



Master Thesis

submitted within the UNIGIS MSc. programme
at the Department of Geoinformatics - Z_GIS
University of Salzburg, Austria
under the provisions of UNIGIS India framework

Habitat Suitability Analysis of Fishing Cat (*Prionailurus viverrinus*) in Northern Sector of Chitwan National Park using Geospatial Approach

by

MSc Geographical Information Science and Systems
(UNIGIS MSc)

Rupesh Maharjan, u105618

A thesis submitted in partial fulfilment of the requirements of
the degree of
Master of Science (Geographical Information Science & Systems) – MSc (GIS)

Supervisor: Dr. Him Lal Shrestha

Co-Supervisor: Ms. Rama Mishra

Kathmandu, Nepal, 25.04.2022

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, 2022.04.25

Rupesh

Place and Date

Signature

Acknowledgements:

I feel privileged with the opportunity to carry out this thesis work and write this report. First and foremost, I would like to acknowledge my supervisor Dr. Him Lal Shrestha, Associate Professor and Coordinator of UNIGIS program of Kathmandu Forestry College (KAFCOL) and Co-supervisor Ms. Rama Mishra, PhD. Scholar from the University of Antwerp, Belgium for their immense support and advice. Also, I would like to thank Dr. Jhamak Bahadur Karki, Dr. Upama Koju, and Dr. Ambika P. Gautam for providing their valuable feedback and support to complete this thesis work.

Secondly, I would like to thank Rufford Foundation and IDEA WILD for providing financial and material support to carry out the research work on fishing cat within my proposed study area. Moreover, I am also grateful to the Survey Department of Nepal for providing high-resolution satellite imageries which were very crucial for the completion of this thesis, and the Department of National Park and Wildlife Conservation (DNPWC) for providing permission and available fishing cat presence points. Furthermore, I would like to appreciate Nepal Tiger Trust, National Trust for Nature Conservation, and the Terai Fishing Cat project for supporting me during the field data collection. Most importantly, I would like to thank the University of Salzburg, Austria and Kathmandu Forestry College (KAFCOL) family for providing a platform to carry out this research work.

Abstract:

Prionailurus viverrinus (Bennett, 1833) also commonly known as fishing cat is a medium sized elusive cat species which are mostly found in wetland and marshy lowlands of the lower Terai region of Nepal. However, their distribution ranges are very limited. It is due to their selective habitat preferences like areas near stagnant water, rivers, and streams. At present, there has been a continuous decline in the fishing cat population globally, and the major cause is due to its habitat destruction and degradation. In Nepal, the conservation planning of fishing cat has been hindered significantly due to the lack of adequate knowledge of its habitat requirements. In addition, there is also insufficient research and information on the habitat suitability of these species at the geospatial domain, making it challenging for ecologists to make an effective management plan to conserve their habitat. So, the aim of this study was to identify potential habitat parameters and prepare a habitat suitability map of fishing cat within the Northern (Kasara) sector of Chitwan National Park (CNP). Using 44 presence points and 10 environmental variables in the Maxent model, a habitat suitability map was generated where area close to wetland are found to be more suitable habitat for fishing cat species. Similarly, the model was found to be performing well with Area under curve (AUC) value of 0.950 and Standard Deviation of 0.022. The analysis of variables contribution showed that distance from road and water were the initial two environmental variables which played a significant role in predicting the potential habitat of the species. However, Jackknife of test gain and Jackknife of AUC of the species, both the analyses displayed distance from agriculture being the most effective in predicting the distribution of the occurrence data. So, based on these results, it is highly important to focus on the water sources along with the consideration of settlement areas, agricultural land, and roads to devise habitat level conservation and management plans.

Key words: Fishing cat species, Maxent, Habitat suitability

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Chapter-1: Introduction

1.1 Background

The fishing cat (*Prionailurus viverrinus*), commonly known as "Malaha Biralo" in Nepalese language, is an elusive and rare cat species. It is mostly found in wetlands and marshy area of South and Southeast Asian countries including Pakistan, Nepal, India, Bangladesh, Myanmar, Thailand, Cambodia and Sri Lanka (Mukherjee et al., 2012). In Nepal, fishing cats are mostly distributed in the Southern or Terai belt of the country (Timilsina et al., 2021). However, according to Mishra (2013) these species are not entirely distributed within those broad areas due to its selective habitat preferences. Mostly, their habitats are associated with vegetated areas near shallow water holes, rivers, and streams (Duckworth et al., 2010; Prater, 1998). Morphologically, fishing cats are larger than domesticated cats and have elongated black spots in longitudinal rows extending over an entire body. Usually, the species head and body length range from 65 to 86 cm with a tail length of 25 to 33 cm and have a weight of about 6-15 kg (Jutzeler et al., 2010).

Normally, fish species are the major diets of the fishing cat, however, a study carried out by Haque & Vijayan(1993) have found the remnants of amphibians, mollusks, arthropods, small birds, and reptiles like snakes and monitor lizards in their scats as well. Similarly, fishing cat also preys on mammals like young chital fawns, small civets, domestic goats, calves, dogs, poultry, water fowls (Mishra, 2013; Myers et al., 2006) and even scavenging the kills of tigers and carcass of livestock (Nowel & Jackson, 1996).

In Nepal, the distribution of fishing cat habitat is majorly confined to the wetlands of the Terai region. Their presence has been documented in different protected areas of Nepal such as Chitwan National Park (CNP), Bardiya National Park (BNP), Shuklaphanta National Park (ShNP), Koshi Tappu Wildlife Reserve (KTWR), and Parsa National Park (PNP) (Amin et al., 2018; Baral & Shah, 2008; Mishra, 2013; Timilsina et al., 2021).

Most importantly, this species is listed in the "Vulnerable" category of the International Union for Conservation of Nature (IUCN) Red list, suggesting that their population has been declining progressively (Mukherjee et al., 2016). Furthermore, habitat degradation and conversion due to anthropogenic and natural factors can be considered as the most severe factors causing the decline in the population of fishing cat species (Mishra, 2013; Mishra et al., 2021). Moreover, there is still insufficient research and information on the habitat suitability of those species at the geospatial level, making it challenging for ecologists to make an effective management plan to conserve its habitat.

So, this research has aimed at recognizing fishing cat potential habitat in the Northern (Kasara) sector of CNP using different geospatial parameters and physical ground data such as Land Use and Land Cover (LULC), fishing cat presence data, etc. The results obtained from the analysis of those data provide immense support to ecologists to make effective conservation and management plans for conserving the habitat of the species.

During the research, an analysis was carried out using the Maximum Entropy (Maxent) tool which uses machine learning algorithms to model the habitat suitability of a species using only presence data (Maharjan, 2016; Phillips, 2005). Moreover, those occurrence data of the species, within the study area, were obtained using the camera trap method and from other secondary sources (published or unpublished). In addition, other geospatial parameters such as anthropogenic, topographic, and climatic data were also used as environmental variables to prepare the Maxent Model. The general purpose of Maxent is to make predictions from limited information using the Maxent model (Phillips et al., 2006; Phillips & Dudik, 2008). So, based on this approach, a habitat suitability map of the fishing cat species was prepared.

1.2 Objectives

1.2.1 General Objective

The general aim of this study is to predict the potential suitable areas of fishing cat in the Northern sector of CNP using geospatial approach.

1.2.2 Specific objectives

The specific objectives of the study are:

- To identify the potentially dominant habitat parameters of fishing cat (*P. viverrinus*) within Northern sector of CNP
- To prepare the habitat suitability map of fishing cat (*P. viverrinus*) within the Northern sector of CNP.

1.3 Area of Focus

Based on the previous study of fishing cat carried out by Mishra (2013) reveals that fishing cat do exist in the low wetlands of CNP and require urgent conservation measures to ensure its existence in future. However, its study inside the protected areas has been archaic and requires fresh or new ground data to develop and implement sustainable conservation measures. Similarly, there is also inadequate research and information on habitat suitability of those species in geospatial level making it challenging for conservationists to make an effective management plan to conserve the habitat of the species. So the research has focused mainly on collection of ground data of fishing cat and used those data to analyze the habitat suitability of the species using contemporary geospatial approaches.

1.4 Literature Review

1.4.1 Introduction

Historically, the population of fishing cat was distributed throughout the South and Southeast Asian countries (Mukherjee et al., 2016). However, their present distribution is confined to only wetlands of its historical ranges. Globally, population of fishing cat is declining significantly due to the excessive conversion of wetland areas into agricultural land, plantation areas and extensive fishing from the wetlands (Cutter & Cutter, 2009; Khadka et al., 2015; Mishra et al., 2021). Based on the studies, fishing cat habitats are not only limited to the wetlands of the protected areas but also are present in agricultural and human dominated landscape (Cutter & Cutter, 2009; Jutzeler et al., 2010; Mishra et al., 2018, 2021). There has been evidence of the species catching large fish from the aquaculture farming within human settlements and eating livestock causing a human-fishing cat conflict (Kolipaka et al., 2019; Haque & Vijayan, 1993). Mishra (2013) mentioned that the status, actual distribution and the habitat suitability of fishing cat is one of the poorly studied topics within CNP in comparison to big cat species. These lack of data have caused a great hindrance in planning and initiation of the fishing cat conservation projects.

Moreover, there are several techniques used in species distribution model (SDM) such as Generalized linear model (GLM), Multivariate adaptive regression splines (MARS), and Genetic Algorithm for Rule set Production (GARP) which can predict the suitable habitat of the given species based on their presence/absence and geo-spatial data. These models generally help to quantify the relationship between the demography and distribution of the species within the given environment (Peterson et al., 2011). Similarly, a Maxent is one of those techniques which can be used to prepare SDM for predicting the habitat suitability of the rare and elusive species (Nezer et al., 2017).

1.4.2 Land use/ Land cover classification

Land use and Land cover is a distinct concept which represents the pattern of features on the earth surface (Estes et al., 1982). While Land cover represents the natural or human designed features present on the landscape and land use is marked by the changes caused due to the human activities which is expressed in the economic terms (Goodin et al., 2015; Weih Jr & White Jr, 2008). In general, land cover can be directly observed using satellite imagery, but land use information must be deduced from the land cover and other relevant data (Townshend et al., 1991).

There are several uses of digital LULC maps. For instance, those LULC maps are mostly preferable for studying and identifying the geological and soil properties present on the earth surface. Mostly, these maps are also used in the planning of urban development and management of large scale natural resource inventory (Anderson, 1976; Vogelmann et al., 1998). In addition, LULC data supports the land use planners by providing the spatial and temporal information on the change of landscape and ecosystem conditions. Also, the use of high spatial and temporal resolution satellite images can bring a great feat in monitoring of land degradation and desertification (Bai et al., 2017).

Over the last decades, numerous research has been conducted on the methodology used for the LULC classification from high to low resolution satellite images (Lu & Weng, 2007; Robles Granda, 2011). Generally, two methods for the classification scheme exist; pixel based classification approach and object- based classification approach. Pixel based approach uses a spectral information present within each pixel which is present in the form of Digital numbers (DNs) (Pradhan & Suleiman, 2009). Nonetheless, the method doesn't take account of spatial, textural and topological relationship of an image (Bhaskaran et al., 2010; Matinfar et al., 2007). Also, the problem of a mixed pixel exists in the resulting classified image which led researchers to adopt a new approach of an image classification technique that uses an object based classification method (Blaschke, 2020; Duro et al., 2012; Gamanya et al., 2009).

1.4.3 Object based classification

Object-Based Image Analysis (OBIA) is one of the classification approach of classifying satellite images by grouping similar pixels called objects or image objects. Those objects are a group of pixels that have similar spectral properties such as shape, size, color, texture, as well as context of nearby surrounding pixels (Abdelkhalek, 2019). This method analyzes an image not only on the basis of spectral but also based on spatial information for classification of an image. This method involves the categorization of pixels based on their spectral information such as texture, shape and the spatial relationship with its surrounding pixels. Generally, OBIA uses image segmentation and feature extraction methods which divide an image into homogeneous regions representing different land cover classes (Pal & Pal, 1993). Unlike pixel based image classification; preferable for medium resolution satellite images (Sekertekin et al., 2017), OBIA method is primarily used to classify an image of high-spatial resolution imagery (Lang, 2008).

Amalisana et al. (2017) used OBIA and pixel based methods to compare the results of land cover classification and its change detection in Bogor. The paper proposed the use of segmentation method for OBIA to determine land cover class and used eCognition software for the analysis. They have used landsat-8 OLI images with 30 m observing 20 years from 1996 to 2016. They have divided land cover into 4 categories through an image segmentation process which captures the spectral value of the nearest pixel and the object's spatial feature. The results of land cover obtained from the OBIA method were cleaner in comparison to the results from the pixel based method with less pixel noise in classified areas. Additionally, the OBIA method produced high overall accuracy of 82.15% while pixel based results produced only 61.48% overall accuracy. Unlike results from pixel based methods, the OBIA classification resulted in clear boundaries with homogenous coverage between different classes with very limited noise effect.

Wahidin et al. (2015) proposed the use of OBIA technique to analyze and map the Coral Reef Benthic Habitat, North Maluku using different classification algorithms. Landsat- 8 OLI

(Operational Land Imager) satellite images was used to map the habitat of coral reefs. In this study, an Object-based classification method was used with the "Multi-resolution segmentation" algorithm where shape, texture, color and weight were used as parameter to perform an image segmentation. Several classification algorithms like Support Vector Machine (SVM), Decision Tree (DT), Bayesian, Random Forest (RF) and K-Nearest Neighbour (K-NN) were used to analyze and prepare the classified habitat map. Their results showed that the accuracy value decreased with the increase in segmentation scale. Nevertheless, results using SVM showed high overall accuracy of 73% in comparison to K-NN and other classification algorithms.

1.4.4 Species distribution model

SDM is one of the most recognized means to carry out a habitat suitability modeling of rare and unevenly distributed species within the surface of an Earth (Gogol-Prokurat, 2011). It generally works by estimating the connection between environmental features of the sites where the target species have been recorded. The results from these models can help in conservation planning by identifying the probable habitat of the focal species and prioritizing lands for protecting the sustainable populations (Gogol-Prokurat, 2011; Prendergast et al., 1999). Recently, the development of new and powerful statistical techniques that can incorporate geo-spatial data have led to the development of several predictive habitat distribution models (Guisan & Zimmermann, 2000). Thomasson (2012) mentioned that these statistical methods are statics and probabilistic in behavior which can relate the geographical distribution of species or its communities to their current environment. These models are incorporated into tools that can be used to study habitat selection at the scale of species range which is also known as habitat suitability modeling. Generally, SDM measures the relationship between species which have been recorded on site and the spatial and/or environmental characteristics of those sites (Franklin, 2001).

Sun et al. (2021) used a multi-scale approach in the Qionglai mountain region to show species-environment connections by assessing the habitat suitability of giant pandas using

multi-scale Maxent models. They collected presence data from the fourth National Giant Panda Survey where their results showed that the optimal scale identified for every single environmental parameter were varied. They also found that the performance of multi-scale models were more accurate than their analogous single-scale models in predicting the habitat of the researched species. Similarly, Su et al. (2021) used Maxent models to map the habitat suitability for Asiatic Black Bear and Red Panda in Makalu Barun National Park (MBNP) using both Maxent and GARP models and compared its results. It showed that distance to settlements, mean annual temperature and elevation were three crucial environmental parameters which impacted the habitat suitability of Asiatic black and red pandas in MBNP. They also found that among two different models, the Maxent model produced better habitat suitability results in comparison to the GARP model. In addition, Maxent distribution prediction Model was found to be most useful in very low sample size to predict the habitat suitability of the species (Deb et al., 2017). Their study showed that using ground truthing on model valuation can give a highly accurate result even in the presence of low training samples. Also, among testing of different models (Domain, Bioclim, GARP, and Maxent) across 18 different species with varying level of sample size treatments and evaluation measures showed that Maxent performed well in predicting significantly improved results in comparison to other models (Deb et al., 2017; Elith & Leathwick, 2009; Gogol-Prokurat, 2011).

