Results

4.1 Leopard Presence Point

Presence points data which have been collected from fieldwork activity and data from interviewing from villagers are displayed below**.**

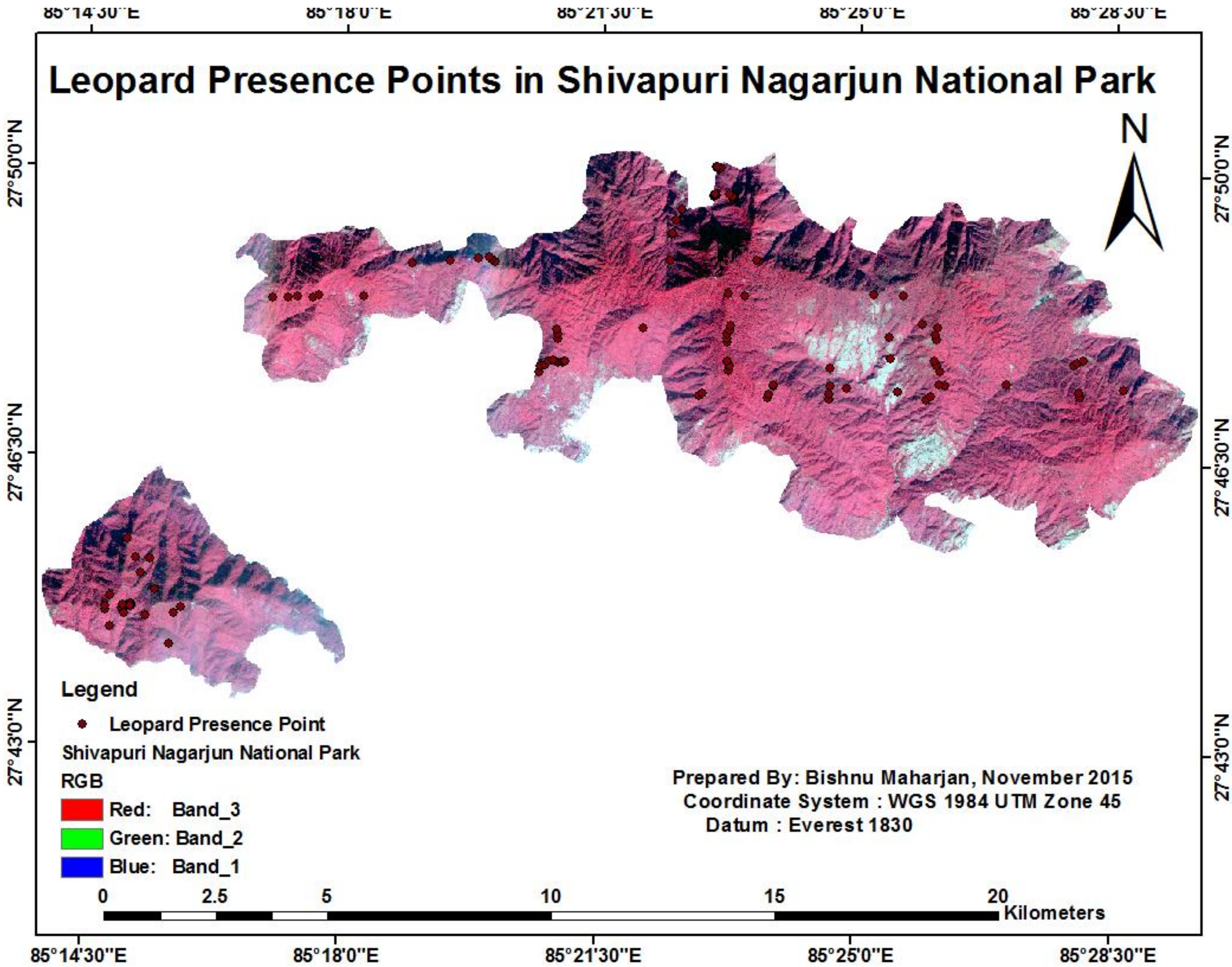
Table 2 Presence Point of Common Leopard in SNNP

Presence	Foot Prints	Scat	Scratch	Total
Common Leopard (*Panthera pardus*)	8	120	10	138

There are 138 of Common Leopard’s presence point in SNNP.

Figure 4 Showing the pugmark and scat of Common Leopard.

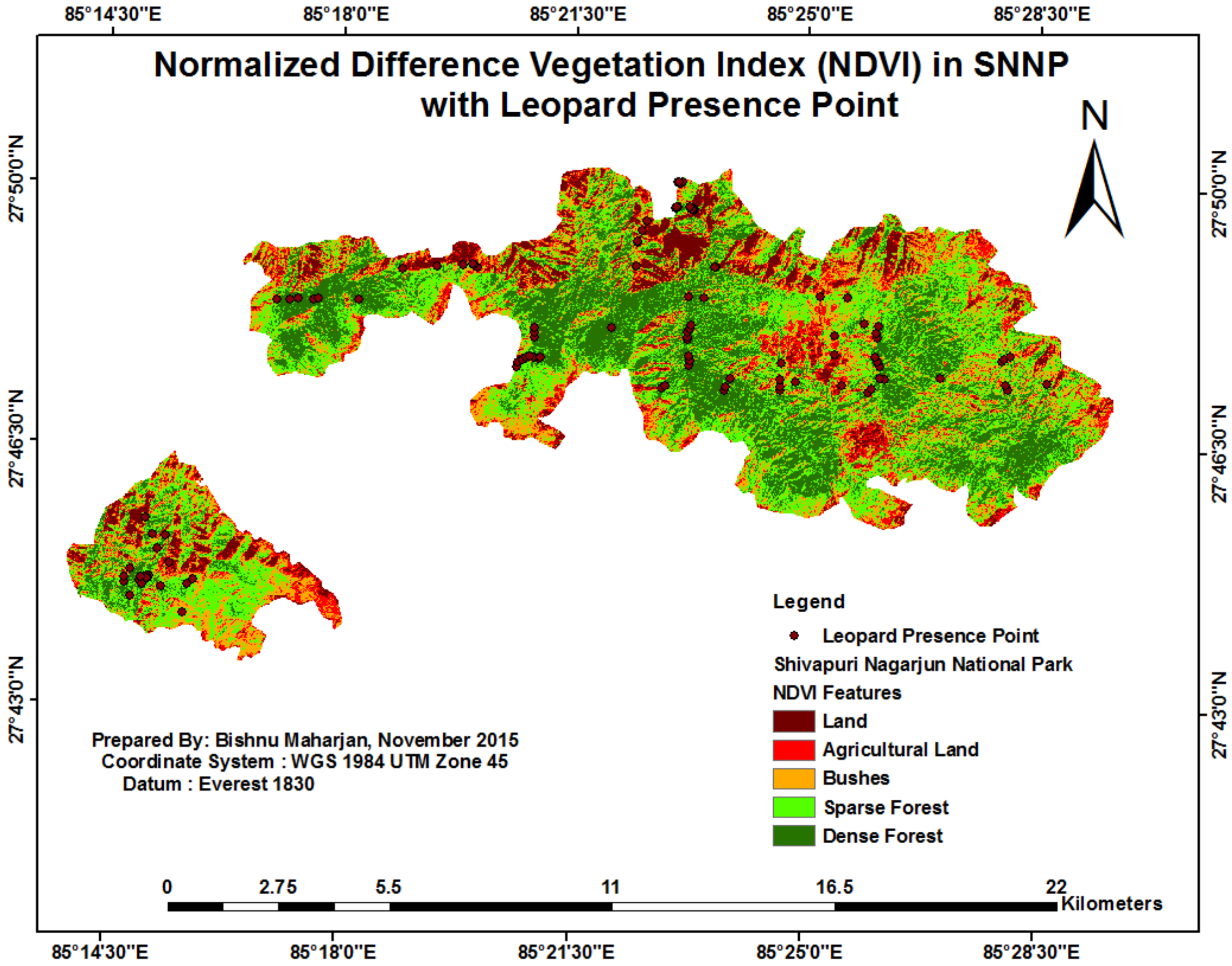
Diameter approach was applied in determining the scats. The characteristics of Common Leopard’s scat diameter is more than 2.2cm **(Swanepoel et al., 2015)** while **(Raharyono & Paripurno, 2001)** argued it is range from 2 – 3 cm. By definition, the scats which have a diameter less than 2cm are assumed as wild cats (**Error! Reference source not found.**).



Map 2 Leopard Presence Points in SNNP

4.2 Normalized Difference Vegetation Index (NDVI)

Meanwhile, the ranges of NDVI in the whole study area is -0.0683 to 0.7872 which indicates the greenness of a patch of land. The National Parks have the high value of NDVI (indicated by bright green color). It means that those areas comprise dense forests as have been specified by **(Ahn, 2014)** that 0.6 – 0.8 of NDVI values are categorized as tropical rain forest (Table 3). However SNNP also have high NDVI value which indicate that those areas are covered by vegetation in a peak growth phase. Based on the result, the landscape of the study area was dominated by bush and forest of area (**Error! Reference source not found.**).



