INTEGRATING GEODESIGN AND GEOAI APPROACHES TO STUDY HUMAN-ELEPHANT INTERACTIONS IN SOUTHERN AFRICA

by

ELLEN C. DELGADO FLORIAN

(Under the Direction of Marguerite Madden)

ABSTRACT

GeoDesign and Geospatial Artificial Intelligence (GeoAI) were to analyze human and elephant interactions in Victoria Falls, Zimbabwe. GPS movement data from 22 male elephants were used to identify their preferred habitat during the 2020 wet season. Human land use for urban development and subsistence agriculture was and input to the Land-Use Conflict Identification Strategy (LUCIS) model. The study found 62% of the study area had moderate-intensity elephant-urban conflict. Although low conflict between elephant habitat and agriculture and between agriculture and urban land uses in 88% of the study area, high conflict was predicted in the city and agricultural fields. Combining the three suitability models resulted in 47% of the study area likely to experience low conflict for elephant, urban, and agricultural land uses, 46% moderate and 4.5% high conflict in the wet season. These findings can inform public policy to support local planning towards reducing human-elephant conflict in Victoria Falls.

INDEX WORDS: Human-elephant interactions, GeoAI, GeoDesign, Victoria Falls, Ecology GIS

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ELLEN C. DELGADO FLORIAN

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ELLEN C. DELGADO FLORIAN

Major Professor: Marguerite Madden

Committee: Sergio Bernardes
Rosanna Rivero
Gengchen Mai

Electronic Version Approved:

Ron Walcott
Vice Provost for Graduate Education and Dean of the Graduate School
The University of Georgia
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DEDICATION

I dedicate this work first and foremost to all Latin American colleagues who strive for excellence and access to quality education.

I also dedicate this work to the new generation of women in academia and especially in the geospatial field who will be change makers and a source of inspiration for future generations.

Finally, I dedicate this work to the environmental conservation movement of the world that seeks to put geospatial technology and artificial intelligence in favor of good deeds, such as the care of life, respect for human intellectual property and in general the defense of humans and all living beings' rights.

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TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

Page

CHAPTER 1

INTRODUCTION, RESEARCH OBJECTIVES, AND STUDY AREA

Introduction

Conflict between humans and elephants, referred to as Human-Elephant Conflict (HEC), is very common wherever they coexist Seoraj-Pillai and Pillay (2017). In Victoria Falls, Zimbabwe, negative interactions are becoming more frequent due to increasing numbers of human and elephants (Teagle, 2022). Historical data from National Parks of Zimbabwe indicate that the stationary population of 2,000 elephant has increased to 45,000 since 1928 (Teagle, 2022). Urban development, pollution, and increased tourism within the Mosi-oa-Tunya/Victoria Falls World Heritage property in both Zimbabwe and Zambia further interrupt the migration routes of elephants and bring people and elephants into ever closer contact (UNESCO, 2006). Today, elephants are both a blessing and a challenge: they are a draw for tourism, but they also damage crops and sometimes come into deadly conflict with people (Karidozo et al., 2016; Teagle, 2022). Elephants that frequently wander into human settlements or become violent are classified as problem animals, and ultimately shot by Parks and Management (Osborn, 2015).

Adverse climate conditions in Africa, such as droughts, also increase competition for natural resources between humans and wildlife (Kappelle, 2020; Salerno et al., 2021). In 2019, Victoria Falls suffered the most severe drought in 20 years; in fact, it was one of the three warmest years on record on the continent (Kappelle, 2020). Consequently, elephant incursions into human settlements in search of food and water increased. Park agencies reported the death of 33 people from animal conflicts in that year alone (Fox, 2019). More than 100 elephants died in nature reserves from water and food scarcity (CBS, 2019), and more than 400 died the following year from cyanobacteria proliferation in waterholes in the neighboring Okavango Delta region of Botswana (BBC, 2020; Veerman et al., 2022). According to climate projections, the southern regions of Africa will experience a demographic expansion and a decrease in precipitation starting in the 21st century for the Representative Concentration Pathway of 8.5 (RCP 8.5). This is a scenario where the concentration of carbon in the atmosphere that delivers global warming would be an average of 8.5 watts per square meter across the planet. In the RCP 8.5 the temperature will increase about 4.3˚C by 2100 (IPCC, 2014; Masson-Delmotte et al., 2021). This climate scenario sets the stage for increased competition between humans and elephants for natural resources, as well as the likelihood of conflict occurrence (Salerno et al., 2021).

Efforts to investigate HEC in Victoria Falls, Zimbabwe are being conducted by researchers of Connected Conservation who have generated a large amount of spatial data on elephant GPS movement, land use and local ecological knowledge (Langbauer et al., 2021; Osborn, 2015; Presotto et al., 2014). This information, analyzed with Geographic Information Systems (GIS), has the potential to increase our understanding of human-elephant space-use (Buchholtz et al., 2019; Buchholtz et al., 2020) and provide tools for local organizations to make decisions related to HEC based on geospatial information. Modeling involving complex data and understanding of the dynamics in urbanized ecosystems merits synergies between GeoDesign and GeoAI (Mortaheb & Jankowski, 2023). GeoAI refers to the integration of geospatial studies and artificial intelligence (AI), especially machine learning and deep learning methods and the latest AI technologies (Gao, 2021). GeoAI can be regarded as a study subject to develop intelligent computer programs to mimic the processes of human perception, spatial reasoning, and discovery about geographical phenomena and dynamics; to advance our knowledge; and to solve problems in human environmental systems and their interactions, with a focus on spatial contexts and roots in geography or geographic information science (GIScience) (Gao, 2021).

GeoAI, has proven to be efficient for modelling spatial problems due to its great flexibility to perform models that explain the influence of spatial variables in the study of land use, species distribution, and the identification of objects of interest in space, among others (Alastal & Shaqfa, 2022). This can improve accuracy and support suitability modeling, which is an important analysis in GeoDesign planning frameworks such as the Land Use Conflict Identification Strategy (LUCIS) (Carr & Zwick, 2007). LUCIS provides a flexible framework for spatial planning with multi-stakeholder involvement, making the process of urban planning inclusive and adapted to local scales.

The objective of this research is to study human-elephant interactions by identifying areas of potential conflict using the LUCIS model framework in the vicinity of Victoria Falls, Zimbabwe in Southern Africa. Combining GeoAI and Geoscience approaches with domain knowledge of elephant ecology, local subsistence agriculture, and urban development in Victoria Falls, three perspectives will be integrated into the LUCIS model. First, suitability analyses for sustainable agriculture and urban/commercial/residential development were conducted using spatial data and expert knowledge of local landscape use. Next, a suitability model of areas important for elephant conservation was created. For this purpose, GPS movement data from 22 male elephants considered problem bulls was analyzed using the presence only Maximum Entropy (MaxEnt) model. Maxent is a correlative machine learning model often used to estimate the presence of a phenomenon in a study area using previously known presence locations and explanatory factors. The three sub-models were aggregated by weighted overlap to obtain potential conflict zones and opportunities for interactions between humans and elephants. The results of this study will be made publicly available in the format of a StoryMap posted on the website of our local partners. This tool will help identify the most vulnerable areas for human-elephant interactions and design strategies to address and mitigate human-elephant conflicts.

Research Objectives

The primary goal of this research is to identify areas of potential conflict between humans and elephants in Victoria Falls using the LUCIS model, to assist in a GeoDesign of best planning practices for urban development, local subsistence farming and elephant conservation. To achieve this goal, there are three objectives:

1. Identify landscape-scale elephant land use preferences using tracking GPS data from 22 elephants collected from 2017- 2021, elephant behavior in response to environmental variables and human features and GeoAI models for the wet season. The results identify critical areas for elephant conservation.

2. Model suitable areas for human development and agriculture sustainability, using raster and vector data, as well as preferences of stakeholders and create suitable maps for the development of human activities (i.e., urban/residential development and sustainable subsistence agriculture).

3. Implement the LUCIS model to identify areas of potential conflict between

different stake holders (urban/residential development, subsistence agriculture) and elephants to mitigate human-elephant conflict and assist in the implementation of a GeoDesign for future development, agriculture and wildlife conservation in Victoria Falls, Zimbabwe.

Study Area

The study area encompasses an area of 52,006.8 km^2 including the city of Victoria Falls, Zimbabwe, communal lands used for subsistence agriculture, and surrounding conservation lands and private game reserves. The city of Victoria Falls had a population of 35,761 inhabitants in 2023 and is in the province of Matabeleland North in Zimbabwe, Southern Africa. It lies on the Southern bank of the Zambezi River at the binational and world-famous Victoria Falls (Figure 1). The city is a few kilometers south of Livingstone, Zambia, and is surrounded by the Zambezi, Mosi-oa-Tunya, and Victoria Falls National Parks. The area encompassing the Kavango and Zambezi River Basins is one of the world’s largest wildlife sanctuaries and is home to a diversity of species (Linell et al., 2019; Reichelt-Zolho et al., 2021).