1.4.5 Maxent modeling

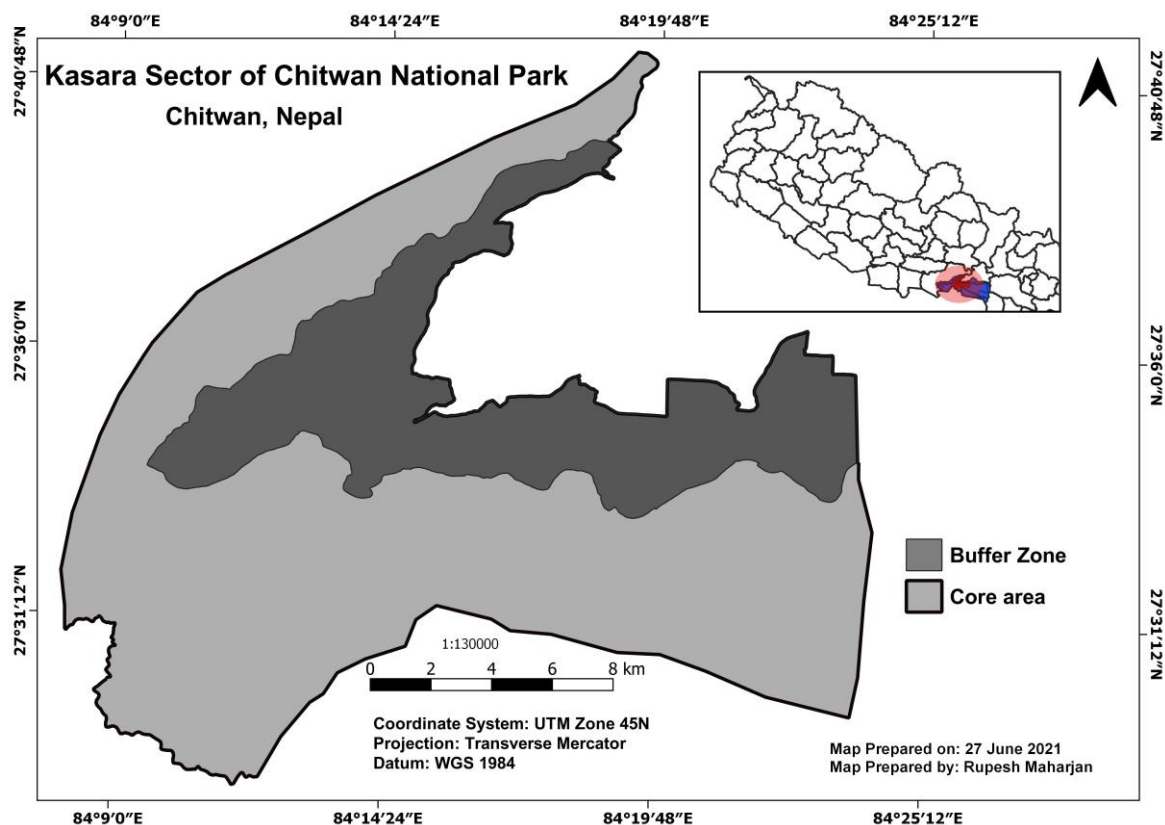
Unlike GLM which uses both presence and absence data for the prediction of the species distribution, Maxent is used for modeling the species distribution using only presence data of the species (Elith & Leathwick, 2009). Gogol-Prokurat (2011) used Maxent for modeling rare endemic plant species in El Dorado County of California and successfully produced the Maxent models which predicted the habitat suitability of four different species at the local scale. In fact, Maxent is more flexible at displaying the habitat suitability results in a continuous layer that ranges from 0 to 1 when used with different spatial scales, which is

thus obtained from the nonlinear relationship between presence of the species and the environmental variables (Gogol-Prokurat, 2011). Jackson & Robertson (2011) also demonstrated that Maxent can perform well even having a very limited presence point of the endangered species along with other predictor variables like several bioclimatic, soil and vegetation types. KC et al. (2019) used Maxent software in order to model the suitable roosting areas of the endangered Egyptian vulture in Rukum district of Nepal. The authors used topographic, vegetation, and anthropogenic parameters as environmental variables to determine the Maxent model with 70% occurrence points for testing the model and the rest of 30% for testing it. As a result, the model performed greatly with AUC of 0.829.

Linshan et al. (2017) also described Maxent as an important habitat analysis method and used it for predicting suitable habitat changes of important species in Central Himalayas. Their study showed that just using bioclimatic variables is useful for generating habitat distribution models for producing suitability maps of the desired species. However there are also other studies which use only environmental variables other than climatic data and generate quite useful models like the study carried out by Matyukhina et al. (2014). Similarly, McCarthy et al. (2015) assessed the habitat distribution and its use by four felid species and used only two of the climatic variables (annual mean temperature and annual precipitation) and other anthropogenic variables to generate the model. They used Pearson's correlation matrix to determine correlation values of 19 different bioclimatic variables and eliminated it based on their redundancy as those variables would not have contributed to generate an accurate Maxent model.

1.5 Study area

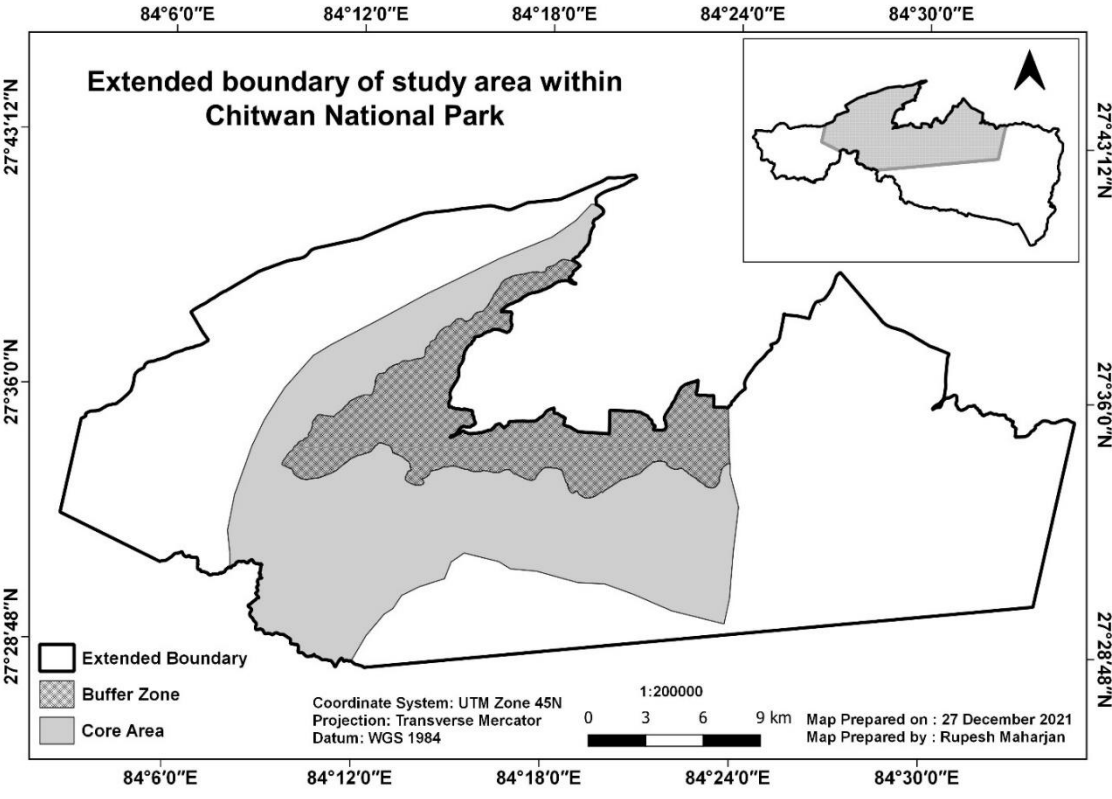
The study area is located in the Northern (Kasara) sector and its buffer zone areas of CNP; it is one of the country's first national parks which was established in 1973 AD. The park had been enlisted as a world heritage site by the United Nations Educational Scientific and Cultural Organization (UNESCO) since 1984 for having a diverse ecosystem of international significance. CNP lies in the lower Terai region in Chitwan, Nawalparasi, Parsa and Makawanpur districts of Nepal. It encompasses a unique and complex ecosystem of Churiya hills, ox-bow lakes and flood plains from different major rivers like Rapti, Reu and Narayani rivers (Baidya et al., 2009).



Map 1. Map of Northern Sector of Chitwan National Park

Geographically, the study area is situated between longitudes 84°7'54" N to 84°23'55"E and latitudes 27°31'54" to 27°31'28"N. Considering the effective management, the entire national park, and its buffer zone areas has been divided into four administrative sectors: Northern (Kasara), Southern (Madi), Eastern (Sauraha), Western

(Amaltari) (Lamichhane et al., 2019). To carry out an effective research work with available resources, the study area was primarily focused on the Northern sector of the park as shown in Map 1. This part of the park is also connected with 5 other buffer zone areas which have been contributing to LULC change due to high anthropogenic activities for a very long period of time. Furthermore, the data of fishing cat within the focused study area was found to be very minimal so to have optimal use of the available data, the study area was extended to the certain extent (longitudes 84°2'37.16"N to 84°34'47.57 " E and latitudes 27°32'20.90" to 27°35'28.53"N) which was beyond the proposed boundary of study area as shown in Map 2.



Map 2. Map showing the extended boundary of study area within Chitwan National Park

1.5.1 Climate

CNP has a tropical monsoon climate with relatively high humidity throughout the year. Since it is located in the central climatic zone most rainfall takes place between the months of mid-May to late-September. Mean annual rainfall in Chitwan ranges between 2000-2100 mm with more than 80% of the total rainfall within those four months (Baidya et al., 2009). Also, the study area has an annual minimum air temperature of 17.4°C and an annual average daily air temperature of 24.1°C (DHM, 1995). However, the temperature drops to a minimum of 5°C in winter (mid-January to mid-march) and rises to a maximum temperature of 38°C (UNEP-Wo, 2009).

1.5.2 Flora and fauna

CNP has one of the diverse ecosystems with a large number of floral and faunal communities in comparison to other national parks of Nepal. The major area of the park is dominated by sal forest (*Shorea robusta*) and encloses many riverine and pine forest consisting of species like chir pine (*Pinus roxburghii*) and Simal (*Bombax ceiba*). Several flood plains of Rapti, Reu and Narayani rivers have also created suitable environments for the growth of various vegetation. These growth are the major reason for the presence of high diversity and density of faunal community in the park (Smith, 1984).

Globally, CNP is considered as one of the top natural sites with presence of 75 mammal species, 643 species of birds, 56 species of herpetofauna, 121 species of fish, 206 species of butterfly and 422 plant species (DNPWC, 2020). It is also home to many endangered mammalian species recorded in IUCN red list such as one-horned rhinoceros (*Rhinoceros unicornis*), royal Bengal tiger (*Panthera tigris tigris*), gaur (*Bos gaurus*), wild Asian elephant (*Elephas maximus*) etc. Fishing cat is also one of those mammalian species which have been listed in the "Vulnerable" category of the IUCN red list but not given a protected status in Nepal. Not to mention, their status and distribution are also one of the least studied topics within CNP (Mishra et al., 2018).

Chapter-2: Methodology

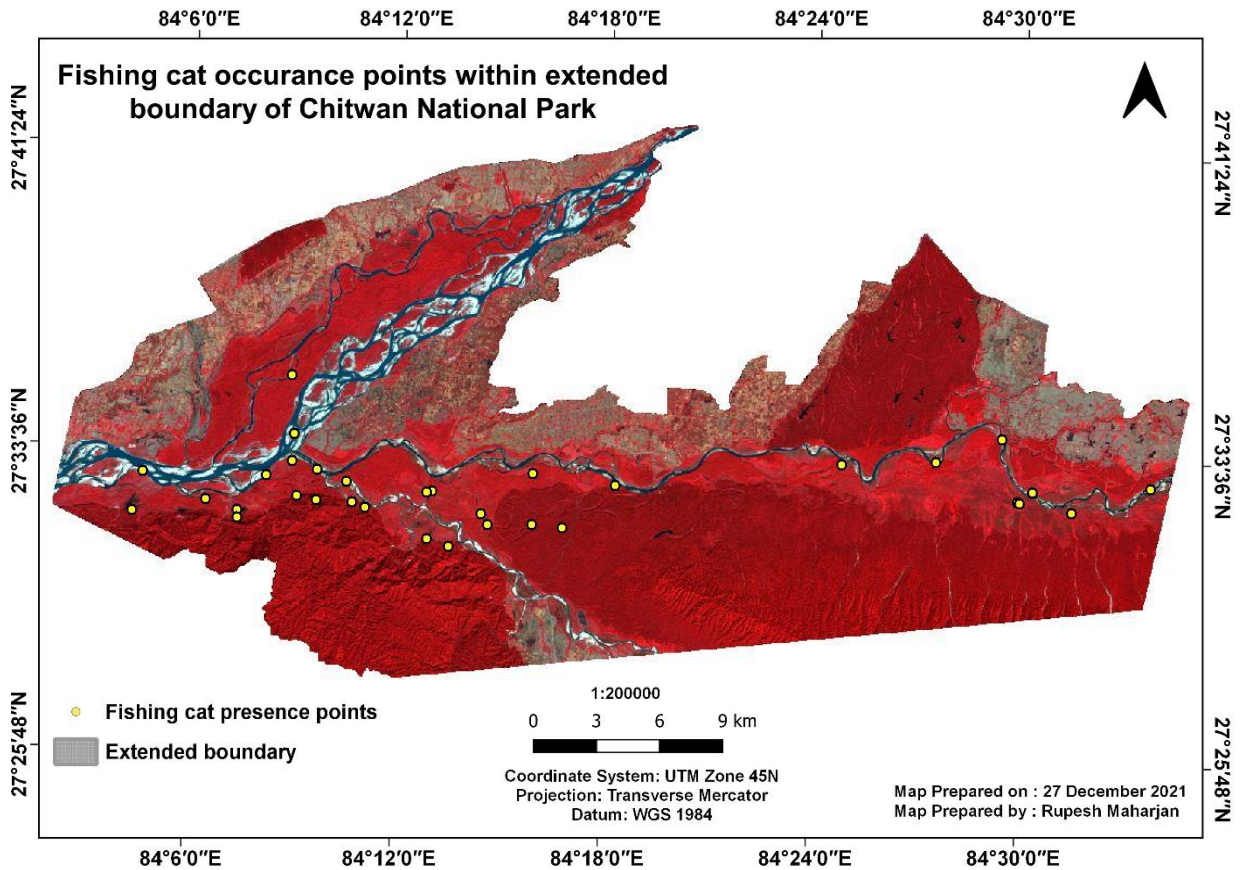
This chapter discusses the process by which this thesis work was constructed and executed. It scrutinizes the data and methodologies used to analyze the results. Section 2.1 narrates the data used for the analysis whereas, section 2.2 provides information about the software used to generate the results. The further section examines the scientific methodology which includes data acquisition, pre-processing, classification scheme, accuracy assessment, and map preparation.

2.1 Data

2.1.1 Fishing cat presence data

The Fishing cat presence data, within the study area, were collected using the camera trap method as a primary source of data collection. Since the species is very elusive in nature as well as their population is also very rare in CNP (Mishra, 2013), the primary source of its data was insufficient for their habitat suitability analysis. So the secondary source of presence data (Annex 1), obtained from published or unpublished literatures, were also used for the analysis.

There were altogether 46 presence records within the entire boundary of CNP during various camera trap years among which 44 records lie within the extended boundary which were the only ones used for an analysis. All of those recorded presence points were only recorded through the camera trap to maintain the certainty of the data.



Map 3. Fishing cat occurrence points within extended boundary of Chitwan National Park

2.1.2 ZY-3 satellite

This thesis work uses high-resolution satellite images from the Zi-Yuan 3 (ZY-3) satellite of the year 2020. It was obtained from the survey department of Nepal. It is among the first optical and stereoscopic earth mapping satellites of China aiming to produce 1:50000 and larger scale maps (ESA, 2022). That specific satellite image was used for our objective so that we could achieve a very precise LULC map. Besides this, the satellite has a plane accuracy of 25m with ground control point (GCP) and 5 m elevation accuracy. The satellite has 4 multispectral bands with 1 panchromatic band which is very useful during LULC mapping as well as for obtaining high-resolution images up to 2.5m.

Table 1. Parameters of ZY-3 satellite

Sensor	Band	Wavelength	Spatial resolution
PAN	PAN-FW	500-800nm	3.5m
	PAN-BW	500-800nm	3.5m
	PAN-ND	500-800nm	2.1m
MS	Blue	450-520nm	5.8m
	Green	520-590nm	5.8m
	Red	630-690nm	5.8m
	Infrared	770-890nm	5.8m
Study Period	2020		
Format	GeoTIFF		
Platform	ZY-3		
Data acquisition Source	Department of Survey, Nepal		

(Source: Huang et al., 2017)

2.1.3 Digital Elevation Model (DEM)

The ALOS PALSAR data of 12.5 m resolution was used, which was obtained from *asf.alaska* - "<https://search.asf.alaska.edu/#/>" website and clipped to the extent of my study area.