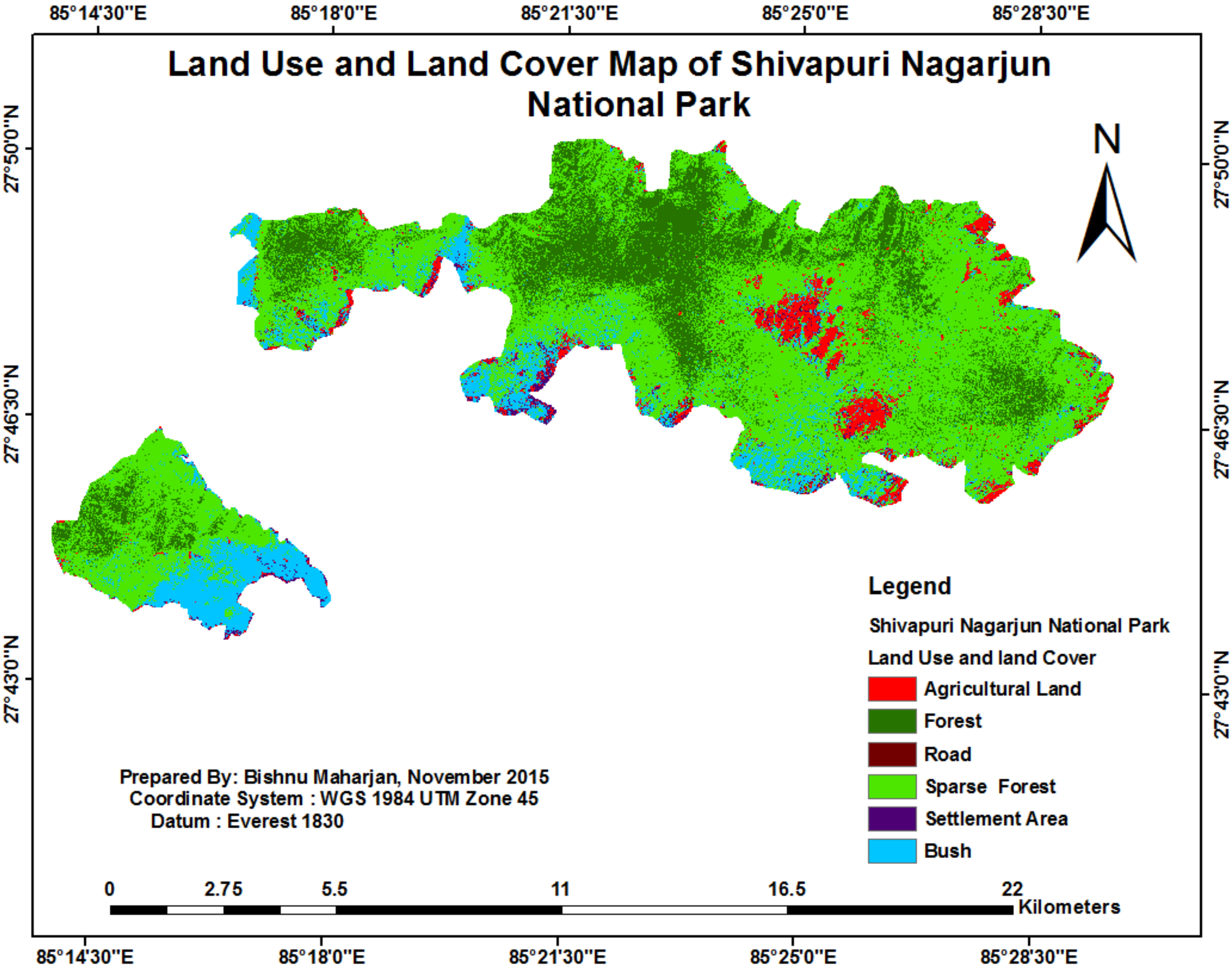
Map 3 Normalized Difference Vegetation Index in SNNP

Table 3 NDVI Value

Land Cover	Range of NDVI Value
Land	0.068 – 0.277
Agricultural Land	0.277 – 0.408
Bush	0.408 – 0.512
Sparse Forest	0.512 – 0.602
Dense Forest	0.602 – 0.787

4.3 Land Cover

(Rimal, 2011) described, Land-use and land-cover change has become a central component in current strategies in managing natural resources and monitoring environmental changes Therefore, satellite images can often be used to detect land-use change through observations of the biophysical characteristics of the land **(Brown, Pijanowski, & Duh, 2000)**. Then forest, agricultural land, bush/shrub/grassland, sparse forest, settlement area, and bush, road, settlement areas covers 79.341km^2, 74.77km^2 , 43.227km^2, 38.522km^2, 4.3km^2 and 1.87km^2 respectively (Table 4).



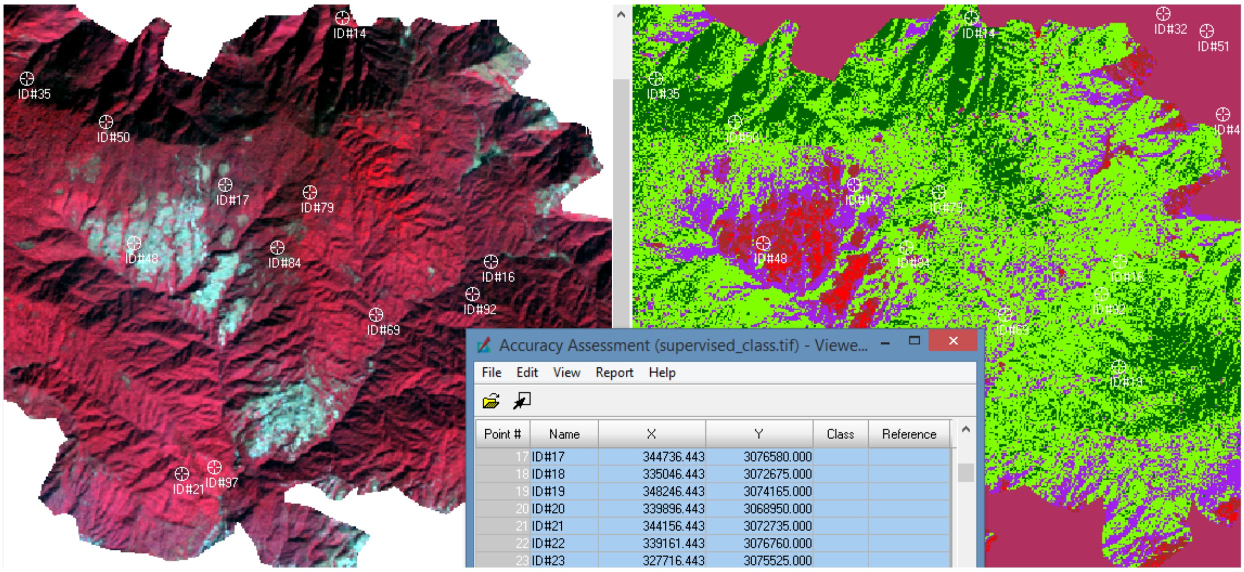
Map 4 Land Use and Land Cover of SNNP

Table 4 Land use and Land Cover of SNNP

Land Use and Land Cover	Total percent
Forest Area	79.341
Agricultural Land	74.77
Bush/Grassland/Bush	43.227
Sparse Forest	38.522
Settlement Area	1.87
Road	4.3

4.4 Accuracy Assessment Result

The average overall accuracy for the supervised maximum likelihood classification was 99.755% (Table 5). The overall Kappa statistics was also high (0.97). Both the producer's and user's accuracy were over 90% for cover classes (Table 5).



Map 5 Performing Accuracy Assessment of SNNP

Table 5 Acccuracy Assessment Value of SNNP

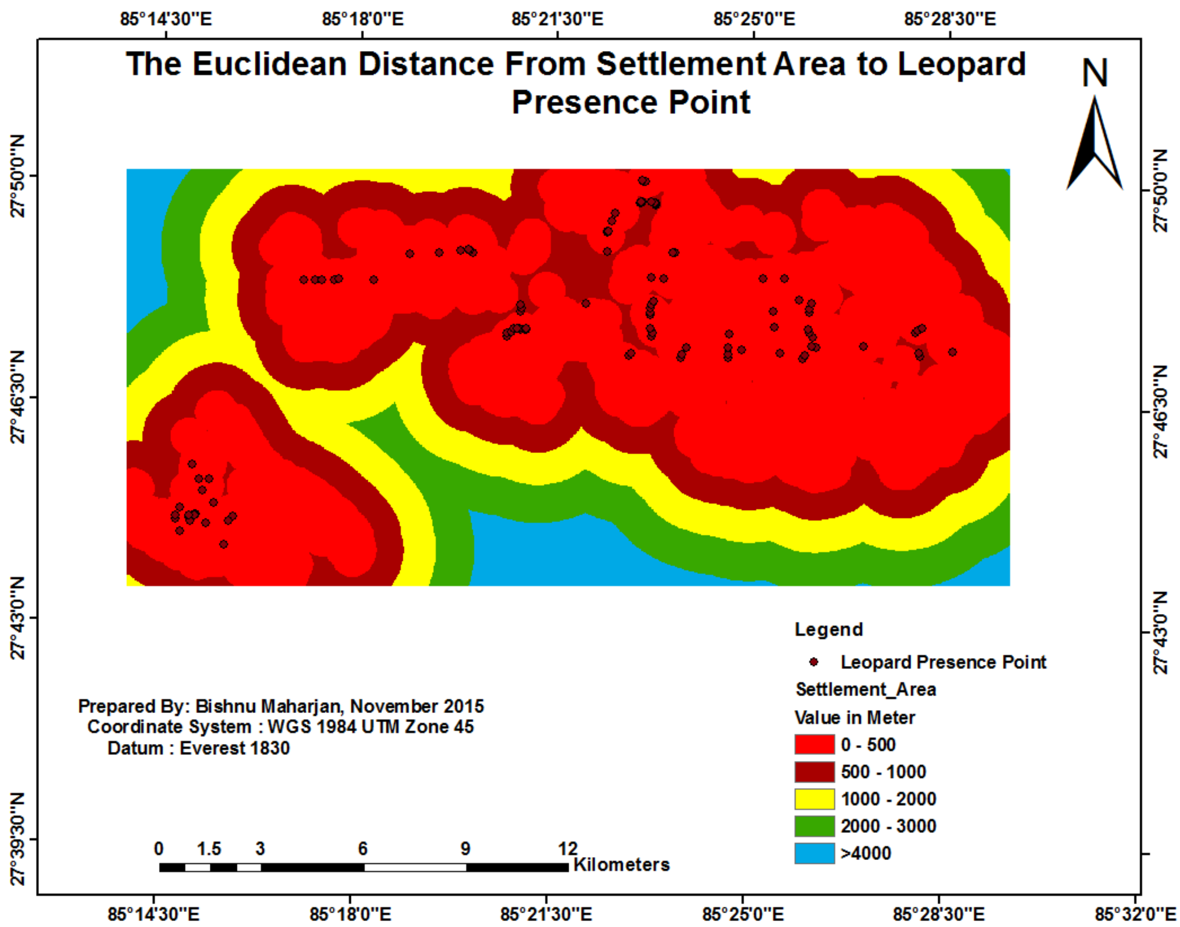
Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	User's Accuracy
Forest	7	8	7	100%	100%
Sparse Forest	12	12	12	100%	100%
Agricultural Land	14	14	14	100%	100%
Bush/Shrub/Grasses	12	12	12	100%	100%
Road	69	68	68	98.55%	98.55%
Settlement Area	6	6	6	100%	100%
Totals	100	100	41	99.755%	99.755%

Though the level of accuracy required is actually defined by its intended use, it can be still said that the classification was in acceptable mode. However, if certain class types occurring in an image have inherently similar spectral response patterns, no amount of retraining and refinement will make them spectrally separable. It will then require other approaches like multi temporal or spatial pattern recognition procedures for better classification results.

