Mapping Human-Elephant Conflict Hotspots in Eastern Chure Landscape, Nepal

Madhu Chaudhari
T.U. Registration No.: 5-2-19-504-2015
T.U. Examination Roll No.: 7930027
Batch: 2079

Central Department of Zoology
Institute of Science and Technology
Tribhuvan University
Kirtipur, Kathmandu
Nepal

A dissertation submitted
In partial fulfilment of the requirements for the award of the degree of Master of Science in Zoology with special paper Ecology and Environment

---

April 2025

Mapping Human-Elephant Conflict Hotspots in Eastern Chure Landscape, Nepal

Madhu Chaudhari
TU Registration No. 5-2-19-504-2015
M.Sc. Zoology (Ecology and Environment)
T.U. Examination Roll No. 7930027

Supervisor
Bishnu Prasad Bhattarai, PhD
Assistant Professor

Co-Supervisor
Suraj Baral
Biodiversity Research and Conservation Society

Central Department of Zoology
Institute of Science and Technology
Tribhuvan University
Kirtipur, Kathmandu

Dissertation submitted in partial fulfilment of the requirements for the degree of Master of Science in Zoology with special paper Ecology and Environment

---

April 2025

April 2025
E-mail: madhuthanet19@gmail.com
Central Department of Zoology
Institute of Science and Technology
Tribhuvan University
Kirtipur, Kathmandu, Nepal
Website: https://www.cdz.tu.edu.np/

Citation: Chaudhari, M. (2025). *Mapping human-elephant conflict hotspots in eastern Chure landscape, Nepal* (MSc dissertation). Central Department of Zoology, Tribhuvan University.

Declaration

I hereby declare that the work presented in this dissertation "**Mapping human-elephant conflict hotspots in eastern Chure landscape, Nepal**" has been done by myself, and has not been submitted elsewhere for the award of any degree. All sources of information have been specifically acknowledged by reference to the author(s) or institution(s).

Madhu Chaudhari

Exam Roll No.: 7930027

Email: madhuthanet19@gmail.com

Date: 04/10/2025

त्रिभुवन विश्वविद्यालय
TRIBHUVAN UNIVERSITY
प्राणी शास्त्र केन्द्रीय विभाग
CENTRAL DEPARTMENT OF ZOOLOGY
कीर्तिपुर, काठमाडौं, नेपाल ।
Kirtipur, Kathmandu, Nepal.

०१-४३३१८९६
01-4331896
Email: info@cdz.tu.edu.np
URL: www.cdztu.edu.np

पत्र संख्या :-
च.नं. Ref.No.:-

Central Department of Zoology T.U., Kirtipur

Recommendation

This is to recommend that the dissertation entitled "**Mapping human-elephant conflict hotspots in eastern Chure landscape, Nepal**" has been carried out by Madhu Chaudhari for the partial fulfilment of Master's Degree of Science in Zoology with special paper Ecology and Environment. This is his original work and has been carried out under my supervision. To the best of my knowledge, this dissertation work has not been submitted for any other degree in any institutions.

....
Supervisor
Bishnu Prasad Bhattarai, PhD
Assistant Professor, TU
Central Department of Zoology
Tribhuvan University
Kirtipur, Kathmandu, Nepal

....
Co-supervisor
Mr. Suraj Baral
Biodiversity Research and Conservation Society
Tarkeshwor, Kathmandu, Nepal

Date: 04/10/2025

त्रिभुवन विश्वविद्यालय
TRIBHUVAN UNIVERSITY
प्राणी शास्त्र केन्द्रीय विभाग
CENTRAL DEPARTMENT OF ZOOLOGY
कीर्तिपुर, काठमाडौं, नेपाल।
Kirtipur, Kathmandu, Nepal.

☎ ०१-४३३१८९६
01-4331896
Email: info@cdz.tu.edu.np
URL: www.cdztu.edu.np

पत्र संख्या :-
च.नं. Ref.No.:-

Central Department of Zoology T.U., Kirtipur

Letter of approval

On the recommendation of supervisor "Bishnu Prasad Bhattarai, PhD" this dissertation submitted by Madhu Chaudhari entitled "**Mapping human-elephant conflict hotspots in eastern Chure landscape, Nepal**" is approved for the examination in partial fulfilment of the requirements for Master's Degree of Science in Zoology with special paper Ecology and Environment.

....

Head of Department
Kumar Sapkota, PhD
Professor
Central Department of Zoology
Tribhuvan University
Kirtipur, Kathmandu, Nepal

Date: 04/10/2025

त्रिभुवन विश्वविद्यालय
TRIBHUVAN UNIVERSITY
प्राणी शास्त्र केन्द्रीय विभाग
CENTRAL DEPARTMENT OF ZOOLOGY
कीर्तिपुर, काठमाडौं, नेपाल ।
Kirtipur, Kathmandu, Nepal.

०१-४३३१८९६
01-4331896
Email: info@cdz.tu.edu.np
URL: www.cdztu.edu.np

पत्र संख्या :-
च.नं. Ref.No.:-

Certificate of acceptance

This dissertation work submitted by Madhu Chaudhari entitled **"Mapping human-elephant conflict hotspots in eastern Chure landscape, Nepal"** has been accepted as a partial fulfilment for the requirements of Master's Degree of Science in Zoology with special paper Ecology and Environment.

Evaluation committee

Supervisor
Bishnu Prasad Bhattarai, PhD
Assistant Professor

Head of Department
Kumar Sapkota, PhD
Professor

External examiner
Dinesh Neupane, PhD
Conservation Biologist
Zoological Society of London (ZSL)

Internal Examiner
Laxman Khanal, PhD
Associate Professor

Date of examination: 04/17/2025

Acknowledgments

Foremost, I would like to express my heartfelt gratitude to my supervisor, Assistant Prof. Dr. Bishnu Prasad Bhattarai, Central Department of Zoology, for his guidance, valuable insights, suggestions, and knowledge regarding the subject matter. This thesis would not have taken its present shape and quality without his support.

I am especially grateful to my co-supervisor, Mr. Suraj Baral, Biodiversity Research and Conservation Society, for allowing me to work under a project funded by Dierenpark Amersfoort Wildlife Conservation Fund, and for his supervision and guidance throughout the study and for his unwavering efforts in making this study possible.

I would like to express my gratitude to Prof. Dr. Kumar Sapkota, Head of the Central Department of Zoology, Tribhuvan University, Kirtipur.

I would like to express my sincere gratitude to the Government of Nepal, the Ministry of Forest and Soil Conservation, for granting research permission. Also, I would like to thank my colleague, Mr. Shree Krishna Devkota, for his assistance during field work and the people of the study area for providing information during the field visit. I am highly obliged and want to extend my thanks to all the respected teaching and non-teaching staff of the Central Department of Zoology for their support, guidance, and feedback on my research project and other academic courses during my study period at the department.

I am indebted and would like to express my sincere gratitude to my guardians, who supported and encouraged me throughout the study period. I am very grateful to all the people who encouraged me to study, and all my friends for their direct and indirect help in completing this study.

Name: Madhu Chaudhari

Email: madhuthanet19@gmail.com

Examination Roll No.: 7930027

Batch: 2079

Abstract

Human-elephant conflict (HEC) is a growing issue that poses a significant conservation challenge within a shared landscape with humans. The identification and prediction of conflict hotspots and the determination of HEC driving factors provide insights to reduce human-elephant conflict and promote the coexistence. This study employed verbal consent-based in-person interviews across 255 spatial grid cells, with single respondent interviewed per grid cell, resulting in a total of 255 interviews. A semi-structured questionnaire was used to identify the HEC hotspots in the Eastern Chure Landscape (ECL). Most of the respondents (n = 190), reported experiencing conflicts, while remaining respondents (n = 65) reported no conflict incidents in last five years. Logistic regression analysis identified Night Light and Shannon's Diversity Index (SHDI) as the significant predictors of HEC. Similarly, a Classification and Regression Tree (CART) model also indicated Night Light as the most influential predictor, suggesting that elephants tend to avoid well-lit areas. The study revealed that highly fragmented landscapes with low Effective Mesh Size (MESH) values and low Largest Patch Index (LPI) increases the probability of HEC, focusing the restoration of habitat connectivity. The areas having high population density increased the likelihood of HEC. The performance of the CART model was evaluated using confusion matrix, where the model achieved 76.2% accuracy, 80.80% sensitivity, and 54.5% specificity, in identifying HEC prone areas. To assess the consistency and predictive performance of the CART model, a Random Forest (RF) model was constructed using same response and predictor variables. The RF model achieved 69.8% accuracy, but lower sensitivity (18.8%), and higher specificity (87.2%). The findings highlight that CART model's performance, particularly in identification of conflict-risk areas, suggesting CART model a reliable tool for HEC risk prediction. HEC hotspots map identified Morang, particularly in Letang, Kerabari, and Miklajung and areas of Jhapa, including Mechinagar and Shivasataxi, are the major HEC hotspots in Eastern Chure Landscape (ECL), indicating the requirement of site-specific mitigation strategies. Therefore, restoration of traditional and degraded elephant migratory routes, and lights should be installed as deterrents to ensure minimal human-elephant encounters.

शोध सारांश

मानव-हात्ती द्वन्द्व (HEC) एक बढ्दो समस्या हो जसले मानिसहरू संग साझा भूपरिधि भित्र संरक्षणका लागी महत्वपूर्ण चुनौती खडा गर्दछ । यस अध्ययनले द्वन्द्वका जोखिम केन्द्रहरुको पहिचान र अनुमान, साथै मानव-हात्ती द्वन्द्वलाई प्रभाव पार्ने कारकहरूको निर्धारणले मानव-हात्ती द्वन्द्वलाई न्यून गर्न र सह-अस्तित्वलाई बढावा दिन जानकारी प्रदान गर्दछ । यस अध्ययनमा पुर्वी चुरे भूपरिधिका २५५ वटा स्थलगत कक्षहरुमा ब्यतिहरुसंग प्रत्यक्ष अन्तर्वार्ता लिइएको थियो, जसमा प्रत्यक कक्षबाट एक उत्तरदाता सहभागी थिए र जम्मा २५५ अन्तर्वार्ता लिइएको थियो । पुर्वी चुरे भूपरिधिमा मानव-हात्ती द्वन्द्वका मुख्य केन्द्रहरुको पहिचान गर्न semi-structured प्रश्नावली प्रयोग गरिएको थियो । अधिकांश उत्तरदाताहरूले (n = 190) द्वन्द अनुभव गरेको बताएका थिए, यद्पी बाँकी उत्तरदाताहरूले (n = 65) विगत पाँच वर्षमा कुनै द्वन्दको घटना नभएको बताएका थिए् । Logistic regression को विश्लेषणका आधारमा Night Light र Shannon's Diversity Index (SHDI) लाई मानव-हात्ती द्वन्द्वको महत्तवपूर्ण पूर्वानुमानकर्ताका रूपमा पहिचान गरिएको छ। त्यसैगरी, Classification and Regression Tree (CART) मोडेलले पनि Night Light लाई सबैभन्दा प्रभावशाली अनुमानकर्ताको रुपमा पहिचान गरेको छ, जस्ले हात्तीहरु उज्यालो ठाउँहरु बाट टाढा रहन खोज्छन् भन्ने संकेत गर्दछ् । यस अध्ययनले न्यून Effective Mesh Size (MESH) र न्यून Largest Patch Index (LPI) भएका अत्याधिक खण्डित भुपरिधिहरुले मानव-हात्ती द्वन्द्वको सम्भावना बढाउँछ भन्ने खुलासा गर्दछ, जसले गर्दा बासस्थान-जडानको पुनर्स्थापनामा ध्यान केन्द्रित गर्नुपर्ने देखिन्छ । मानव जनसंख्याको उच्च घनत्व भएका क्षेत्रहरूले मानव-हात्ती द्वन्द्वको सम्भावना बढाएको देखिएको छ । CART मोडेलको कार्यसम्पादन confusion matrix को प्रयोग गरेर मुल्यांकन गरिएको थियो, जहाँ मोडेलले ७६.२% accuracy, ८०.८०% sensitivity र ५४.५% specificity प्राप्त गरेको थियो । CART मोडेलको स्थिरता र अनुमान मुल्यांकन गर्न, CART मोडलमा प्रयोग गरिएको उही प्रतिक्रिया र अनुमान चरहरू प्रयोग गरेर एक Random Forest (RF) मोडेल निर्माण गरिएको थियो । RF मोडेलले ६९.८% को accuracy, तर न्यून sensitivity (१८.८%) र अधिक specificity (८७.२%) हासिल गरेको छ । निष्कर्षहरूले द्वन्द्वको जोखिमका क्षेत्रहरूको पहिचानमा CART मोडेलको कार्यसम्पादनलाई प्रकाश पार्दछ, जसले CART मोडललाई मानव-हात्ती द्वन्द्व जोखिम अनुमानको लागि भरपर्दो उपकरण भएको सुझाव दिएको छ । मानव-हात्ती द्वन्द्वका जोखिम केन्द्रहरुको नक्साले मोराङ, बिशेष गरि लेटाङ, केराबारी र मिक्लाजुङ र झापाका क्षेत्रहरू, मेचिनगर र शिवसताक्सीलाई पुर्वी चुरे भुपरिधिका प्रमुख मानव-हात्ती द्वन्द्वका जोखिम केन्द्रहरु हुन् भनि पहिचान गरेको छ, जसले स्थलगत विशिष्ट न्युनिकरण रणनीतिहरूको आवश्यकतालाई संकेत गर्दछ । तसर्थ, मानव र हात्ती बिच न्यूनतम मुठभेड सुनिश्चित गर्नको लागि परम्परागत र क्षय भएका हात्तीहरूको आवागमन मार्गहरूको पुनर्स्थापना, र रोकथामका उपाएको रुपमा बत्तीहरु जडान गरिनु पर्दछ ।

Table of Contents

List of tables

List of figures

List of photographs

List of abbreviations

Abbreviated form	Details of abbreviation
AICc	Akaike Information Criterion corrected
BNP	Bardiya National Park
CART	Classification and Regression Tree
CNP	Chitwan National Park
CRS	Coordinate Reference System
CTML	Chure Terai Madhesh Landscape
ECL	Eastern-Chure Landscape
ED	Edge Density
EN	Endangered
ENN	Euclidean Nearest Neighbor Distance
FUGs	Forest User Groups
GEE	Google Earth Engine
GLM	Generalized Linear Model
GPS	Global Positioning System
HEC	Human-Elephant conflict
HWC	Human-Wildlife Conflict
IAPS	Invasive Alien Plant Species
IUCN	International Union for Conservation of Nature
KTWR	Koshi Tappu Wildlife Reserve
LPI	Largest Patch Index
LULC	Land Use and Land Cover
MESH	Effective Mesh Size
PAs	Protected areas

PNP	Parsa National Park
RF	Random Forest
SHDI	Shannon’s Diversity Index
ShNP	Shuklaphanta National Park
UTM	Universal Transverse Mercator

1. Introduction

1.1 Background

The Asian elephant (*Elephas maximus*), the largest terrestrial mammal among all mammals in Nepal (Shrestha & Shrestha, 2021), is native to 13 Asian countries, including Nepal (Blake & Hedges, 2004). The Asian Elephant belongs to the family Elephantidae and is categorized as Endangered (EN) under the International Union for Conservation of Nature (IUCN) Red List (Choudhury et al., 2008). It is listed as Appendix I species under the Convention on International Trade in Endangered Species of Wild Fauna and Fauna (CITES, 2023). Additionally, in Nepal, the Asian elephant is protected under the National Parks and Wildlife Conservation Act, 1973 (Government of Nepal, 1973).