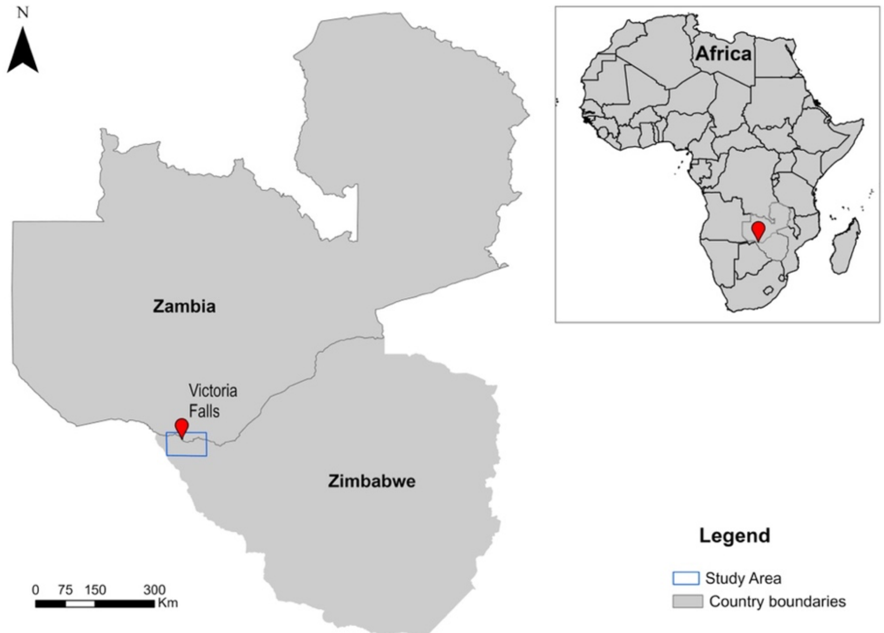

Figure 1. The Victoria Falls study area is in the northwest corner of Zimbabwe and extends into Zambia north of the Zambezi River.

This area is designated as the Kavango-Zambezi Transfrontier Conservation Area (KAZA TFCA) (Figure 2) and includes more than 3,000 plant species and 500 bird species in savannas, wetlands, and forests. According to the World Wildlife Fund (WWF), the KAZA TFCA is home to Africa's largest contiguous and free ranging elephant population (TFCA, 2019).

The elevation in the study area ranges from 200 m to 840 m, featuring a wide diversity of ecological habitats (Dennis, 2000). The average precipitation in the area is between 450 and 500 mm with rainfall varying greatly between the dry and wet seasons (Victoria falls-guide, 2023). In winter, May to mid-August, the average high temperatures range from 25-27°C (77-81°F) and average lows between 7-10°C (45-50°F). Summer, mid-August to the end of April, includes a rainy season (mid-November to April). The average highs are between 32-34°C (90-93°F) and average lows between 15-19°C (59-66°F) (Victoria falls-guide, 2023). Recently, land cover vegetation mapped by the German World Wildlife Fund (WWF) identified 18 land cover/land use types (Gebhardt, 2021). The main land cover types are sparse herbaceous, open herbaceous wetland, closed forest, woodland, closed bushland, sparse/open bushland shrubs, open woodland/bushland/shrubs, and permanent and stationary water bodies. The area is well known as a destination for international visitors, largely maintained by tourist activities which are popular due to the excellent view of Victoria Falls (UNESCO, 2006).

Figure 2. The Kavango-Zambezi Transfrontier Conservation Area (KAVA TFCA) includes the Kavango River and Zambezi River Basins extending over five countries in Southern Africa (i.e., Angola, Namibia, Botswana, Zimbabwe, and Zambia). This research focuses on the red circle area (adapted from: https://www.kavangozambezi.org/maps).

CHAPTER 2

REVIEW OF CONCEPTS AND LITERATURE

This chapter provides an overview of the literature and key concepts that are fundamental to this research. The discussion covers: 1) Human- Wildlife Interactions literature; 2) Human Wildlife Conflict; 3) Historical Perspective of Human-Wildlife Conflict; 4) Remote Sensing and GIS Modeling for Wildlife Conservation; 5) Land- Use Conflict Identification Strategy (LUCIS) Model and 6) Previous Studies on Human-Elephant Conflict and Elephant Movements.

Human-Wildlife Interactions

At some point in their lives, animals living in or in proximity to urban areas will likely interact with humans because of the high density of human population in these areas. These interactions vary on a continuum from positive and neutral through to negative, vary in intensity from minor to severe, and vary in frequency from rare to common (Nyhus, 2016). Negative interactions, more correctly termed human–wildlife conflict, arise as a product of socio-economic and political influences, primarily because of competition between people and predators for shared, limited resources (Graham et al., 2005).

While humans and animals have co-existed for millennia, the frequency of conflicts has grown in recent decades, largely because of the exponential increase in human populations and the resultant expansion of human activities (Conover, 2002). However, it has been studied that ecologically similar species that co-occur and share similar habitats typically display some degree of niche partitioning as natural selection favors traits that reduce competition. By consuming different resources or by utilizing resources in different places or at different times, sympatric species manage to coexist (Syme et al., 2023).

Human interactions with wildlife, however, are often framed negatively even if important positive benefits exist. Wildlife may contribute to the provision of ecosystem services in urban areas, and some recent work has shown how interactions with wildlife can provide a range of benefits to health and wellbeing (Soulsbury & White, 2015). As a result, there is a growing convergence around the phrase human-wildlife conflict (HWC) and coexistence to connote the recognition of both problems and solutions (Nyhus, 2016). For example, this may be accomplished through the establishment of financial instruments called "Payments to encourage coexistence" (PEC) (Dickman et al., 2011) or suggesting management of HWC that is responsive to conflict in a holistic and creative way including social, cultural, historical, biological, ecological, political, historical, economic, and geographical components (Madden, 2004). Although some authors question that coexistence is confused with, what is in fact, co-occurrence (Harihar et al., 2013).

Human-Wildlife Conflict

In the manuscript, "Human–Wildlife Conflict and Coexistence," Nyrus (2016) describes Human–Wildlife Conflict (HWC), including perspectives from various authors, as "conflict that occurs between people and wildlife (Woodroffe et al., 2005); actions by humans or wildlife that have an adverse effect on the other; threats posed by wildlife to human life, economic security, or recreation (Treves & Karanth, 2003); or the perception that wildlife threatens human safety, health, food, and property (Birckhead et al., 2010)." It is also mentioned that the term "wildlife" is defined broadly as non-domesticated plants and animals (Reidinger & Miller, 2013), although domesticated and feral animals are sometimes included in the HWC literature.

Human-Wildlife Conflict escalates when local people feel that the needs or values of wildlife are given priority over their own needs, or when local institutions and people are inadequately empowered to deal with the conflict. If protected area authorities fail to address the needs of the local people or to work with them to address such conflict adequately, the conflict intensifies, becoming not only conflict between humans and wildlife, but also between humans about wildlife (Madden, 2004). The impact of HWC is more serious in the tropics of the developing world than in the developed world because of these countries' greater dependence on livestock as a livelihood strategy and source of income. In the KAZA TFCA, there are at least four aspects of HWC, namely: (1) space conflict; (2) crop raiding; (3) death of humans; and (4) predation of livestock. In addition, conflict also occurs when there is general destruction of property by wild animals (Osborn, 2004).

Historical Perspective of Human-Wildlife Conflict

Our earliest historical records document close interactions with wildlife in paleolithic cave paintings of people interacting with wildlife on multiple continents (Guthrie, 2005). Humans competed with wildlife for natural resources and habitat, and eventually became the dominant ecological force on the planet (Nyhus, 2016). The net effect of human alteration of the planet has been the loss of natural biomes to agriculture, cities, roads and other human developments, and the replacement of wild animals and plants with domesticated species to meet the growing demand for food. (Waters et al., 2016). For hundreds of years people viewed wildlife as adversaries and sought to reduce their impact by killing them (Frank et al., 2019). At its most extreme, this has included a strategy of eradicating entire animal populations or even entire species (Treves & Karanth, 2003). This conflict has led to the extinction of numerous species (Woodroffe et al., 2005) including Pleistocene megafauna (Barnosky et al., 2014), changing ecosystem's structure and functions (Conover, 2002); and immeasurable loss of human life, crops, livestock, and property (Conover, 2002; Woodroffe et al., 2005). Nowadays, conflicts tend to be long running and are of considerable economic importance in many parts of the world. They share the common characteristic of a well-defined regime of management of land, human and animal resources (Graham et al., 2005). Conflict frequency can be highly variable within and among geographic regions (Nyhus, 2016). As a tropical continent with substantial anthropogenic development, Africa is a hotspot for biodiversity (Myers et al., 2000) and therefore, for human-wildlife conflict (Seoraj-Pillai & Pillay, 2017). In South Africa, approximately 30% to 55% of poor, local community members reported HWC occurrences due to problem animals from neighboring protected areas (Spenceley, 2005). Livestock depredation by lion (Panthera leo) and spotted hyena (Crocuta crocuta), crop raiding by baboon (Papio papio) and African elephant (Loxodonta African) were reported (Seoraj-Pillai & Pillay, 2017; Spenceley, 2005).