2.1.4 Road Network

The vector data of the road network of my study area was obtained from the Survey department and Open Street Map (OSM). Similarly, some of those road networks were also manually digitized from topographic maps to generate recent road networks.

2.1.5 Climate data

Mean annual temperature and Mean annual precipitation data obtained from WorldClim database (<http://www.worldclim.org/bioclim>) were used as two climatic variables for my analysis.

Table 2. Description of types of data used in analysis

S.N	Data Name	Data Format	Resolution	Source
1	Fishing cat presence data	Vector	-	Field Survey, DNPWC
2	Road Network data	Vector	-	Survey Department, OSM
2	ZY-3 Satellite image	Raster	2.5 (after pan sharpening)	Survey Department
3	Elevation data (DEM)- ALOS PALSAR (ASF)	Raster	12.5m	<i>asf.alaska-</i> https://search.asf.alaska.edu/#/
4	Climate data	Raster	1km	WorldClim: http://www.worldclim.org/bioclim

2.2 Software

To produce environmental variables and carry out its analysis from available data, four different software had been used. The software were used in the pre-processing of the satellite imageries; radiometric correction, geometric correction, and pan sharpening were done using ERDAS Imagine software but the segmentation and classification were done in ArcGIS Pro. Additionally, the same software were used to manage vector datasets and prepare the final LULC layer while Maxent tool was used to analyze the environment variables to produce a habitat suitability map. Lastly, Microsoft Excel was used to prepare statistics of classification results and display them in the form of graphics.

2.3 Methodology

2.3.1 Methodology Overview

This part of the thesis work scrutinizes the methodology that is used to achieve the research objectives. The entire methodological steps are divided into four successive stages. The

first stage includes data acquisition, which includes high resolution satellite images (ZY-3, ALOS PALSAR), fishing cat presence data, Climate data, and vector datasets (boundary map of CNP, Road Network) of the study area. The second stage comprises pre-processing steps of those datasets; band composite, geometric correction, pan sharpening, re-projection, and clip Area of Interest (AOI). The third stage comprehends scientific analysis on the pre-processed datasets. The methodology in this stage uses an Object based classification approach to prepare the LULC data layer followed by its accuracy assessment using the KAPPA statistics method. Later, 10 other environmental variables (Table 3) having the same extent, projection, cell size, and cell numbers were prepared. The fourth and final stage includes Maxent analysis to produce a habitat suitability map of fishing cat within the study area using available environmental layers (Table 3). All of the environmental variables that were used in this study were selected based on the study carried out by McCarthy et al. (2015).

Table 3. Environment variables used in Maxent modeling

S.N	Variables	Categories	Source	Units	Original Resolution	
1	Elevation	Topographic	ASF	m	12.5m	
2	Road distance		OSM	m	2.5m	
3	Water distance	Anthropogenic	ZY-3	m	2.5m	
4	Settlement distance			m	2.5m	
5	Agricultural land distance			m	2.5m	
6	Grassland distance	Vegetation		m	2.5m	
7	Forest distance			m	2.5m	
8	Land Use and Land Cover			Category	2.5m	
9	Annual Mean Temperature	Climate		BioClim	°C	1 km
10	Annual Mean Precipitation				mm	1 km

2.3.2 Methodological framework

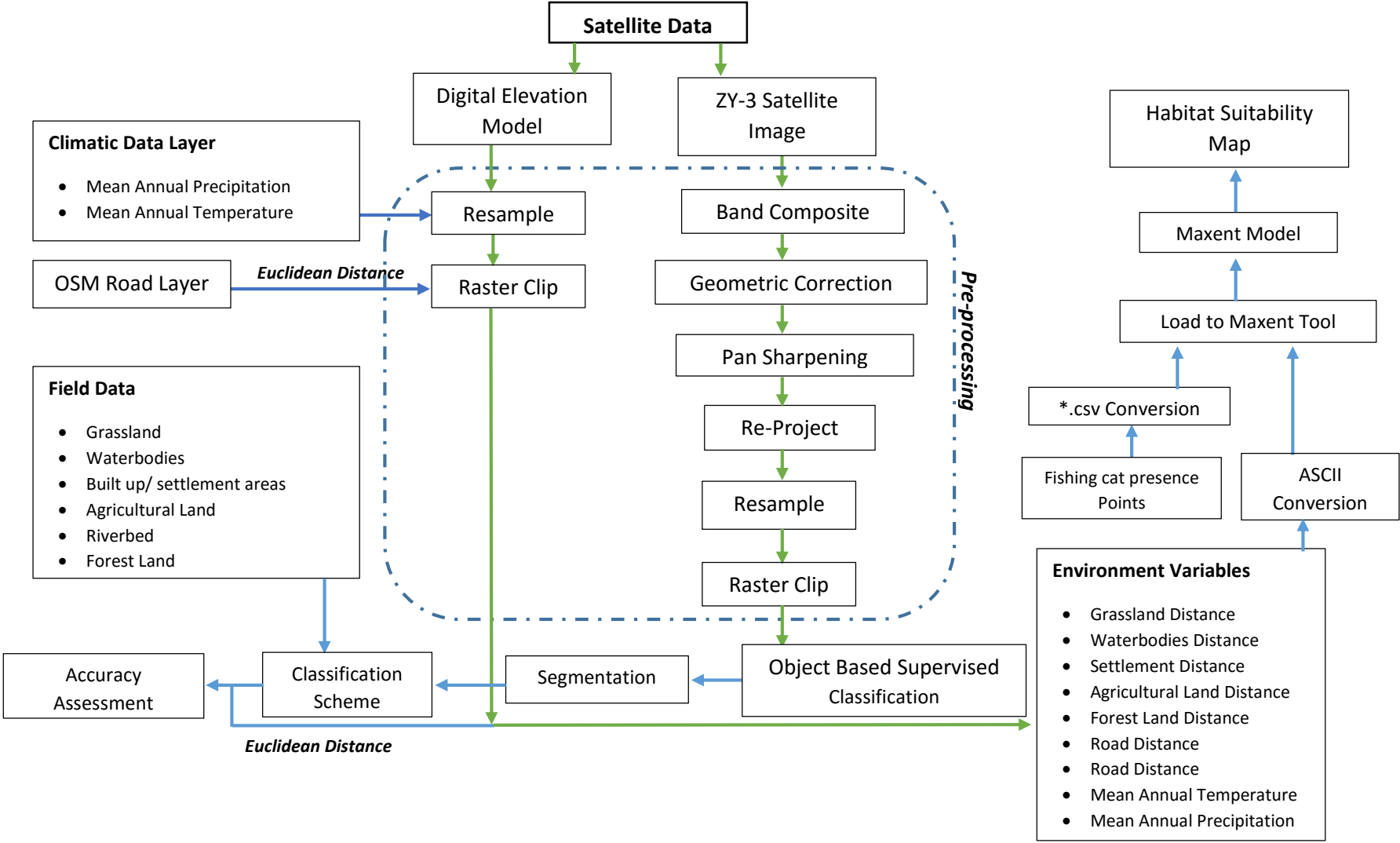


Figure 1. Methodological framework showing the process of habitat suitability analysis

2.3.3 Data Acquisition

A high resolution ZY-3 satellite image, which was obtained from the Department of Survey (DoS) of Nepal, covered the study area for the year 2020. The image was obtained free of cost with the college recommendation to encourage students to perform scientific works. Similarly, a vector dataset of the protected areas of Nepal was provided by the faculty staff of Kathmandu forestry college (KAFCOL). Similarly, other datasets are obtained from different open geospatial sources as shown in table 2.

2.3.4 Data Pre-Processing

2.3.4.1 Band composite

Band composite refers to a combination of different bands of a satellite image, which generate the correct color composite image (Abdelkhalek, 2019). Satellite captures multispectral image bands individually because of which each single band image has its own particular wavelength. Without combining those bands the images displayed are in black and white. Nonetheless, if we want to display the true color of satellite images, its band combination should consist of red, green and blue bands. While, false color composite requires blue, green and infrared bands. Since, computer screen can only display three bands image i.e. Red, Green and Blue (RGB), allocating different bands to those three color bands can display various features that the normal human eye cannot detect.

Similarly, the ZY-3 satellite image has 7 bands; 4 Multispectral and 3 panchromatic bands. However, a band composite of only 4 multispectral bands were present. The image received had already been layer-stacked into 4 different bands (Red Green Blue- RGB, Near-Infrared-NIR). This band composite was later used to delineate various cover classes such as agriculture Land, built up/settlement areas, water bodies, grassland, river bed, and forest area.

2.3.4.2 Radiometric correction

Radiometric correction is used to improve the surface reflectance, emittance and back-scattered measurement accuracy of satellite imageries (Johannsen & Daughtry, 2009). It is used to calibrate and fix the pixel values to improve the interpretability and the quality of remote sensing data. Principally, these corrections are useful for obtaining the true ground radiance or reflectance values. The radiance values measured by the satellite sensors are not only the record of reflected radiations from the earth surface but also the radiations scattered by the particles in the atmosphere (Chen et al., 2005).

However, the radiometric correction was not applied to the provided datasets in this study due to various reasons: Firstly, datasets didn't have information about the radiance and reflectance value. Secondly, the atmospheric correction had already been done within the satellite image given by DoS before providing the data.

2.3.4.3 Geometric correction

Geometric error is one of the common problems of every airborne or space-borne remote sensing data where images are distorted and don't lie in the correct place. It is caused due to various factors like orientation of the satellite, Earth's rotation, instrument error, and platform instability (Green et al., 2000). Geometric correction is a pre-processing step of analyzing a satellite image that minimizes or eliminates spatial distortions and assigns the geometric properties to an original image.

The ZY-3 satellite image was already geometrically corrected. So, additional geometric correction was not proceeded. Also the image was visually parsed to see if there was still a disparity in the geometric alignment. However, in the satellite image dataset, the composite Multi-spectral Image (MSI) image was not spatially aligned with its Pan-chromatic band of the same datasets. So, a co-registration step was executed to corroborate that both images align spatially and all the features of one image overlaps with the same features in another image.

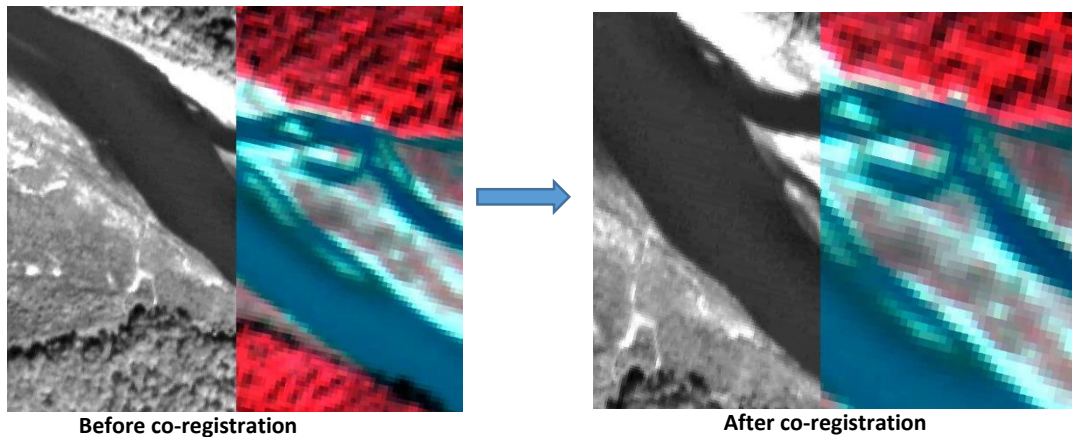


Figure 2. Images showing before and after co-registration of ZY-3 satellite image

2.3.4.4 Pan sharpening

Pan sharpening is an image fusion technique in which two or more images are used to produce enhanced images (Alidoost et al., 2015; Javan et al., 2021; Pohl & Van Genderen, 1998). In this technique, course resolution MSI and high resolution PAN images of the same scene, collected from the same satellite, were fused together to produce synthesized MSI images. The pan sharpened image consists of both spatial and spectral information which is similar to its input MSI and PAN imageries (Javan et al., 2021). Generally, the pan sharpening methods are categorized into three methods i.e. pixel, feature and decision level methods (Pohl & Van Genderen, 1998). Moreover, the pixel based method is a commonly used fusion method to generate high spatial-spectral fused images (Javan et al., 2021).

Similarly, a pixel based pan sharpening method was used to fused MSI and PAN images to produce a high resolution image of the study area. However, the image had to be co-registered before performing a pan-sharpening method to ensure that all the features are aligned together in an enhanced image. In this step, High pass filter (HPF) Resolution Merge was used as a pan-sharpening algorithm. HPF based pan sharpening algorithm is considered as one of the best performing fusing algorithms which showed the best scores in spectral quality indices (Borana et al., 2019; Witharana et al., 2013). This algorithm collects high frequency information from PAN images and adds that information to each band of low resolution MSI with a specified weight (Zhang & Mishra, 2014).

More importantly, the pan sharpened image was automatically resampled to the same spatial resolution as that of the high resolution panchromatic image. After resolution merge, low resolution MSI was resampled to that of high resolution panchromatic image from 5.8m to 2.5m pixel size.

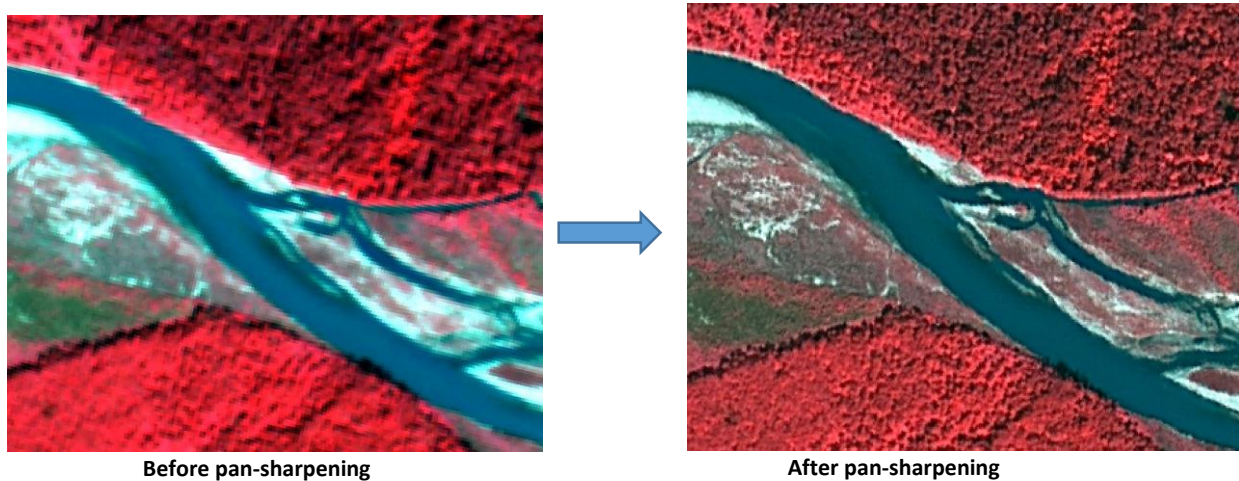


Figure 3. Multispectral images before and after pan sharpening

2.3.4.5 Re-projection

Previously, the raw satellite datasets were present in a geographic coordinate system with datum WGS 84. However, all the datasets were not projected into the same projection system i.e. Universal Transverse Mercator (UTM) zone. So, all of the datasets were re-projected into the projected coordinate system of UTM, zone 45N, Spheroid: WGS 84, Datum: WGS 84, and EPSG: 32645 to bring consistency in all of them.

2.3.4.6 Resample

Initially, all of the available datasets had different extent, cell size and cell rows and columns. In order to carry out analysis in Maxent, all of those environmental variables (datasets) must have the same parameters. So, all of the raster datasets were resampled to the parameters as same as of LULC layer whose extent is Top: 3067237.25, Left: 208021.25, Right: 263501.25, Bottom: 3035369.75, cell size 2.5m and cell rows: 12747 cell columns: 22192.

2.3.4.7 Raster clipping

The raster image was clipped to the required extent area using a vector dataset. This step was enacted to minimize the data load during analysis and narrow down my focus to the proposed study area.