Accelerated loss of vegetation and fragmentation of forest patches have increased human-wildlife conflict (Tiller et al., 2021). Controlling human-wildlife competition for resources and space is a critical conservation concern (Woodroffe et al., 2005). This issue is notably intense in territories that border the protected areas, where increasing human intervention and agricultural expansion (Wittemyer et al., 2008), frequently causes human-elephant conflict (Nyhus, 2016). Asian elephants often spend their time in areas that are shared with humans along the protected areas, which raises the likelihood of encounters and confrontations (Fernando & Pastorini, 2014; Thouless et al., 2016). Human-elephant conflict (HEC) poses a significant threat to both humans and the Asian elephant population globally, as the natural habitats shrink with the increasing human population, the intensity and frequency of human-elephant interactions rise (Yang et al., 2023). Reduction of landscape connectivity, expansion of agricultural fields, and fragmentation of habitats have forced the elephants to invade the human settlements, and HEC has been an intimidating problem in Asian countries (Jiang & Yang, 2021; Tiller et al., 2021).

In Nepal, Asian elephant's distribution is characterized into four distinct landscapes: eastern, central, western, and far-western, each landscape representing a geographically isolated subpopulation (Neupane et al., 2022). The eastern subpopulation occurs in Jhapa District and Koshi Tappu Wildlife Reserve (KTWR), the central population in Parsa National Park (PNP) and Chitwan National Park (CNP), the western subpopulation in Bardiya National Park (BNP) and Khata Corridor, and the far-western subpopulation in Shuklaphanta National Park (ShNP) and along the adjacent municipalities (Pradhan et al., 2011). In the 1990s, the wild elephant population was in danger of going extinct, but it has increased mostly due to transboundary migration from India (Pradhan et al., 2011). At present, a total of 227 wild elephants are estimated, comprising 43 in the eastern, 45 in the central, 113 in the western, and 26 in the far-western subpopulations in Nepal (Ram & Acharya, 2020). However, a robust and scientifically accurate population assessment is needed to ensure long-term and effective conservation strategies. An increase in these sub-populations of Asian elephants has severely increased the HEC (Pradhan et al., 2011), mostly in eastern Nepal, where the Asian elephants mostly inhabit areas outside the protected areas (Neupane et al., 2022).

Eastern Chure foothill regions in Nepal have been a significant transboundary route for the Asian elephant population between India and Eastern Nepal (Neupane et al., 2022). Bahundangi in Jhapa district, which borders India to the east (Shrestha & Koirala, 2013), has been identified as the main entry point for migratory wild elephants in Nepal (Baidya & Nabin, 2010). Increasing demand for shelter, food, and resources in the eastern region by the growing human population has led to a shrinkage of forest cover (Sudhakar Reddy et al., 2018), that has disrupted elephant movement and degraded the fragile ecosystem in the Chure region. The transboundary elephant herds in the eastern region are limited to degraded forest patches, fragmented forest corridors, and along with the only protected area in the east, Koshi Tappu Wildlife Reserve that has limited forest area of coverage 4.59 km^2, which has markedly increased HEC (DNPWC/MoFSC/GoN, 2009). In addition, KTWR faces challenges of invasive alien plant species (IAPS) with highest level of invasion (Dhungana et al., 2024), which has degraded the limited elephant habitat and reduced the availability of natural forages. The continual use of corridors by elephants has increased the confrontation between humans and elephants, escalating the severe conflicts (Ram & Acharya, 2020). The HEC is considered as the biggest challenge for the conservationists and the local communities (Ram & Acharya, 2020). Owing to the larger home range and roaming behavior of the elephant, their conservation demands considerable public support, wide favorable natural habitats, and managed landscape connectivity (Shaffer et al., 2019). However, the rising number of HEC cases has driven the negative perceptions rapidly, hindering the conservation strategy in the region (Ram et al., 2021; Ram & Acharya, 2020). Apart from fear among local communities, HEC has several effects, it mainly includes death, crop raiding, and property damage (Parker et al., 2007).

Asian elephants frequently inhabit areas at the edge of the forests and the transitional zones in between adjacent communities and natural habitats due to their diverse range of habitat preferences and varied range of feeding requirements (Zhao et al., 2023). Communities living near the forest face a higher risk of conflicts (Ram et al., 2022). HEC is mainly rising due to the shrinkage of elephant habitats as humans are extending their settlements and disrupting the natural corridors and migratory routes of elephants (Sitati et al., 2003). In this study, a semi-structured questionnaire survey was conducted among communities residing in the Eastern Chure Landscape of Nepal to understand the HEC conflict hotspots and to identify a management strategy that reduces conflicts with humans while ensuring the survival of a healthy Asian elephant population. The goal of the study was to assess the factors influencing the HEC and predict the HEC hotspots. Therefore, Logistic regression was used to access the strength and direction of relationships between predictors and HEC occurrence, and the Classification and Regression Tree (CART) model (Breiman et al., 1984) was applied to explore the non-linear interactions and the decision patterns that may drive the HEC risk.

1.2 Statement of the problem

Human-elephant conflict is a burgeoning issue in the Eastern landscape of Nepal, although the resident elephant population is low (Ram et al., 2022). Eastern Nepal is predominantly inhabited by bull elephants, distributed in various regions throughout the landscape (Ram et al., 2021). The aggressive nature of bulls increases the probability of conflict with humans (Ram et al., 2022). The landscape is facing challenges due to increasing population density, agricultural intensification, land-use changes, and infrastructure development. These factors lead to habitat fragmentation, breakdown of migratory corridors, and increase the risk of HEC. Despite various conservation and management efforts, the eastern landscape, particularly Jhapa and Koshi, faces the highest challenges of HEC (Ram et al., 2022). Therefore, this study aims to identify the factors influencing the HEC and identify and predict conflict hotspots in the Eastern Chure Landscape to mitigate the conservation challenges and support coexistence.

1.3 Objectives

1.3.1 General objective

The general objective of this study was to identify the factors influencing human-elephant conflict and to identify and predict human-elephant conflict hotspots in Eastern Chure Landscape, Nepal.

1.3.2 Specific objectives

i. To investigate the factors influencing the human elephant conflict in the Eastern Chure Landscape, Nepal.

ii. To identify and predict the human-elephant conflict hotspots in the Eastern Chure Landscape, Nepal.

1.4 Research hypothesis

Landscape metrics indicating a higher state of fragmentation will have greater human-elephant conflict probabilities.

1.5 Significance of the study

This study is crucial for understanding, mapping HEC hotspots, and mitigating HEC in the Eastern Chure Landscape (ECL) of Nepal. Elephants are experiencing challenges in migrating through their traditional migratory routes due to habitat fragmentation, expanding human settlements, and changing landscapes, resulting in frequent HEC. Insights from the identification of factors influencing HEC and predicting conflict hotspots will support policymakers, conservationists, and local stakeholders in planning conservation at the community level, habitat management, policy development, and implementing hotspot-targeted mitigation strategies. Additionally, this contributes to conservation efforts by promoting coexistence, ensuring the healthy survival of the majestic animal while safeguarding communities sharing the landscape.

1.6 Limitations of the study

1. The logistic regression model used in the study explained only 10% variation, indicating that important social or ecological factors influencing HEC might be missing.

2. Literature review

2.1 Factors influencing human-elephant conflict

Negative interaction between wildlife and humans, referred to as human-wildlife conflict, occurs when humans are physically and economically affected, and in retaliation, wild animals are also affected negatively. Therefore, to conserve biodiversity, people's disagreements need to be solved (Peterson et al., 2013). Human-Wildlife Conflict (HWC) is handled by supporting the victims of conflict cases through compensation in most elephant range countries, including Nepal (Barua et al., 2013; Lewis et al., 2011; Redpath et al., 2013). The growing human population and the degrading natural habitats, forest areas, have increased the interactions with wild species such as Asian elephants, which has intensified the consequences of crop damage and human casualties (Pradhan et al., 2011). HWC in Nepal is mainly caused by animals such as tigers, leopards, rhinoceroses, Asian elephants, and snow leopards due to habitat loss, competition for resources, and retaliation. Among them, 30% of the conflicts are caused by Asian elephants (Acharya et al., 2017; Neupane et al., 2017) resulting in property damage, crop depredation, and human casualties. HEC reflects conflict between humans and elephants, describing its outcome as significant harm to both humans and elephants (Amwata & Mganga, 2014).

The natural habitat of Asian elephants has been continuously shrinking throughout their geographical range due to habitat destruction and fragmentation driven by various land use activities (Owen smith, 1988; Sukumar, 1990), limiting the access to resources, isolating the populations, degrading the corridors and reducing the habitat size available for elephants to roam and for shelter. Habitat loss and fragmentation due to increasing human settlement, agricultural expansion and infrastructure development have increased the competition for resources (Joshi & Singh, 2007) and intensified the frequency of HEC (Sukumar, 1994). Annually, India, Sri Lanka, Bangladesh, and Nepal report an average of 500, 81, 37, and 18 HEC deaths, respectively (Acharya et al., 2016; Prakash et al., 2020). HEC is predicted to increase with expanding human settlements towards the elephant migratory route (Khanal, 2022). Although Nepal has a comparatively low human population than other countries, 80% of its natural elephant habitat has experienced habitat loss due to the expansion of human settlements (Koirala et al., 2016). In Nepal, the elephant range is continuously under fragmentation due to agricultural expansion, habitat degradation and infrastructural development (DNPWC/MoFSC/GoN, 2009), and the rise in HEC is mainly driven by the fragmentation of forests into smaller and isolated areas and the increasing number of seasonal migratory elephants mostly in eastern Nepal from India (Pradhan et al., 2011).

The escalating human activities and habitat fragmentation have increased the HEC (Suksavate et al., 2019). Due to expanding human activities such as agriculture, infrastructure development, and urbanization, encroaching on the forests and grasslands, the Asian elephants are facing challenges from habitat loss, poaching for ivory, skin, and increasing encounters with humans, leading to HEC (Zhao et al., 2023). Habitat loss and fragmentation due to increasing human populations and intensified extraction of resources have significantly reduced the wild Asian elephant population (Leimgruber et al., 2003). Due to several ecological and socio-economic factors such as the size of protected areas, food availability, human population density, seasonal climatic fluctuations, and cultural beliefs, the degree of HEC within elephant range countries differs greatly (de Boer et al., 2015; Shaffer et al., 2019).

Historically, elephants used to travel from Assam to eastern Nepal and from India's protected areas such as Katarniyaghat, Dudhuwa, Plilibhit, and Nandaur wildlife sanctuaries towards western Nepal (Lamichhane et al., 2017; Ram & Acharya, 2020; ten Velde, 1997). At present, both local and transboundary migratory elephants have been increasing, directly intensifying the negative interaction and conflict cases (Ram & Acharya, 2020). HEC poses a complicated issue that often causes serious problems among the local people (Gross et al., 2018; Hoare, 2015) and has affected the livelihood with multidimensional consequences (Selier et al., 2016). The nature of elephant groups, seasons of migration, and proximity to human settlements influence the HEC (Nyirenda et al., 2012; Pozo et al., 2017; Songhurst et al., 2016). HWC typically occurs within the approximate range of five km, mostly at the communities that are close to the natural habitat (Ruda et al., 2018).

Small-scale farmers, who rely on farming and sometimes overharvest natural resources, are mostly affected by HEC, resulting in various forms of conflict, including social, economic, and political issues (Kalaba et al., 2013). HEC has a significant impact on people's way of living, as it affects aspects that represent community relationships, health, infrastructure, and property damage (Kahler & Gore, 2015). Human casualties and crop damage were identified as the most significant issues among other challenges due to HEC (Pant et al., 2016). Asian elephants move across different and even across countries beyond the boundaries declared by the governments as they are driven by the availability of food, space, and habitats (ten Velde, 1997). The mobility between the four sub-populations of elephants in Nepal has been complicated due to unmanaged connectivity and conflict issues (Pradhan et al., 2007). HEC is mainly influenced by: (a) the loss of forests along the migratory routes, which disrupts the traditional migratory routes and forces the elephants to enter into human-dominated areas (Sukumar, 1989, 2003), (b) the shrinkage of natural habitats (Chaudhary et al., 2021; Zhang & Wang, 2003), limiting the availability of space and resources, and (c) escalated encounters with the local community members, largely dependent on subsistence crop farming (Distefano, 2005). Despite extensive research on the ecological and social aspects of HEC in eastern Nepal, understanding how spatial and environmental factors interact to influence HEC intensity is still limited.

2.2 Human-elephant conflict hotspots mapping

HEC is a serious conservation and socio-economic challenge to many communities in elephant range countries (Shaffer et al., 2019). HEC usually occurs due to overlap in space use utilization by humans and elephants, increasing the competition for resources. Thus, mapping HEC hotspots is crucial for reducing negative human-elephant interactions (Pozo et al., 2018). Geographic Information System (GIS) and remote sensing techniques are used to map habitat features and conflict high-risk zones (Leimgruber et al., 2003). GIS and remote sensing techniques employed in Sri Lanka indicated that the high HEC hotspots were closer to forest boundaries, demanding the need for conservation and mitigation efforts (Gunawansa et al., 2024).

The likelihood of experiencing HEC risk increases in the vicinity of protected areas within the human settlements and farmlands (Fernando et al., 2022; Khanal, 2022). HEC cases in central Nepal were mostly found within the buffer zones- areas adjacent to Chitwan National Park (CNP) boundary, representing more than 80% of HEC cases within Chitwan district (Pant et al., 2016). In Chure Terai Madhesh Landscape (CMTL), Nepal, the Jhapa and Koshi in the eastern part, Chitwan and Parsa in central and Bardiya and Kanchanpur in western part were identified as the HEC hotspots and communities living near forest and protected areas were more susceptible to HEC (Ram et al., 2022), as it extends beyond the protected areas. Similarly, Neupane et al. (2014) found that HEC incidents were higher in eastern Terai of Nepal compared to central and western regions and major HEC hotspots were along the transboundary corridor of eastern border with India and within the buffer zones of KTWR, CNP, BNP and forest patches in eastern lowlands. Kurmi and Koju (2021) reported that crop lands within 1 km of protected area boundaries were vulnerable to HEC and the frequency of crop-raiding decreased with increasing distance from the forest. In Bara district, nearly 80% of the local individuals residing within 3 km of the forest areas experienced crop damage by wild elephants (Chaudhary et al., 2021). In Jhapa district, most of the HEC risk-prone areas were the settlements closer to the Jalthal forest (Neupane et al., 2018). Therefore, mapping the HEC hotspots in the ECL is crucial for management and conservation.