The impact of HWC is more serious in the tropics of the developing world than in the developed world because of these countries' greater dependence on livestock as a livelihood strategy and source of income (Karidozo et al., 2016).

Remote Sensing and GIS Modeling for Wildlife Conservation

Understanding spatial interactions between humans and wildlife can be performed using geospatial mapping, modeling, and analysis. Geospatial models can quantify landscape attributes that correlate with incident sites (Ruda et al., 2018). Such information is vital for wildlife management purposes, protection of the elephant population, maintenance of ecosystem health, decision making and effective mitigation of HEC within the park and neighboring local communities (ALERT, 2023).

In recent years, conservation project managers have increasingly turned to technological innovations to enhance wildlife monitoring, and remote-sensing devices deployed in space, in the air and on the ground are more realistic and affordable options than ever before (Stephenson, 2019). Satellite-based remote sensing of wildlife habitats and (sometimes) wildlife populations (Pettorelli et al., 2014) has been implemented by the newest generation of ground-based sensors, including camera tramps, acoustic recordings devices (Alvarez-Berríos et al., 2016) and unmanned aerial vehicles (Christie et al., 2016; Thapa et al., 2018). These remote sensing technologies provide new opportunities for enhancing the quality and volume of wildlife monitoring data and reducing the time people need to spend on the ground to collect it (Stephenson et al., 2015).

Some authors suggest that remote sensing needs to be applied only when appropriate to the local situation and when it can be used to answer specific monitoring questions with the budget and necessary technical skills (Schmeller et al., 2017; Stephenson, 2019). However, in the last years, Geoservers have been launched and online applications that reduce the technical knowledge and accessibility to remote sensing data in the world, such as Climate Engine, Google Earth Engine, Global Forest Watch (Hansen et al., 2013) and with emphasis in the Tropics like the Norway's International Climate & Forests Initiative (NICFI) (NICFI, 2023) to mention a few examples.

MaxEnt

A facet of spatial analysis focuses on modeling and estimating the occurrence of an event across geography. While common examples relate to modeling species presence for ecological and conservation purposes, presence prediction problems span a variety of domains and applications (Elith et al. 2011).

As explained by Esri (2022), “In some cases, presence data is recorded as a count of presence events in quadrat cells: each observation increments a count at its location, and a variety of modeling approaches can be used to model this count, such as the Poisson method of the Generalized Linear Regression tool. In other cases, explicit presence and absence data is recorded at specified intervals in known locations, such as air quality monitoring stations recording unhealthy ozone levels. In these cases, modeling presence and absence is a binary classification problem that can benefit from a variety of methods, such as logistic regression” (Esri, 2022).

“In the case of ecological species modeling and several other domains, where the presence of an event is often recorded but the absence of the event rarely is, the lack of explicit absence data makes it challenging to model presence and absence using multiclass prediction methods” (Esri, 2022).

MaxEnt is a general-purpose model for making inferences from incomplete information (Phillips et al., 2006). Unlike other predictive modeling methods, it does not assume nor require absence data and uses a set of known presence locations and other explanatory variables that describe the situation and the study area. MaxEnt compares the conditions of the presence locations, the study area wherein the presence is possible, known as background points, and covariates that characterize environmental factors potentially related to the presence of the phenomenon to be predicted (Esri, 2022). The outcome is a presence probability surface that can take many forms. The selected form most closely resembles the environment the presence points were taken from, while also reducing all other assumptions (i.e., maximizing entropy). “It agrees with everything that is known, but carefully avoids assuming anything that is not known." (Jaynes, 1990)

Land- Use Conflict Identification Strategy (LUCIS) Model: A GeoDesign approach

GeoDesign is a design framework and supporting technology that leverages geographic information to create designs that more closely follow natural systems (Esri, 2014). GeoDesign draws inspiration from various fields, including architecture, engineering, landscape architecture, urban planning, traditional sciences, etc., and takes a holistic and complementary view of the design process that incorporates the various stakeholders (Dangermond, 2010). In the context of GeoDesign, design is facilitated by a collaborative process where the computers respond to changes in design as it is being built by various stakeholders (Rivero et al., 2015).

The LUCIS model is a long-term GeoDesign planning framework that facilitates local stakeholders to explore a space of common interest to identify areas of potential conflicts and opportunities based on their interaction in space (Carr & Zwick, 2007, Zwick et al. 2015). The methodology was introduced by Paul D. Zwick and Margaret H. Carr of the University of Florida in their paper Using GIS Suitability Analysis to Identify Potential Future Land Use Conflicts in North Central Florida (Carr & Zwick, 2005). In essence, LUCIS is a GIS suitability analysis that divides the landscape into three differing land-use classes based on potential future land-use conflict (Carr & Zwick, 2007). This model allows users to identify suitable locations within a user-defined extent for any land use based on any number of social, economic, ecological, or other criteria the user chooses (Godfrey, 2010). In this case, areas of suitability represent areas of interest for the development of certain activities and can show real areas of convergence when all these areas of suitability overlap. The result can be interpreted as areas of potential conflict or opportunity if one looks in detail at the form, the intensity with which these activities are carried out in the same space, as well as the natural resources that are compromised. One of the advantages of this model is its flexibility to design scenarios based on preferences and agreements. This can help local stakeholders to visualize the consequences of certain decisions and contribute to the decision-making process for local resource management (Carr & Zwick, 2007).

Multiple applications of the LUCIS model have been conducted in areas of critical concern to human activities and of high biodiversity value. Trust et al. (2020) implemented LUCIS to identify the areas of greatest conflict between the solar farm development and the habitat of key threatened species, such as the gopher tortoise (*Gopherus polyphemus*) and the American black bear (*Ursus americanus*) in Georgia. In 2014, Miami-Dade County partnered with a NASA DEVELOP team from the University of Georgia to incorporate space-based observations into the Greenway planning. The project team integrated NASA satellite data on land cover, vegetation, and tree canopy parameters into the LUCIS model. The team used LUCIS to determine the best locations along the Greenway for recreation, conservation, and ecotourism. In turn, this helped guide more specific design elements of the Greenway project, such as the alignment of trails (NASA Applied Sciences, 2020).

In the tropics, the LUCIS model has been helpful in modeling land-use conflicts between agricultural use, urban development, and indigenous land rights. Markham et al. (2020) and a NASA DEVELOP team worked with La Amistad International Park in southern Costa Rica and northern Panama to implement sustainability objectives and communication strategies within the region. The process included partners from Costa Rica and Panama, for the construction of objectives, collection of spatial information, and validation of the model. The team created a LUCIS model based on land cover maps for 2019 and 2029 that were created in Term I of the DEVELOP project using Landsat 8 Operational Land Imager (OLI) imagery. With input from partners, the team applied weightings to the different targets and combined suitability maps to identify areas of potential biodiversity conflict.

In Africa, research conducted by Ecoexist Director, Anna Songhurst, in collaboration with local communities, the land management authority, other government stakeholders and USAID enabled the implementation of the LUCIS model to manage human-elephant conflict. (Equator Initiative, 2022). This process had community participation and local resource and land use needs and preferences at its core. The development of the model involved several years of consultations, expert GIS mapping, and frequent stakeholder exchanges. The model also incorporated other land use conflicts and sustainable benefit-generating activities in the corridors, resulting in a comprehensive land use plan and map to guide future land allocation. The territory authorities have asked Ecoexist to conduct corridor identification and analysis of similar elephant movements on the western side of the Okavango Delta, with a view to initiating the same land use planning process and planning map development there as well. The need for this process is increasingly recognized as part of a holistic strategy to reduce wildlife conflict, promote human-wildlife coexistence, enhance food security, and generate alternative livelihood opportunities with a sustainable development approach. The LUCIS process and the resulting land use plan map have also been approved by the Ministry of Lands and have recently been included in the country's National Development Plan No. 11 (Equator Initiative, 2022).

Previous Studies on Human-Elephant Conflict and Elephant Movements

Animal size is often a good predictor of conflict (Nyhus, 2016). Large vertebrate herbivores dynamics such as trampling or directly consuming natural resources, can alter ecosystems (Estes et al., 2011), mostly to the detriment of other species, including humans (Ripple et al., 2015). A wide variety of animals, including species in the order Proboscidea (elephants), commonly come into conflict with people. When conflict occurs, the most common solution is to kill the elephant (Osborn, 2015). This has led to the reduction of large herbivore communities and collapsing home ranges (Ripple et al., 2015). For instance, elephant, hippopotamus (*Hippopotamus amphibious*), and black rhinoceros (*Diceros bicornis*), now occupy just small fractions (19 percent) of their historical ranges in Africa (Ripple et al., 2015). As a result, HEC is rapidly increasing as elephants are being compressed within their natural range alongside burgeoning human populations, resulting in damage, economic losses, injuries, and death of people and elephants (Dunham et al., 2010; Henley et al., 2023).