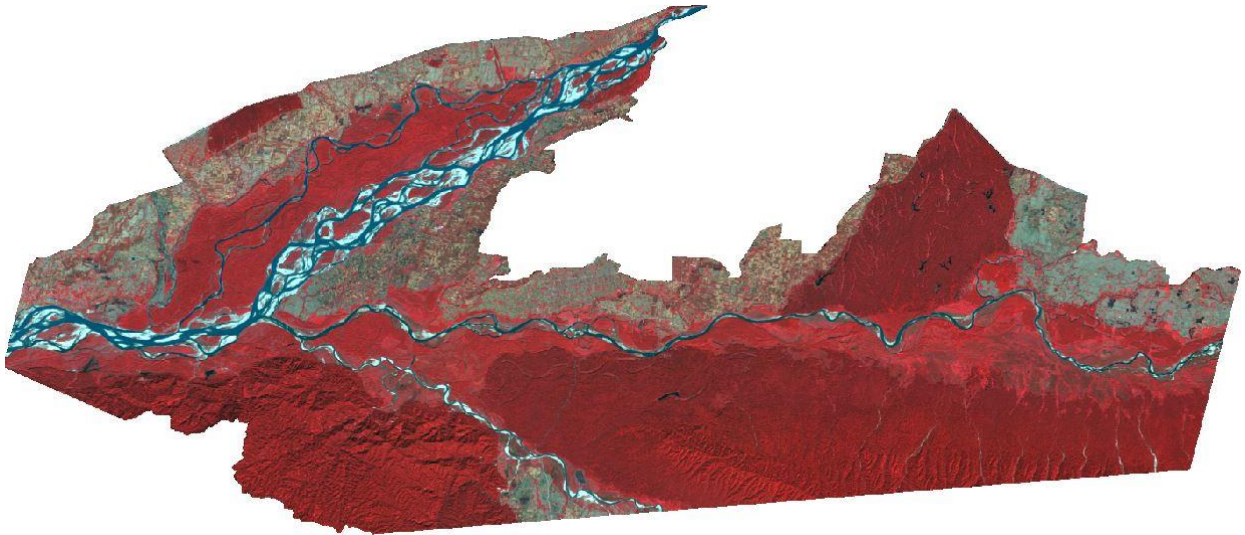


Figure 4. Multispectral image of the extended boundary of study area after clipping

2.3.5 Data Analysis

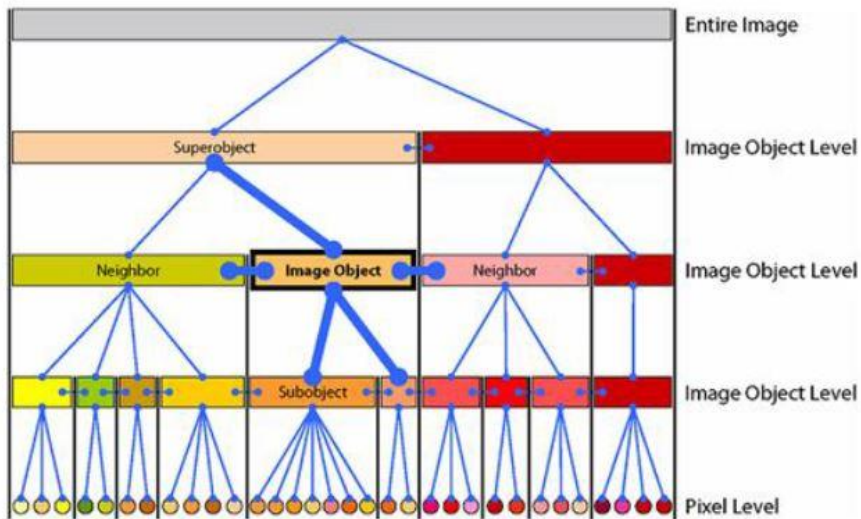
In this stage, different data analysis steps were performed to prepare environmental variables using available datasets. Initially, the Object-Based approach was used to prepare LULC classes of the year 2020, whose classification accuracy was examined to increase the quality of the product. Secondly, Euclidean distance layers of different classes, produced from previous LULC layer, were generated and a total of 10 environmental variables were fed in Maxent tool to carry out habitat suitability analysis and its map generation.

2.3.5.1 Object-Based Classification

Geographic Object-Based Image Analysis (GEOBIA) which is also known as Object-Based Image Analysis (OBIA) is one of the image analysis technique that uses image-objects to delineate the features within an image (Abdelkhalek, 2019; Castilla & Hay, 2008). It is a novel technique of image classification which uses image-object rather than individual pixels

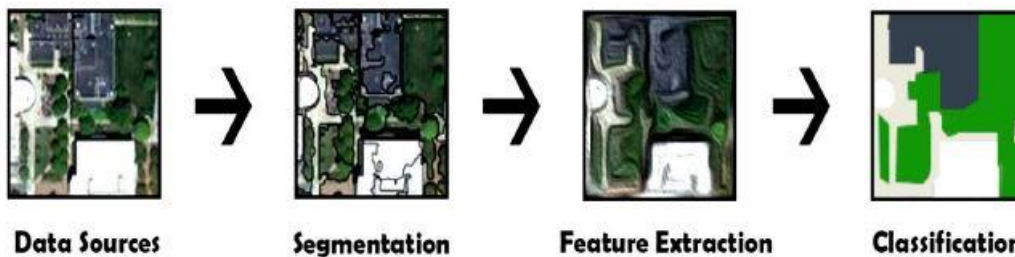
as a means of classifying very high resolution (VHR) images (Castilla & Hay, 2008). This method involves the categorization of pixels based on their spectral information such as texture, shape and the spatial relationship with its surrounding pixels. This approach uses information of mean reflectance value, perimeter, and area which is obtained as parameters of different spectral, spatial and textural domains. Generally, OBIA uses image segmentation and feature extraction methods which divide an image into homogeneous regions representing different land cover classes (Pal & Pal, 1993). Unlike pixel based image classification; preferable for medium resolution satellite images (Sekertekin et al., 2017), OBIA method is primarily used to classify an image of high-spatial resolution imagery (Lang, 2008).

In addition, the OBIA has the aptness to analyze the given image at several hierarchical levels (Abdelkhalek, 2019). These levels are obtained through the means of image segmentation process. Generally, the image-object levels are created from the pixel level where objects with similar spectral properties are merged together to develop new sub-levels or super-levels. Murcko (2017) showed that hierarchical relationships can be useful in describing the image class properties where image-objects which are near to each other have the same hierarchical relationship. The image classification at an object level can be lowered down from super-objects to sub-object which can then merge the image based on the pixel level information. Similar to human visualizing the objects within an image, OBIA also uses the same principle but requires several sophisticated stages to achieve the desired result (Abdelkhalek, 2019).



(Source: Abdelkhalek, 2019)

Figure 5. Image object hierarchy and relationship



(Source: Abdelkhalek, 2019)

Figure 6. Images showing the steps of Object Based Image Analysis (OBIA)

2.3.5.1.1 OBIA Segmentation

The foremost and important part of object-based image classification is segmentation of a given image. This step of the OBIA process uses segmentation algorithms to merge homogeneous pixels into image elements to differentiate between heterogeneous neighboring regions while forming each individual class (Schiewe, 2002). Additionally, there are two approaches for segmentation of an image. But, several algorithms are available to perform those segmentation processes. Firstly, the top-down approach consists of Spectral Difference Segmentation, Multi-Threshold Segmentation, and Contrast Split Segmentation. Secondly, the bottom-up approach includes algorithms such as Chessboard Segmentation, Quadtree-Based Segmentation or Multi-resolution Segmentation. Among those algorithms, Multi-Resolution Segmentation, one of the most popular segmentation algorithms, where

each pixel of an image is considered as a separate object and later pairs those image objects and form bigger segments by merging them together (Rahman & Saha, 2008).

Based on local homogeneity criterion, which describe the similarity with adjacent image objects are used to make a merging decision. When there is small increase in the defined criterion the pair of objects are merged together and the process terminates once homogeneity parses a user-defined scale (Rahman & Saha, 2008). In multi-resolution segmentation process scale parameters help to determine the permitted change of heterogeneity in an entire segmentation process. So, higher scale parameters will allow more objects to merge making the objects size bigger and vise-versa. In addition, the segmentation process does not only consider the statistical information of pixel values but also the pattern, texture, shape and position of features within the hierarchical network (Rahman & Saha, 2008).

In this study, object-based supervised classification was implemented to classify the image. A machine learning based SVM algorithm was used as a classifier to train the classification algorithm. The segmentation process is carried out in ArcGIS pro software using its in-built classification wizard tool. The spectral parameter was set as 15, and scale parameter as 50. Using these parameters the image segmentation process was carried out. As a result figure 7 was obtained.

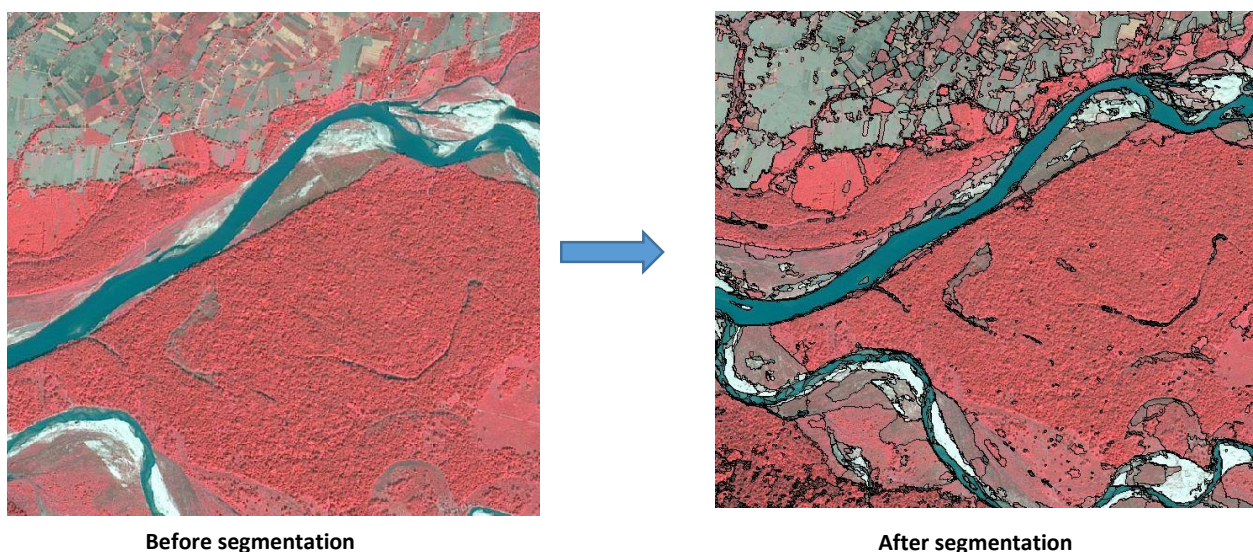


Figure 7. Multispectral images before and after image segmentation

2.3.5.1.2 OBIA Classification

The second step of the OBIA approach involves the collection of training samples. The samples of six classes were collected i.e. Forest Land, Water bodies, River bed, Agricultural Land, Built up areas, and Grassland. At least 50 training samples for each class were collected for each LULC class from field, Google Earth, and visual interpretation of previous pre-processed infrared image. The spectral value of each pixel lying in those samples were collected and used for the classification in ArcGIS Pro software. In this approach, a spectral, shape, size and texture based approach collected from training samples were used in classifying the objects. Later, the object-based classification was carried out using a machine learning based supervised classifier algorithm i.e. SVM.

2.3.5.1.3 Accuracy Assessment

Accuracy Assessment is one of the important steps of every classification process. This step helps to identify how accurate my classified products have been prepared in comparison to the true land cover condition (Congalton, 1991; Stehman, 2009). It uses ground truth data collected either from the field or based on knowledge from visual interpretation in VHR images. Normally, the accuracy of a result will be low only when a classification error occurs where the pixel of one class or category is allocated to another class. So the evaluation of those classes are found to be critical to ascertain the quality of my classified product. Additionally, there are several methods for checking the accuracy of the produced LULC product. However, I have used the KAPPA analysis technique to scrutinize the accuracy of the LULC product obtained from the Object-based classification approach (Rosenfield & Fitzpatrick, 1986).

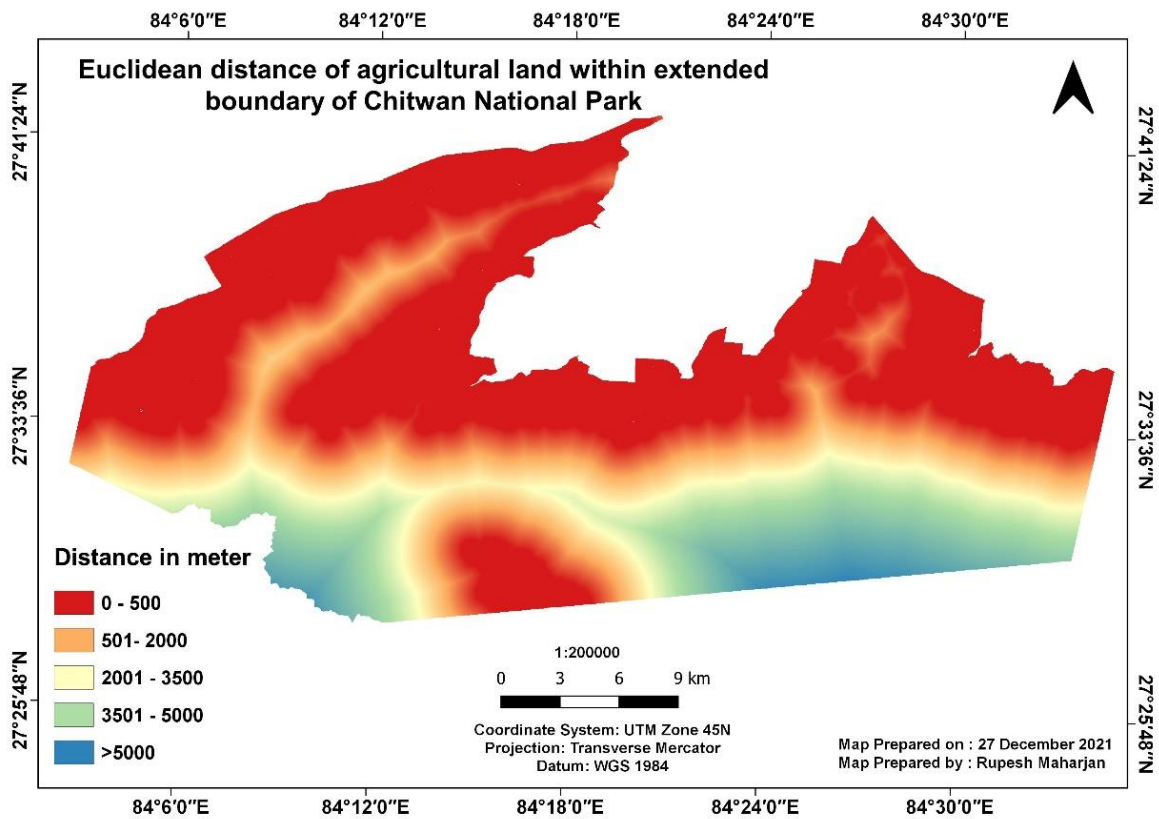
In this step, I have used 500 randomly selected points and implemented a stratified random sampling method to measure the accuracy of the products. The accuracy assessment of the product obtained from object classification was carried out in ArcGIS pro software where the confusion matrix was derived. The ground truth information was obtained using visual interpretation of previously pre-processed infrared images. Later, these assessment tools

generated the error matrix which determines the producer's, users, overall accuracy, and the KAPPA accuracy level (Rahman & Saha, 2008). Moreover, results of producer's accuracy, which shows how well the training set pixels are classified for given LULC types, user's accuracy indicating the probability of the classified pixels which represents the ground data were also derived. Similarly, Kappa statistics which shows how well the classification is compared with randomly assigned class value to each pixel were also attained.