3. Materials and methods

3.1 Study area

The research was conducted in the Eastern Chure Landscape of Nepal, including four districts: Sunsari, Morang, Jhapa, and Illam (Chulachuli), located between 26.60° to 26.90° North and 87.20° to 87.50° East. It consists of a sub-tropical climate and three ecological zones; Chure hills (350–735 meters above sea level), Bhawar (200–350 meters above sea level), and alluvial floodplain (120–200 meters above sea level).

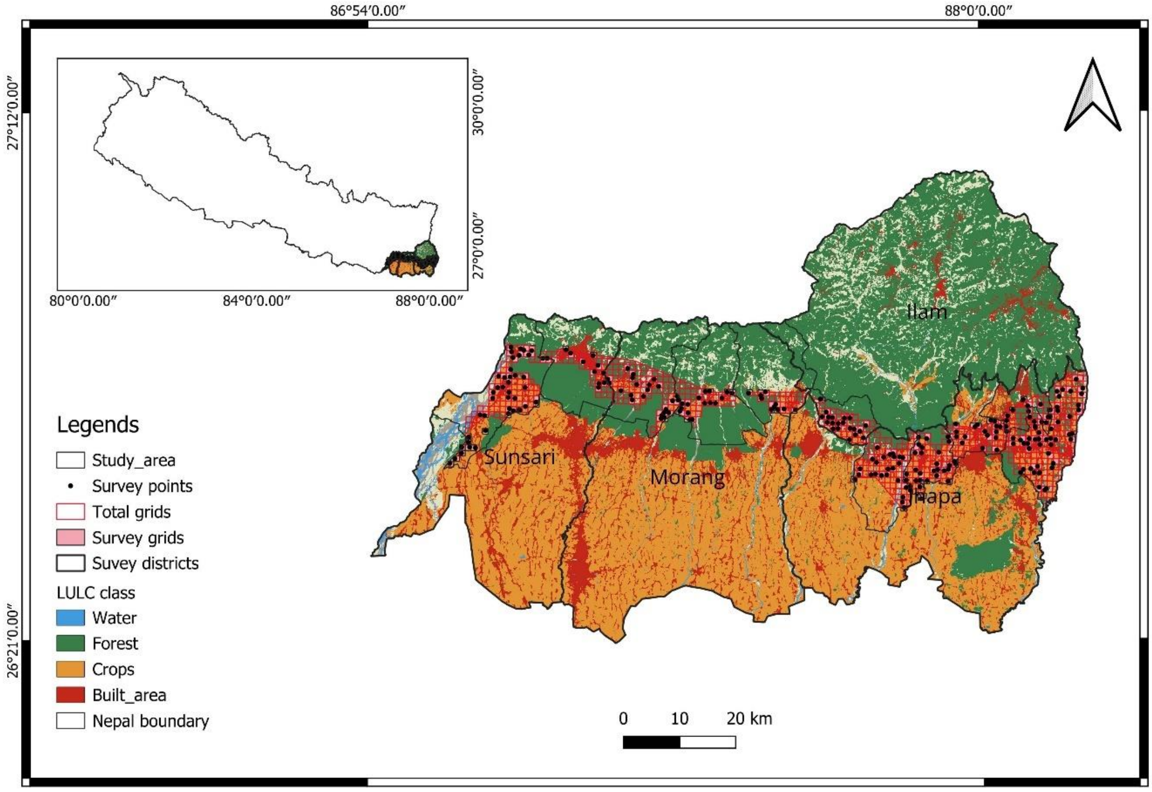

Figure 1. Study area map showing survey grids along with survey points.

Sunsari district borders the Koshi River in the east and the Indian state of Bihar in the south. Sunsari features subtropical forests and agricultural landscapes, but has undergone habitat loss and fragmentation due to rapid urbanization and land-use changes (Rai et al., 2022). Koshi Tappu Wildlife Reserve within Sunsari further highlights its importance for conservation and HEC management. The easternmost district, Jhapa, with its adjoining border to India, consists of mixed tropical and sub-tropical forests and increasing human settlements (Central Bureau of Statistics, 2024). Jhapa and Koshi (Sunsari) are the major HEC hotspots in the eastern region (Ram et al., 2022). Similarly, Morang district, adjacent to Sunsari, contains extensive lowland forests, farmlands, and rivers. However, deforestation and human encroachment have decreased the forest cover (Baidya & Nabin, 2010), and escalated the HEC. The elephants frequently migrate between Nepal and the Indian forest from West Bengal, and conflicts persist (Neupane et al., 2017). Chulachuli (Illam) is characterized by fragmented forest patches, tea gardens, and agricultural fields.

3.2 Methods

3.2.1 Research design and data collection

Initially, the study area was divided into multiple grids (1 km × 1 km) using QGIS. To maintain the spatial relevance to HEC, grids lying outside the elephant's migratory routes (Baidya & Nabin, 2010) were removed. The remaining grids (n = 815) located within the administrative divisions along the Chure foothills were considered for the survey.

To attain the desired statistical precision, the required number of survey grids were calculated using sample size calculator (https://www.calculator.net) at confidence level (95%), margin of error (5%), population proportion (50%) resulting a total of sample size 262. However, 7 grids were excluded as the grids included area <50% within the grid and some grids did not contain households for questionnaire survey. Therefore, targeted survey grids (n = 255) were selected randomly for the questionnaire survey, where HEC and the presence of elephants are mostly reported (Baidya & Nabin, 2010). In each grid, a single respondent (>18 years old) was interviewed to avoid the spatial overlap in responses. A semi-structured questionnaire was used to gather information about the last five years along the survey grids. Before starting the interview, verbal consent was obtained from the respondent. Google Earth, a mobile application, was used to navigate and locate the grids. The household nearest to the centroid was selected to reduce the overlapping HEC reports among the nearby grids. GPS coordinates were recorded using a GPS device (Garmin eTrex 10) in each survey location to identify conflict areas accurately.

3.2.2 Predictor variables

GIS-based landscape-level predictor variables were calculated using the ESRI Sentinel-2 land use and land cover map resampled at a resolution (1 km × 1 km). Initially, the study area was extracted, and the boundary of the study area was buffered (2 km), ensuring the potential movement and habitat utilization by Asian elephants. Then, the buffered study area was reprojected into the Universal Transverse Mercator (UTM) zone 45° North projection to ensure consistent spatial analysis. The buffered and reprojected study area was then dissolved for the proper representation of the study area. The vector boundary of the study area was used to extract the raster layer of the study area with grids (1 km×1 km) that defined the grid cells. Again, the raster grids were converted into vector grids that represented the spatial extent of the grid cells whose landscape metrics were to be calculated. Then, the raster layer of the study area, Land Use and Land Cover (LULC) (Impact Observatory, Microsoft, 2022) was reclassified into habitat and non-habitat category (Table 1), where, 1= habitat (Water, Trees, Flooded vegetation, Rangeland) and 0 = non-habitat (Built area, Bare ground) in R studio (R Core Team, 2023), to generate the raster layer of landscape metrics; Perimeter (Perim)- perimeter values of each habitat patches (class = 1) excluding non-habitat patches (class = 0) using metric "perim" was calculated within each grid and added as total perimeter of habitat patches and value was assigned to respective grid cell, Area- area values of each habitat patches and their total sum was calculated and filtered by metric "area-mn" to calculate the mean patch area, that represented the average size of the habitat patch within each grid, Largest patch index (LPI)- the proportion of largest habitat patch within each grid was calculated and assigned as LPI value, Effective Mesh Size (MESH)- MESH value of only habitat patches was calculated, and assigned to the respective grids, Edge density (ED)- ED was calculated between each habitat patch boundaries within each grid and total sum of the ED values were assigned to the corresponding grids, and Euclidean Nearest Neighbor Distance (ENN)- ENN value was calculated from centroid of a patch to the centroid of its nearest neighboring patch of same category (habitat) excluding non-habitat patches (class = 0) within each grids and then mean values of those ENN values was calculated and assigned to the corresponding grids.

Similarly, the raster layer of Shannon's Diversity Index (SHDI) and proportion of built-up area (reclassified into built-up and non-built-up), was generated using the raster layer (LULC map) of the study area. All the raster layers were generated using raster grid cells and a vector study area boundary. Night light data (Elvidge et al., 2021) was obtained from Google Earth Engine (GEE), and the variable, population density, was obtained from worldPop.org (https://hub.worldpop.org), and both were reprojected to match the Coordinate Reference System (CRS), cropped to match spatial extent, and resampled using the nearest neighbor method (ngb) for reference raster; rasterized grid layer. Global Positioning System (GPS) coordinates were applied to extract the raster values at point locations. Reprojection, cropping the layers, resampling, and generation of raster layer and extraction of all those variables were done using packages; landscapemetrics (Hesselbarth et al., 2019) (for landscape metrics calculation), raster (Hijmans, 2023) (handling spatial raster data), sf (handling spatial vector data), dplyr (data manipulation), terra (Hijmans et al., 2025) (spatial data analysis), using the statistical software package, R Studio (R Core Team, 2023).

Table 1. Classification of habitat and non-habitat categories for Human Elephant Conflict analysis.

Category	Class	Description
Habitat	Water	• Rivers, wetlands, lakes • Availability of water significantly affects elephant's movement and ranging pattern (Singh & Sharma, 2018), as they depend on water for survival, drinking, bathing, and wallowing (Williams et al., 2020).
	Trees	• Asian elephants are generalists and inhabit forest (tropical evergreen, semi-evergreen, moist deciduous, dry deciduous, dry thorn, cultivated, and secondary forests (Williams et al., 2020).
	Flooded vegetation	• Supports as a seasonal foraging area that is particularly important during food scarcity and dry seasons (Koirala et al., 2016)
	Rangeland	• Supports seasonal movement patterns between forested areas and open grasslands depending upon food availability, where grasslands are used to forage during dry seasons (Koirala et al., 2016)
Non-habitat	Built area	• Expanding built areas lead to habitat loss, increase encounters, and cause conflicts (Fernando & Pastorini, 2014).
	Bare ground	• Such areas are marked by high human activity that restricts elephant mobility (Huang et al., 2019), lack access to suitable habitats, and escalate HEC cases.

3.2.3 Data analysis

To achieve the objectives of the study, Logistic regression and CART model was employed. These methods were implemented to access both linear relationships and non-linear decision patterns driving HEC occurrence.

All the variables were screened for a correlation test in the R statistical software package, R Studio (R Core Team, 2023). Effective Mesh Size (MESH) and Area, Perimeter (Perim), and Largest Patch Index (LPI) were highly (Cor > 80%) correlated (Figure 5). Here, the variables, MESH and LPI, were retained for the analyses. MESH represents both connectivity and fragmentation (Jaeger, 2000) and LPI (McGarical et al., 2002) represents the dominant habitat type, which may be the core habitat for Asian elephants. The variables used in the analysis are mentioned along with their corresponding hypothesis (Table 1).

At first, Logistic regression was employed using the Generalized Linear Model (GLM) with binomial family and logit link function. The binary response variable, HEC presence (1) and absence (0), and the selected landscape variables (LPI, ED, MESH, SHDI, ENN), and anthropogenic variables (Proportion of built-up area, Nightlight, and Population density) were included in the model, fitted with glm() function in R statistical software package, R Studio (R Core Team, 2023). Model selection was performed based on the Akaike Information Criterion corrected (AICc), using the dredge() function from the "MuMIn" package. Top models were selected based on ΔAICc < 2 and were averaged using "model.avg() function and relative importance of each predictor was calculated based on sum of Akaike weights across all models in which the variable appeared. Finally, model performance was evaluated using McFadden's pseudo R^2 and likelihood ratio tests, to identify the effectiveness of the predictors in explaining the variation in HEC occurrence.

Classification and Regression Tree (CART) model (Breiman et al., 1984) was employed to explore the non-linear interactions and hierarchical decision patterns among the predictors influencing the HEC using the package rpart (Therneau et al., 2025) and caret (Max et al., 2024), in the statistical software package, R Studio (R Core Team, 2023). The CART analysis was performed using the package rpart (Therneau et al., 2025) and caret (Max et al., 2024), in the statistical software package, R Studio (R Core Team, 2023), using the same response variable and the predictors used in the logistic regression.

The dataset was randomly divided into training data (75%) and test data (25%) for robust model training and evaluation (Kuhn & Johnson, 2013). Variable importance was calculated to identify the contribution of each variable to its respective prediction in R Studio (R Core Team, 2023) and was plotted using the "ggplot2" package (Wickham, 2016). The "rpart" function was used to generate a decision tree using the method "class" appropriate for categorical conflict presence-absence data, and also to evaluate the model using a confusion matrix, accuracy, sensitivity, and specificity for classification (James et al., 2013). To prevent overfitting, the CART model was tuned using a complexity parameter (cp = 0.02), generated by 10-fold cross-validation. The decision tree was then developed based on the importance of the variables, and the model performance was evaluated using a confusion matrix. Furthermore, the model was pruned using complexity parameter to enhance performance and reduce overfitting.

A probability HEC hotspots map was generated using the pruned CART model, to identify and spatially predict conflict hotspots. The predicted probability map was reclassified into classes: low (0-0.5 = 1), medium (0.5-0.75 = 2), and high (0.75-1 = 3) HEC probability areas using a reclassification matrix in R Studio (R Core Team, 2023). Then, the Zonal histogram function in QGIS software was used to calculate total area of conflict risk for each local government jurisdiction along the study site (Table 3), to prioritize management initiatives.

To assess the consistency, predictive performance, and robustness across modelling techniques, a Random Forest (RF) (Breiman, 2001) model was also applied using the same predictor variables used in the Logistic regression and CART model. Similarly, the dataset was split into training (75%) and test (25%) subsets. The RF model was constructed with 500 trees (n = 500). The performance of the model was evaluated using a confusion matrix predicted on the test dataset. The performance metrics included accuracy, sensitivity, and specificity.

Table 2. List of predictors with their description and their hypothesized influence on human-elephant conflict.