In the Kavango-Zambezi Transfrontier Conservation Area (KAZA TFCA), there are at least four aspects of HWC, namely: (1) space conflict; (2) crop raiding; (3) death of humans; and (4) predation of livestock. In addition, conflict also occurs when there is general destruction of property by wild animals (Karidozo et al., 2016). Human-Elephant Conflict is growing as the wildlands that still have elephants, especially around national parks, reserves, and wildlife corridors, are increasingly being settled or encroached upon (Chang'a et al., 2016). However, the corridor regions link protected areas where most of the conflict occurs (Henley et al., 2023).

Current conflict management approaches focus on prevention through exclusion, on-site deterrents, and mitigation via elephant translocation or selective culling and monetary compensation for losses (Shaffer et al., 2019). Some deterrent methods, such as the use of beehives (King et al., 2018; Van de Water et al., 2020), chili fences (Chang'a et al., 2016) and electric fences (Kioko et al., 2008), seem to reduce, but not eliminate, HEC and property loss (Karidozo et al., 2016). However, the required permanent infrastructure is expensive and difficult to deploy quickly. As with most HEC, it is individual elephants, not the species, that are responsible for this conflict (Langbauer et al., 2021). Bull elephants are especially prone to HEC between the time they are forced to leave their family groups in their teens and when they are strong enough to challenge the largest bulls breeding with cows in family groups (personal communication). For approximately 30-40 years, bull elephants travel alone or in small groups, spending much of their time foraging, and exhibiting aggressive behavior due to their annual hormonal cycle of musth that lasts days to several months and doubles their testosterone levels (Wildlife SOS, 2020).

Using spatial data to understand human and elephant interaction and use of space has been studied by local and international research groups. Osborn (2002) and Karidozo and Osborn (2015) studied the effects of elephant movement in communal lands under the influence of chili pepper (Capsicum oleoresin), an elephant repellent. Analyzing GPS elephant movement and crop damage they found elephants were repelled from fields significantly faster, confirming the potential fuse of chili pepper as a deterrent to mitigate HEC. Later, in 2021, a study revealed information on spatial movement responses before and after the effects of disrupting darting on elephants at Victoria Falls using chili wax (Langbauer et al., 2021; Presotto, 2021). The results showed that the elephant appeared to associate the unpleasant event of being darted and rubbed with chili wax, with a particular location, and perhaps with the people at that location, rather than with people in general. This research is increasing our understanding about the cognitive processes of an intelligent non-human animal in the area and showed an alternative method to killing with beneficial long-term results (Langbauer et al., 2021).

Inclusion of ecological knowledge (IEK) has been included in the study of human and wildlife knowledge in Kenya (Sitati & Ipara, 2012). They found that respondents had in-depth knowledge of some key ecological processes, confirming the potential of working with local communities in the modelling process of HEC using spatial data. Overlapping landscape utilization by elephants and people in the Western Okavango Panhandle have revealed that elephants ranged increasingly farther from permanent water sources as the wet season progressed, while in the same time frame elephants moved closer on average to human land-use. Elephants were more likely to be near human land-use during the night than they were during the day. Diel patterns of elephant proximity to human land-use did not match patterns of proximity to water (Buchholtz et al., 2019a).

Buchholtz et al., (2019b) also investigated how humans and elephants in Botswana utilize trees, comparing spatially explicit firewood collection locations and movement data from elephant GPS collars to model resource selection by people and elephants. They found that people and elephants utilized the same species of trees and had correlated spatial patterns of resource selection. Proximity to settlements was a strong driving factor for people in firewood collection, while various factors including vegetation characteristics played a role in predicting elephant movement. Areas where people collect firewood were negatively correlated with daytime elephant movement and positively correlated with nighttime elephant movement. (Buchholtz et al., 2019b). Similar research has been conducted in Sumatra using second-order resource selection functions (Sitompul et al., 2013). Results indicate that elephants probably utilize a variety of forest types, ranging from open canopy to closed canopy. Open and mid-canopy land covers are probably the most important habitats for foraging, whereas closed-canopy forests may be the most important for thermoregulation. They also reported that elephant distribution is influenced by human activities in some areas; when forests are completely replaced by agriculture, elephant conflicts are likely to arise, and elephants are less likely to use even closed-canopy forests close (on the edge or border) to such human activities (Sitompul et al., 2013).

Using tracking data from 101 African elephants collected between 2001 and 2016, Bastille-Rousseau et al., (2020) investigated elephant behavior in response to vegetation cover, topography, productivity, water, human characteristics, and human predation risk using third-order resource selection functions. Using a mixed-effects multinomial regression analysis to identify temporal changes in habitat use, they assessed temporal changes in movement patterns by estimating mean square displacement at different periods of productivity. They found that in all periods, elephants showed a strong selection of productive and near-water areas. Temporal changes in habitat use showed that, during the dry period, elephants clustered around permanent water sources where humans also congregated. At the onset of the wet period, elephants tend to move away from permanent water and permanent settlements towards seasonal water sources and seasonal settlements. The authors concluded that foraging and access to water are important limiting factors affecting elephants and potentially constraining their spatial responses to humans at the regional scale.

Connectivity models also have been developed for the African savanna elephant in northwestern Botswana based on step-selection functions of movement data for 15 elephants; and it was tested whether areas of high connectivity were correlated with occurrences of crop raiding (Buchholtz et al., 2020)). The step-selection model revealed that linear boundaries such as rivers, fences, and dune crests were barriers to movement that impacted connectivity, while high vegetation index values and distance from villages were strong positive predictors of movement. Connectivity values were positively and significantly correlated with frequency of conflict incidents. However, connectivity had no predictive value for whether fields were raided or how frequently a field was raided during a single growing season (Buchholtz et al., 2020).

MaxEnt has been successfully used to model the presence of wildlife in their habitat. Howard et al. (2015), for example, used MaxEnt to model the movement of wild bearded capuchin monkeys (*Sapajus libidinosus*) related to landscape features in northeastern Brazil. Elephant movement using clustering has been extensively studied. Glazer et al., (2021) used K-means and DBSCAN to find locations of interest in Sub-Saharan Africa. They obtained promising results using DBSCAN for discriminating locations of foraging or resting from trajectories. This confirmed that elephants tend to cluster their movement around sources of water as well as some human settlements, especially those with water holes. In India, K-means was used to determine hotspots of HEC (Tripathy et al., 2021). Crop damage was the most frequent form of HEC in the study area, followed by house damage and loss of human lives (Tripathy et al., 2021). This work though, not only addresses the problem of identify critical areas for elephant habitat conservation using a Maximum Entropy (MaxEnt) machine learning model, but also integrates these methodologies into improving suitability analyses to identify potential areas of land use conflict.

CHAPTER 3

METHODOLOGY FOR MODELLING POTENTIAL AREAS OF HUMAN-ELEPHANT CONFLICT

Spatial Data Sources

To investigate areas of potential conflict between humans and elephants in the Victoria Falls study area, a search was conducted to locate existing spatial data related to human and elephant land use. Details on the data sources are described below.

Landscape-scale Elephant Habitat Preferences

To understand the landscape-scale elephant habitat preferences, elephant GPS movement data collected in Victoria Falls since 2017 by the NGO, Connected Conservation, was used in this study (Figure 3). Raster data of land use were also collected to identify elephant resources selection. These covariates included a 10-m land cover classification derived from 2020 Sentinel-2 A/B satellite imagery by the German World Wildlife Fund (Gebhardt 2021). Water bodies and roads were obtained from OpenStreetMap.org using the OSMD Downloader and QuickMapServices extension of QGis 3.22.3, and the Accumulate Distance was calculated. We Also download the boundaries of KAZA protected areas from Living Atlas in ArcGIS Pro. Since elephants have different levels of tolerance and exposure to humans' presence and can modify their foraging routes according resources availability (Bastille-Rousseau, 2020), the influence of human disturbance on elephant resources selection was investigated using variables of distance to build areas and crops extracted from the 2020 Sentinel Land Cover Classification of the KAZA TFCA (Gebhardt, 2021).