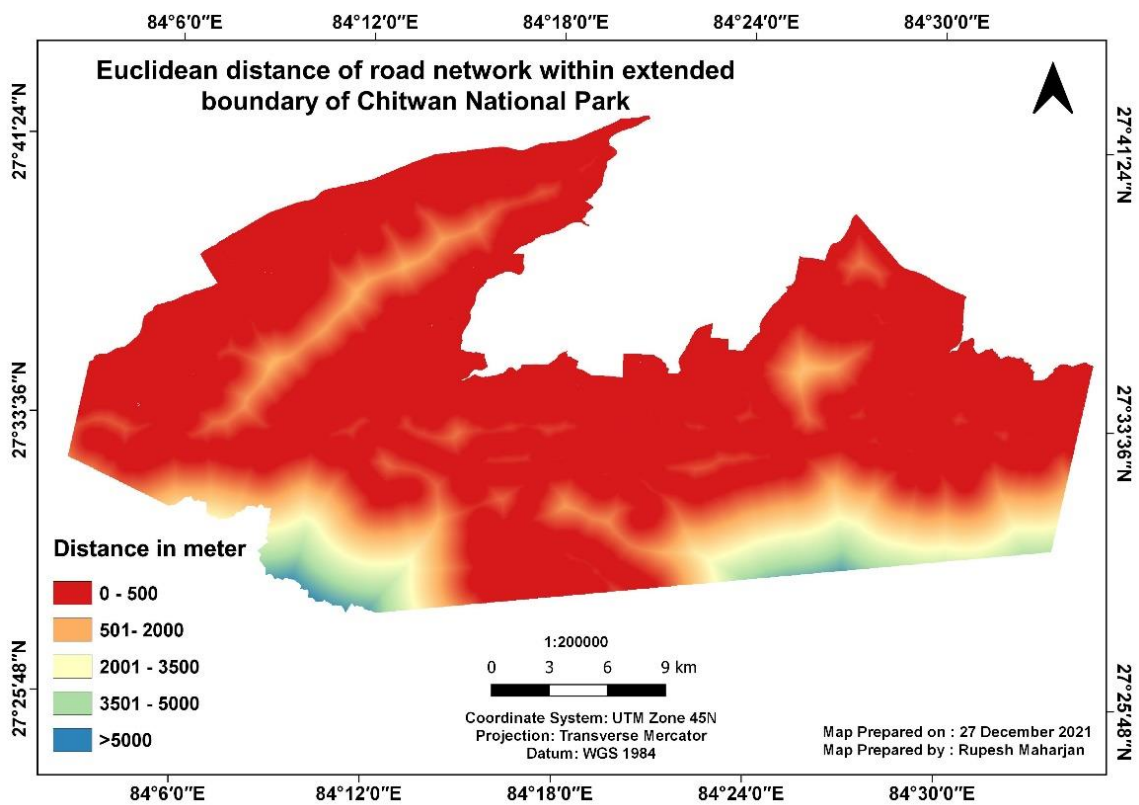
2.3.5.2 Preparing Environmental Variables for Maxent Model

2.3.5.2.1 Anthropogenic variables

Human activities have been considered a major threat to the existence of the fishing cat population and its distribution in the wild as people have been altering the landform for their own benefit. Due to the rapid growth of encroachment of wetland for agriculture and urbanization, habitat of fishing cat have been diminishing rapidly causing the decline of the species population (Mishra, 2013; Nowel & Jackson, 1996; Mishra et al., 2021). So considering these threats, distance from road, distance from agriculture and distance from settlement were incorporated in the Maxent model as anthropogenic variables. Two of those continuous datasets were obtained from LULC classes and one from OSM data. These layers were produced by using the Euclidean distance tool of agriculture, settlements and road network layer in ArcGIS pro.



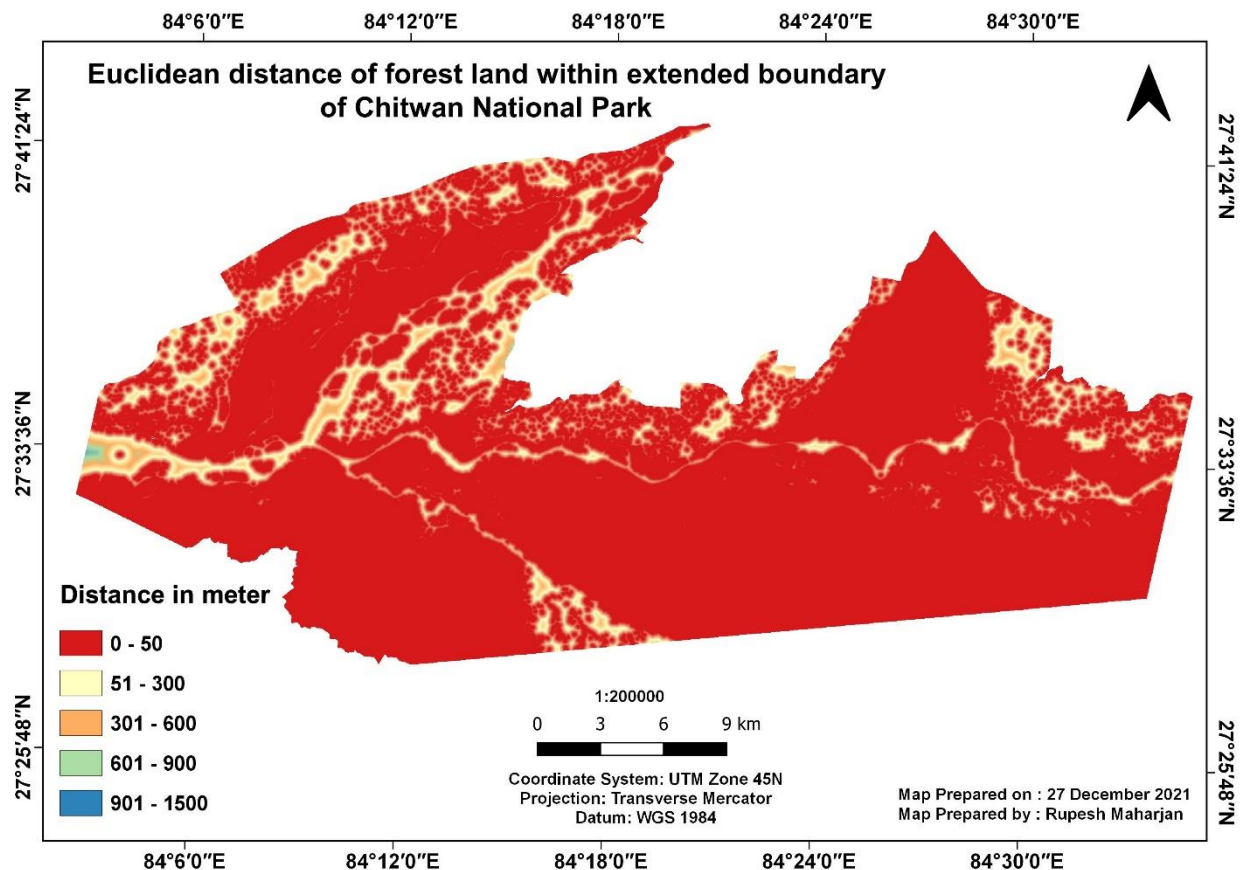
Map 4. Euclidean distance of agricultural land within extended boundary of Chitwan National Park



Map 5. Euclidean distance of road network within extended boundary of Chitwan National Park

2.3.5.2.2 Topographic variables

In this analysis, DEM was considered as one of the environmental variables. Initially, the layer was in 12.5m but it was resampled to 2.5m resolution (Similar to that of the LULC layer) and also clipped to the area of the LULC layer. Similarly, distance from waterbodies, forest, grassland were also produced using the Euclidean distance tool.



Map 6. Euclidean distance of forest land within extended boundary of Chitwan National Park

2.3.5.2.3 Climatic variables

Bioclimatic variables of present (1997-2000) were downloaded from WorldClim-Global Climate Data. Two environmental variables (Mean annual precipitation and Mean annual temperature layer) layers were considered as environmental variables for my model (McCarthy et al., 2015) which were received in a grid format with spatial resolution of around 1km.

2.3.5.3 Maxent Modeling

Maxent, generally means maximum entropy modeling, predicts suitable habitat of a species using species distribution model from geo-referenced presence points and environmental data. The model uses occurrence or presence data (Phillips et al., 2006) where the algorithm compares and identify the influence of environmental variables on species occurrence within the available study area (Aryal et al., 2016; Bista et al., 2018; KC et al., 2019; Pokharel et al., 2016). Similarly, the Maxent tool gathers a sample of background locations that it contrasts against the location of the presence point and calculates the density of presence across the entire landscape (Merow et al., 2013; Bista et al., 2018; Phillips et al., 2006).

As mentioned, Maxent tool requires presence points and environmental layers to carry out habitat suitability modeling. For fishing cat habitat distribution modeling, the presence point was saved as *.csv (comma separated values) format while other environmental layers were saved in ASCII (American Standard Code for Information Interchange) format as accepted by the tool. Similarly, all of the environmental variables were inserted as continuous format while only the LULC layer was changed as categorical format because of having different classes. Prediction pictures and jackknife test, which evaluates the relative contribution of each variable to the model (Matyukhina et al., 2014; Phillips et al., 2006), were ticked with continuous 'logistic' output. This output format was specifically used because it calculates threshold to maximize the sum of sensitivity and specificity as recommended for SDM having presence only data (KC et al., 2019; Liu et al., 2013).

For the analysis, 70% of species occurrence points were considered as a training set and 30% as for testing the model (KC et al., 2019). Additionally. The parameters used for this analysis were: regularization multiplier = 1, Max number of background points = 10000, number of replicates = 10, maximum iterations = 1000, convergence threshold = 0.00001, maximum replicates = 10. Similarly, 'Bootstrap' was selected as a replicated run type, which is considered to perform better analysis by handling a small number of presence point data

(Phillips & Dudík, 2008; Shrestha et al., 2021). Lastly, 'Write background predictions' option was chosen to get pseudo background data of Area Under the receiver operator Curve (AUC) calculation process, which is used for evaluating models and is a threshold dependent accuracy assessment index (Maharjan, 2016).

2.3.5.4 Model Evaluation and performance

Model evaluation is one of the most important steps in building a model which requires both testing and validation to get the predictive performance (Maharjan, 2016). In this process, model evaluation or accuracy was checked by using both threshold independent and threshold dependent methods (Sharma et al., 2020). Pearce & Ferrier (2000) mentioned that model performance with AUC >0.9 is considered excellent, 0.7-0.9 moderately useful, and model performance less than 0.7 as poorer and 0.5 as randomness, which is part of threshold dependent method. Similarly, the model was also evaluated using Receiver Operating Characteristics (ROC) curve, which is a threshold independent method. The ROC curve produced by plotting sensitivity values against 1-specificity values for every possible threshold (Esselman & Allan, 2011; Tuanmu et al., 2010). The sensitivity of the model is reduced by omission error and specificity is reduced by commission error thus contributing equally in the reduction of the AUC value (Phillips & Dudík, 2008). So, based on the area under the ROC curve (AUC), the performance of the model is determined.

2.3.5.5 Response Curve

Response Curve is the graph shown by Maxent as a result, which can help to visualize how a prediction is responding or how our species is responding to the single environmental variable. It shows a value of the variable and a measure of suitability. For instance, if the graph is moving in an upward curve, it shows that species like the particular variable when its value goes higher. Similarly, there are two sets of response curves created by Maxent for each environmental variable. The first set of graphs which is also known as the marginal curve shows the suitability of each environmental variable keeping all the other variables at their average values (Maharjan, 2016). However, the response curve shows flat line if the

model finds that variables are highly correlated. The second set of curves shows how the model responds to that particular variable without considering any other variables because of which correlation between variables is not considered.

2.3.5.6 Analysis of variable contribution

There are generally two ways to estimate the importance of variables to the model for predicting the suitable habitat. First method is to assess the 'Analysis of variable contribution' table produced by Maxent software itself. This table summarizes the contribution of each environmental variable to the model and the permutation importance/stability of the variables. The contribution of the variables is scrutinized by level of model fit, also known as gain, caused by each iteration of the Maxent algorithm from each environmental variable (Maharjan, 2016). Likewise, permutation importance is determined from changing the values of an environmental variable randomly within the model training points. Therefore, the model is considered more stable if its value is lower and vice versa.

Second method used by Maxent to determine the contribution of variables is through the Jackknife test. This test trains the model by removing each variable to calculate which of the environmental variables brings the largest decrease in model gain. The Jackknife test also trains the model using individual environmental variables by using its own values.

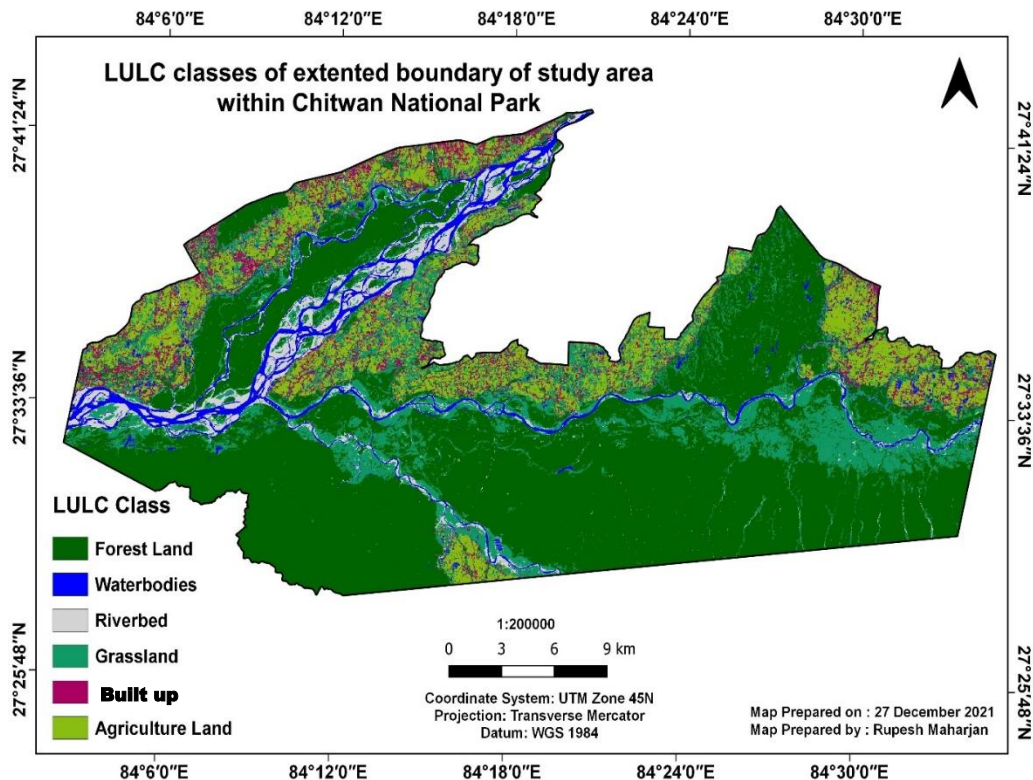
Chapter - 3: Result

In this chapter, LULC along with its accuracy assessment, obtained OBIA classification approach, and habitat suitability results from Maxent model are presented.

3.1 Results

3.1.1 Land Use and Land Cover

An object based supervised classification was carried out to produce a LULC layer of the entire extent of the year 2020 AD using the VHR image of ZY-3 Satellite. This approach of classification produces more accurate LULC results rather than other traditional classification methods like pixel based classification (Wei et al., 2010). Unlike pixel based image classification, which produces the "Salt and pepper" effect, OBIA method eliminates it by classifying images based on the segmentation. In combination with high resolution images, OBIA methods result into smooth and highly accurate classified images (Lang, 2008; Pal & Pal, 1993; Sekertekin et al., 2017).



Map 3. LULC classes of extended boundary of Chitwan National Park

Table 4. Area of Land use and Land cover classes from Object based classification

Land use/Land cover	Object-based classification	
	Area in ha	% of the total area
Forest	42069.0	54.2
Grassland	14846.3	19.2
Water bodies	3818.3	4.9
River bed	3456.5	4.7
Agricultural Land	9049.3	11.7
Built up/ Settlement areas	4130.3	5.3
Total	77369.7	100

Based on the result from table 4, it was found that the highest area obtained from classification was forest class which covered around 54.2% and lowest area was covered by River bed with 4.7% of the total area. Table 4 also shows that only 4130.3 ha was covered by built up areas while 9049.3 ha was covered by agricultural land. From the visualization of LULC map it was found that certain pixel areas of agricultural land were misclassified with built up and grassland class. Generally, these differences were seen due to the fact that spectral values of most of the agricultural land are similar with built up and river bed area. This might have caused the algorithm to assign the false class value to another class. However, these problems can be solved by classifying the image using a rule based approach so that only assigned areas as per the rule will be classified which minimizes the falsely classified objects.