S.N.	Predictor variables	Description/Source and Range	Assumed hypothesis
1.	Landscape metrics (McGarical et al., 2002)		
	Largest Patch Index (LPI)	• LPI represents the total percentage of the largest patch within a landscape. • Units = Percentage (%) • 0-100	Higher LPI is associated with a lower frequency of HEC, as larger core habitat decreases the probability of elephants entering settlements.
	Edge Density (ED)	• Total length of the edges (m) within a landscape in relation to the total area (m^2), multiplied by 10,000. • Units = Meters/hectare • 0-144.7	Higher edge density is directly associated with HEC, fragmented habitats increase space between core habitat areas and conflict probability in human-dominated landscapes.
	Effective Mesh Size (MESH)	• MESH estimates the connectivity of habitat patches by determining the probability that two randomly selected locations within the landscape will fall within the same continuous habitat patch. Higher mesh size results in less fragmentation (Jaeger, 2002). • Units = Hectares • 0-100	Higher MESH leads to a decrease in HEC because it represents well-connected habitat patches that facilitate the movement of elephants and reduce the probability of encountering human settlements.
	Shannon's Diversity Index (SHDI)	• SHDI represents the diversity of landcover types within a landscape; higher SHDI values	Higher the SHDI value, higher will be the conflict as it increases the

		• resemble more heterogeneous landscape. • Units = Dimensionless • 0-1.8	chances of human intervention.
	Euclidean Nearest Neighbor Distance (ENN)	• ENN refers to the shortest distance from the centroid of a habitat patch to the neighboring patch of the same type (class). • Units = Meters • 0-1336.45	The lower the ENN distance, lower will be the HEC as it decreases the probability of interactions.
2.	Anthropogenic variable		
	Proportion of built-up area	• It refers to the percentage of land covered by artificial surfaces relative to the total area of the landscape. • Unit = % • 0-100	A higher proportion of built-up area is directly associated with the HEC because increasing built-up area increases competition for space.
	Nightlight (Average radiance value)	• Units = $nW/cm^2/sr$ • https://earthengine.google.com • 0.26-9.07 • Average value (January 2019-December 2023)	Higher Night Light might decrease the HEC because it represents the urbanization and infrastructural developments beyond the elephant range.
	Population density	• https://hub.worldpop.org • 1,554-27,441	Population density is directly proportional to HEC because settlements near the elephant range increase the chance of encounters.

4. Results

4.1 Factors influencing human-elephant conflict

In this study, a total of 255 individuals from different local government jurisdictions in the Chure region of Eastern Nepal were interviewed using a semi-structured questionnaire. Among them, the majority of the respondents (n = 190) reported experiencing HEC, while the remaining (n = 65) reported no conflict events in the last five years. Majority of the respondents, 47.1% were dependent on agriculture for their livelihood, 18.8% were dependent on remittance, 16.1% relied on business, 4.3% were engaged in government jobs, and 13.7% were involved in other forms of employment.

The logistic regression model employed to identify the factors influencing the HEC, explained approximately 10% variation in HEC incidents (Mc Fadden's pseudo R^2 = 0.1035). Although the model achieved relatively low R^2 value, the model performed better than the null model with a likelihood ratio statistic of G^2 = 29.97 (log-likelihood of fitted model = -129.77, log-likelihood of null model = -144.75). The most significant and important factors influencing the HEC were Night Light (coefficient = -2.1341, $p < 0.001$) and SHDI (coefficient = 1.1330, $p < 0.045$), with relative importance values higher than 0.8. Other predictors (ED, ENN, MESH, and Proportion of built-up Area) did not show statistically significant effects in HEC in the model-averaged results (Table 3). The predictors (LPI and Population density) were not included in the model-averaged results as they were absent from top-ranking candidate models (ΔAICc ≤ 2) used for model averaging (Table 4). Relationship between significant predictors and the probability of conflict was plotted (Figure 2) using "ggplot2" package to visualize and interpret effectively in R studio (R Core Team, 2023).

To further classify and predict the HEC probabilities based on predictor variables, the CART decision tree (Figure 3) was developed. The tree started to split with the variable Night light, where the Night light (≥1.1) represented 91% probability of HEC absence, and Night light (<1.1) further led to another node, MESH, prioritizing as an alternative for HEC. The MESH value (>11) split into population density. The population density (≥207) indicated 69% probability of HEC. whereas, the population density value (<207) further split on edge density (ED), where ED <29 indicated a 94% probability of HEC and ED value (≥29), increased the probability of HEC absence by 94%. However, the MESH value (<11) split into another predictor SHDI. The SHDI value (≥0.87) indicated 93% chance for

HEC occurrence and the SHDI value (<0.87) was further subdivided into ED. The ED (<14) predicted 70% probability of HEC and ED (≥14) considered LPI for refinement. Then, the LPI (<91) predicted 92% probability for HEC and LPI (≥91) had only 4% probability of HEC, indicating 94% probability of absence.

Table 3. Model-averaged coefficients (conditional averages) from logistic regression analysis of HEC predictors.

	Estimate	Std. Error	Adjusted SE	Z value	Pr (>|z|)
(Intercept)	1.746906	0.5456592	0.5482765	3.186	0.00144**
Night_Light	-2.13414	0.5550014	0.5576562	3.827	0.00013***
SHDI	1.133034	0.5627585	0.5651721	2.005	0.04499*
ED	-0.008015	0.004944	0.0049581	0.315	0.75287
ENN	0.001017	0.0006556	0.0006576	0.285	0.77599
MESH	0.00169	0.0023139	0.0023244	0.096	0.92343
Prop_builtup_area	0.002279	0.0031343	0.0031486	0.096	0.92386

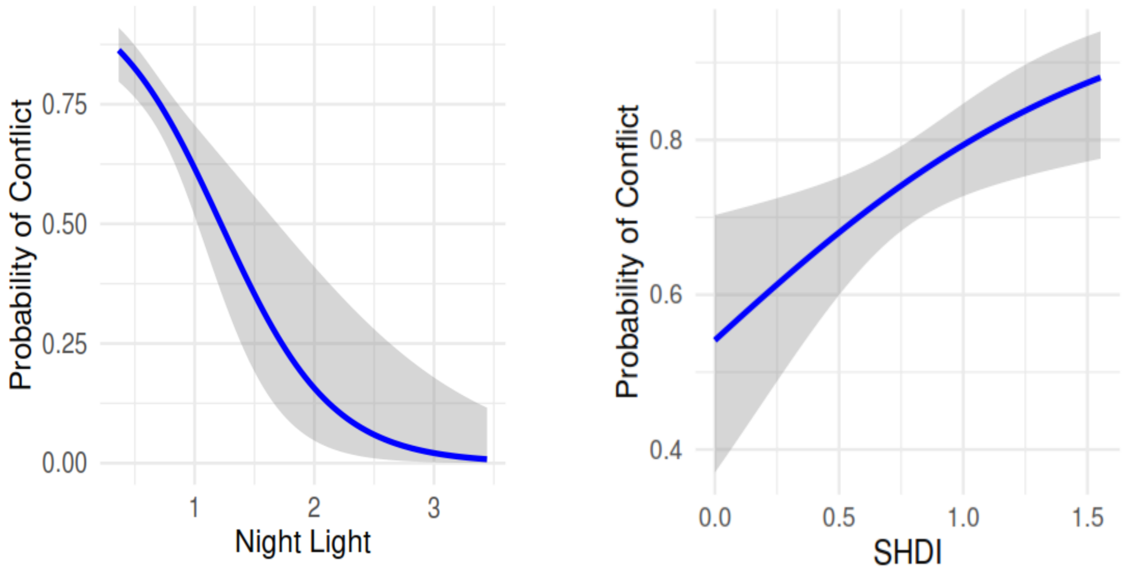

Figure 2. Relationship between significant predictors (Night Light, Shannon's Diversity Index) and probability of human-elephant conflict, derived from averaged-model of logistic-regression analysis.

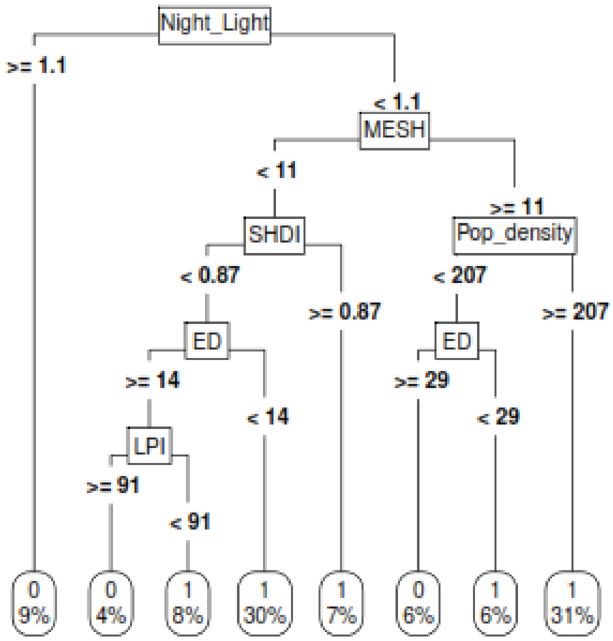

Figure 3. Classification and Regression Tree model displaying the probabilities of human-elephant conflict based on predictor variables and the associated probability of the alternate outcome.

In determining the probability of HEC, the CART model (Figure 3) revealed that the intensity of artificial light at night, Night Light, is the most crucial variable in the context of HEC, contributing to the splits at early nodes with its raw importance score of 11.4, corresponding to a normalized importance of 20.09%. Similarly, other influential predictors were ED (9.45 raw, 17.3% normalized), MESH (7.9 raw, 14.4% normalized), and SHDI (7.88 raw, 14.4% normalized). The comparatively less influential variables included Proportion of built area (6.4 raw, 11.7% normalized), LPI (5.6 raw, 10.3% normalized), Population density (4.997 raw, 9.1% normalized), and ENN (1.017 raw, 1.9% normalized).

Furthermore, the CART model exhibited 76.2% accuracy in predicting HEC probabilities, with its sensitivity 80.8% at detecting conflict and specificity 54.5% at detecting conflict absence probabilities. To assess the consistency and predictive performance of the model, a RF model was trained using the same predictor variables and response variables used in the CART model. The RF model was built using 500 decision trees with a training-test data split of 75:25. The RF model achieved 69.8% accuracy. However, the sensitivity (18.8%) was relatively low and the specificity (87.2%) was high.

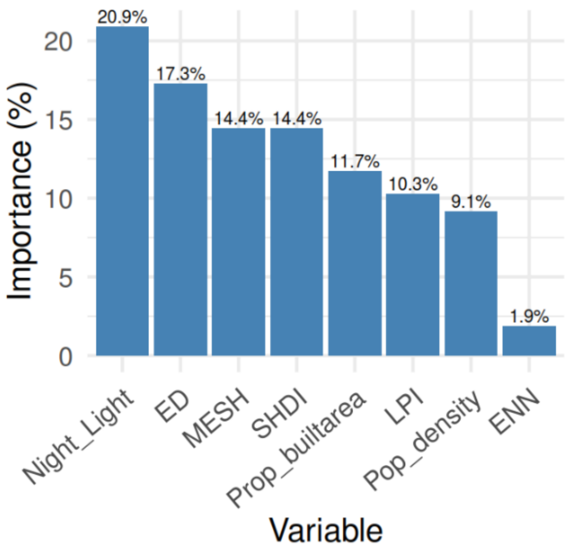

Figure 3. Normalized variable importance in the prediction of human-elephant conflict hotspots from the Classification and Regression Tree model showing the relative contribution of each predictor to the contribution of human-elephant conflict presence or absence.

4.2 Human-elephant conflict hotspots

The spatial HEC probability map (Figure 4) predicted across the ECL using the pruned CART model identified HEC hotspots are concentrated in Morang and Jhapa districts. The areas under HEC probability category are particularly in local jurisdictions such as Letang, Kerabari, Miklajung in Morang and Mechinagar, Shivasataxi, and Arjundhara in Jhapa. The Morang covered three local government jurisdictions and Jhapa district covered five local government jurisdictions as high HEC probability zones with prediction of high spatial dominance of conflict risk zones in Morang followed by Jhapa. The Sunsari district also displayed extensive HEC probability areas but only in two local government jurisdictions and Ilam also revealed high HEC probability but only in one local government jurisdiction.

Table 3. Human-elephant conflict probabilities predicted at local government jurisdictions level along the study site.

S.N.	Name of survey districts within ECL	Local government jurisdictions or administrations	Conflict risk prediction based on spatial extent (Km^2)		
			Low HEC probability area	Medium HEC probability area	High HEC probability area
1	Illam	Chulachuli	2	4	106
2	Jhapa	Arjundhara	10	10	95
		Buddhashanti	1	3	72
		Kankai	8	2	70
		Mechinagar	45	15	131
		Shivasataxi	6	32	106
3	Morang	Kerabari	24	1	196
		Letang	15	2	200
		Miklajung	11	0	150
4	Sunsari	Barah	8	12	196
		Dharan	32	0	158

Here, (Table 3) represents the conflict risk prediction analysis for HEC, categorized into three levels- low, medium, and high HEC probability area based on spatial extent (km^2), across different local government jurisdictions in four districts of eastern Nepal: Illam, Jhapa, Morang, and Sunsari. The study represented that the Morang and Jhapa districts as the most critical districts in ECL based on high HEC probability areas.

In Morang, the local government jurisdictions, Letang (200 km^2 out of 217 km^2), Kerabari (196 km^2 out of 221 km^2), and Miklajung (150 km^2 out of 161 km^2) covered high HEC probability areas with the largest total area (546 km^2), predicted as high-risk for conflcit. Similarly, in Jhapa, Mechinagar (131 km^2 out of 191 km^2), Shivasataxi (106 km^2 out of 144 km^2), Arjundhara (95 km^2 out of 115 km^2), Buddhashanti (72 km^2 out of 76 km^2), and Kankai (70 km^2 out of 80 km^2) covered a total of 474 km^2 as high HEC probability areas. In Sunsari, a total of 354 km^2 and 106 km^2 in Chualachuli was predicted as high-risk area. Therefore, the prediction of high HEC areas across different local government jurisdictions represents Morang and Jhapa as critical hotspots for HEC and indicates priority areas for mitigation efforts.