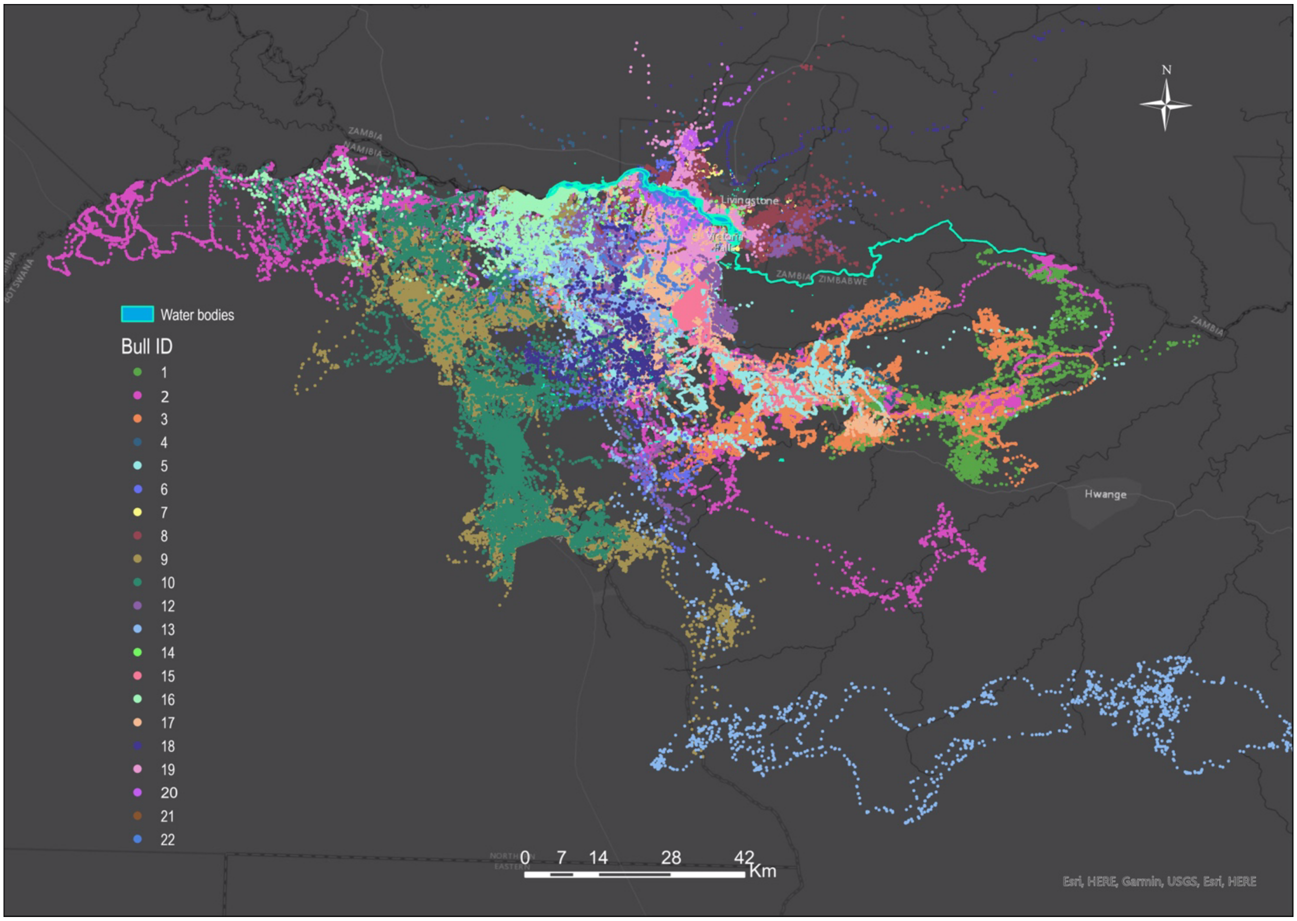

Figure 3. GPS Movement Data for 22 Elephants in the Vicinity of Victoria Falls. Data Have Been Aggregated from 2017 to 2021 and Color Coded by Bull Elephant.

Suitable Areas for Human Activities of Development and Agriculture

The Land Cover Classification based on 2020 Sentinel imagery for Kavango Zambezi Transfrontier Conservation Area (KAZA TFCA) identified 14 land use/land cover types in our study area (Gebhardt, 2021, Figure 4). To complete the goals and objectives defined by the partners we prepared a suitability matrix that guided the data collection and modelling for agriculture and urban/commercial development.

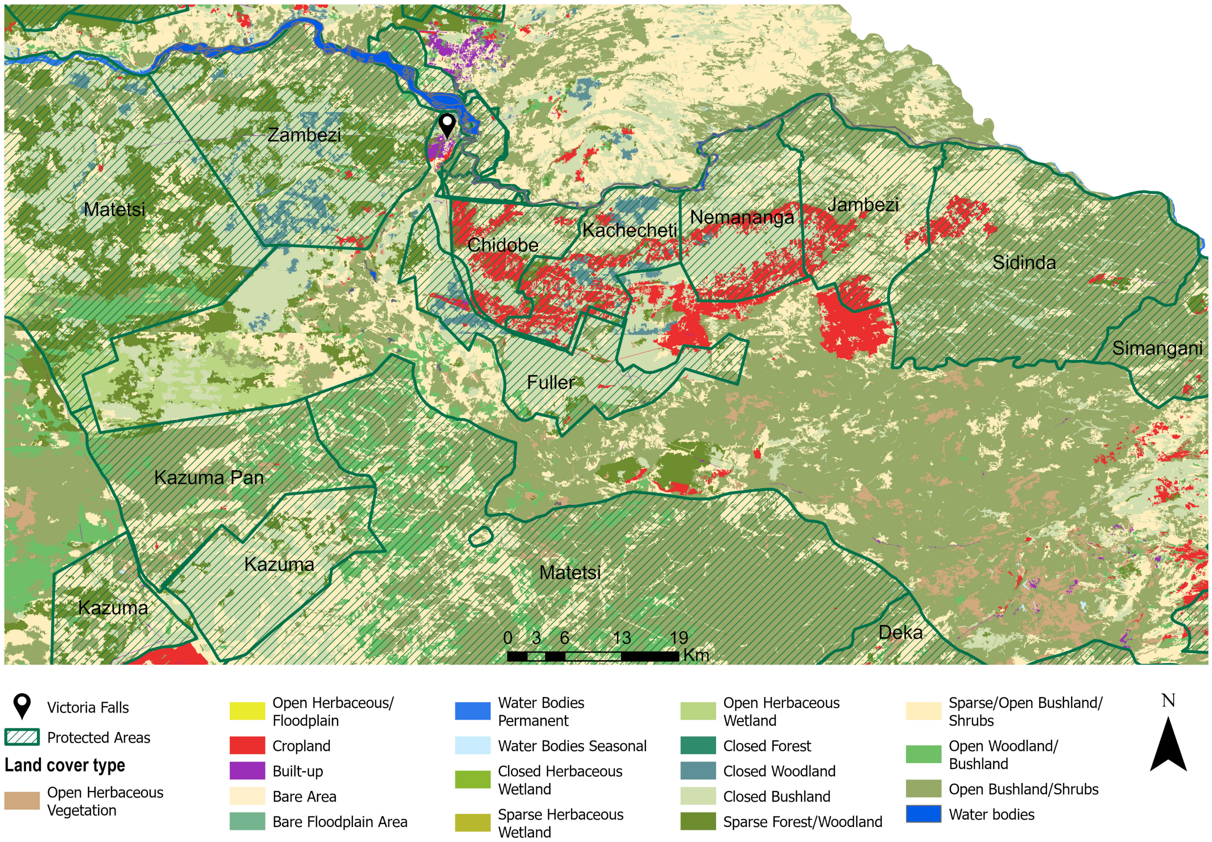

Figure 4. Land Use/Land Cover in the Study Area Based on 2020 Sentinel-2 Imagery. KAZA Land Cover (Gebhardt, 2021).

Vector data of different urban uses were downloaded from OpenStreetMap using the OSMD Downloader and QuickMapServices extension of QGis 3.22.3. This dataset included existing built areas, roads, commercial areas, tourist attractions, water bodies and wildlife viewing sites. The Euclidean distance to all these layers was calculated and reclassified to 0, 500, 100, 1000 and 1500 m.

To model suitable areas for subsistence agriculture, raster data of the existing crop areas in Victoria Falls were extracted from the Kavango Zambezi Transfrontier Conservation Area (KAZA TFCA) Land Use/Land Cover layer. The Euclidean distance to roads, water bodies, communal lands, and existing crop areas was also calculated. The resulting proximity layers were then reclassified to 0, 500-, 100-, 1000- and 1500-m distances to feature.

Data Analysis

The data sources are diverse and thus allow the LUCIS model to be a robust representation of the complex problem areas of potential human-elephant conflict. By combining socioeconomic factors related land use and elephant movement GPS data, most facets of the conflict problem will be addressed. The data analysis section is organized by a description of each of the three sub-models: Suitable areas for elephant conservation, areas of agricultural activity and urban/ commercial development, and the last section describes the implementation of the LUCIS model.

Suitable Areas for Elephant Habitat Conservation

To identify critical areas for elephant habitat conservation we modelled their potential presence in the wet season of 2020 in the study area using GPS collar data of 22 elephants, categorical variables (LUC) and distance features using the Presence-only Prediction (MaxEnt) tool in ArcGIS Pro.

Presence-only Prediction (MaxEnt) tool in ArcGIS Pro

MaxEnt was implemented using categorical (land use land cover) and continuous variables (Distance feature) (Table 1). This approach uses a maximum entropy approach (MaxEnt) (Phillips et al., 2009) to estimate the probability of presence of a phenomenon. The tool uses known occurrence points and explanatory variables in the form of fields, raster, or distance features to provide an estimate of presence across a study area (Esri, 2022).

The easiest way to understand this tool is to think of it as a special logistic regression. First, some transformations to the explanatory training variables (i.e., distance to water bodies, distance to roads, distance to protected areas, distance to build- up areas) were applied. This added a little bit of complexity to the model, but also a better fit and better prediction power. To obtain these variables the “Aaccumulate Distance” function was calculated.