4.4 Distance from Road/Settlement/Bush/Forest/Agricultural Land

Based on the presence data of Common Leopard in SNNP, their proximity to road/settlement/bush/forest/agricultural land were calculated by applying Euclidean distance in ArcGIS 10.2 software. There was a point where the scat has been found on the path in SNNP and a point reported by people in SNNP which located by nearby forest. There was also a point of Common Leopard's occurrence which located to forest as it was reported by local people of SNNP whom cattle have been preyed by the leopard. In order to provide a robust group in proximity to those criteria, for map displaying purposes, the distances were classified into five groups (0 – 500m, 500 – 1000m , 1000 – 2000m, 2000

– 3000m, 3000m – 4000m, 4000m – 5000m and greater than 5000m) (**Error! Reference source not found.**).



Map 6 Euclidean Distance from Settlement Area to Leopard Presence Point of SNP

4.5 MaxEnt Output

The X - Axis shows the cumulative threshold and Y– Axis shows the fractional value. Red line indicate fractional of background predicted and blue line indicate the omission on training samples and skyline indicate the omission on test samples whereas black straight line indicate the predicted omission rate. This graph shows how testing and training omission and predicted area vary with the choice of cumulative threshold. So, omission on test samples is good to match for test data drawn from the MaxEnt distribution itself. The below graph displays the omission rate and predicted area as a function of cumulative thresholds. The omission rate is calculated both on training presence records, and (if test data are used) on the test records. The omission rate should be close to the predicted omission because of the definition of the cumulative thresholds (Philips et al. 2006). Therefore analysis of omission rate and predicted areas as function of cumulative threshold (Philips et al., 2005) showed that omission rate was close to the predicted omission depicting the model to be robust to conduct further analysis (**Error! Reference source not found.**).

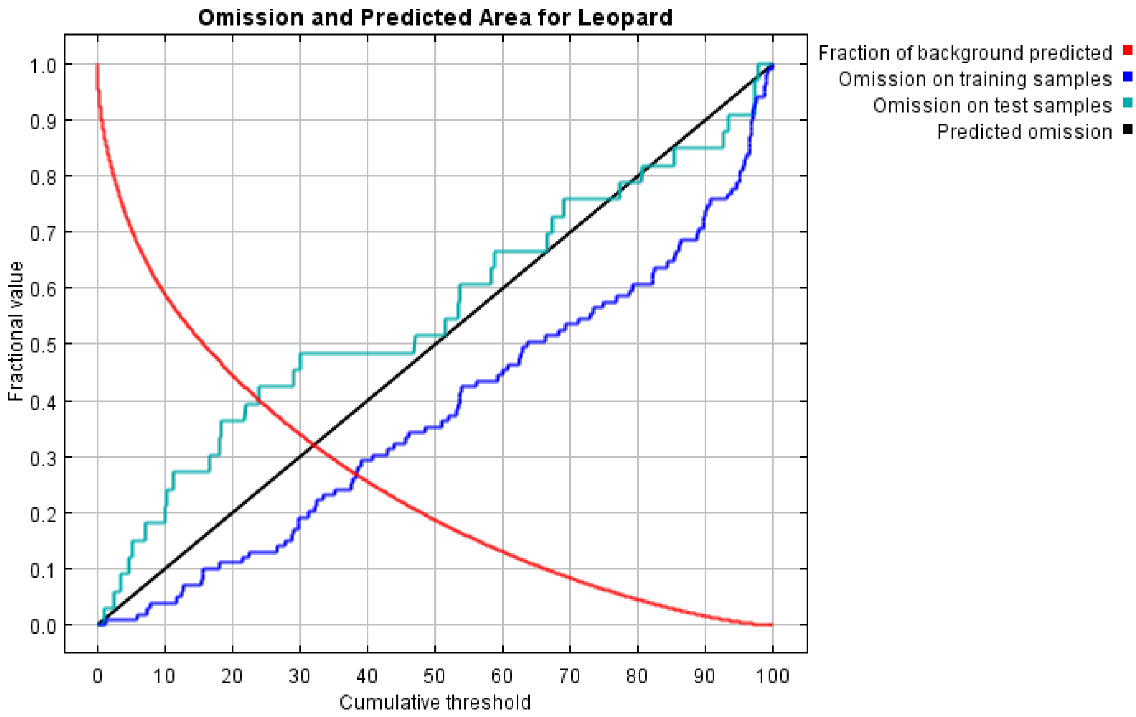


Figure 5 Omission rate and predicted area by using cumulative threshold

X – Axis shows the (1 – Specificity) which means “fractional predicted area” and Y – axis shows the Sensitivity which means “1 – omission rate”. The red training line shows the “fit” of the model to the training data. The blue “testing” line indicates fit of the model to the training data and is the real test of the models predictive power. The black line shows the line which we would expect of our model was no better than random. When the blue line (testing line) falls below the black line then it indicates that our model performs worse than a random model. The line towards the top left of the graph that the blue line is the better the model is at predicting the presence contained in the test sample data (**Error! Reference source not found.**).

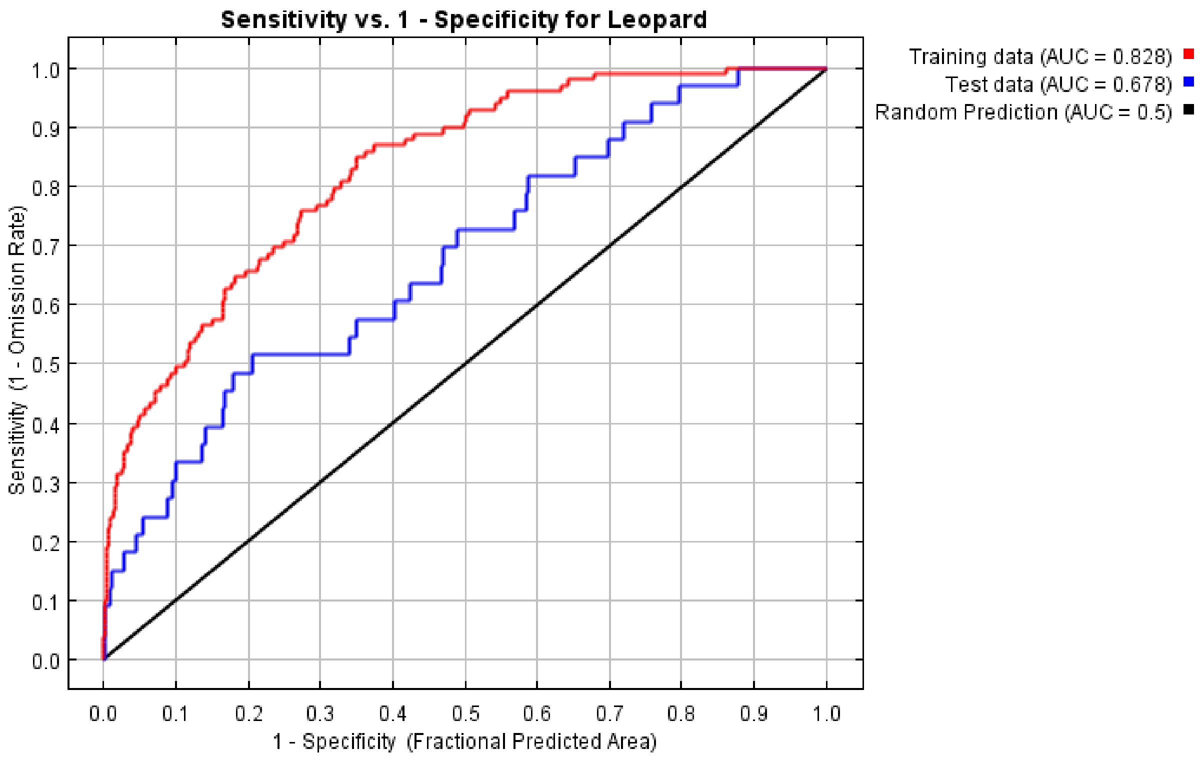


Figure 6 Receiver Operating Characteristics (Sensitivity Vs 1 - Specificity) on Leopard

The area under the Receiver Operating Characteristics (ROC) curve or AUC. The AUC value allow us to compare the performance of one model with another model and these are most value able for evaluating multiple MaxEnt model. The AUC value of 0.5 indicates that the performance of the model is no better than random, while values closer to 1.0 indicate better model performance **(Young et al., 2011)**.

The ROC curves in this model ROC curves shows high accuracy of the generated model with AUC 0.828 for training data and 0.678 for test data. The red line shows the “fit” of the model to the training data. The value indicates of 0.5 that the performance of the model is no better than random while values greater than 0.5 represents the good model performance (**Error! Reference source not found.**).