3.1.2 Accuracy Assessment

The table 5 shows the error matrix for object based classification. The result shows overall accuracy of 88.7% and overall kappa accuracy of 81.1%. Based on the matrix results, the producer accuracy for forest class was found to be highest with 98.6% and water bodies of 97.4%. But, the producer accuracy of built up areas seemed to be lowest with 47.4% in comparison to other class accuracy results. In addition, the user's accuracy of river bed was found to be highest with 100% followed by water bodies with 97.4% accurate result.

However, the user's accuracy of built up area was found to be lowest with % value of 69.2 in comparison to other classes.

Table 5. Error matrix: accuracy assessment for object based LULC classification

Classified data	Reference data from object based classification							User Accuracy
	Riverbed	Built up areas	Agricultural Land	Water bodies	Forest Land	Grassland	Total	
Riverbed	13	0	0	0	0	0	13	100.0
Built up/settlement areas	2	9	1	0	0	1	13	69.2
Agricultural Land	2	7	72	1	2	9	93	77.4
Water bodies	0	0	1	37	0	0	38	97.4
Forest Land	0	2	8	0	291	12	313	93
Grassland	0	1	7	0	2	31	41	75.6
Total	17.0	19.0	89.0	38.0	295.0	53.0	511.0	0.0
Producer Accuracy	76.5	47.4	80.9	97.4	98.6	58.5	0.0	88.7
Overall accuracy (%)	88.7							
Overall Kappa accuracy (%)	81.1							

3.1.3 Maxent Performance

Based on the input environmental variables and fishing cat presence point data, the results produced by Maxent were illustrated in the form of various types of graphs. These results were discussed based on the Analysis of omission/ commission graph, Response curves, and lastly, analysis of variable contributions.

3.1.3.1 Analysis of Omission/ commission graph

The graph shown in figure 8 representing the AUC scrutinizes the performance of the model. The AUC value produced after 10 replicate runs was shown as 0.950 with SD (standard deviation) of 0.022. Based on this result, the obtained AUC value was close to 1, which signifies that the model generated can thus predict the distribution of fishing cat with a high accuracy.

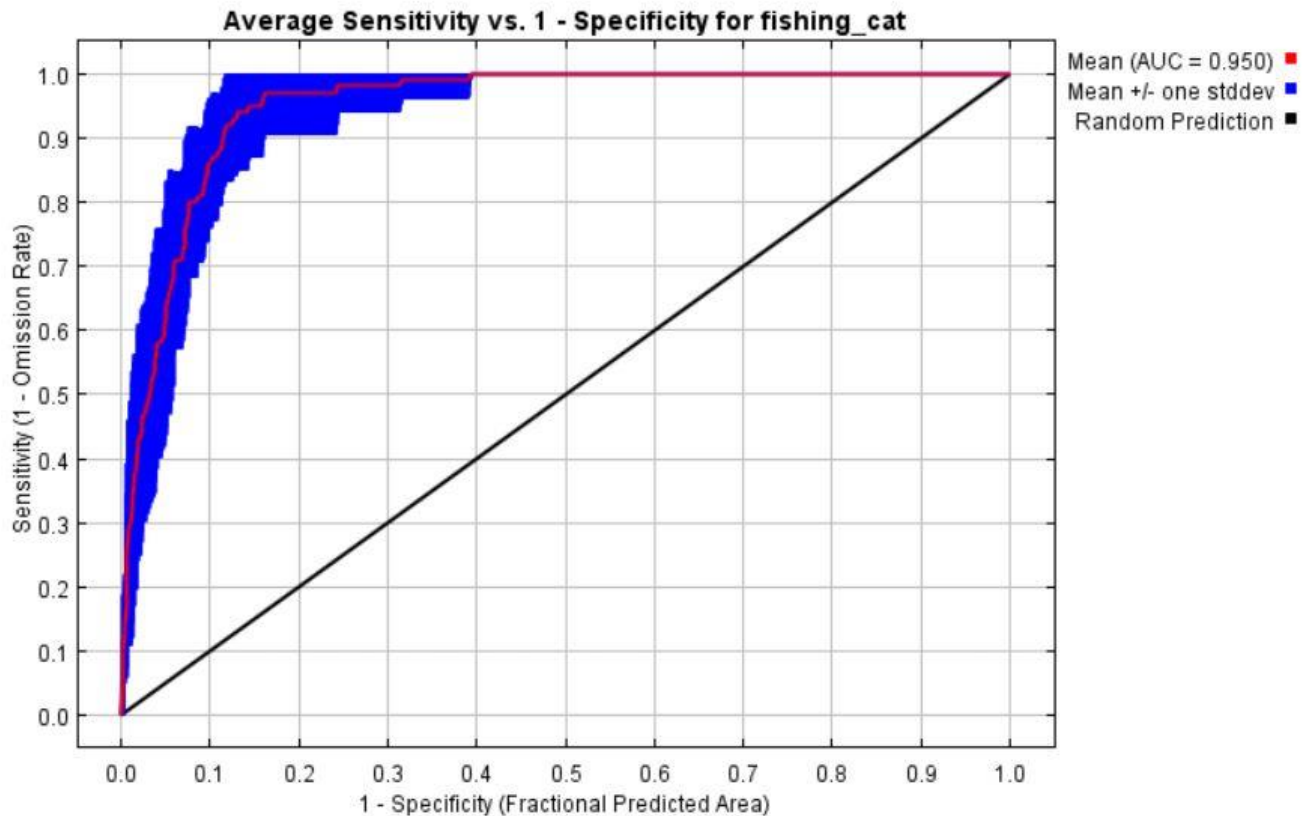


Figure 8. Receiver Operating Characteristics (Sensitivity Vs. 1- Specificity) on fishing cat

3.1.3.2 Response Curves

The response curve shown in figure 9 illustrates how each environmental variable affects the Maxent prediction. The curve shows how predicted probability values of presence changes when there is change in each environmental variable while keeping all other environmental variables at their average sample value. Based on the graph showing response curve of fishing cat to distance of road, the mean probability of occurrence of fishing cat increased rapidly to around 0.7 and started to decline gradually with increase in distance. Similarly, the probability of species occurrence inclined gradually from around 0.35 and reached a highest value of around 0.95 while reaching at about 9000 m in distance to the settlement response curve.

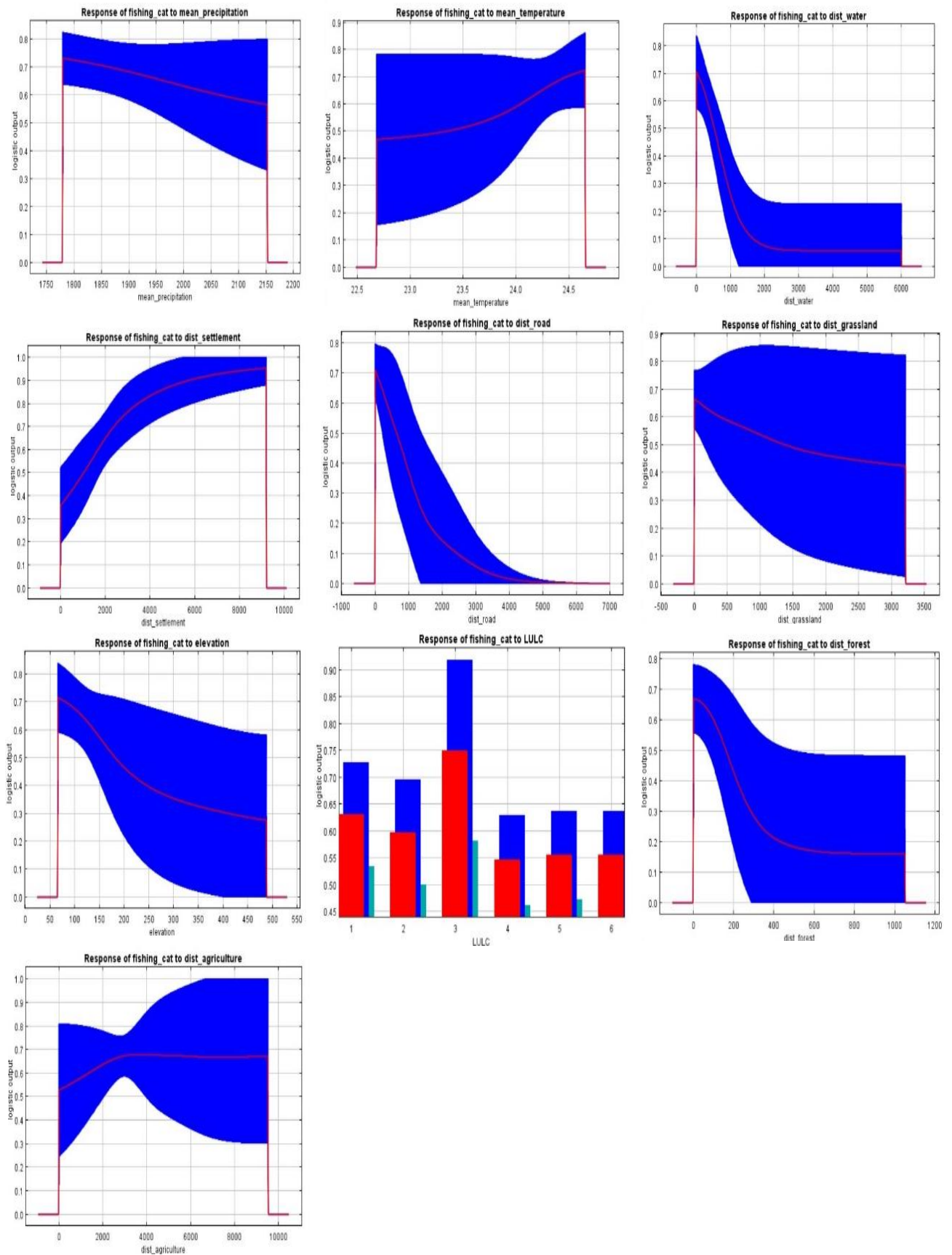


Figure 9. Response curves showing the effect of each environmental variables on Maxent prediction

3.1.3.3 Analysis of variable contributions

The table 6 shows the estimates of relative contribution of each environmental variables to the Maxent model. The table signifies that road distance plays a significant role in predicting the potential habitat of fishing cat within the study area with 26.7% contribution which is then followed by water distance covering 19.6%. Similarly, settlements distance and agriculture distance contribute 14.7% and 7.8%. However, forest distance, mean precipitation and mean temperature contributed less in predicting the habitat suitability of the species with 5.2%, 1.8% and 1.8% respectively.

Table 6. Analysis of variable contribution

Variable	Percent contribution	Permutation importance
Road Distance	26.7	13.6
Water Distance	19.6	23.4
Settlement/built up distance	14.7	21.6
LULC	13.9	6.3
Agriculture Distance	7.8	10.8
Elevation	5.6	10.6
Forest Distance	5.2	6.1
Grassland Distance	2.9	2.1
Mean Precipitation	1.8	3
Mean Temperature	1.8	2.5

3.1.3.4 Evaluation of predictor performance under Jackknife analysis

Jackknife analysis is useful in evaluating the importance of each environmental variable or predictor in the Maxent model. This analysis shows how important each variable is in explaining fishing cat presence separately and how the model is affected when each

environmental variable is left out. In figure 10, Maxent jackknife test of variable importance shows distance from road as an environmental variable which has good fit to the training data. The environmental variable with highest gain when used in isolation is distance from road which appears to have most useful information by itself in the model. Also, all the values which are displayed are averages over replicate runs.

Note: Blue bar indicating the importance of that particular variable in explaining the differences in the data when that variable is used separately. Green bar indicates the loss in total model gain when the specific variable is omitted which points out that the variable has important information for explaining the model. Red Bar indicates the total model gain.

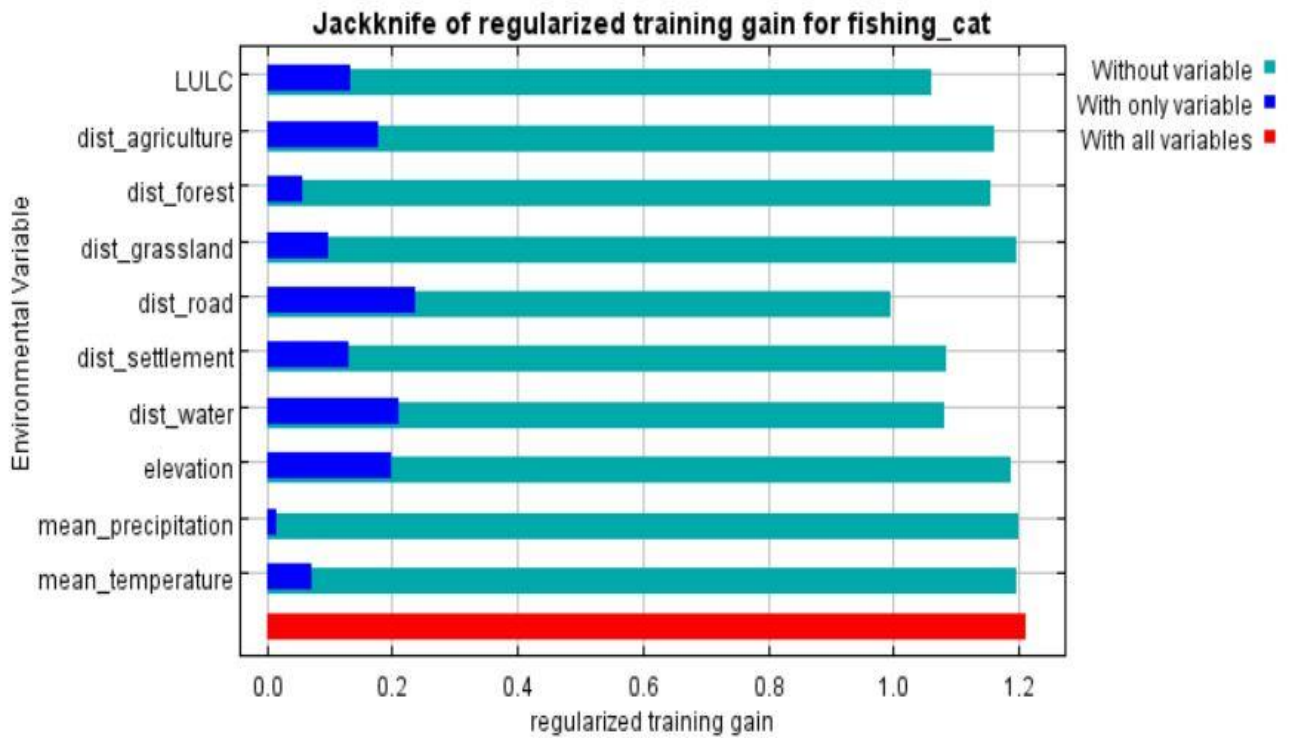


Figure 10. Jackknife result of variable in regularized training gain for fishing cat

Figure 11, shows the result of the same jackknife test using test gain instead of training gain. This figure shows that distance from agriculture as an important environmental variable in the test gain. The test gain plot showed that the model obtained from using only distance from forest and mean precipitation variable resulted in a negative test gain. So,

these variables which are used in a model for predicting the distribution of occurrences is not useful as predictor because of the negative test gain.