Second, background points were generated in the extent of the study area. Those were locations in the study area that have potential to see the presence of the elephants. What is cared for the most in this process, is whether presence locations are predicted to be present, but not if background locations are predicted to be absent. Third, the model used elastic net, which is a combination of lasso regression and ridge regression, to eliminate non-necessary variables and give relatively small betas to the variables.

Like most machine learning methods, the MaxEnt model trains, validates, and predicts. This process was included inside the Presence-Only Prediction tool of ArcGIS Pro, together with some upfront data processing steps, including spatial thinning (Esri, 2022). The geoprocessing time took around six hours per iteration, in the end Geoprocessing Messages and charts were created to help interpret the results.

Since the combination of continuous and categorical variables did not allow prediction over the entire study area and it presented limitations to prepare all the trained products like the response of categorical variables, it was decided to run two models. One model was for categorical land use/land cover and the other model for continuous variables, which used cumulative distances to water bodies, protected areas, build-up area, and roads as explanatory variables. The ArcGIS Pro Distance Accumulation tool calculates the cumulative distance from each cell to the sources, considering the straight-line distance, the cost distance and the actual surface distance, as well as the vertical and horizontal cost factors. (Esri, 2023a). The second model was prepared using only the land use categorical variable. The result provided information of the probability of presence of elephants according to each land use type. Finally, the two trained rasters with elephant probability of presence were reclassify to scale of 1 to 5, where 1 indicated no presence and 5 very high probability of presence. Subsequently, both layers overlapped using the weighted overlay of ArcGIS Pro giving more weight to the categorical trained raster (2X). The results were interpreted as suitable areas for elephant habitat conservation.

K-fold cross-validation was performed to evaluate the performance of the model. A Random resampling scheme was chosen, and the data were divided into three validation groups. In each iteration, one group served as the validation subset, and the model predicted the presence of features. The results included the percentage of correctly classified presence features and the percentage of background features classified as potential presence. These diagnostics provide insights into the model's performance in estimating presence in unknown locations (Esri, 2022).

Table 1. Criteria to Model Suitable Areas for Elephant Habitat Conservation.

Elephant Habitat Conservation	
The categorical variables:	
Land use/land cover type	Land use/land cover, WWF-Germany
Continuous variables:	
Distance to build up	Build-up OpenStreetMap
Distance to roads	Roads OpenStreetMap
Distance to protected areas	Living Atlas-ArcGIS Pro
Distance to water bodies	Streams OpenStreetMap

Suitable Areas for Human Activity

To identify suitable areas for human activity we created two sub models for urban/commercial development and agriculture sustainability based on different criteria defined for the partners. A detailed table of the criteria for each sub model can be found in Tables 2 and

3. The suitability maps were created using the raster overlay method (Mitchell, 2012) in ArcGIS Pro 3.0.0. The data were reclassified using weights based on expert knowledge according to the framework of LUCIS model. The result of each weighted overlay is a suitability map for each sub model.

Urban/Commercial Development

Modelling urban grown in African cities presents significant uncertainties in urban pattern predictions, due to low temporal dependence of the urban growth process. Temporal dependence is defined as the relationship between what happens at one period and what happens in the following one. Cities in Africa are very heterogeneous in terms of size, spatial pattern, economic level and geographical environment, they also present different levels of development (Linard et al., 2013).

For this reason, to model important areas for urban and commercial development in Victoria falls a weighted overlap of selected suitability factors was performed from four key categories: the condition of the socio-economic, the ecological factor, and prohibitive factors (see Table 2). Topographic factors were excluded since variables like slope are not significant in urban development in African cities (Linard et al., 2013). Instead, socio-economic factors were included that included land-use type, proximity to roads, and proximity to built-up urban areas. The ecological factors include the importance of access water. Prohibitive factors also were included to strictly protect against development, such as distance to special protection areas. In this study, a special protection area is defined as areas with an official recognition of natural reserves, scenic resorts, historic sites, and source water protection areas. To aggregate the data, weighted overlap using criterion weights was implemented.

Table 2. Criteria to Model Suitable Areas for Urban/Commercial Development

Goal	Preferred Criteria	Datasets
Urban/Commercial Development		
The socio-economic factors:		
Land use/land cover	Savanna, grasslands, and existing built areas	Land use/land cover
Proximity to roads	Access to main roads	Roads, OpenStreetMap
Proximity to build areas	Closer to build areas	Land use/land cover, built areas from OpenStreetMap
The prohibitive factors:		
Distance to protected areas	Further away from protected areas	Protected areas Living Atlas
The ecological factors:		
Proximity to water bodies	Access to water	Streams, OpenStreetMap

As for determining the criteria weights, the Analytic Hierarchy Process (AHP) method that is often used in decision making was used, as well as expert knowledge. The AHP, developed by (Saaty, 1984), uses pairwise comparison questions to elicit a matrix of judgments of the relative preference between each pair of alternatives with respect to each attribute, and a matrix of judgments of the relative importance of each pair of attributes (Ramanathan, 2004). In this technique, the processes of rating alternatives and aggregating to find the most relevant alternatives are integrated. The technique is employed for ranking a set of alternatives or for the selection of the best in a set of alternatives. The ranking/selection is done with respect to an overall goal, which is broken down into a set of criteria. The application of the methodology consists of establishing the importance weights to be associated to the criteria in defining the overall goal (Ramanathan, 2004).

Agriculture Sustainability

Many factors can positively or negatively influence the suitability of land for agricultural production. These can be physical attributes, land use, natural resources, accessibility, geology, and soil properties (Table 3) (Ustaoglu et al., 2021). Existing 2021 land use created by the German WWF was the starting point for analyzing land use preferences for agricultural sustainability. Based on image interpretation and previous research conducted in the area by Gebhardt (2021) and Markham et al. (2021), existing crops were located southeast of Victoria Falls. Results show that land covers such as closed, open, and "sparse bushland/shrubs", are more likely to be transformed into crops. On the other hand, expert knowledge on landscape use in the area informed the model that areas near forests or wetlands were less preferable, as they are also attractive to elephants. These areas would be more at risk of elephant crop raiding, especially at night, which is when most crop raiding occurs (Buchholtz et al., 2019; Karidozo et al., 2016; Markham et al., 2021).

Most of the areas that are suitable for agriculture are located near water bodies (e.g., subsurface water wells and the Zambezi River) as well as roads. These results are aligned with the literature review that mentions many rural communities that live close to elephant communities move closer to more permanent water sources during dry periods to ensure stable water access for their household needs, crops, and livestock (Bastille-Rousseau et al., 2020; Mariki et al., 2015; Osborn, 2004; Shaffer, 2010). Yet competition for increasingly scarce water sources and other resources during and/or after droughts increases the risk of conflict between elephants and humans (Bastille-Rousseau et al., 2020; Osborn, 2004).

Table 3. Criteria to Model Suitable Areas for Agriculture Sustainability

Agriculture Sustainability		
The socio-economic factors:		
Land use/land cover type	Existing crops areas, grasslands, and savanna	Land use/land cover, WWF-Germany
Proximity to communal lands	Closer to communal lands	Protected areas, Living Atlas-ArcGIS Pro
Accessibility:		
Proximity to roads	Closer to roads	Roads, OpenStreetMap
The prohibitive factors:		
Proximity to protected areas	Further from protected areas	Protected areas Living Atlas
Physical attributes:		
Proximity to streams	Access to water bodies	Streams, OpenStreetMap

Land Use Conflict Analysis using the LUCIS Model.

To identify areas where suitability was high for multiple objectives (i.e., areas of potential conflict because they are suitable for elephant conservation, urban development, and agriculture), the Land Use Conflict Identification Strategy (LUCIS) model, was used (Carr and Zwick, 2005 and 2007). Essentially, the LUCIS protocol combines the results of three suitability models and codes areas of highest suitability for all three perspectives (i.e., areas of highest conflict), areas suitable for two of the three perspectives (i.e., areas of medium conflict for two perspectives) and areas suitable for only one perspective or areas not suitable of any of the perspectives (i.e., areas of low conflict).

To find this area of conflict, suitable maps were integrated using the weighted overlay tool in ArcGIS Pro. This procedure overlays several rasters using a common measurement scale and weights each according to its importance (Esri, 2023b). The weighted overlay analysis rescales the reclassified values back to an evaluation scale, in this case, 1-5, where 1 is no conflict and 5 is very high conflict. For this analysis, suitable raster layers were transformed to integer values to be used as inputs. A detailed description of the reclassification schema for the suitability analysis and the LUCIS model can be found in Appendix 1. The spatial analysis was conducted in ArcGIS Pro as it has a broader range of spatial statistic tools. The geoprocessing workflow was organized and executed in a Model Builder in ArcGIS Pro and then exported in a Python Script format (Appendix 2).