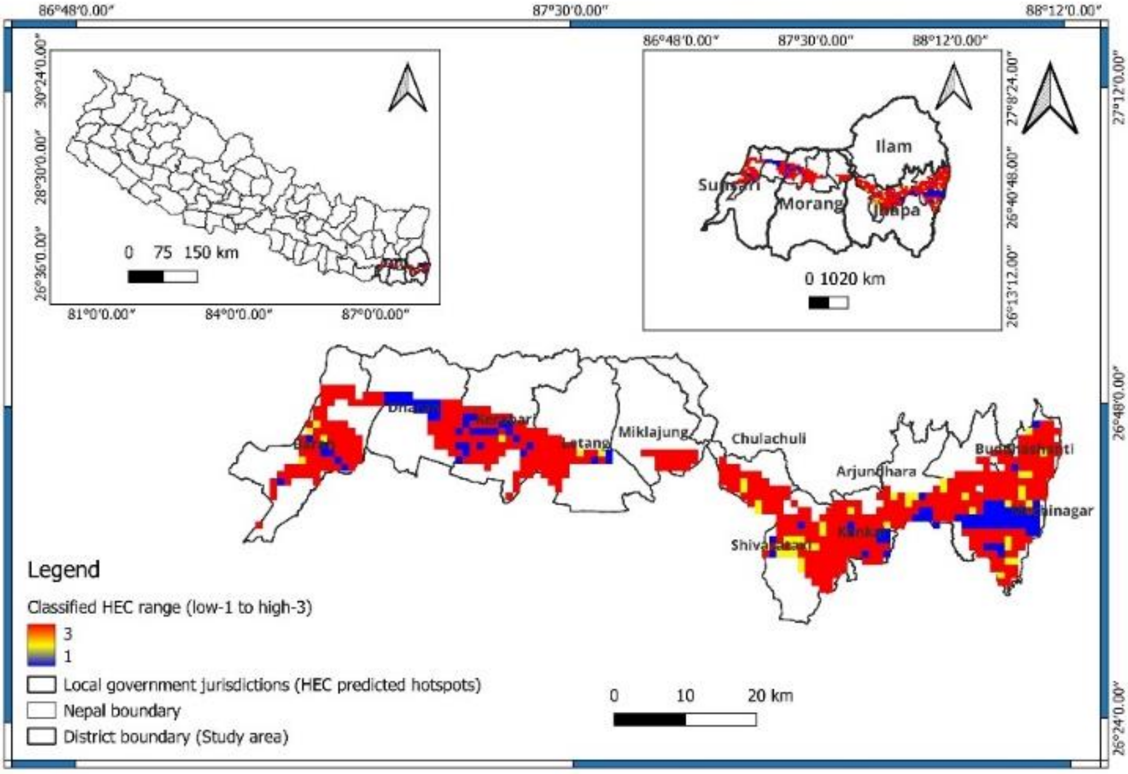

Figure 4. Human-elephant conflict hotspots predicted map in Eastern Chure Landscape.

5. Discussion

This study emphasized the importance of landscape metrics in understanding the nature and the extent of HEC in ECL, revealing that the dynamics of HEC are complicated and influenced by multiple anthropogenic and landscape features. The averaged-model logistic regression analysis indicated that Night Light and SHDI as significant predictors of HEC occurrence. The CART model predicted Night Light, ED, SHDI, and MESH as the most influential predictors of HEC at the spatial level in ECL. Similarly, Ram et al. (2022) also found that SHDI and MESH are the significant predictors of HEC. Therefore, the results across the models focused the contribution of artificial light (Night Light) and landscape heterogeneity (SHDI) in influencing HEC risk and highlighted the need to consider Night Light and SHDI in HEC risk mitigation strategies.

Generally, elephants enter the agricultural lands after dusk and return to their core habitats before dawn (Sukumar, 1990) and most cases of crop raiding and property damage by elephants are reported to occur during the night (Pradhan et al., 2011), potentially due to low-light, avoiding human disturbances, and reducing the likelihood of retaliation. Areas with high night light had a higher probability of HEC absence, possibly because elephants prefer low-light areas near forest, which provide fodder, water, and avoid high-light urban areas (Neupane et al., 2022), illustrating artificial lights as a potential mitigation strategy. However, increasing artificial light near forests may distract the Asian elephant's movement patterns and increase encounters between humans and Asian elephants in the adjoining communities.

The management of ecological connectivity has emerged as a critical strategy to conserve the remaining wild species and mitigate the impacts of habitat loss and fragmentation (Alkemade et al., 2009). Landscape connectivity is crucial for the conservation of endangered wild species, such as the Asian elephant (Suksavate et al., 2019). The Asian elephant, having a larger home range that covers a variety of ecosystems to meet its ecological requirements, should be prioritized during landscape planning (Roberge & Angelstam, 2004; Wiens et al., 2008). Habitat fragmentation may result in small, isolated populations facing a higher risk of extinction because of random changes in genetic composition and demographic fluctuations (Frankham et al., 2002). Corridors serve as important extensions of protected areas (PAs) that facilitate species movement and contribute to the maintenance of biodiversity within and outside the PAs by promoting ecological connectivity. However, in recent years, the corridors have been degraded increasingly, mainly due to human activities (Ebenezeri Kileo & Emmanuel Mbije, 2021), isolating the populations and intensifying the probability of local extinctions. Management of habitat corridors and land-use practices facilitates the dispersal among the sub-populations and reduces risk of biodiversity loss ensuring the ecological balance within a landscape (Alkemade et al., 2009), and plays important role in gene flow (Crooks & Sanjayan, 2010; Rabinowitz & Zeller, 2010), and establishment of new populations. MESH, which measures habitat connectivity, was another significant variable in HEC prediction. The higher mesh size, associated with higher population density, representing the overlap with human settlements, increased the probability of HEC. Therefore, it aligns with the previous studies that state densely populated areas increase habitat fragmentation and loss, and increase HEC risks (Leimgruber et al., 2003). It suggests that higher habitat connectivity may facilitate elephant movement in human-dominated areas and increase the risk of conflict. Across landscapes, conflict and connectivity are significantly interrelated issues for wildlife conservation. Therefore, connectivity supports species persistence, but it also intensifies the conflict probability within the shared landscape (Lamb et al., 2020), with species such as the Asian elephant.

The lower population density was further refined by ED, indicating that higher ED reduces the probability of HEC, and the areas with lower ED are more vulnerable to HEC, which suggests that elephants tend to avoid fragmented landscapes, possibly due to habitat loss and infrastructures as physical barriers (Leimgruber et al., 2003). Lower edge density indicates less fragmentation and continuous habitats that support Asian elephants for foraging and migration, but HEC risk increases in the human-dominated landscapes bordering the habitats (Ram et al., 2022). Whereas, the lower MESH size led to the next important factor, SHDI, which influences the HEC. The significance of SHDI in predicting HEC resembled (Ram et al., 2022), where the fragmentation metric SHDI was associated with higher conflict severity. The diverse landscapes intermixed with natural and agricultural sources face a higher risk of HEC, mostly during the peak seasons (June-July and September-November) of crop raiding and harvesting (Pradhan et al., 2011; Sukumar, 1990). Higher SHDI represents more fragmented and heterogeneous landscapes often shared by local communities for grazing cattle and forest products, increasing human-elephant interactions (Acharya et al., 2016; Lamichhane et al., 2017). Due to increasing forest fragmentation, elephants and wild animals are compelled to share the space with humans (Carter et al., 2012), escalating encounter rates and conflict (Choudhury, 2004;

Ram et al., 2021). The movement of elephants depends upon the availability of food and water (Sukumar, 2006). Higher SHDI values significantly increased conflict probability, suggesting that higher SHDI might be associated with low habitat features and drive elephants to search for food and resources in human-dominated landscapes. In eastern Nepal, most of the forest corridors are highly fragmented mainly due to agricultural expansion and increased human settlement (Pradhan et al., 2011), that significantly contributes to HEC, particularly in areas with high SHDI where agricultural fields, settlement areas and natural forest areas exist nearby, increasing the rate of encounters between elephants and local community members.

On the other hand, lower SHDI led to ED, where lower ED predicted higher conflict probability, and higher ED represented the dependency on LPI for HEC management. LPI, which measures the extent of the largest patch in a landscape (McGarical et al., 2002), played a significant role in determining HEC probability. Forests outside the PAs are severely degraded because the marginal communities living at the forest edges mostly rely upon forest resources, increasing deforestation and habitat degradation (Pradhan et al., 2011). The greater LPI predicted the absence of HEC because larger habitat patches support resources, space for movement, which reduces the negative interaction with humans (Sukumar, 2006). Conversely, the lower LPI increased the conflict risk probability as the smaller patches are associated with higher fragmentation, reduced core habitats that have limited resources, and the elephants are compelled to move towards adjacent agricultural fields and human settlements in search of food, increasing HEC (Leimgruber et al., 2003).

Investigation of conflict risk areas is an effective method for controlling and designing conflict mitigation strategies between humans and wildlife globally (Treves et al., 2011). The probability map of HEC demonstrated significant variations across the different local government jurisdictions along the survey districts, identifying Morang as the highest conflict probability zone, probably due to habitat fragmentation (Acharya et al., 2016). Similarly, Jhapa, particularly in Mechinagar and Shivasataxi, was identified as a major conflict hotspot, potentially due to agricultural expansion and the shrinkage of forest areas (Baidya & Nabin, 2010). In this study, although the RF model has high specificity, the CART model's justifiable accuracy with a higher sensitivity and moderate specificity, indicated the overall robustness of the CART model compared to the RF model. This highlights the CART (Breiman et al., 1984) model as a more reliable tool for predicting HEC hotspots probabilities.

In contrast to earlier studies, which identified Jhapa and Sunsari as the highest HEC conflict hotspots in the eastern Nepal (Baidya & Nabin, 2010; Ram et al., 2022), and Morang was reported to experience comparatively fewer HEC incidents (Baidya & Nabin, 2010), this study predicted Morang and Jhapa, as the major HEC hotspots. The Morang district was identified as high probability areas, which may be due to the decreasing forest cover (Baidya & Nabin, 2010). The findings are based on the predicted spatial extent of the HEC probability areas, rather than solely dependent on reported HEC incidents from last five years. Habitat degradation, proximity to forest, and landscape fragmentation are the major factors in the spatial patterns of HEC (Ram et al., 2022). Higher night light reduced the HEC probability and highlighted the potential for light-based HEC management, and also indicated that maintaining connectivity, ED, and SHDI is crucial to support elephant movement and decrease encounters with humans. Therefore, conservation and mitigation of HEC should include habitat restoration, land-use planning, and community-based initiatives for human-elephant coexistence.

6. Conclusions and recommendations

6.1 Conclusions

The findings of this study suggest that higher Night Light plays an important role in mitigating HEC in ECL. The implementation of artificial Night Light illumination, non-invasive strategies such as street lights or solar lights within the high HEC prone areas can be a strong deterrent to Asian elephants, and serve as a beneficial tool influencing their movement patterns and decreasing the probability and frequency of HEC. Insights from this study emphasized that fragmented habitats and areas adjacent to elephant habitats intensify the HEC probabilities, as elephants are compelled to migrate through human-dominated landscapes. Therefore, mitigating HEC demands a systematic approach, including the regulation of artificial lights along the HEC prone areas, management of connectivity, and implementing land-use policies to reduce habitat fragmentation. To assist the long-term conservation of elephants and promote coexistence, reducing human-elephant interactions, understanding the migratory routes, connectivity, and the overlapping spatial areas is crucial. Mapping and identifying conflict zones can support in habitat management and restoration, the establishment of corridors, and facilitate safe migratory patterns for elephants, promoting community-based landscape-level planning.

6.2 Recommendations

Based on the findings of the study, here are some recommendations to consider:

i. Restoration of habitat corridors across fragmented habitats to ensure minimal human-elephant encounters.

ii. Maintain migratory routes for ecological connectivity.

iii. Installation of lights ($\geq$1.1 nW/cm^2/sr) as deterrents along the HEC risk areas, and along the boundaries of communities bordering the elephant habitats.

iv. Further studies need to focus on mapping migratory routes, assessing the role of habitat connectivity, and community-based HEC mitigation measures for sustainable conservation planning.

7. References

Acharya, K. P., Paudel, P. K., Jnawali, S. R., Neupane, P. R., & Köhl, M. (2017). Can forest fragmentation and configuration work as indicators of human–wildlife conflict? Evidences from human death and injury by wildlife attacks in Nepal. *Ecological Indicators*, *80*, 74–83. https://doi.org/10.1016/j.ecolind.2017.04.037

Acharya, K. P., Paudel, P. K., Neupane, P. R., & Köhl, M. (2016). Human-wildlife conflicts in Nepal: Patterns of human fatalities and injuries caused by large mammals. *PLoS ONE*, *11*(9), 1–18. https://doi.org/10.1371/journal.pone.0161717

Alkemade, R., Van Oorschot, M., Miles, L., Nellemann, C., Bakkenes, M., & Ten Brink, B. (2009). GLOBIO3: A framework to investigate options for reducing global terrestrial biodiversity loss. *Ecosystems*, *12*(3), 374–390. https://doi.org/10.1007/s10021-009-9229-5

Amwata, D. A., & Mganga, K. Z. (2014). The African elephant and food security in Africa: Experiences from Baringo District, Kenya. *Pachyderm*, *55*(55), 23–29.

Baidya, N., & Nabin, S. (2010). *Transboundary movement of elephants in eastern Nepal.* (Vol. 37, Issue 4). https://www.researchgate.net/publication/342343443

Barua, M., Bhagwat, S. A., & Jadhav, S. (2013). The hidden dimensions of human-wildlife conflict: Health impacts, opportunity and transaction costs. *Biological Conservation*, *157*, 309–316. https://doi.org/10.1016/j.biocon.2012.07.014

Blake, S., & Hedges, S. (2004). Sinking the flagship: The case of forest elephants in Asia and Africa. *Conservation Biology*, *18*(5), 1191–1202. https://doi.org/10.1111/j.1523-1739.2004.01860.x

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*, 5–32. https://doi.org/10.1007/978-3-030-62008-0_35

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and Regression Trees*.

Carter, N. H., Shrestha, B. K., Karki, J. B., Pradhan, N. M. B., & Liu, J. (2012). Coexistence between wildlife and humans at fine spatial scales. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(38), 15360–15365. https://doi.org/10.1073/pnas.1210490109

Central Bureau of Statistics. (2024). *Census Nepal*. https://censusnepal.cbs.gov.np/results/population?district=11&province=1

Chaudhary, A., Timilsina, S., Gautam, S., & Subedi, P. B. (2021). An assessment of the Human-Elephant conflict in Sapahi and Kakadi Village of Kolhabi Municipality, Bara, Nepal. *Our Nature*, *19*(1), 27–36. https://doi.org/10.3126/on.v19i1.41223

Choudhury, A. (2004). Human–Elephant conflicts in Northeast India. *Human Dimensions of Wildlife*, *9*(4), 261–270. https://doi.org/10.1080/10871200490505693

Choudhury, A., Lahiri Choudhury, D. K., Desai, A., Duckworth, J. W., Easa, P. S., Johnsingh, A. J. T., Fernando, P., Hedges, S., Gunawardena, M., Kurt, F., Karanth, U., Lister, A., Menon, V., Riddle, H., Rübel, A., & Wikramanavake, F. (2008). *Elephas maximus*. The IUCN Red List of Threatened Species 2008: e.T7140A12828813. *The IUCN Red List of Threatened Species 2008*, *8235*, 17. https://dx.doi.org/10.2305/IUCN.UK.2008.RLTS.T7140A12828813.en.