4.5.1 Analysis of variable contributions

The (Table 6) gives estimates of relative contributions of the environmental variables to the MaxEnt model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages. As with the variable jackknife, variable contributions should be interpreted with caution when the predictor variables are correlated.

Table 6 Analysis of Variable Contribution

Variable	Percent Contribution
Settlement Area	52.5
Road	16.5
Forest Area	15.8
Agricultural Area	14.1
Bush	1
Sparse Forest	0.3

4.5.2 Jackknife Test

The Jackknife evaluation of relative importance of environmental variables indicated Settlement area, forest area, road and agricultural land made the highest contribution to the Leopard distribution. Forest and settlement area had the highest AUC gain when run in isolation. Jackknife of regularized training gain for Common Leopard (*Panthera pardus*), it shows the result of Jackknife variable test of variable importance. The environmental variable with highest gain when used in isolation is “Settlement Area” which therefore appears to have the most useful information through itself. Here X – axis show the regularized training gain and Y – axis shows the environmental variables whereas sky color shows the without variables and blue color shows only variable and red color shows with all variables.

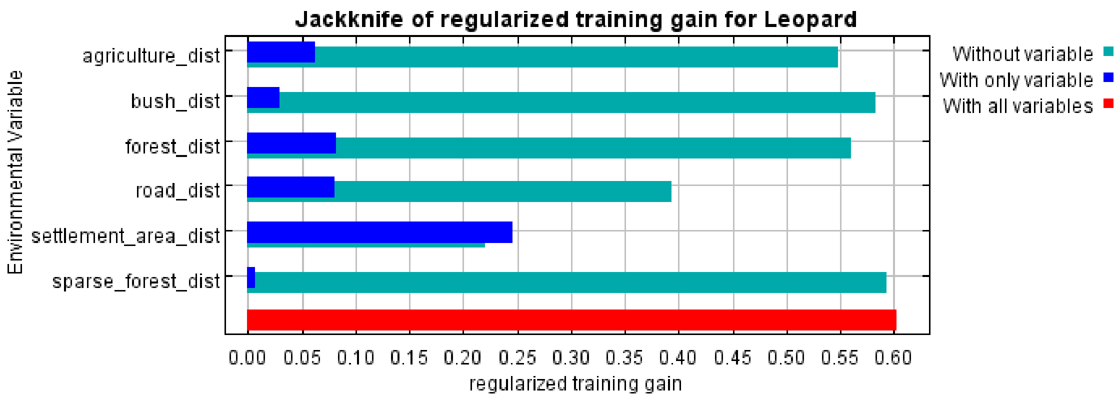


Figure 7 Jackknife result of variable in regularized training gain for Common Leopard (*Panthera pardus*)

Likewise, the Jackknife shows the training gain of each variable if the model was run in the isolation and compares it to the training gain all the variables. This is useful to identify which variables contribute the most individually (Error! Reference source not found.). The Common Leopard (*Panther pardus*) model also provides a Jackknife for test gain of the species and AUC.

Again It shows the same Jackknife test using AUC on test data. Comparing the six Jackknife plots become very informative. The AUC plot shows that settlement area, forest, bush, road, agricultural land and sparse forest are the most effective variable for predicting the distribution of the occurrence data that was set aside for testing when predictive performance is measured using AUC (**Error! Reference source not found.**).

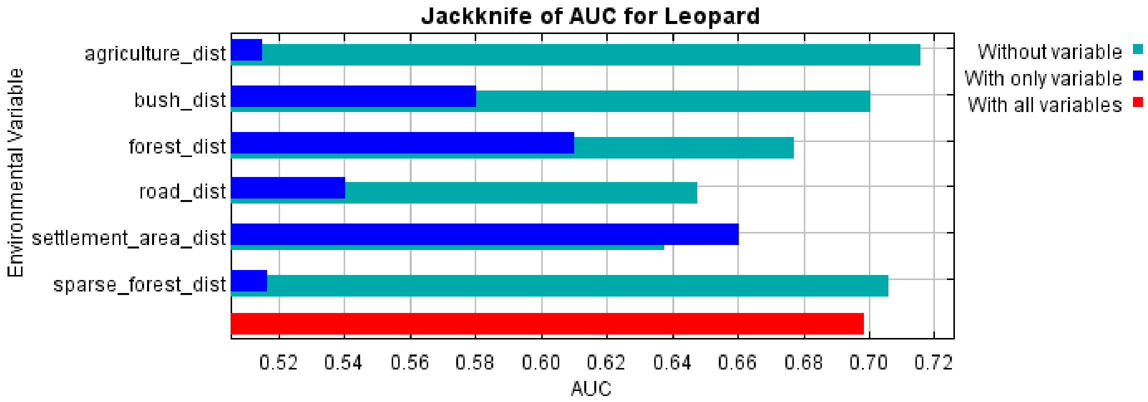


Figure 8 Jackknife result of variable in the AUC for Common Leopard *(Panthera pardus)*

The (**Error! Reference source not found.**) illustrate the Jackknife of test gain of common leopard and it shows different Jackknife test using test gain instead of training gain. The agricultural area shows opposite trend of environmental variable. That means it does not support Jackknife of test gain for common leopard. It does not play vital role to in test gain for leopard. It is remainder that conclusion about which variables are most important can change, now that I'm looking at test data. So X – axis shows the test gain and Y – axis shows the environmental variables.

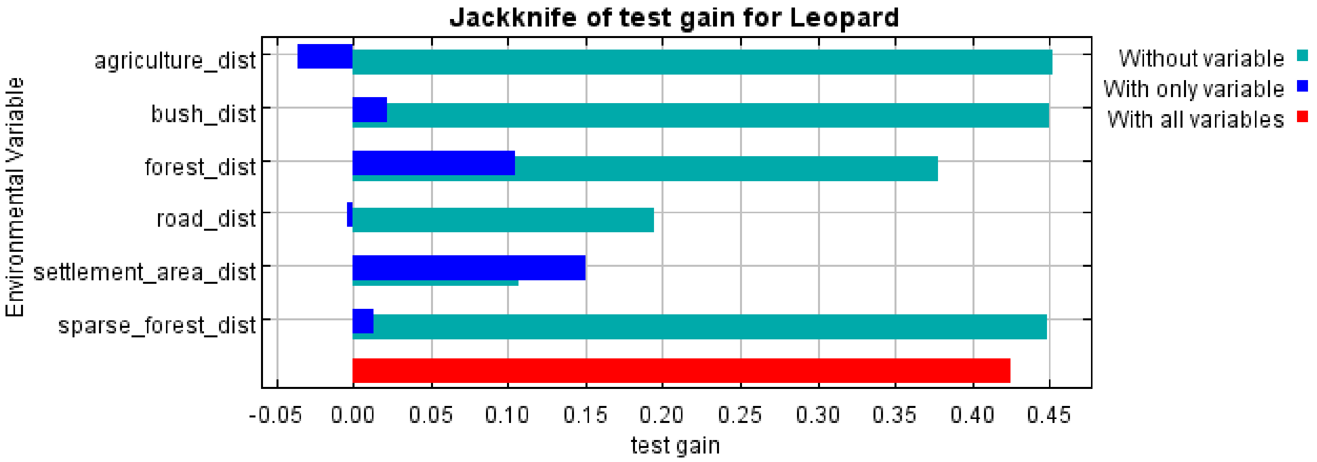


Figure 9 Jackknife results of variable importance in the test gain for Common Leopard (*Panthera pardus*)

Therefore jackknife test shows the result of the test of environmental variable importance for this model. The environmental variable with highest training gain when used in isolation is Distance from settlement area which become most useful information through itself. This pattern is followed by distance from forest, distance from bush, distance from sparse forest, distance from road, and distance from agricultural land have low gains when used in isolation. The environmental variables that decreases the gain the most when excluded from the model which are therefore most useful information that is not present in other variable. Hence resultant AUC has higher in the case of the variables "distance from settlement area, distance from forest, distance from bush, distance from sparse forest, distance from road and distance from agricultural land have significant gain. This may be because of the most of the common leopard presence point were falling in the settlement area, agricultural land, forest, bushes and along the trails (**Error! Reference source not found.**).

4.5.3 Response Curve

The response curves show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. Note that the curves can be hard to interpret if we have strongly correlated variables, as the model may depend on the correlations in ways that are not evident in the curves. In other words, the curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together.

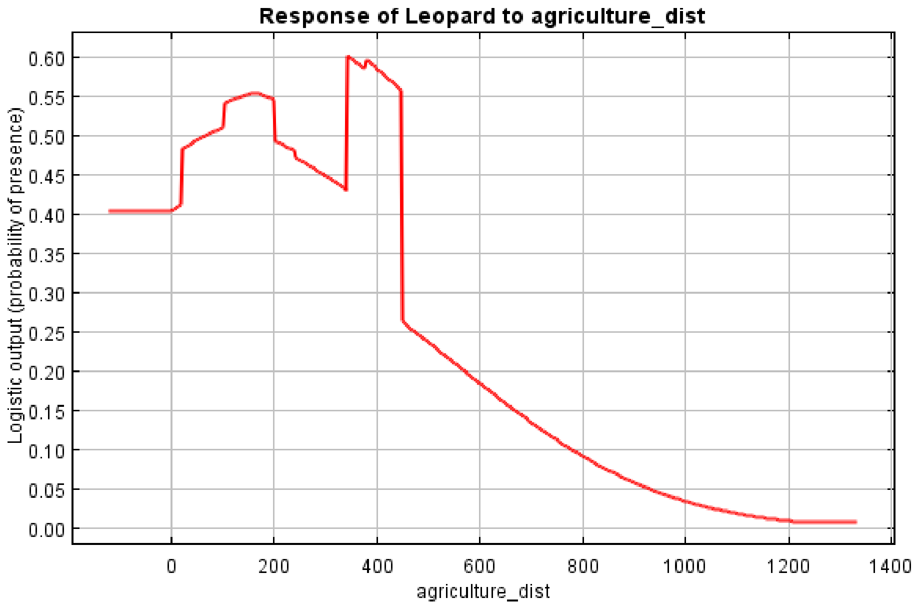


Figure 10 Response of Common Leopard (*Panthera pardus*) presence to Distance from Agricultural Land

The probability of occurrence of the Leopard in “Distance from Agricultural Land” increased up to 0.60 ad sharply decreased up to 0.27. Again it sharply decreased up to 0.01 at a distance of 1200m (Error! Reference source not found.).