CHAPTER 4

MODELING ANALYSIS

Areas of Potential Human-Elephant Conflict

Areas with high pixel values of suitability for all three perspectives of stakeholders were identified to analyze potential areas of conflict or opportunities related to human and elephant interaction. Once that percentage of conflict is determined, critical areas for human and elephant interaction were identified. The model then explored the relationships between the three main land use preferences (development, agriculture, and elephant habitat conservation) and land use conflict, with each input having a different weight within the model. Initially, the weights for the input variables for the suitability maps were equal, however, the weights for the final suitability maps overlay changed based on feedback from stakeholders. For example, this research aims to determine how conflict areas would be reduced if local initiatives prioritized elephant habitat conservation. Therefore, the suitable map for the elephant habitat conservation map was given a higher weight (40%) and the agriculture and urban suitability obtained 30% of the wait out of a 100% each. The final products of this research included a conceptual LUCIS model enhanced with GeoAI and remote sensing approaches and cartographic representations of model outputs (i.e., which areas are more vulnerable to potential human-elephant conflicts because of incremental urban development and increased agriculture) (Figure 5).

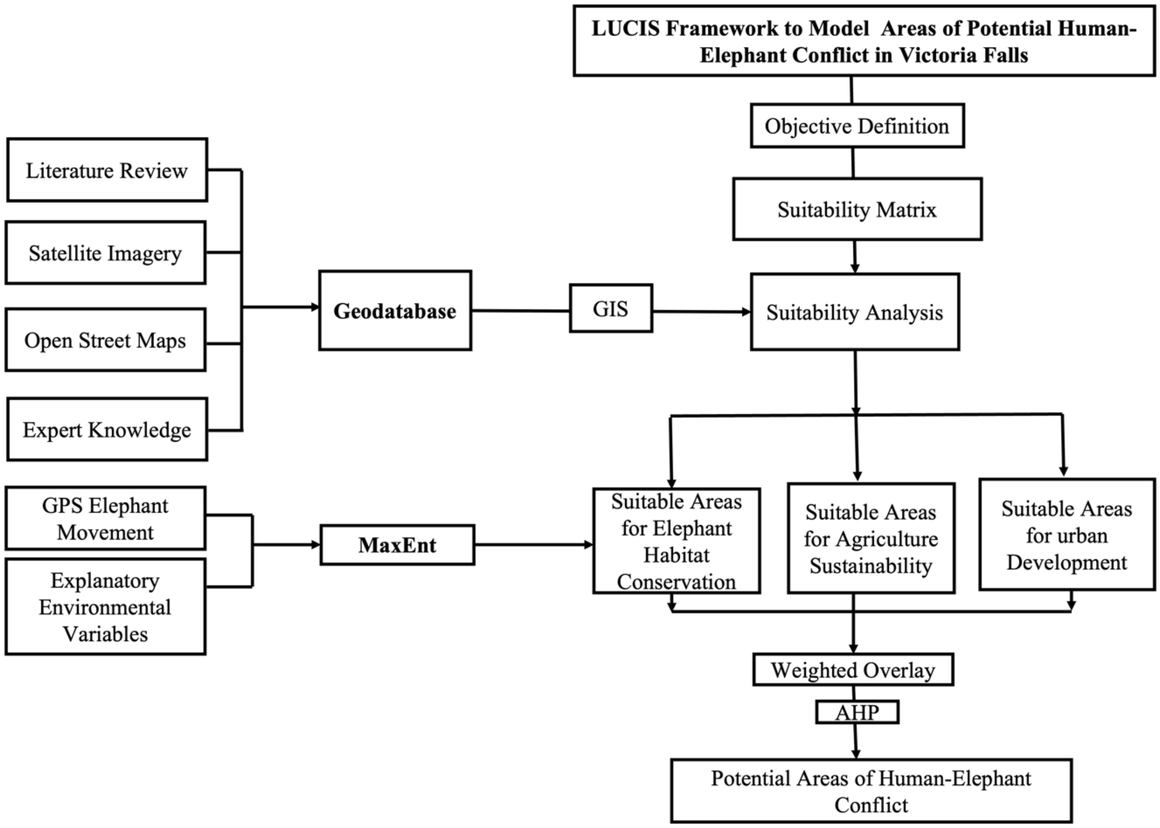

Figure 5. LUCIS Framework to Model Areas of Potential Human-Elephant Conflict in Victoria Falls.

Insights for resource management and human development can be gained by understanding the relationships between land use/land cover, social-economic conditions, and physical/ecological processes. The linkages between environmental conditions and elephant and human land use preferences will help in understanding the possible causal factors of human-elephant interactions and, therefore, possible scenarios for alleviating human-elephant land use conflicts. Local NGOs and government institutions in Victoria Falls could also use this information for management, policy, and funding decisions. Specifically, the findings can be used to more appropriately direct funding and other assistance programs to handle human-elephant conflict in targeted critical areas. Internationally, this information can be applied to other areas with land use change and human-wildlife conflict.

Although understanding the connections between the two issues of human-elephant land use and land use conflict are the primary goals of this study, each part of this research can be beneficial to the scientific community. The identification of areas of potential conflict for land use between humans and elephants can lead to recommendations for the allocation of NGO resources to address human-wildlife interactions that increasingly results in the loss of elephant and human life. The project illustrates how environmental variables and current land use are spatially related to human and wildlife interactions. It also demonstrates how models using incorrect input variables or solely non-spatial aspects of the problem may result in poor outcomes, ultimately not effectively addressing and alleviating the problem of Human-Elephant Conflict.

CHAPTER 5

DISCUSSION OF MODELING COMPONENTS AND RESULTS

Based on Landsat and Copernicus images from Google Earth Pro from November 2021, the characteristics of the vegetation cover and preferred locations for development were identified. Four types of urban land use were identified. The most important are: a) urban areas with more vegetation coverage that are mainly residential, b) commercial/ residential land uses located in the center of Victoria Falls, c) an expanding residential area located around the airport in the western part of Victoria Falls; and d) urban areas focused on tourism infrastructure such as hotels and resorts located on the banks of the Zambezi River near the entrance to Victoria Falls (Figure 6).

The characteristics of land cover were also examined to understand the ecosystem preferences of elephants. Based on the characteristics and quantity of vegetation, existence of water bodies, forest, wetlands, and current land use, land covers most at risk of being transformed were identified. This allowed the weights of land use preferences for certain activities such as urban use and agriculture to be determined when performing suitability analysis.

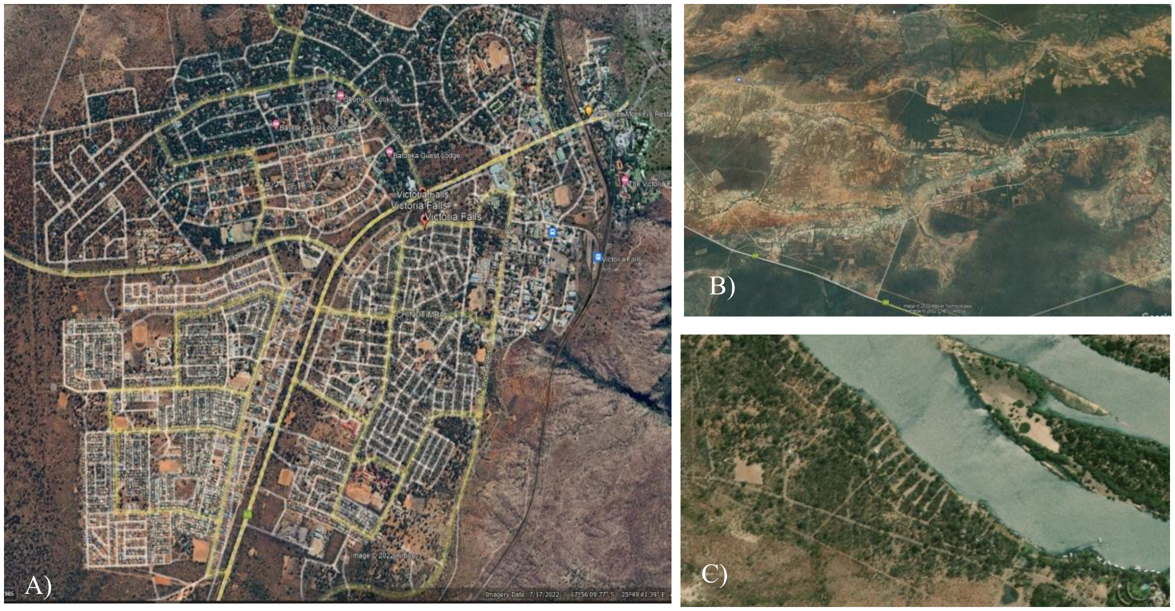

Figure 6. Identification of Urban Uses Using High-Resolution Images from Google Earth Pro. A) shows the three most predominant urban zones in the center of Victoria Falls, as well as the location of the commercial zone. B) Displays characteristics of the agricultural zone which is mostly subsistence farming in character; and C) the location of the hotel, lodging and restaurant zone on the banks of the Zambezi River in the northern part of Victoria Falls is illustrated.

Presence-only Prediction (MaxEnt)

The Cross-Validation Summary (Table 4) includes each cross-validation group's ID, count of observations in its training validation subsets, percent of observed presence features predicted as presence, and percent of observed background features predicted as background using the K-fold cross-validation. As can be seen, the percentage of presence points correctly classified is over 50% and around 28% of the background points were classified as potential for elephant presence.