CITES. (2023). Convention on International trade in endengered species of wild fauna and flora Appendices I, II and III. *Convention on International Trade in Endengered Species of Wild Fauna and Flora*, 1–81. https://cites.org/eng/app/index.php

Crooks, K. R., & Sanjayan, M. (2010). Connectivity conservation: Maintaining connections for nature. *Connectivity Conservation*, 1–20. https://doi.org/10.1017/cbo9780511754821.001

de Boer, W. F., Van Oort, J. W. A., Grover, M., & Peel, M. J. S. (2015). Elephant-mediated habitat modifications and changes in herbivore species assemblages in Sabi Sand, South Africa. *European Journal of Wildlife Research*, *61*(4), 491–503. https://doi.org/10.1007/s10344-015-0919-3

Dhungana, S., Yuangyai, N., & Sinutok, S. (2024). Impact, management, and use of invasive alien plant species in Nepal's protected area: a systematic review. *Journal of Ecology and Environment*, *48*(2), 19. https://doi.org/https://doi.org/10.5141/jee.23.081

Distefano, E. (2005). *Human-Wildlife Conflict worldwide: collection of case studies, analysis of management strategies and good practices*. 29. http://www.fao.org/3/a-au241e.pdf

DNPWC/MoFSC/GoN. (2009). *Elephant Conservation Action Plan for Nepal-2009.*

Ebenezeri Kileo, L., & Emmanuel Mbije, N. (2021). Land Use Practices along Saadani-Wami-Mbiki Wildlife Corridor and their Implications to Wildlife Conservation. *Asian Journal of Environment & Ecology*, *16*(4), 126–143. https://doi.org/10.9734/ajee/2021/v16i430264

Elvidge, C. D., Zhizhin, M., Ghosh, T., Hsu, F. C., & Taneja, J. (2021). Annual time series of global viirs nighttime lights derived from monthly averages: 2012 to 2019. *Remote Sensing*, *13*, 1–14. https://doi.org/10.3390/rs13050922

Fernando, C., Weston, M. A., Corea, R., Pahirana, K., & Rendall, A. R. (2022). Asian elephant movements between natural and human-dominated landscapes mirror patterns of crop damage in Sri Lanka. *Oryx*, *57*(4), 481–488. https://doi.org/10.1017/S0030605321000971

Fernando, P., & Pastorini, J. (2014). Range-wide status of Asian elephants. *Gajah*, *35*, 15–20. https://doi.org/10.5167/uzh-59036

Frankham, R., Ballou, J. D., & Briscoe, D. A. (2002). *Introduction to Conservation Genetics.* Cambridge: Cambridge University Press.

Government of Nepal. (1973). *National Parks and Wildlife Conservation Act*. https://www.dnpwc.gov.np/

Gross, E. M., Lahkar, B. P., Subedi, N., Nyirenda, V. R., Lichtenfeld, L. L., & Jakoby, O. (2018). Seasonality, crop type and crop phenology influence crop damage by wildlife herbivores in Africa and Asia. *Biodiversity and Conservation*, *27*(7), 2029–2050. https://doi.org/10.1007/s10531-018-1523-0

Gunawansa, T. D., Perera, K., Apan, A., & Hettiarachchi, N. K. (2024). Identifying human elephant conflict hotspots through satellite remote sensing and GIS to support conflict mitigation. *Remote Sensing Applications: Society and Environment*, *35*, 101261. https://doi.org/10.1016/j.rsase.2024.101261

Hesselbarth, M. H. K., Sciaini, M., With, K. A., Wiegand, K., & Nowosad, J. (2019). landscapemetrics: An open-source R tool to calculate landscape metrics. *Ecography*, *42*, 1648–1657. https://doi.org/10.1111/ecog.04617

Hijmans, R. J. (2023). *The raster package*. https://rspatial.org/raster/pkg/RasterPackage.pdf

Hijmans, R. J., Barbosa, M., & Bivand, R. (2025). *Spatial Data Analysis*.

https://rspatial.org/, https://rspatial.github.io/terra/

Hoare, R. (2015). Lessons From 20 Years of Human–Elephant Conflict Mitigation in Africa. *Human Dimensions of Wildlife*, *20*(4), 289–295. https://doi.org/10.1080/10871209.2015.1005855

Huang, C., Li, X., Khanal, L., & Jiang, X. (2019). Habitat suitability and connectivity inform a co-management policy of protected area network for asian elephants in China. *PeerJ*, *7*, e6791. https://doi.org/10.7717/peerj.6791

Impact Observatory, Microsoft, & E. (2022). *Esri 2022 Land Cover (10 m)*. https://livingatlas.arcgis.com/landcover/

Jaeger, J. A. G. (2000). Landscape division, splitting index, and effective mesh size: New measures of landscape fragmentation. *Landscape Ecology*, *15*, 115–130. https://doi.org/10.1023/A:1008129329289

James, G., Witten, D., & Hastie, T. (2013). *An introduction to statistical learning with applications in R.* Springer.

Jiang, W., & Yang, Y. (2021). *Elephant-Human Conflict Mitigation: An Autonomous Uav Approach*. https://doi.org/10.48550/arXiv.2201.02584

Joshi, R., & Singh, R. (2007). Asian elephants are losing their seasonal traditional movement tracks: a decade of study in and around the Rajaji National Park, India. *Gajah*, *27*, 15–26.

Kahler, J. S., & Gore, M. L. (2015). Local perceptions of risk associated with poaching of wildlife implicated in human-wildlife conflicts in Namibia. *Biological Conservation*. https://doi.org/10.1016/j.biocon.2015.02.001

Kalaba, F. K., Quinn, C. H., & Dougill, A. J. (2013). The role of forest provisioning ecosystem services in coping with household stresses and shocks in Miombo woodlands, Zambia. *Ecosystem Services*, *5*, 143–148. https://doi.org/10.1016/j.ecoser.2013.07.008

Khanal, B. (2022). *Using machine learning to predict the risk of human-elephant conflict in the Nepal-India transboundary region*. University of Twente.

Koirala, R. K., Ji, W., Aryal, A., Rothman, J., & Raubenheimer, D. (2015). Dispersal and ranging patterns of the Asian Elephant (*Elephas maximus*) in relation to their interactions with humans in Nepal. *Ethology Ecology and Evolution*, *28*(2), 221–231. https://doi.org/10.1080/03949370.2015.1066872

Koirala, R. K., Raubenheimer, D., Aryal, A., Pathak, M. L., & Ji, W. (2016). Feeding preferences of the Asian elephant (*Elephas maximus*) in Nepal. *BMC Ecology*, *16*(1), 1–9. https://doi.org/10.1186/s12898-016-0105-9

Kuhn, M., & Johnson, K. (2013). *Applied Predictive Modeling*. Springer New York Heidelberg Dordrecht London. https://doi.org/10.1007/978-1-4614-6849-3

Kurmi, S. K., & Koju, N. P. (2021). Spatiotemporal association of human-elephant conflict around Parsa National Park, Nepal. *Nepalese Journal of Zoology*, *5*(1), 8–12. https://doi.org/10.3126/njz.v5i1.38283

Lamb, C. T., Ford, A. T., McLellan, B. N., Proctor, M. F., Mowat, G., Ciarniello, L., Nielsen, S. E., & Boutin, S. (2020). The ecology of human–carnivore coexistence. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(30), 17876–17883. https://doi.org/10.1073/pnas.1922097117

Lamichhane, B. R., Subedi, N., Pokheral, C. P., Dhakal, M., Acharya, K. P., Pradhan, N. M. B., Smith, J. L. D., Malla, S., Thakuri, B. S., & Yackulic, C. B. (2017). Using interviews and biological sign surveys to infer seasonal use of forested and agricultural portions of a human-dominated landscape by Asian elephants in Nepal. *Ethology Ecology and Evolution*, *30*(4), 331–347. https://doi.org/10.1080/03949370.2017.1405847

Leimgruber, P., Gagnon, J. B., Wemmer, C., Kelly, D. S., Songer, M. A., & Selig, E. R. (2003). Fragmentation of Asia's remaining wildlands: Implications for Asian elephant conservation. *Animal Conservation*, *6*(4), 347–359. https://doi.org/10.1017/S1367943003003421

Lewis, D., Bell, S. D., Fay, J., Bothi, K. L., Gatere, L., Kabila, M., Mukamba, M., Matokwani, E., Mushimbalume, M., Moraru, C. I., Lehmann, J., Lassoie, J., Wolfe, D., Lee, D. R., Buck, L., & Travis, A. J. (2011). Community Markets for Conservation (COMACO) links biodiversity conservation with sustainable improvements in livelihoods and food production. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(34). https://doi.org/10.1073/pnas.1011538108

Max, K., Wing, J., Weston, S., Williams, A., Keefer, C., Engelhardt, A., Cooper, T., Mayer, Z., Ziem, A., Scrucca, L., Hunt, T., & Kuhn, M. M. (2024). *Classification and Regression Training*. CRAN. https://github.com/topepo/caret/

McGarical, K., Marks, B. J., McGarigal, K., Cushman, S. A., Neel, M. C., & Ene, E. (2002). FRAGSTATS: spatial pattern analysis program for categorical maps. *General Technical Report PNW-GTR-351. US*, *97331*(503), 134.

Neupane, B., Budhathoki, S., & Khatiwoda, B. (2018). Human-elephant conflict and mitigation measures in Jhapa district, Nepal. *Journal of Forest and Livelihood*, *16*(1). https://doi.org/10.3126/jfl.v16i1.22885

Neupane, D., Baral, S., Risch, T. S., & Campos-Arceiz, A. (2022). Broad scale functional connectivity for Asian elephants in the Nepal-India transboundary region. *Journal of Environmental Management*. https://doi.org/10.1016/j.jenvman.2022.115921

Neupane, D., Johnson, R. L., & Risch, T. S. (2014). Temporal and spatial patterns of human-elephant conflict in Nepal. *2013 International Elephant & Rhino Conservation & Research Symposium Proceedings*, *April*. https://www.researchgate.net/publication/261551760

Neupane, D., Johnson, R. L., & Risch, T. S. (2017). How do land-use practices affect human-elephant conflict in nepal? *Wildlife Biology*. https://doi.org/10.2981/wlb.00313

Nyhus, P. J. (2016). Human-Wildlife Conflict and Coexistence. *Annual Review of Environment and Resources*, *41*, 143–171. https://doi.org/10.1146/annurev-environ-110615-085634

Nyirenda, V. R., Myburgh, W. J., & Reilly, B. K. (2012). Farm household level impacts of information communication technology (ICT)-based agricultural market information in Ghana. *Journal of Development and Agricultural Economics*, *5*(4), 161–167. https://doi.org/10.5897/jdae12.143

Owen-Smith, R. N. (1988). *Megaherbivores: The Influence of Very Large Body Size on Ecology*. Cambridge University Press.

Pant, G., Dhakal, M., Pradhan, N. M. B., Leverington, F., & Hockings, M. (2016). Nature and extent of human-elephant *Elephas maximus* conflict in central Nepal. *Oryx*, *50*(4), 724–731. https://doi.org/10.1017/S0030605315000381

Parker, G. E., Karidozo, M., & Osborn, F. V. (2007). Human–Elephant Conflict Mitigation: A Training Source for Community-Based Approaches in Africa. *Trainer's Manual Elephant Pepper Development Trust*.

Peterson, M. N., Peterson, M. J., Peterson, T. R., & Leong, K. (2013). Why transforming biodiversity conservation conflict is essential and how to begin. *Pacific Conservation Biology*, *19*(2), 94–103. https://doi.org/10.1071/PC130094

Pozo, R. A., Coulson, T., McCulloch, G., Stronza, A. L., & Songhurst, A. C. (2017). Determining baselines for human-elephant conflict: A matter of time. *PLoS ONE*, *12*(6), 1–17. https://doi.org/10.1371/journal.pone.0178840

Pozo, R. A., Cusack, J. J., McCulloch, G., Stronza, A., Songhurst, A., & Coulson, T. (2018). Elephant space-use is not a good predictor of crop-damage. *Biological Conservation*, *228*, 241–251. https://doi.org/10.1016/j.biocon.2018.10.031

Pradhan, N. M. B., Wegge, P., & Moe, S. R. (2007). How does a re-colonizing population of Asian elephants affect the forest habitat? *Journal of Zoology*, *273*(2), 183–191. https://doi.org/10.1111/j.1469-7998.2007.00313.x

Pradhan, N. M. B., Williams, A. C., & Dhakal, M. (2011). Current Status of Asian Elephants in Nepal. *Gajah*, *35*. https://www.researchgate.net/publication/282602174

Prakash, T. G. S. L., Wijeratne, A. W., & Fernando, P. (2020). Human-elephant conflict in Sri Lanka: Patterns and extent. *Gajah*, *51*.

R Core Team. (2023). *R: A Language and Environment for Statistical Computing*. https://www.r-project.org/

Rabinowitz, A., & Zeller, K. A. (2010). A range-wide model of landscape connectivity and conservation for the jaguar, Panthera onca. *Biological Conservation*, *143*(4), 939–945. https://doi.org/10.1016/j.biocon.2010.01.002

Rai, R., Development, I., Tandan, R. P., & Baniya, B. (2022). Hisorical Land Use and Land Cover Change of Eastern Nepal: A case of Dharan Sub-Metropolitan City. *The Geographic Base*. https://doi.org/10.3126/tgbv8i01.43458

Ram, A. K., & Acharya, H. (2020). Status distribution and habitat use by Asian elephants (*Elephas maximus*) in Nepal Abstracts: *Journal of Chemical Information and Modeling*, *43*(1), 7728.