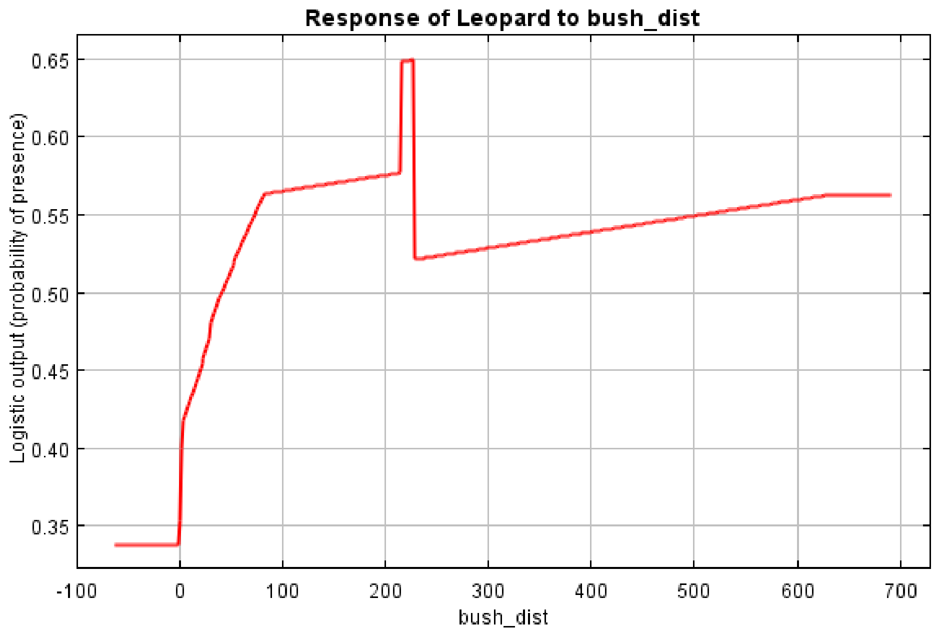


Figure 11 Response of Common Leopard (*Panthera pardus*) presence to Distance from Bush

The probability of occurrence of Leopard in "Distance from Bush" increased from the point 0.2up to 0.65, then it sharply decreased up to 0.53 then again it slightly increased up to 0.56 and distance increased up to 690m (**Error! Reference source not found.**).

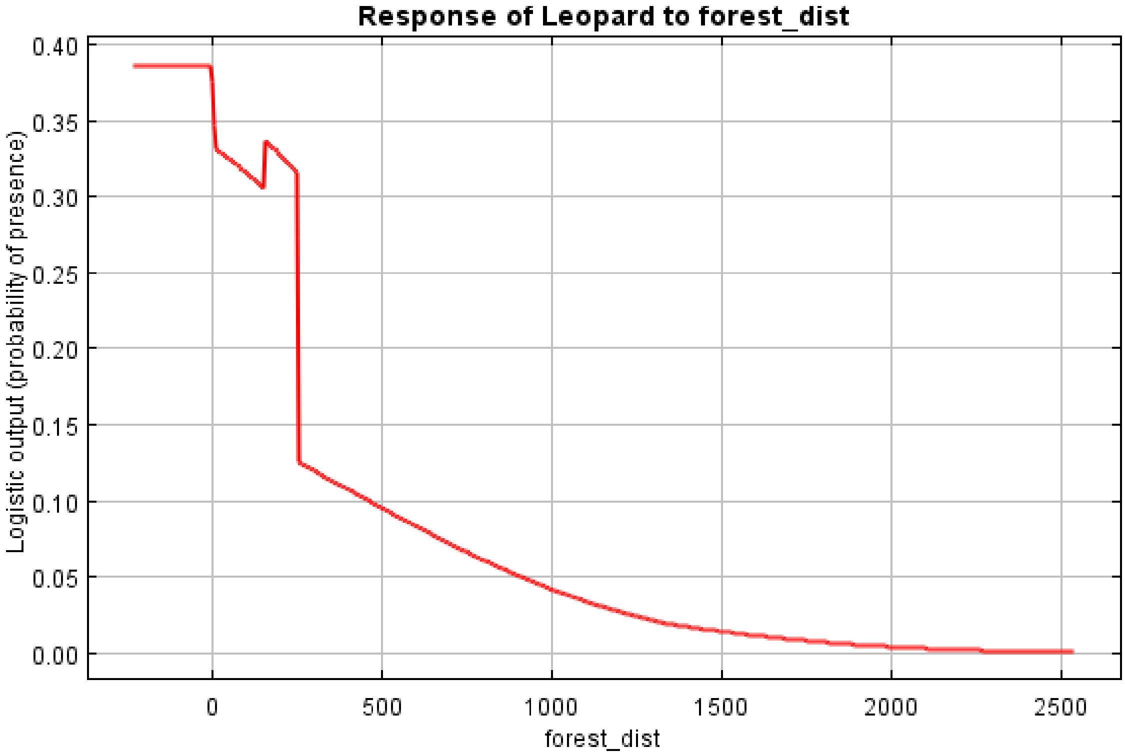


Figure 12 Response of Common Leopard (*Panthera pardus*) presence to Distance from Forest

The probability of Leopard occurrence in "Distance from Forest" where leopard occurrence decreased sharply from 0.38 up to the point 0.13 and occurrence become slanting linear from the distance 1500m to above 2500m (**Error! Reference source not found.**).

Figure 13 Response of Common Leopard (*Panthera pardus*) presence to Distance from Road

The probability of leopard occurrence in "Distance from Road" where it starts increase from 0.28 and gradually increase up to 0.46 while it again increased up to 0.56 and again increased to 0.74. In contrast the probability occurrence decreases sharply decreased to 0.42 and then it can be clearly seen that the occurrence decreased at 0.1 at distance 1500m (**Error! Reference source not found.**).

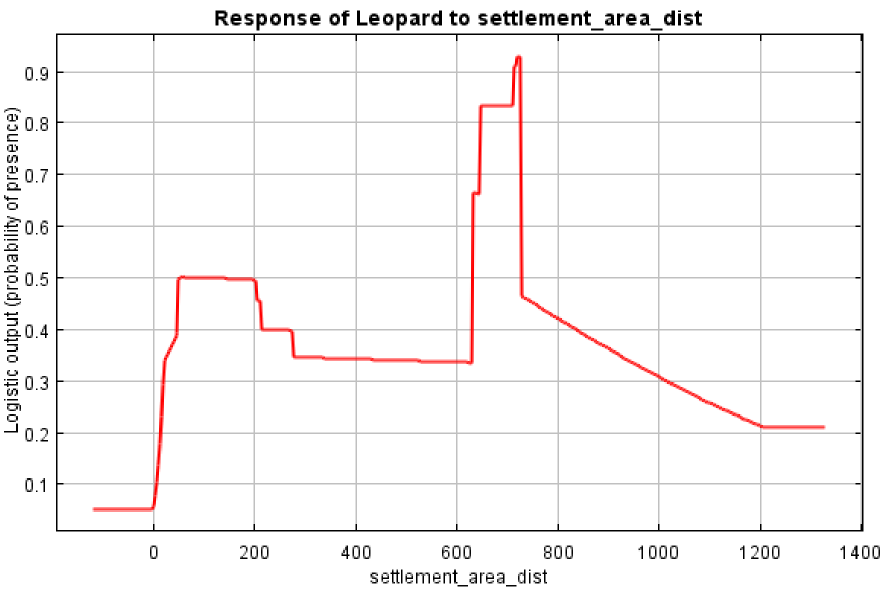


Figure 14 Response of Common Leopard (*Panthera pardus*) presence to Distance from Settlement Area

The probability of leopard occurrence in “Distance from Settlement area” where leopard occurrence increased from 0.05 to 0.5 and again slight decreased up to 0.35 and remain linear. Thereafter it again increased sharply up to 0.91 and from that it again sharply decrease to 0.48. In contrast it again decreased gradually up the 0.21 to the distance 1200m (**Error! Reference source not found.**).