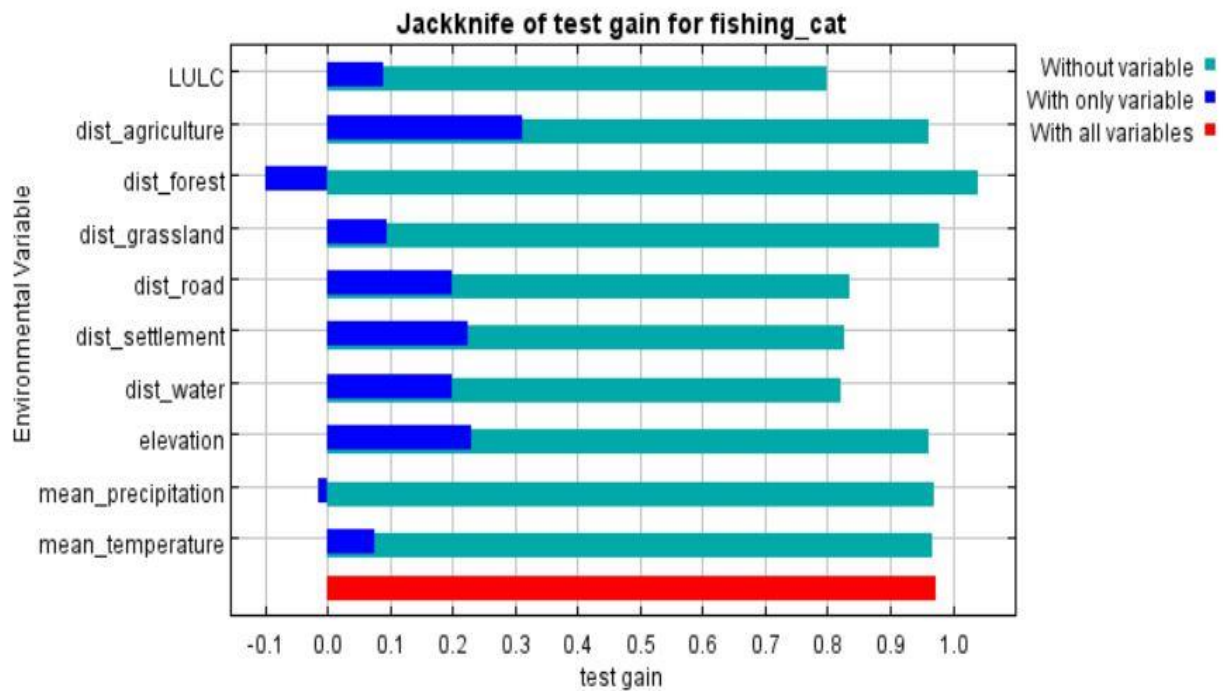


Figure 11. Jackknife results of variable importance in the test gain for fishing cat

Based on the Jackknife test using AUC plot (figure 12), distance from agriculture is again seen as the most effective individual environmental variable for predicting the distribution of the occurrence data which was left aside for testing. The result, which is obtained when the predictive performance is measured using AUC, showed the importance of distance from water, road and elevation is good fit to the model.

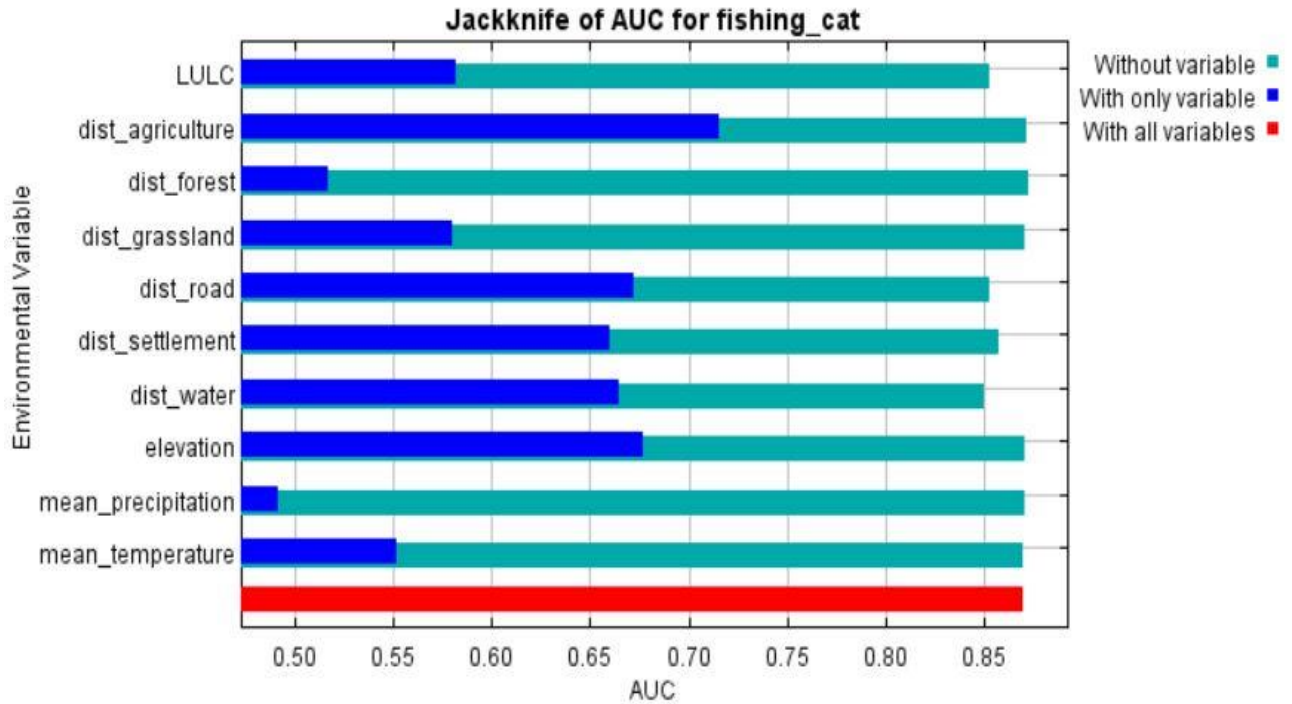


Figure 12. Jackknife result of variable in the AUC for fishing cat

3.1.4 Habitat suitability map

Based on the input environmental variables and the model generated in Maxent produced a habitat suitability map (Figure 13). The map was initially generated in ASCII format whose projection was later defined to its original source (UTM, zone 45N, Spheroid: WGS 84, Datum: WGS 84). The map was later classified based on four different species occurrence probability thresholds such as "Highly Suitable, Moderately Suitable, Suitable, Least Suitable" (Table 7). The Maxent generated suitability map was then differentiated into several categories of suitable areas which were color coded using red as highly suitable areas while blue as the areas predicted as least suitable areas. The areas which are considered as least suitable define that those areas have least probability of fishing cat occurrence.

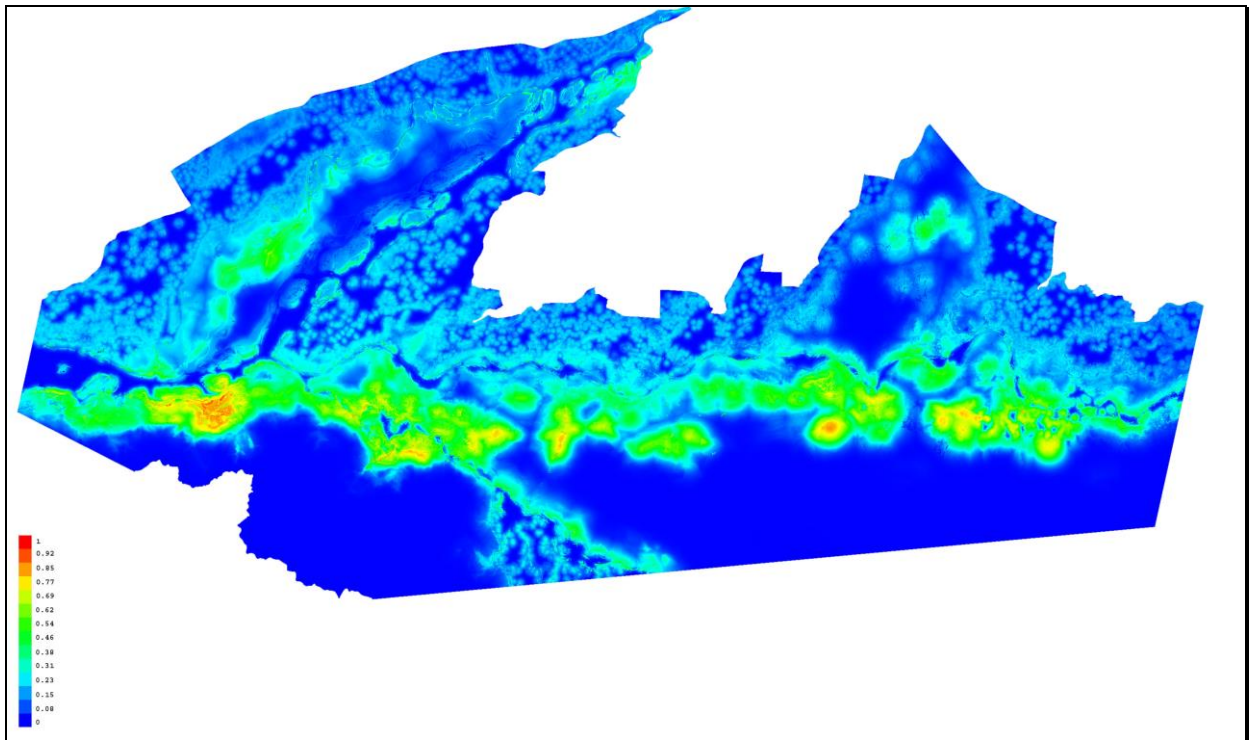
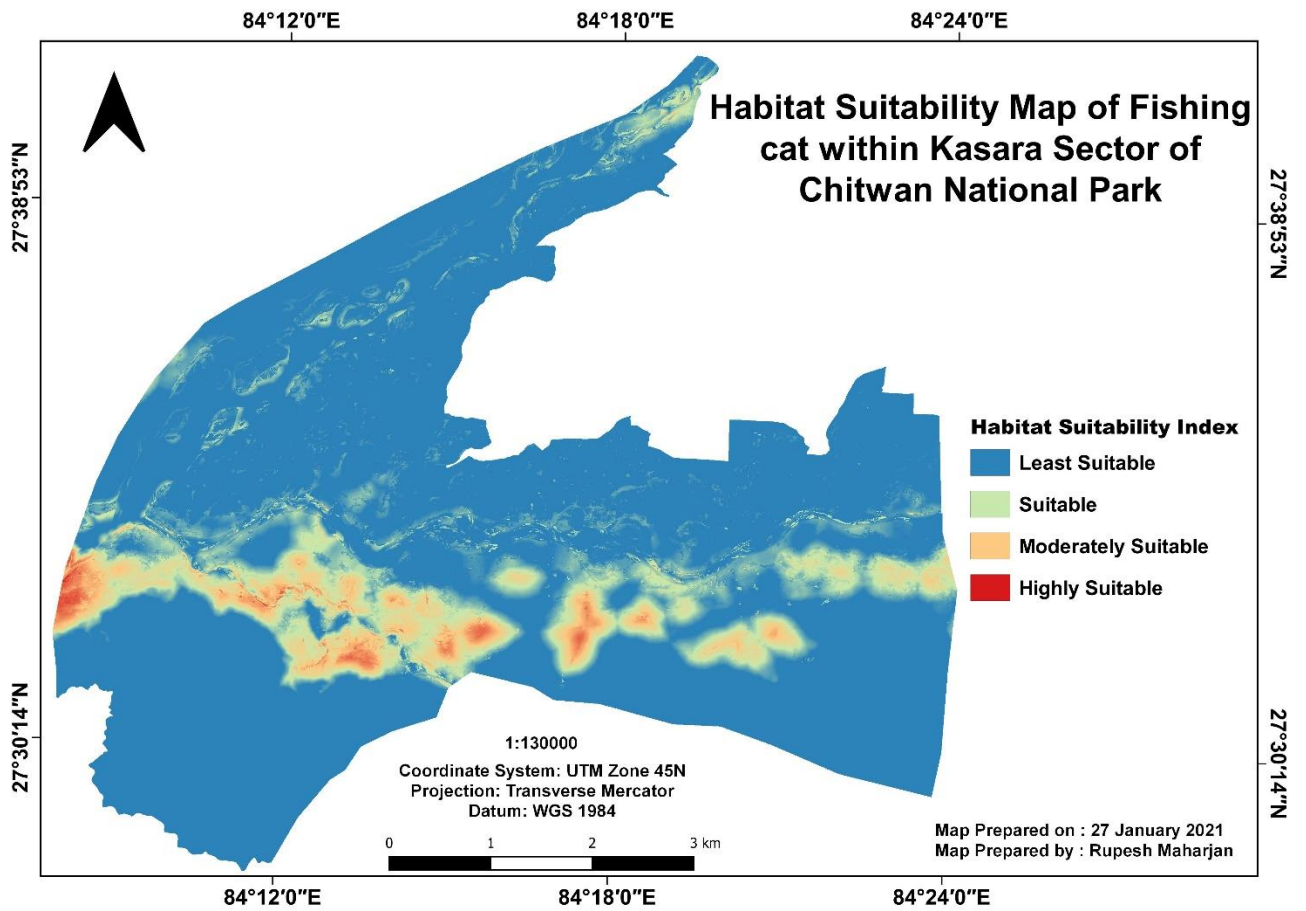


Figure 13. Maxent produced habitat suitability map for fishing cat species



Map 4. Habitat suitability map of fishing cat using habitat suitability index.

3.1.4.1 Predicted suitability area based on the habitat class

Based on the result generated for the study area, table 7 shows that 188 km² area was predicted as least suitable for the fishing cat while 59 km² was moderately suitable and only 6 km² area was predicted to be extremely suitable for fishing cat species.

Table 7. Predicted suitability area based on the threshold used to predict logistic outputs into classes.

Habitat Suitability Class	Probability Value	Area (km ²)	% coverage
Least Suitable	0.00 - 0.20	188	68.2
Moderately Suitable	0.20 – 0.40	59	21.3
Highly Suitable	0.40 – 0.60	23	8.3
Extremely Suitable	0.60 – 0.94	6	2.2

3.2 Discussion

Fishing cat being the elusive species are tricky to be seen in the wild. Globally, the population of these species are declining rapidly due to its habitat loss through the excessive conversion of wetland areas into agricultural lands. On top of that, there is also an inadequate research and information on habitat suitability of the species in geospatial domain. In order to fill the research gaps, I have carried out fishing cat research in Northern sector of CNP using wildlife tools and enacted contemporary geospatial approaches to prepare habitat suitability map. Primarily, I implemented wildlife monitoring tools and technique such as camera trapping method. It was executed to obtain the presence location of the species within the Kasara Sector of CNP. However, due to the difficulty in obtaining a large number of occurrence points, which Maxent requires to produce a highly accurate suitability map, data from previous studies were also used. Furthermore, the data enclosed within the study area were less so the Maxent analysis was performed in the extended boundary within the area of CNP.

Naturally, fishing cat species prefers areas near settlements and water sources in order to meet their need for food supply i.e livestock and fish (Haque & Vijayan, 1993; Myers et al., 2006; Mishra, 2021). Similarly, my study also showed that environmental variables like distance from water, settlement and road were major contributing variables in defining the suitable habitat of fishing cat species. Furthermore, Mishra et al. (2018) also mentioned that fishing cat often use aquaculture and rice field plantation areas to hunt for their prey which might also be reason why fishing cat prefer settlement areas. Furthermore, it has been recorded that the species frequently visits seasonal water holes, formed from the rise in rivers during monsoon season and dries in winter season, trapping the fishes in it. This makes it easier for the species to catch larger fish with less effort. However, due to the alteration of habitat and rapid drying of wetland areas are severely causing negative impacts on the distribution and abundance of the species (Mishra et al., 2018). Khadka et al. (2015) has also described the situation of such wetland areas being lost and has been converted into grassland at present.

In addition, the result also showed that fishing cat habitat is highly determined by the distance from road and the reason might be because the majority of fishing cat presence points were falling in the distance close to forest path. The only reason to explain this is by understanding the behavior of the cat family as they tend to avoid obstacles while choosing their path and prefer areas with easy pathways to cover large areas in search of their prey. The outcome of the analysis predicted that fishing cat habitat is extremely suitable only in a small part of the park because the majority of the areas within the park were covered by dense forest while only a small part consisted of wetland areas. However, on using similar environmental variables used by McCarthy et al. (2015) found that felid species (clouded leopard, golden cat, leopard cat and marbled cat) habitat were majorly influenced by forest distance, however, my study showed that forest distance played least role in the Maxent model. Perhaps, due to the presence of these factors and the selective habitat preference of fishing cat species, their distribution is substantially limited to vegetated areas near

shallow water, rivers and streams (Duckworth et al., 2010; Mishra, 2013; Prater, 1998). Thus, it is evident that fishing cat habitat is directly influenced by the distance from settlement areas, forest path, and water sources. However there are also other factors which do contribute in the prediction of the habitat like Land use and Land cover (especially river bed), distance from grassland and agriculture. But the model showed less preference in deriving the habitat suitability using other environmental variables like distance from forest, annual precipitation, and annual temperature. Based on these output we can see that there are certain factors which can be improved to increase the habitat of the species and conserve it from extinction.

Chapter- 4: Conclusion

In CNP, the habitat suitability analysis of fishing cat has never been carried out so its information within geospatial level has always been limited. The information gap for this species has been causing great challenges in planning and initiating its conservation measures. This study can help to address those challenges by providing the information on the status and distribution of the species within the park and its bufferzone as well as provide a habitat suitability map to visualize the area where conservation efforts are needed. Since the fishing cat population is very limited in the wild and its numbers are declining, it is extremely important to address their conservation needs both at local as well as government level.