Ram, A. K., Mondol, S., Subedi, N., Lamichhane, B. R., Baral, H. S., Natarajan, L., Amin, R., & Pandav, B. (2021). Patterns and determinants of elephant attacks on humans in Nepal. *Ecology and Evolution*, *11*(17), 11639–11650. https://doi.org/10.1002/ece3.7796

Ram, A. K., Yadav, N. K., Subedi, N., Pandav, B., Mondol, S., Khanal, B., Kharal, D. K., Acharya, H. B., Dhakal, B. K., Acharya, K. P., Baral, H. S., Dahal, B. R., Mishra, R., Naha, D., Pradhan, N. M. B., Natarajan, L., & Lamihhane, B. R. (2022). Landscape predictors of human elephant conflicts in Chure Terai Madhesh Landscape of Nepal. *Environmental Challenges*, *7*, 100458. https://doi.org/10.1016/j.envc.2022.100458

Redpath, S. M., Young, J., Evely, A., Adams, W. M., Sutherland, W. J., Whitehouse, A., Amar, A., Lambert, R. A., Linnell, J. D. C., Watt, A., & Gutiérrez, R. J. (2013). Understanding and managing conservation conflicts. *Trends in Ecology and Evolution*, *28*(2), 100–109. https://doi.org/10.1016/j.tree.2012.08.021

Roberge, J. M., & Angelstam, P. (2004). Usefulness of the Umbrella Species Concept as a Conservation Tool. *Conservation Biology*, *18*, 76–85. https://doi.org/10.1111/j.1523-1739.2004.00450.x

Ruda, A., Kolejka, J., & Silwal, T. (2018). GIS-assisted prediction and risk zonation of wildlife attacks in the Chitwan National Park in Nepal. *ISPRS International Journal of Geo-Information*, *7*(9), 1–21. https://doi.org/10.3390/ijgi7090369

Selier, S. A. J., Slotow, R., & Di Minin, E. (2016). The influence of socioeconomic factors on the densities of high-value cross-border species, the African elephant. *PeerJ*, *2016*(10), 1–16. https://doi.org/10.7717/peerj.2581

Shaffer, L. J., Khadka, K. K., Van Den Hoek, J., & Naithani, K. J. (2019). Human-elephant conflict: A review of current management strategies and future directions. *Frontiers in Ecology and Evolution*, *6*. https://doi.org/10.3389/fevo.2018.00235

Shrestha, R., & Koirala, D. P. (2013). Elephant–Human Conflict in Bahundangi Region, Jhapa District, Nepal. *Journal of Natural History Museum*, *27*(GoN 1972), 59–65. https://doi.org/10.3126/jnhm.v27i0.14153

Shrestha, S., & Shrestha, J. (2021). Asian elephants and their status in Nepal: a review. *Journal of Agriculture and Natural Resources*, *4*(2), 227–237.

https://doi.org/10.3126/janr.v4i2.33828

Singh, A. P., & C.Sharma, R. (2018). UC Davis | UC Davis. *Dermatology Online Journal, 24*(11), 0–18. https://www.ucdavis.edu/

Sitati, N. W., Walpole, M. J., Smith, R. J., & Leader-Williams, N. (2003). Predicting spatial aspects of human-elephant conflict. *Journal of Applied Ecology*, *40*(4), 667–677. https://doi.org/10.1046/j.1365-2664.2003.00828.x

Songhurst, A., McCulloch, G., & Coulson, T. (2016). Finding pathways to human-elephant coexistence: A risky business. *Oryx*, *50*(4), 713–720. https://doi.org/10.1017/S0030605315000344

Sudhakar Reddy, C., Vazeed Pasha, S., Satish, K. V., Saranya, K. R. L., Jha, C. S., & Krishna Murthy, Y. V. N. (2018). Quantifying nationwide land cover and historical changes in forests of Nepal (1930–2014): Implications on forest fragmentation. *Biodiversity and Conservation*, *27*(1), 91–107. https://doi.org/10.1007/s10531-017-1423-8

Suksavate, W., Duengkae, P., & Chaiyes, A. (2019). Quantifying landscape connectivity for wild Asian elephant populations among fragmented habitats in Thailand. *Global Ecology and Conservation*, *19*, e00685. https://doi.org/10.1016/j.gecco.2019.e00685

Sukumar, R. (1989). *The Asian Elephant: Ecology and Management* (1st ed.). Cambridge University Press. https://doi.org/10.1017/9781108562836.002

Sukumar, R. (1990). Ecology of the Asian elephant in southern India. II. Feeding habits and crop raiding patterns. *Journal of Tropical Ecology*, *6*(1), 33–53. https://doi.org/10.1017/S0266467400004004

Sukumar, R. (1994). *Elephant Days and Nights:Ten Years with the Indian Elephant*. Oxford University Press.

Sukumar, R. (2003). The Living Elephants: Evolutionary Ecology, Behavior, and Conservation. In *The Living Elephants* (1st ed.). Oxford University Press. https://doi.org/10.1093/oso/9780195107784.001.0001

Sukumar, R. (2006). A brief review of the status, distribution and biology of wild Asian elephants. *International Zoo Yearbook*, *40*(1), 1–8. https://doi.org/10.1111/j.1748-1090.2006.00001.x ten Velde, P. F. (1997). *A Status Report of Nepal's Wild Elephant Population*. WWF Nepal Program, Kathmandu, Nepal

Therneau, T., Atkinson, B., & Ripley, B. (2025). *Recursive Partitioning and Regression Trees*. CRAN. https://github.com/bethatkinson/rpart, https://cran.r-project.org/package=rpart

Thouless C.R., Dublin, H. T., Blanc, J. J., Skinner, D. P., Daniel, T. E., Taylor, R. D., Maisels, F., Frederick, H. L., & Bouché, P. J. C. (2016). *African elephant status report 2016: an update from the African elephant database. Occasional paper series of the IUCN Species Survival Commission*.

Tiller, L. N., Humle, T., Amin, R., Deere, N. J., Lago, B. O., Leader-Williams, N., Sinoni, F. K., Sitati, N., Walpole, M., & Smith, R. J. (2021). Changing seasonal, temporal and spatial crop-raiding trends over 15 years in a human-elephant conflict hotspot. *Biological Conservation*, *254*(January), 108941. https://doi.org/10.1016/j.biocon.2020.108941

Treves, A., Martin, K. A., Wydeven, A. P., & Wiedenhoeft, J. E. (2011). Forecasting environmental hazards and the application of risk maps to predator attacks on livestock. *BioScience*, *61*(6), 451–458. https://doi.org/10.1525/bio.2011.61.6.7

Wickham, H. (2016). Statistics and computing in disease clustering. Proceedings of a conference. Vancouver, Canada, 21-22 July 1994. *Statistics in Medicine*, *15*(7–9), 681–952. http://www.ncbi.nlm.nih.gov/pubmed/9132895

Wiens, J. A., Hayward, G. D., Holthausen, R. S., & Wisdom, M. J. (2008). Using surrogate species and groups for conservation planning and management. *BioScience*, *58*(3), 241–252. https://doi.org/10.1641/B580310

Williams, C., Tiwari, S. K., Goswami, V. R., De Silva, S., Kumar, A., Baskaran, N., Yoganand, K., & Menon, V. &. (2020). *Elephas maximus*. The IUCN Red List of Threatened Species. *Elephas Maximus*, *2020*(The IUCN Red List of Threatened Species 2020), 1–29. https://www.iucnredlist.org/species/7140/45818198

Wittemyer, G., Elsen, P., Bean, W. T., Burton, A. C. O., & Brashares, J. S. (2008). Accelerated human population growth at protected area edges. *Science*, *321*(5885), 123–126. https://doi.org/10.1126/science.1158900

Woodroffe, R., Thirgood, S., & Rabinowitz, A. (Eds.). (2005). *People and wildlife: Conflict* *or coexistence?* Cambridge University Press.

Yang, N., Dai, X., Wang, B., Wen, M., Gan, Z., Li, Z., & Duffy, K. J. (2023). Mapping potential human-elephant conflict hotspots with UAV monitoring data. *Global Ecology and Conservation*, *43*, e02451. https://doi.org/10.1016/j.gecco.2023.e02451

Zhang, L., & Wang, N. (2003). An initial study on habitat conservation of Asian elephant (*Elephas maximus*), with a focus on human elephant conflict in Simao, China. *Biological Conservation*, *112*(3), 453–459. https://doi.org/10.1016/S0006-3207(02)00335-X

Zhao, F., Zhang, Y., Zhao, Z., Wang, X., Zhang, S., Luan, G., Zhang, Q., Zhu, L., & Liu, H. (2023). Monitoring of human activities around the Asian elephant reserve based on NPP-VIIRS night light remote sensing images: A case study in Xishuangbanna, China. *Frontiers in Ecology and Evolution*, *11*, 1088722. https://doi.org/10.3389/fevo.2023.1088722

8. Appendices

Appendix 1. Photographs

Photograph 1. A paddy field trampled by *Elephas maximus* during a nighttime raid highlights the severity of human-elephant conflict in the Eastern Chure Landscape, Nepal.

Photograph 2. Footprints of elephants in a cultivated field, recorded as field-level evidence of human-elephant conflict in the Eastern Chure Landscape.

Appendix 2. Figures

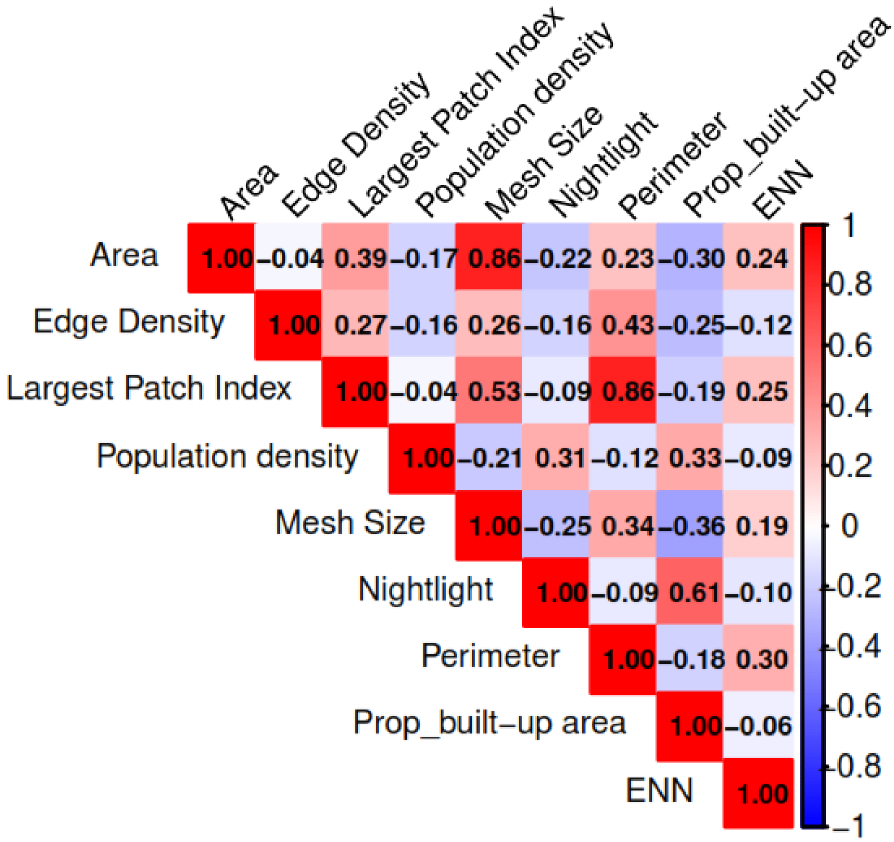

Figure 5. Correlation test between the predictors of human-elephant conflict in Eastern Chure Landscape.

Appendix 3. R codes

```
#Logistic regression codes#

# Load necessary libraries

library(MuMIn)   # For model dredging and model averaging

library(pscl)    # For calculating pseudo R-squared

library(ggplot2) # For visualization

# Step 1: Read the dataset

my_data <- read.csv("E:/Eelephant_final_pa_latlong/var_TO_ANALYSIS.csv")

# Step 2: Prevent automatic NA removal during model selection

options(na.action = "na.fail")

# Step 3: Fit the full logistic regression model

model1 <- glm(P_A ~ ., data = my_data, family = binomial)

# Step 4: Perform model selection based on AICc

dd <- dredge(model1, rank = "AICc")

# Step 5: Convert dredge results to data frame (optional: save to CSV)

dd1 <- as.data.frame(dd)

# write.csv(dd1, "E:/Eelephant_final_pa_latlong/result_all_model_glm.csv", row.names =
FALSE)

# Step 6: Select top models with ΔAICc < 2

top_models <- subset(dd, delta < 2)

# Step 7: Perform model averaging across selected models

avg_mod <- model.avg(top_models, fit = TRUE)

# Step 8: View summary of the averaged model

summary(avg_mod)

# Step 9: Extract relative importance values of predictors

importance_vals <- sw(avg_mod)
```

```r
# Step 10: Sort and convert importance values to a data frame
importance_df <- data.frame(Variable = names(importance_vals),
                            Importance = as.numeric(importance_vals))
importance_df <- importance_df[order(-importance_df$Importance), , drop = FALSE]
# Step 11: Print all relative importance values
print("Sorted relative importance of predictors:")
print(importance_df)
# Step 12: Print variables with high importance (> 0.8)
high_importance_df <- importance_df[importance_df$Importance > 0.8, ]
print("Variables with high relative importance (> 0.8):")
print(high_importance_df)
# Step 13: Evaluate model fit statistics
fit_stats <- pR2(model1)
print("Model fit statistics:")
print(fit_stats)
# Step 14: Plot logistic regression for Night Light
model_nl <- glm(P_A ~ Night_Light, data = my_data, family = binomial)
ggplot(my_data, aes(x = Night_Light, y = P_A)) +
  stat_smooth(method = "glm",
              method.args = list(family = "binomial"),
              se = TRUE,
              formula = y ~ x,
              color = "blue") +
  labs(title = "Logistic Regression Curve: Night_Light vs. Conflict Presence",
       x = "Night Light",
       y = "Probability of Conflict") +
```

```
  theme_minimal()
# Step 15: Plot logistic regression for SHDI
model_shdi <- glm(P_A ~ SHDI, data = my_data, family = binomial)
ggplot(my_data, aes(x = SHDI, y = P_A)) +
  stat_smooth(method = "glm",
              method.args = list(family = "binomial"),
              se = TRUE,
              formula = y ~ x,
              color = "blue") +
  labs(title = "Logistic Regression Curve: SHDI vs. Conflict Presence",
       x = "SHDI",
       y = "Probability of Conflict") +
  theme_minimal()
```