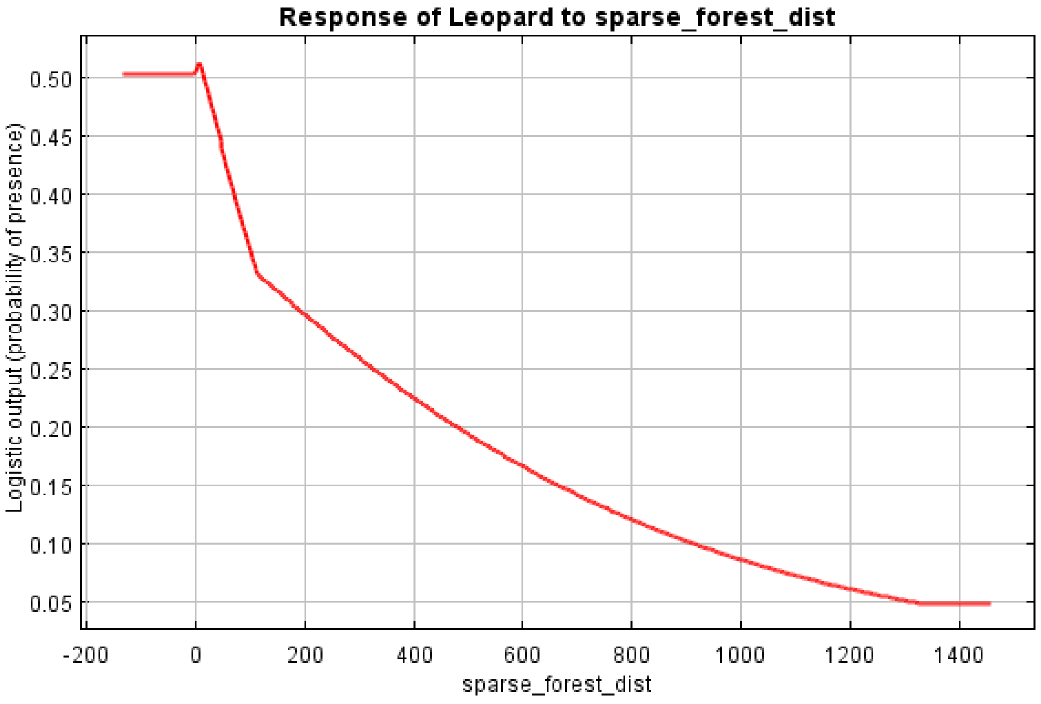


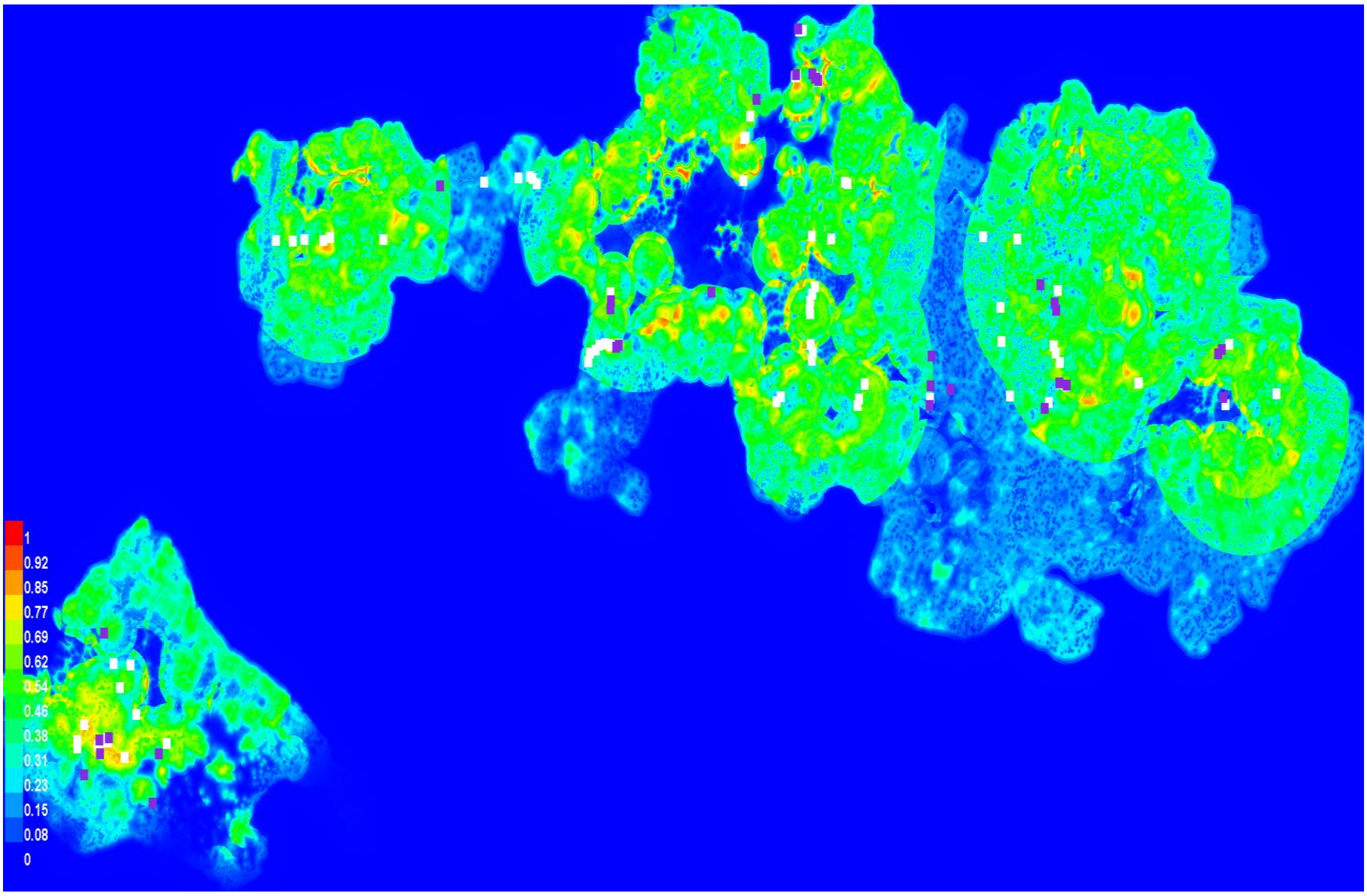
Figure 15 Response of Common Leopard (*Panthera pardus*) presence to Distance from Sparse Forest

The probability of leopard occurrence in “Distance from Sparse Forest” where leopard occurrence gradually decreased up to 0.33 and again gradually decreased up to the 0.05 at a distance 1300m (**Error! Reference source not found.**).

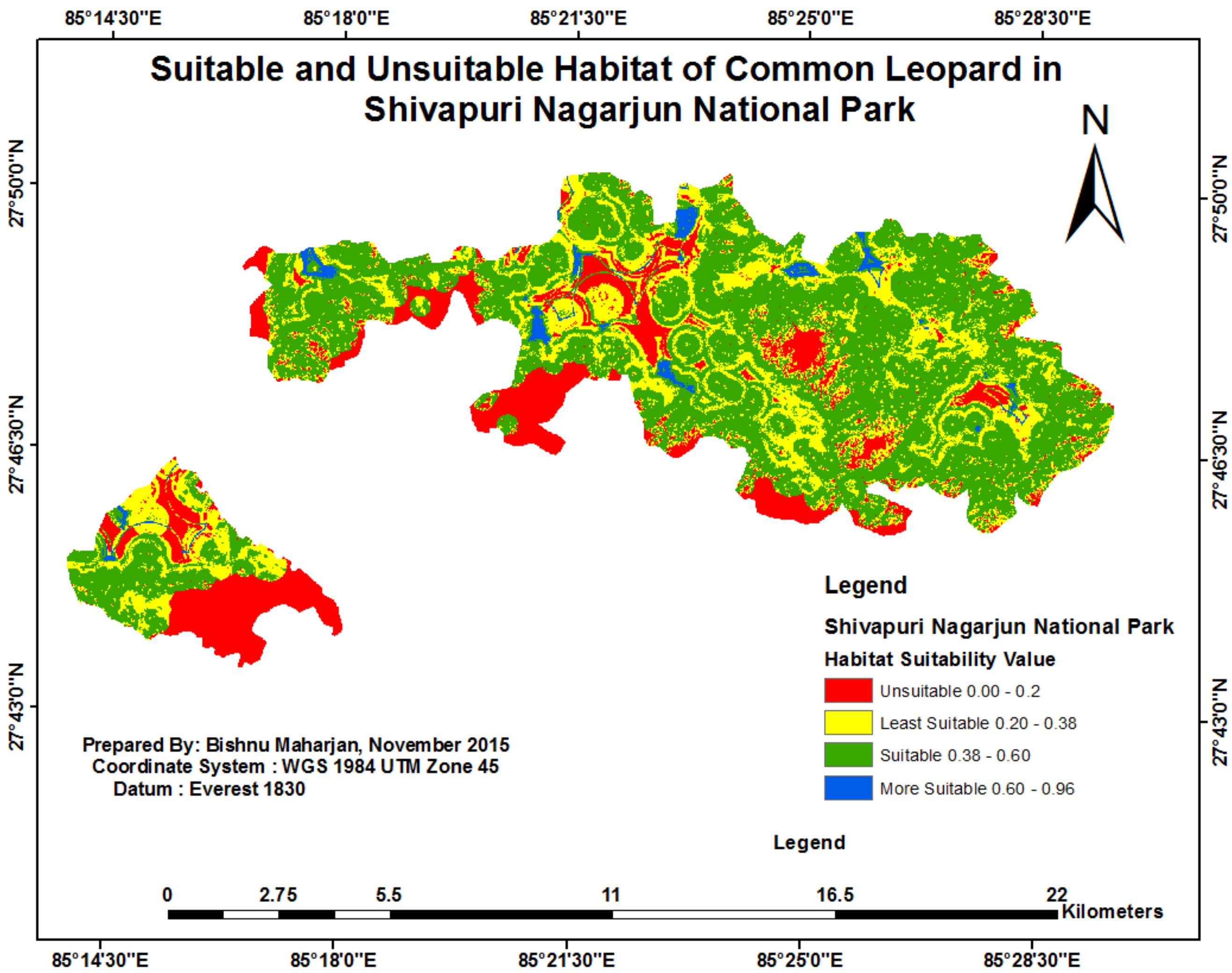
The above display response curves shows how each of the most important predictor variables distance affect the MaxEnt prediction. The response curve for the model showed fairly accurate trend for Common Leopard (*Panthera pardus*) suitability. However in the response curve the probability occurrence of Common Leopard decreases as increase in distance of the environmental variable. In response curve of variables like distance from Settlement Area, distance from Forest, distance from Road, distance from Agricultural Land, distance from Bush and distance from Sparse Forest showed that increase in distance from variable increases the probability of occurrence of Common Leopard (*Panthera pardus*). The curves showed this trends up to certain distance approx. 2.5km distance from forest, 1.2 km from settlement, 1.35 km from road, 1.2 km from agriculture, 700m from bushes and 1.3km from sparse forest, beyond these variables occurrence probability decreased. This may be due to absence of Common Leopard beyond these distances of the respective cover types.