The study demonstrated probable areas, might be used by fishing cat species, in the form of habitat suitability map as well as categorically illustrated those areas based on habitat suitability probability values. Furthermore, the study also presented the environmental variables which might be influencing the habitat suitability of the species. Based on the result, it is evident that water source is one of the major factors which has a significant influence in the habitat of the fishing cat species. So conservation of wetlands must be prioritized along with the minimization of illegal fishing and wetland degradation. Also, the species are found to live close to settlement areas, preying on livestock and fish from fishing ponds, which can cause a human-fishing cat conflict. So both park and buffer zone community must focus on the proper management of fishing cat habitat. Most importantly, the habitat suitability map obtained from this study can help ecologist to understand the core areas need to be focused, while planning for the actions, to conserve the habitat of the fishing cat species.

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ANNEX

ANNEX 1: Fishing cat presence points

S.N	Date	Latitude	Longitude	Habitat Type	Records Type
1	2009	27.57066	84.157	River bank	Camera trapping
2	2009	27.59536	84.15563	River bank edge Narayani R/F	Camera trapping
3	2009	27.53836	84.03977	Sal mixed stream and water hole	Camera trapping
4	2009	27.5351	84.13119	Sal mixed forest	Camera trapping
5	2009	27.54473	84.1591	mixed stream and small river bank	Camera trapping
6	2009	27.55943	84.15627	Tall grass land	Camera trapping
7	2009	27.54242	84.11586	mixed forest	Camera trapping
8	2009	27.54028	84.19116	Sal mixed forest	Camera trapping
9	2009	27.54242	84.11586	mixed forest	Camera trapping
10	2009	27.57419	84.49193	R/F	Camera trapping
11	2009	27.53453	84.27057	Sal forest	Camera trapping
12	2009	27.53345	84.28493	Sal forest	Camera trapping
13	2010	27.55470	84.56258	Grassland	Camera trapping
14	2010	27.55470	84.56258	Grassland	Camera trapping
15	2010	27.56239	84.41631	Riverine forest	Camera trapping
16	2010	27.55208	84.50666	Grassland	Camera trapping
17	2011	27.54750	84.50068	Near wetland grassland	Death found
18	2012	27.54815	84.49961	Grassland, marsh land	Camera trapping
19	2012	27.52784	84.22099	Marshy land	Camera trapping
20	2012	27.52784	84.22099	Marshy land	Camera trapping
21	2012	27.52784	84.22099	Marshy land	Camera trapping

22	2012	27.52784	84.22099	Marshy land	Camera trapping
23	2012	27.53825	84.13084	Marshy land	Camera trapping
24	2012	27.56421	84.46119	NA	Camera trapping
25	2013	27.55386	84.08595	Grassland	Camera trapping
26	2013	27.53730	84.08124	Wetland	Camera trapping
27	2013	27.53730	84.08124	Wetland	Camera trapping
28	2013	27.53730	84.08124	Wetland	Camera trapping
29	2013	27.52457	84.23104	Grassland /Riverine forest	Camera trapping
30	2013	27.54395	84.52535	Grassland	Camera trapping
31	2013	27.39494	84.61070	Mixed forest	Camera trapping
32	2017	27.54271	84.18496	Mixed Forest	Camera trapping
33	2017	27.53871	84.24613	Grassland	Camera trapping
34	2018	27.54747	84.22051	Forest/river	Camera trapping
35	2018	27.53433	84.24965	Grassland	Camera trapping
36	2018	27.55163	84.30934	Forest	Camera trapping
37	2018	27.55569	84.16835	Forest/river	Camera trapping
38	2018	27.55569	84.16835	Forest/river	Camera trapping
39	2018	27.55317	84.14433	Grassland	Camera trapping
40	2018	27.54325	84.16817	Mixed Forest	Camera trapping
41	2018	27.54271	84.18496	Mixed Forest	Camera trapping
42	2018	27.54271	84.18496	Mixed Forest	Camera trapping
43	2018	27.54271	84.18496	Mixed Forest	Camera trapping
44	2021	27.55102	84.1824	River bed	Camera trapping
45	2021	27.54715	84.22154	River Bed	Camera trapping
46	2021	27.55663	84.24209	River bed	Camera trapping

ANNEX 2: Images of field survey

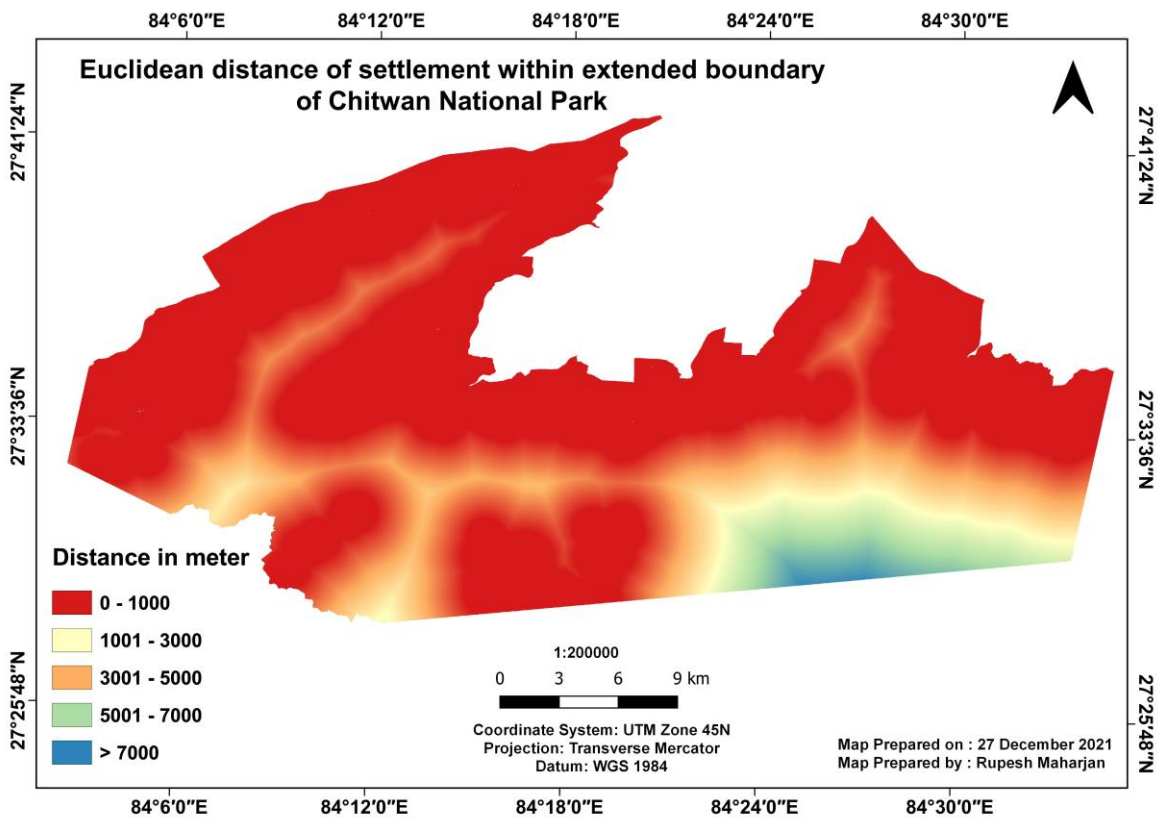
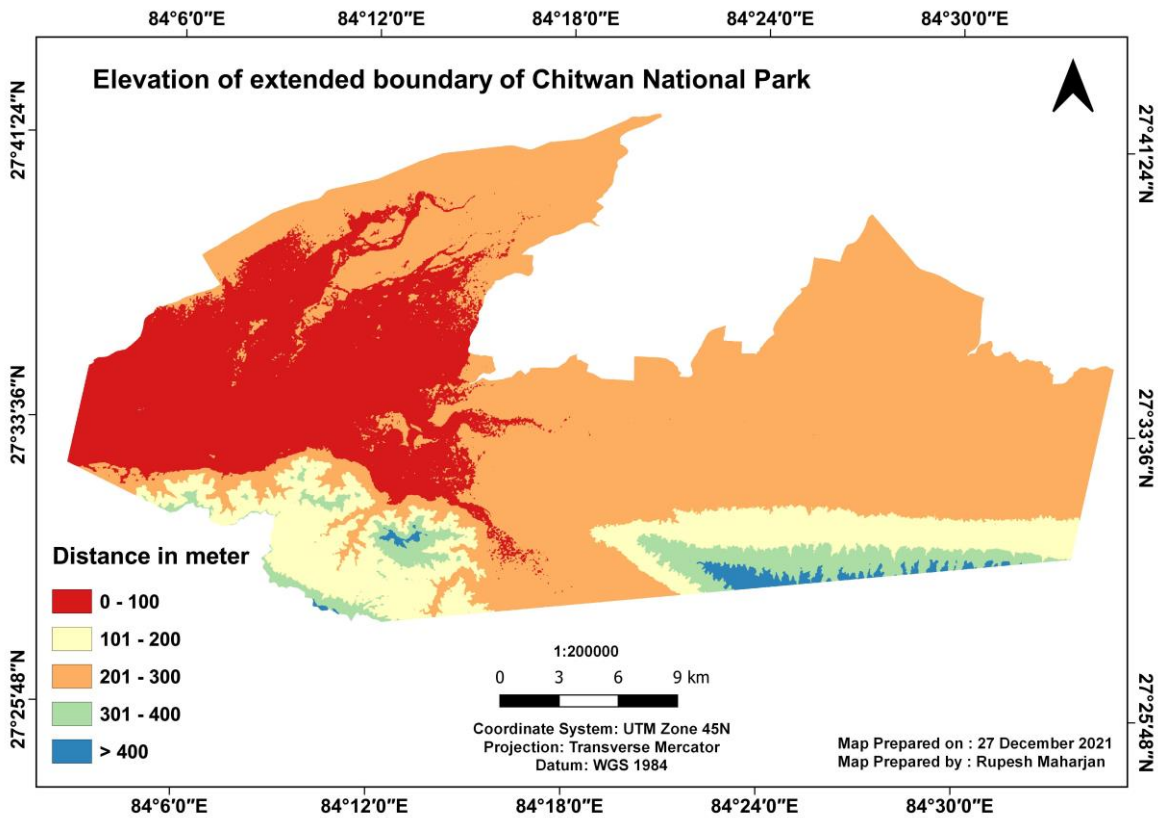


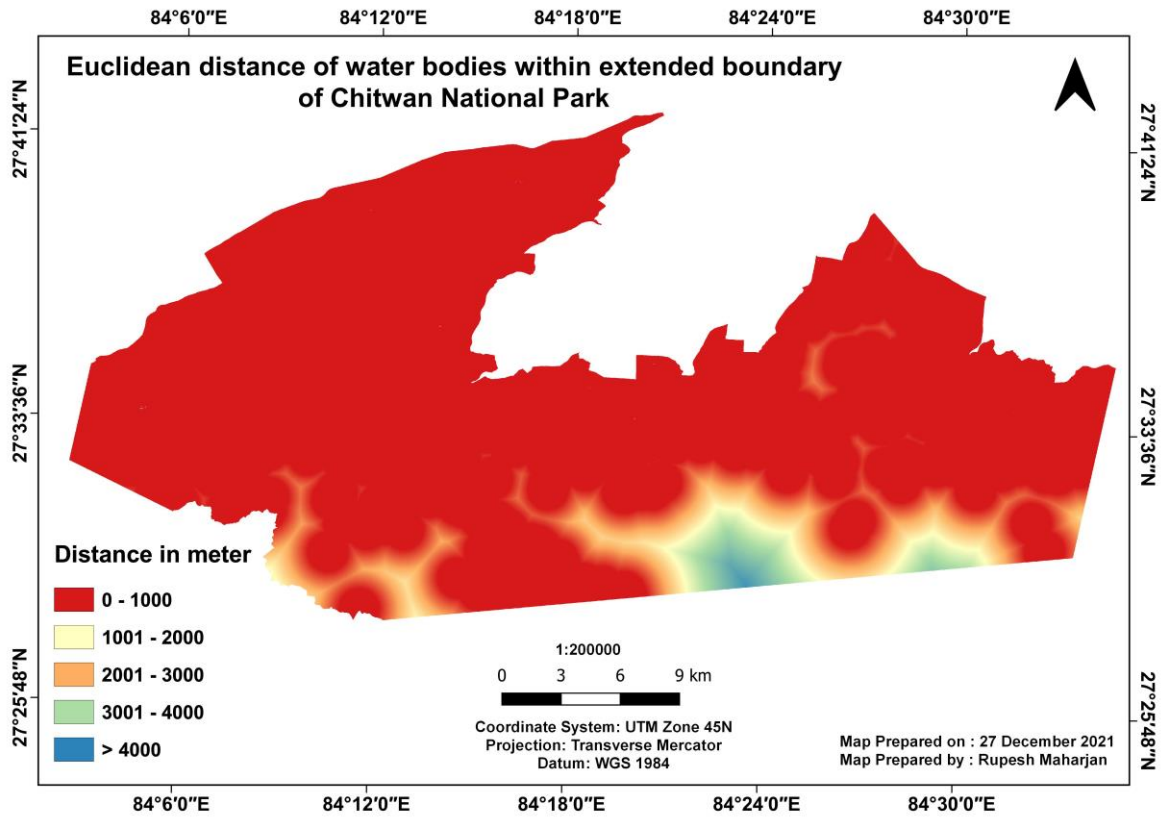


ANNEX 3: Fishing cat images from field survey



ANNEX 3: Environmental Variables





ANNEX 4: Maxent parameters for habitat suitability analysis

Maximum Entropy Species Distribution Modeling, Version 3.4.4

Samples		Environmental layers	
File	data\FishCat_fieldData\FishCat_data.csv <input type="button" value="Browse"/>	Directory/File	\\Local\ESRI\Desktop10.4\SpatialAnalyst <input type="button" value="Browse"/>
<input checked="" type="checkbox"/> fishing_cat		<input checked="" type="checkbox"/> LULC <input checked="" type="checkbox"/> dist_agriculture <input checked="" type="checkbox"/> dist_forest <input checked="" type="checkbox"/> dist_grassland <input checked="" type="checkbox"/> dist_road <input checked="" type="checkbox"/> dist_settlement <input checked="" type="checkbox"/> dist_water <input checked="" type="checkbox"/> elevation <input checked="" type="checkbox"/> mean_precipitation <input checked="" type="checkbox"/> mean_temperature	Categorical Continuous Continuous Continuous Continuous Continuous Continuous Continuous Continuous Continuous
<input checked="" type="checkbox"/> Linear features <input checked="" type="checkbox"/> Quadratic features <input checked="" type="checkbox"/> Product features <input type="checkbox"/> Threshold features <input checked="" type="checkbox"/> Hinge features <input checked="" type="checkbox"/> Auto features	<input checked="" type="checkbox"/> Create response curves <input checked="" type="checkbox"/> Make pictures of predictions <input checked="" type="checkbox"/> Do jackknife to measure variable importance Output format: Logistic Output file type: asc Output directory: C:\maxent_analysis_2 <input type="button" value="Browse"/> Projection layers directory/file: <input type="button" value="Browse"/>	<input type="button" value="Run"/> <input type="button" value="Settings"/> <input type="button" value="Help"/>	

Maximum Entropy Parameters

Basic | Advanced | Experimental

Random seed
 Give visual warnings
 Show tooltips
 Ask before overwriting
 Skip if output exists
 Remove duplicate presence records
 Write clamp grid when projecting
 Do MESS analysis when projecting

Random test percentage: 70
 Regularization multiplier: 1
 Max number of background points: 10000
 Replicates: 10
 Replicated run type: Bootstrap

Test sample file:

Maximum Entropy Parameters

Basic **Advanced** Experimental

Add samples to background
 Add all samples to background
 Write plot data
 Extrapolate
 Do clamping
 Write output grids
 Write plots
 Append summary results to maxentResults.csv file
 Cache ascii files

Maximum iterations: 1000
 Convergence threshold: 0.00001
 Adjust sample radius: 0
 Log file: maxent.log
 Default prevalence: 0.5
 Apply threshold rule: ▼

Bias file: Browse

Maximum Entropy Parameters

Basic **Advanced** Experimental

Logscale raw/cumulative pictures
 Per species results
 Write background predictions
 Show exponent in response curves
 Fade by clamping
 Verbose
 Use samples with some missing data

Threads: 1
 Lq to lqp threshold: 80
 Linear to lq threshold: 10
 Hinge threshold: 15
 Beta threshold: -1
 Beta categorical: -1
 Beta lqp: -1
 Beta hinge: -1
 Default nodata value: -9999