##**CART model codes**###

```
library(terra)
library(rpart)
library(rpart.plot)
library(caret)
# Load dataset
my_data <- read.csv("E:/Eelephant_final_pa_latlong/var_TO_ANALYSIS.csv")
# Define selected variables
selected_vars <- c("SHDI", "LPI", "Pop_density", "MESH",
                   "Night_Light", "Prop_builtarea", "ENN", "ED", "P_A")
# Convert response variable to a factor (Presence-Absence)
my_data$P_A <- as.factor(my_data$P_A)
# Split into training (75%) and testing (25%) datasets
```

```
set.seed(123)  # For reproducibility
train_index <- createDataPartition(my_data$P_A, p=0.75, list=FALSE)
train_data <- my_data[train_index, ]
test_data <- my_data[-train_index, ]
# Fit the Classification Tree Model (CART)
cart_model <- rpart(P_A ~ SHDI + LPI + Pop_density + MESH +
                     Night_Light + Prop_builtarea + ENN + ED,
                   data = train_data,
                   method = "class",
                   control = rpart.control(cp = 0.01))  # Complexity parameter to prevent overfitting
# Display variable iP_A# Display variable importance
print(cart_model$variable.importance)
# Create the variable importance data frame
var_imp <- cart_model$variable.importance  # Get variable importance
# Convert variable importance to a data frame
var_imp_df <- data.frame(
  Variable = names(var_imp),  # Variable names
  Importance = var_imp         # Importance values
)
# Sort the data frame by Importance in descending order
var_imp_df <- var_imp_df[order(var_imp_df$Importance, decreasing = TRUE),]
# Load ggplot2 library for plotting
library(ggplot2)
# Plot using ggplot2
ggplot(var_imp_df, aes(x = reorder(Variable, Importance), y = Importance)) +
```

```
  geom_point(color = "skyblue", size = 4) +   # Points representing variable importance
  geom_segment(aes(xend = Variable, yend = 0), color = "skyblue", size = 1) +   # Segments to the x-axis
  coord_flip() +  # Flip coordinates for better readability
  theme_minimal() +   # Minimal theme
  labs(title = "Variable Importance from CART Model", x = "Variable", y = "Importance") + # Title and axis labels
  scale_y_continuous(breaks = seq(0, max(var_imp_df$Importance), by = 1))  # Set y-axis breaks to integers
# Visualize the decision tree
rpart.plot(cart_model,
           main = "CART Model for Presence-Absence Conflict",
           extra = 106,
           type = 3,
           fallen.leaves = TRUE,
           box.palette = "RdBu",
           shadow.col = "gray",
           cex = 0.6)
summary(cart_model)
# Predict on the test dataset
test_predictions <- predict(cart_model, test_data, type="class")
# Confusion Matrix
confusion_matrix <- table(Predicted = test_predictions, Actual = test_data$P_A)
print(confusion_matrix)
# Compute Accuracy, Sensitivity, and Specificity
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
sensitivity <- confusion_matrix[2, 2] / sum(confusion_matrix[2, ])
```

```
specificity <- confusion_matrix[1, 1] / sum(confusion_matrix[1, ])
print(paste("Accuracy: ", round(accuracy, 3)))
print(paste("Sensitivity: ", round(sensitivity, 3)))
print(paste("Specificity: ", round(specificity, 3)))
# Prune the model to avoid overfitting
cart_model_pruned <- prune(cart_model, cp = 0.02)
# Visualize pruned tree
par(mar = c(1,1,1,1))
rpart.plot(cart_model_pruned,
        main = "Factors influencing HEC prediction",
        extra = 100,
        type = 5,
        fallen.leaves = TRUE,
        box.palette = "white",
        cex = 0.5)
summary(cart_model_pruned)
# Predict on the test dataset
test_predictions1 <- predict(cart_model_pruned, test_data, type="class")
# Confusion Matrix
confusion_matrix <- table(Predicted = test_predictions1, Actual = test_data$P_A)
print(confusion_matrix)
# Compute Accuracy, Sensitivity, and Specificity
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
sensitivity <- confusion_matrix[2, 2] / sum(confusion_matrix[2, ])
specificity <- confusion_matrix[1, 1] / sum(confusion_matrix[1, ])
print(paste("Accuracy: ", round(accuracy, 3)))
```

```
print(paste("Sensitivity: ", round(sensitivity, 3)))
print(paste("Specificity: ", round(specificity, 3)))
########add var_imp#####
# Display variable iP_A# Display variable importance
print(cart_model_pruned$variable.importance)
# Create the variable importance data frame
var_imp <- cart_model_pruned$variable.importance  # Get variable importance
# Convert variable importance to a data frame
var_imp_df <- data.frame(
  Variable = names(var_imp),  # Variable names
  Importance = var_imp        # Importance values
)
# Sort the data frame by Importance in descending order
var_imp_df <- var_imp_df[order(var_imp_df$Importance, decreasing = TRUE),]
# Load ggplot2 library for plotting
library(ggplot2)
# Ensure Variable is ordered by Importance
var_imp_df$Variable <- factor(var_imp_df$Variable, levels =
var_imp_df$Variable[order(var_imp_df$Importance)])
# Create ggplot
ggplot(var_imp_df, aes(x = Variable, y = Importance)) +
  geom_bar(stat = "identity", fill = "black", color = "black") +
  theme_minimal() +
  labs(title = "Variable Importance from CART Model", x = "Variable", y = "Importance")
+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))  # Rotate x-axis labels for
readability
```

```
###Next to improve var_importance##added this for varibale importance and so on##
# Create the variable importance data frame
var_imp <- cart_model_pruned$variable.importance  # Or cart_model$variable.importance
var_imp_df <- data.frame(
  Variable = names(var_imp),
  Importance = var_imp
)
# Sort by importance
var_imp_df <- var_imp_df[order(var_imp_df$Importance, decreasing = TRUE), ]
# Normalize importance
var_imp_df$Normalized <- var_imp_df$Importance / sum(var_imp_df$Importance)
# Ensure Variable is a factor for plotting
var_imp_df$Variable <- factor(var_imp_df$Variable, levels = var_imp_df$Variable)
# Plot
library(ggplot2)
ggplot(var_imp_df, aes(x = Variable, y = Normalized * 100)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  geom_text(aes(label = paste0(round(Normalized * 100, 1), "%")),
            vjust = -0.3, size = 2) +
  theme_minimal() +
  labs(title = "Normalized Variable Importance from CART",
       x = "Variable", y = "Importance (%)") +
  theme(axis.text.x = element_text(angle = 40, hjust = 1))
#####FOR_HOTSPOTMAP_FROM CARTMODEL#########
library(terra)
# Load Raster Files for Variables (use the correct file paths for your raster data)
```

```
ED <- rast("E:/Eelephant_final_pa_latlong/var_madhu/Final_ed1.tif")

LPI <- rast("E:/Eelephant_final_pa_latlong/var_madhu/Final_lpi1.tif")

Pop_density <- rast("E:/Eelephant_final_pa_latlong/var_madhu/Pop_resampled.tif")

MESH <- rast("E:/Eelephant_final_pa_latlong/var_madhu/Final_mesh.tif")

Night_Light <-
rast("E:/Eelephant_final_pa_latlong/var_madhu/Final_nightlight_resampled.tif")

Prop_builtarea <-
rast("E:/Eelephant_final_pa_latlong/var_madhu/Final_Prop_builtarea1.tif")

SHDI <- rast("E:/Eelephant_final_pa_latlong/var_madhu/Final_shdi1.tif")

ENN <- rast("E:/Eelephant_final_pa_latlong/var_madhu/Final_enn1.tif")

# Stack Raster Files

hotspot_stack <- c(LPI, ED, Pop_density, MESH, Night_Light, Prop_builtarea, SHDI,
ENN)

crs(hotspot_stack)

# Convert Raster Stack to Data Frame (xy=TRUE includes coordinates as columns)

hotspot_df <- as.data.frame(hotspot_stack, xy=TRUE, na.rm=TRUE)

# Check the column names of the dataframe

print(names(hotspot_df))  # Check the structure of the dataframe

# Now assign names based on the actual columns in hotspot_df

names(hotspot_df) <- c("x", "y", "LPI", "ED", "Pop_density", "MESH", "Night_Light",
"Prop_builtarea", "SHDI", "ENN")

# Ensure Data Format Consistency (remove missing or NA rows)

hotspot_df <- hotspot_df[, c("x", "y", "LPI", "ED", "Pop_density", "MESH",
"Night_Light", "Prop_builtarea", "SHDI", "ENN")]

# Predict conflict probabilities using the pruned CART model

# Use type = "prob" to get the probability of each class (Presence/Absence)
```

```
hotspot_df$conflict_prob <- predict(cart_model_pruned, newdata = hotspot_df, type = "prob")[, 2]  # Probability for "Presence"
# Check the predicted probabilities
head(hotspot_df$conflict_prob)
# Convert to Raster for Visualization
# Use 'x' and 'y' as coordinates and 'conflict_prob' as the probability value
hotspot_raster <- rast(hotspot_df[, c("x", "y", "conflict_prob")], type = "xyz")
##either#########
# Define a continuous color palette for better visualization
color_palette <- colorRampPalette(c("blue", "yellow", "red"))  # Low to High Conflict
# Plot the raster with a gradient color scale
plot(hotspot_raster,
    main = "Predicted Conflict Hotspot Map (Gradient Color)",
    col = color_palette(10),  # Generates 100 shades from blue to red
    legend = TRUE)  # Include a legend for interpretation
# Plot the Conflict Hotspot Prediction Map as a continuous gradient
plot(hotspot_raster, main = "Predicted Conflict Hotspot Map (Probability)",
    col = rev(terrain.colors(10)), # Change color palette to a gradient
    legend = TRUE)  # Include a legend
writeRaster(hotspot_raster, "E:/after_predefence/af_pred_all/AF_PREDall_Hmap.tif", overwrite = TRUE)
###################MAP_COMPLETE_GO_TO_RECLASSIFICATION############
library(landscapemetrics)     # landscape metrics calculation
# Load required libraries
library(raster)   # Spatial raster data reading and handling
# Load the raster file
```

```
my_raster <- raster("E:/after_predefence/af_pred_all/AF_PREDall_Hmap.tif")
# Plot the raster
plot(my_raster)
# Define the reclassification matrix
reclass_matrix <- matrix(c(
  0, 0.5, 1,  # Low
  0.5, 0.75, 2,  # Medium
  0.75, 1.00, 3   # High
), ncol=3, byrow=TRUE)
# Reclassify the raster
hotspot_map <- reclassify(my_raster, reclass_matrix)
# Plot the reclassified raster
plot(hotspot_map)
writeRaster(hotspot_map,"E:/after_predefence/af_pred_all/PREDall_reclassified_Hmap.ti
f")
##ZONAL HISTOGRAM IN QGIS >>CALCULATE TOTAL AREA PER CLASS >>
CLIP BY STUDY AREA###
```

#**Random Forest Codes**##

```
library(randomForest)
library(caret)
library(ggplot2)
library(terra)
my_data <- read.csv("E:/Eelephant_final_pa_latlong/var_TO_ANALYSIS.csv")
my_data$P_A <- as.factor(my_data$P_A)
selected_vars <- c("SHDI", "LPI", "Pop_density", "MESH",
                   "Night_Light", "Prop_builtarea", "ENN", "ED", "P_A")
my_data <- my_data[, selected_vars]
```

```
set.seed(123)

train_index <- createDataPartition(my_data$P_A, p=0.75, list=FALSE)

train_data <- my_data[train_index, ]

test_data <- my_data[-train_index, ]

rf_model <- randomForest(P_A ~ ., data = train_data, ntree = 500, importance = TRUE)

print(rf_model)

test_pred_rf <- predict(rf_model, newdata = test_data)

conf_mat <- confusionMatrix(test_pred_rf, test_data$P_A)

print(conf_mat)

# Accuracy, Sensitivity, Specificity

conf_mat$overall['Accuracy']

conf_mat$byClass[c("Sensitivity", "Specificity")]
```

Appendix 4. Top-ranked logistic regression models

Table 4. Top-ranked logistic regression models predicting human-elephant conflict, based on ΔAICc<2 values.

S.N.	Predictors	df	loglik	AICc	ΔAICc	Weight
1	NL + SHDI	3	-130.5671	267.2298	0	0.096763
2	ED + NL + SHDI	4	-130.141	268.4421	1.212323	0.052779
3	ENN + NL + SHDI	4	-130.1985	268.5571	1.327319	0.04983
4	MESH + NL +SHDI	4	-130.529	269.2179	1.988191	0.035808
5	NL + Prop_Built_ area + SHDI	4	-130.5296	269.2193	1.989523	0.035784

Appendix 5. Letter of permission from Department of Forest and Soil Conservation,

नेपाल सरकार
वन तथा वातावरण मन्त्रालय
वन तथा भू-संरक्षण विभाग

फोन नं. ४-२२७५७४, ४-२२०३०३
फ्याक्स: ४-२२७३७४

(कृपया पत्रोत्तरमा प्राप्त पत्र संख्या र मिति उल्लख गर्नुहोला ।
बबरमहल, काठमाडौं, नेपाल

प्राप्त पत्र संख्या र मितिः-
पत्र संख्याः- ०८१/०८२
च. नं.:- १९९६

मिति : २०८१/०४/१५

नेपाल सरकार वन तथा वातावरण मन्त्रालय वन तथा भू-संरक्षण विभाग बबरमहल, काठमाडौं

विषयः अनुसन्धान अनुमति सम्बन्धमा ।

श्री मधु चौधरी,
नवलपरासी, नेपाल ।

प्रस्तुत विषयमा Biodiversity Research and Conservation Society मा आवद्ध तपाईले "Mapping Human-Elephant Conflict in Eastern Nepal" को विषयमा अनुसन्धानका लागि अध्ययन अनुमति उपलब्ध गराइदिनु हुन भनि मिति २०८१/०४/०६ गते यस विभागमा दिनु भएको निवेदन साथ प्रपोजल प्राप्त भयो । सो सम्बन्धमा कारवाही हुँदा उक्त अध्ययन अनुसन्धानबाट अध्ययन क्षेत्रमा The Conflict hotspots of Asian Elephant in Eastern Nepal को बारे जानकारी प्राप्त हुने भएकोले उक्त प्रपोजलमा उल्लेखित Methodology (Field Visit and Questionnaire Survey) अनुसार तपसिलको शर्तहरुको अधिनमा रही डिभिजन वन कार्यालयहरुसँग समन्वय गरि सन् २०२४, अगष्ट १st देखि सन् २०२४, डिसेम्बर ३०th सम्मका लागि अनुसन्धान गर्नु निर्देशानुसार अनुरोध छ।

शर्तहरु

१. अनुसन्धानकर्तालि वन ऐन २०७६ तथा वन नियमावली २०७९, राष्टिय निकुञ्ज तथा वन्यजन्तु संरक्षण ऐन, २०२९ र नियमावली २०३० तथा यस मातहतका नियमावलीहरुको पूर्ण पालना गर्नुपर्नेछ ।
२. अनुसन्धान कार्य डिभिजन वन कार्यालयसँगको समन्वयमा गर्नुपर्नेछ ।
३. नमूना संकलन गर्न पाईने छैन ।
४. अनुसन्धानको क्रममा प्राप्त भएको जैविक विविधता संरक्षणसँग सम्बन्धित संवेदनशिल सूचनाहरु गोप्य राखु पर्नेछ अनाधिकृत रुपमा त्यस्ता सूचनाहरु कसैलाई पनि उपलब्ध गराउन पाइने छैन ।
५. अनुसन्धान कार्य समाप्त भए पश्चात एक प्रति रिपोर्ट/प्रतिवेदन (कागजी तथा विद्युतिय) यस विभागमा अनिवार्य रुपमा बुझाउनु पर्नेछ ।
६. तोकिएका शर्तहरुको पालना नगरिएमा विभागले कुनै पनि समयमा अनुसन्धान अनुमति रद्द गर्न सक्नेछ ।

(सबनम पाठक)
वन अधिकृत

बोधार्थ
श्री डिभिजन वन कार्यालय, सुनसरी, मोरङ्ग र झापा। : आवश्यक सहयोग तथा अनुगमनको लागि अनुरोध छ ।

Kathmandu, Nepal

Appendix 6. A semi-structured questionnaire used during the field survey of human-elephant conflict in the Eastern Chure Landscape

The survey is intended to access the perception on the elephant conservation and Human-Elephant Conflict in the Chure region of Eastern Nepal. With your permission we would like to fill up the questionnaire for the purpose. The data will only be used for propose of the research. We do not indent to publicize the information you have provided for that may in any case your privacy.

Name of Surveyor: Municipality Surveyed:

GPS: Date:

Name of Respondent: Gender:

Education: Occupation:

Age:

Annual Income (NRS per annum):

<20000 50000-100000 >500000

20000-50000 100000-500000

Are you a member of any conservation Society: Yes No

Have you seen an elephant?

Do you like observing elephants?

Do you think elephants are directly or indirectly beneficial to you? Why?

In the past 5 years, have you or someone around you seen an elephant around your locality?

How far did you observe the elephant?

Did the elephant damage people, households, crops, or livestock?

Do you think the human-elephant conflict has increased lately?

Which season is most affected by the Human-Elephant Conflict?

Spring Autumn None

Rainy Winter