4.6 Habitat Suitability Map

MaxEnt generated a habitat suitability map (**Error! Reference source not found.**). This map is then classified on the different species occurrence probability threshold class. By using specific probability thresholds to classify suitability map into different suitability classes. However the MaxEnt predicted map was uses colors that indicate predicted probability that conditions are suitable. Warmer colors (red) indicate high probability of suitable conditions for the species and blue indicates low probability. Therefore suitability map was reclassified into two classes; suitable and Unsuitable. The Unsuitable category included the areas that have least probability for Common Leopard to occur.



Map 7 MaxEnt Habitat Suitability Map



Map 8 Habitat Suitability Map of Common Leopard (*Panthera pardus*) in Shivapuri Nagarjun National Park

Table 7 Threshold used to predicted logistic output into classes

Habitat Class	Probability Value
Unsuitable Habitat	0.00 – 0.20
Least Suitable Habitat	0.20 – 0.38
Suitable	0.38 – 0.60
More Suitable	0.60 – 0.96

The map was categorized using the threshold 0.00 – 0.20 as unsuitable while from 0.20 – 0.38 as least suitable. The suitability of Common Leopard in Shivapuri Nagarjun National Park are categorized (Table 7). The result of habitat suitability map shows that the total potential suitable habitat for Common Leopard in SNNP is $166km^2$ while other remain unsuitable habitat for Common Leopard of area $143km^2$ in SNNP. As it includes the land use and land cover types there in proximity of Agricultural Land. For achieving this extent of areas as suitable, number of water bodies has to be significantly increased and maintained. When water resource has maintained, automatically the agricultural land becomes increases which significantly increases the occurrence of Common Leopard in Shivapuri Nagarjun National Park (Table 8).

Table 8 Predicted Suitable and Unsuitable areas for Common Leopard in SNNP

Habitat Class	Area (km^2)
Unsuitable	24.28
Least Suitable	18.44
Suitable	123.21
More Suitable	3.156

MaxEnt modeling has proven to be very effective at determining habitat use and species distributions for a variety of species and localities. It shows suitability map that shows majority of “Suitable” patches around the SNNP. For enhancing the habitat improvement of Common Leopard in SNNP, certain improvement and interventions has to be carried out. This model also suggest that increasing number of “agricultural land, bushes and Forest” helps in increasing suitable habitat of Common Leopard (*Panthera pardus*).

Chapter-5: Discussion

Suitable habitat for Common Leopard (Panthera pardus) has been identified and mapped as 166km^2 which occupies 54% of the total area. Agricultural Land, forest, bushes areas are occupied by the Common Leopard which are predicted as suitable habitat for leopard. The leopard prefers to habitat type of agricultural land until bush and forest as these areas have greater affinity towards prey base that serves as food for them. The result of MaxEnt model of Common Leopard has performed the AUC value of 0.99. It is considered as an excellent model because of the value more than 0.9 **(Steves et al., 2011).** Therefore, this presence distribution prediction was suitable for Common Leopard. On this model, variables which were represented by environmental layers showed its contribution percentage. Among the 6 variables which have been deliberately chosen, the most important variables of this model consist of settlement area, forest, bush, sparse foerst and roads. The potential threat in terms of land use which might be faced by the settlement area become the most serious threat to conservation and sustainable development in general. The prediction at the NP's boundary can be regarded as the potential distribution as well as the prone area for conflict between the leopard and humans (their cattle). Delimit human access to particular zones which are restricted to any disturbances and intensify the survey of wildlife can be the noticeable action to conserve Common Leopard.

Chapter -5: Conclusion

There has never been a scientific research conducted in SNNP about Common Leopard. Thus a detailed, scientific study of common leopard is very necessary in SNNP. This could provide an estimation of the number of common leopards in SNNP. The livestock depredation caused by the species should also be addressed during the study. Conservation education must be included in the curriculum of school which provides students the knowledge about the importance of the leopard. Conservation education must also be provided to the villagers about the role the species plays in balancing the ecosystem by acting as the supreme predators of hilly region in the food chain. Brochures, posters, leaflets and other publications must be prepared and distributed showing the importance of common leopard and the benefits one can get from it. This could help in making people aware of its importance thus helping in its conservation. Meanwhile local government particularly Kathmandu district can take this issue of connecting ecology into account on its spatial planning. In order to make sure the prediction of Common Leopard's presence in SNNP deploying several camera traps within the areas denoted as presence would be beneficial for the next level of wildlife management. By using camera traps, either Common Leopard or other wildlife can be recorded as the main attention in managing the park. Conducting presence – absence survey of Common Leopard in SNNP will give another option of species distribution modelling such as GLM, GAM, and BRT etc. As the prominence of land cover, environmental layer, NDVI and satellite imagery, applying very high resolution of remotely sensed imagery to obtain more detain Landover will produce more precise result in predicting Common Leopards' distribution and connects human wildlife welfare scenario. As the prominence of Land Use and Land Cover on this model, applying high resolution of remotely sensed imagery to obtain more detail land cover produce more precise result in predicting Common Leopard's distribution in SNNP. During the study, it was evident that habitat destruction is quite rampant in the study area. Habitat encroachment is one of the main reasons for the leopard to turn its attention towards human settlements that results in livestock depredation. Therefore deforestation and encroachment of the leopard habitat must be discouraged properly. A database must be prepared and maintained by conducting a detailed study about the leopard in the area by the concerned authority which contains everything about the leopard's situation/condition in the area. For e.g. it's potential and actual habitat, its natural prey base, prey – predator relationship and so on.

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ANNEX I

Common Leopard presence point in Shivapuri Nagarjun National Park

Species	X-Coordinate	Y-Coordinate
Leopard	345562	3074704
Leopard	345560	3074706
Leopard	343377	3074740
Leopard	342005	3074742
Leopard	349005	3074759
Leopard	345645	3074786
Leopard	340463	3074795
Leopard	342033	3074839
Leopard	343387	3074842
Leopard	348963	3074855
Leopard	340539	3074861
Leopard	344903	3074877
Leopard	349977	3074904
Leopard	343775	3074964
Leopard	343394	3075011
Leopard	345975	3075013
Leopard	345969	3075016
Leopard	345979	3075020
Leopard	342148	3075032
Leopard	342142	3075041
Leopard	345844	3075048
Leopard	347347	3075050
Leopard	347349	3075050
Leopard	345845	3075050
Leopard	345857	3075330

Leopard	336880	3075343
Leopard	341129	3075367
Leopard	343411	3075429
Leopard	348862	3075457
Leopard	345777	3075461
Leopard	336912	3075469
Leopard	341151	3075470
Leopard	337023	3075500
Leopard	348935	3075518
Leopard	337412	3075544
Leopard	337310	3075561
Leopard	345730	3075563
Leopard	337460	3075570
Leopard	337094	3075577
Leopard	337275	3075583
Leopard	337469	3075583
Leopard	349070	3075583
Leopard	341112	3075588
Leopard	337201	3075593
Leopard	344748	3075624
Leopard	341103	3076001
Leopard	345779	3076055
Leopard	341098	3076068
Leopard	337307	3076077
Leopard	344721	3076094
Leopard	345755	3076154
Leopard	341107	3076179
Leopard	337311	3076181
Leopard	341147	3076277
Leopard	337299	3076293

Leopard	339224	3076305
Leopard	345818	3076324
Leopard	341190	3076376
Leopard	345479	3076400
Leopard	331265	3077001
Leopard	331839	3077013
Leopard	330944	3077018
Leopard	332982	3077020
Leopard	331482	3077027
Leopard	345044	3077036
Leopard	341501	3077039
Leopard	341501	3077039
Leopard	331972	3077052
Leopard	344394	3077060
Leopard	341134	3077072
Leopard	334062	3077763
Leopard	335899	3077793
Leopard	341811	3077794
Leopard	341763	3077816
Leopard	334905	3077818
Leopard	339833	3077831
Leopard	335820	3077863
Leopard	335553	3077873
Leopard	335778	3077897
Leopard	339856	3078411
Leopard	339852	3078422
Leopard	339851	3078422
Leopard	339877	3078436
Leopard	339968	3078720
Leopard	340086	3078956

Leopard	341256	3079207
Leopard	341251	3079210
Leopard	341257	3079211
Leopard	341248	3079211
Leopard	341253	3079218
Leopard	341257	3079242
Leopard	341196	3079246
Leopard	341263	3079246
Leopard	341221	3079248
Leopard	341253	3079250
Leopard	341249	3079250
Leopard	341206	3079251
Leopard	341223	3079251
Leopard	340815	3079261
Leopard	340819	3079261
Leopard	340819	3079271
Leopard	340835	3079272
Leopard	340836	3079277
Leopard	340829	3079285
Leopard	340854	3079293
Leopard	340849	3079294
Leopard	340841	3079294
Leopard	340856	3079296
Leopard	340837	3079296
Leopard	340838	3079298
Leopard	341144	3079300
Leopard	340925	3079893
Leopard	340897	3079894
Leopard	340961	3079900
Leopard	340964	3079901

Leopard	340875	3079921
Leopard	340878	3079922
Leopard	328174	3071176
Leopard	327977	3070861
Leopard	327162	3070037
Leopard	327675	3071617
Leopard	327291	3069668
Leopard	328279	3070499
Leopard	327553	3070066
Leopard	327596	3069958
Leopard	327290	3070354
Leopard	328067	3069907
Leopard	327162	3070132
Leopard	327763	3070174
Leopard	327746	3070114
Leopard	327730	3070163
Leopard	327718	3070119
Leopard	328863	3070095
Leopard	328718	3069956
Leopard	327579	3070146
Leopard	328598	3069274
Leopard	327853	3071194

ANNEX II

Photo Plates of Field Activities

Photo 1: Shivapuri Nagarjun National Park

Photo 2: Common Leopard Pugmarks

Photo 3: Common Leopard Scats

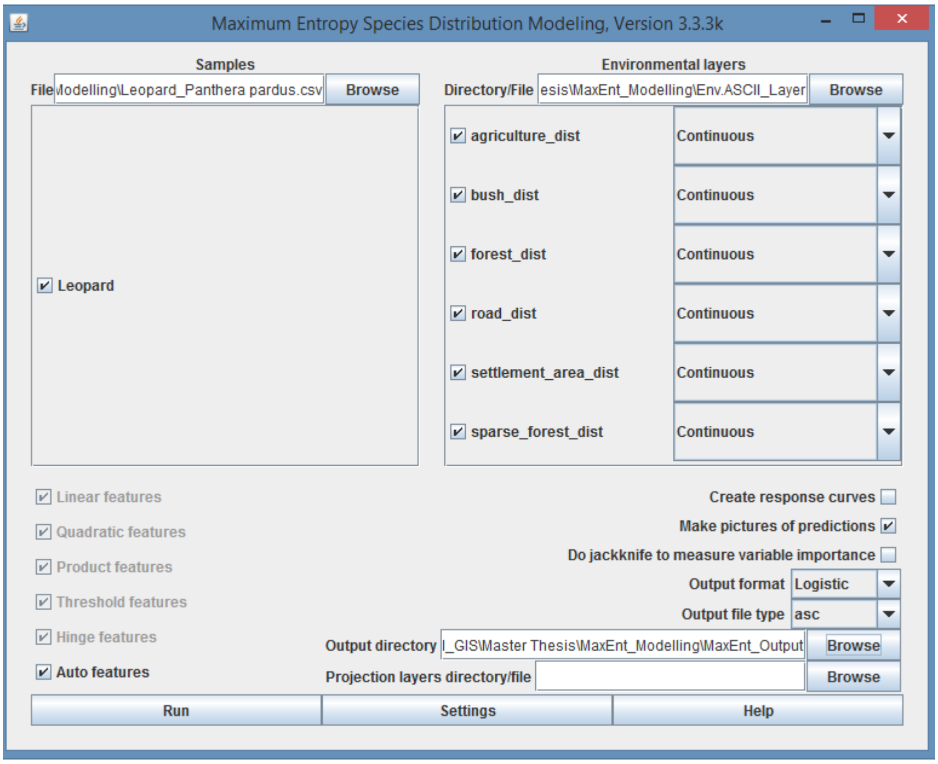
Photo 3: Monkeys and Barking Deer

Photo 4: Domestic Animals Grazing in the Forest

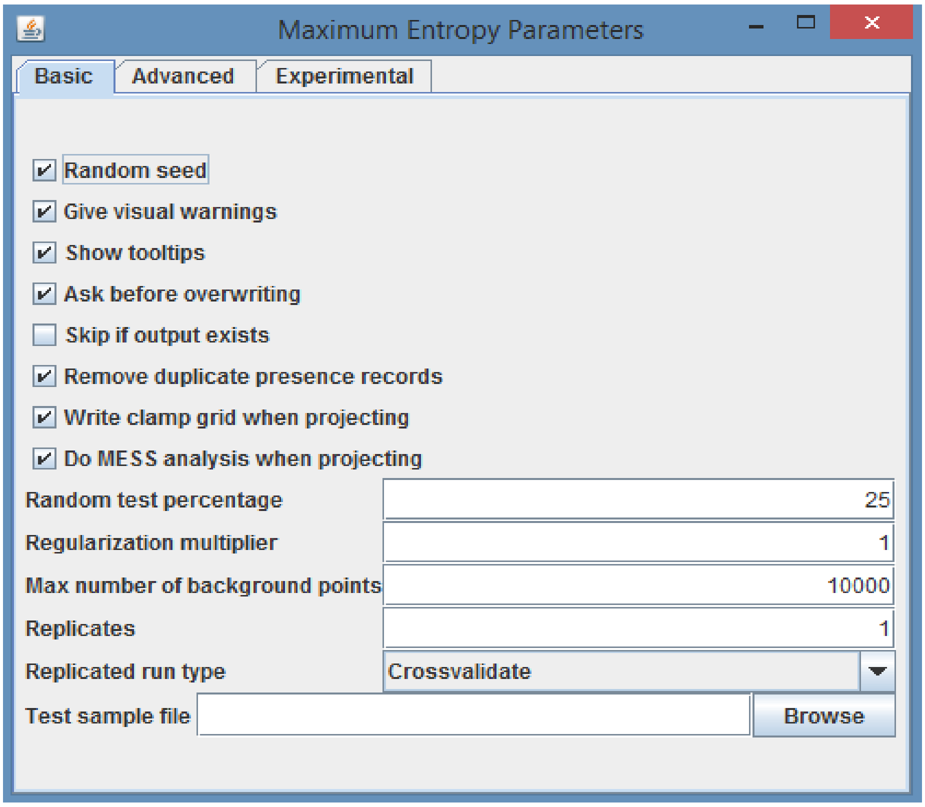
Photo 5: Villagers cutting and Carrying Fire woods.

Photo 6: Field Observation

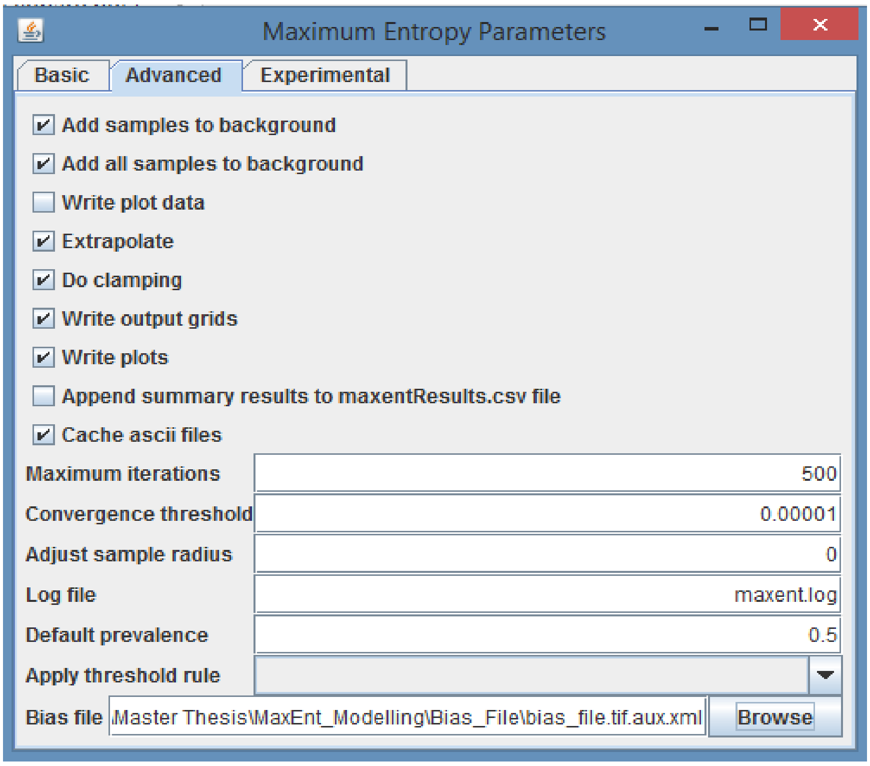
ANNEX III



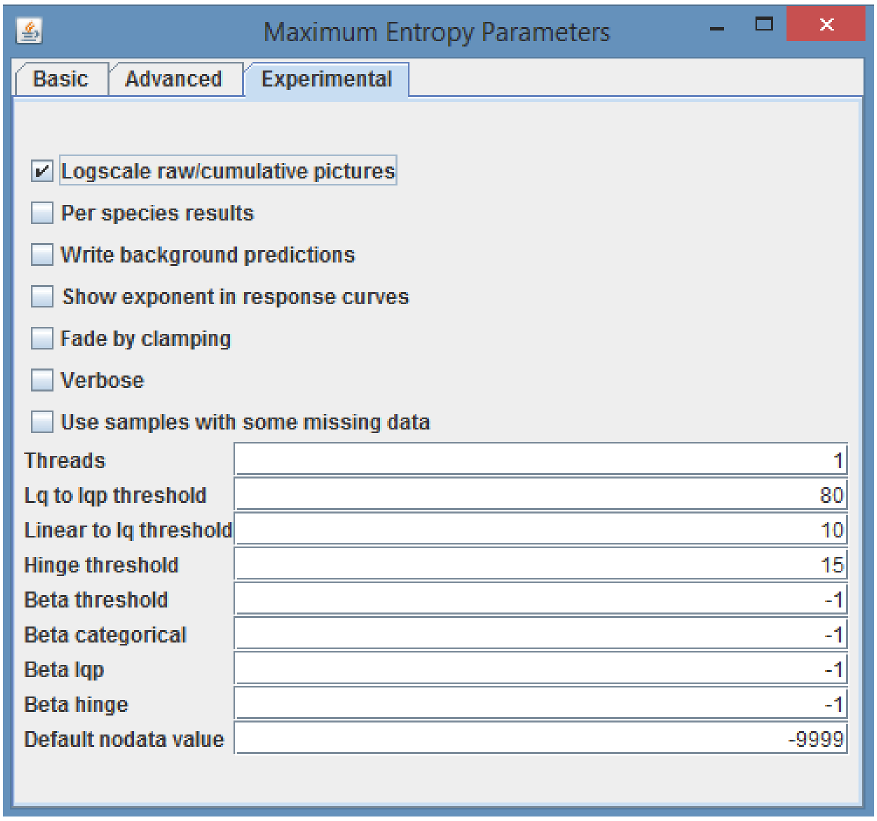
Maximum Entropy Species Disribution Modelling, version 3.3.3k



Basic Setting up of MaxEnt Modelling



Advance Setting up of MaxEnt Modelling



Experimental Setting of MaxEnt Modelling