Table 4. Cross-validation Summary.

Group ID	Training Size (pixels)	Validation Size (pixels)	% Presence – Correctly Classified	% Background-Classified as Potential Presence
1	35474001	17737001	55.90	28.09
2	35474001	17737001	57.35	28.12
3	35474002	17737000	56.72	28.10

Probability of elephant presence using continuous and categorical variables

Figure 7 shows the classification results of percentages of the continues variables. To understand the results, focus on the "presence" bar on the right. The larger the portion in blue, the more that presence points are correctly classified, suggesting an appropriate model. Next, check the "Background" bar on the left: the larger the presence in grey, the more that potential presence locations are being discovered from background points. Note that for this case the model got a 60% accuracy at correctly identifying the presence of elephant movement, which can be considered a good performance. It can also be seen that no potential elephant presence was discovered from background points from continuous variables. However, the categorical variables were able to predict potential elephant presence in a range of 40% and 50% from background points.

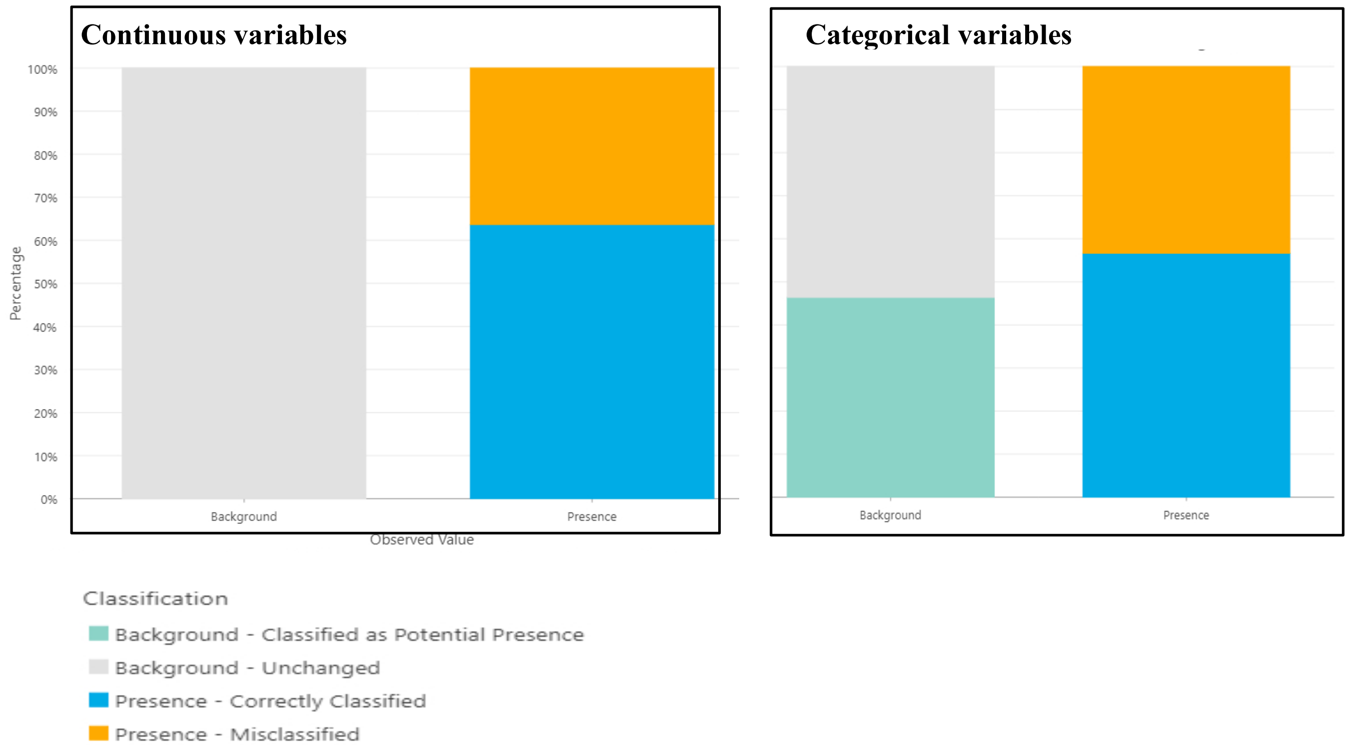

Figure 7. Classification Results Percentages (Cutoff=0.5) for Continuous and Categorical Explanatory Variables Using MaxEnt.

The count of presence and background by probability ranges was used to compare how the model's distribution of presence probability values compares with observed presence and background classification. In Figure 8, the response for the continuous variables can be seen ranging between 0.5- and 0.75 and contains a larger number of background and presence points. This range indicates a high presence of elephant movement (Figure 8).

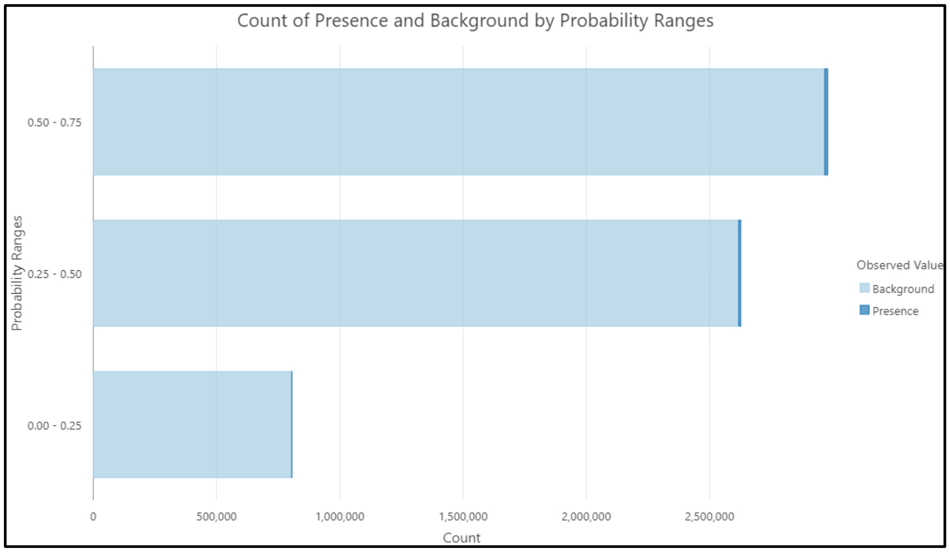

Figure 8. Count of Presence and Background by Probability Ranges for Continuous and Categorical Variables Using MaxEnt.

The distribution of probability of presence by classifications is used to see the distribution of presence probability ranges by classification designation. It can be seen in Figure 9 that the distribution of background classified as potential presence (green) and presence correctly classified (blue) are in the 0.5 -0.7 range of probability of presence, which belongs to the ranges of the high and very high probability of elephant presence, respectively.

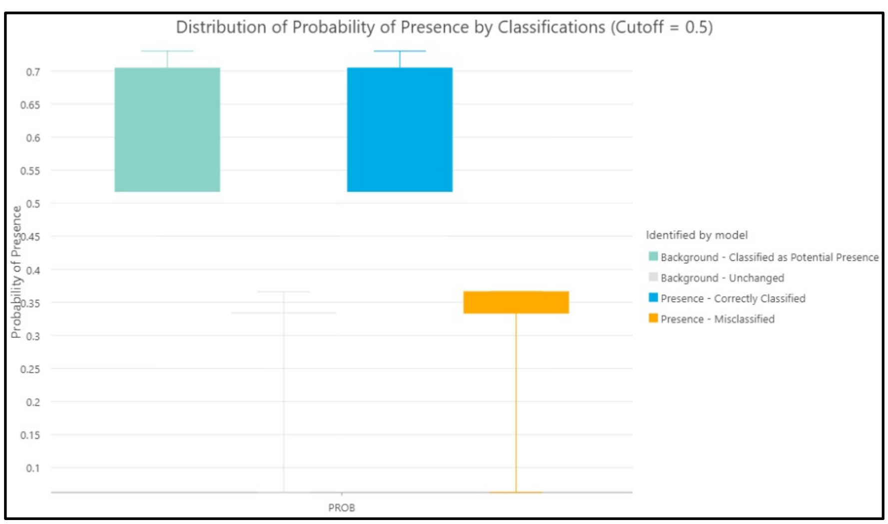

Figure 9. Distribution of Probability of Presence by Classification for Continuous and Categorical

Explanatory Variable Using MaxEnt.

The Omission Rates chart is utilized to evaluate the percentage of known presence points that were incorrectly classified as non-presence by the model (Esri, 2022). It involves using various presence probability cutoff values ranging from zero to one. According to Esri (2023), a lower omission rate is preferred. However, in this initial iteration, the omission rate is 0.2 for the 0.5 cut-off value was used with the continuous variables and around 0.25 using the same cut-off for the categorical variable (Figures 10 and 11). To potentially reduce the omission rate, future studies could concentrate on training the model with different cut-off values. However, it is important to evaluate this optimal value observing how this new value could potentially affect the number of background points classified as potential presence (Esri, 2022).

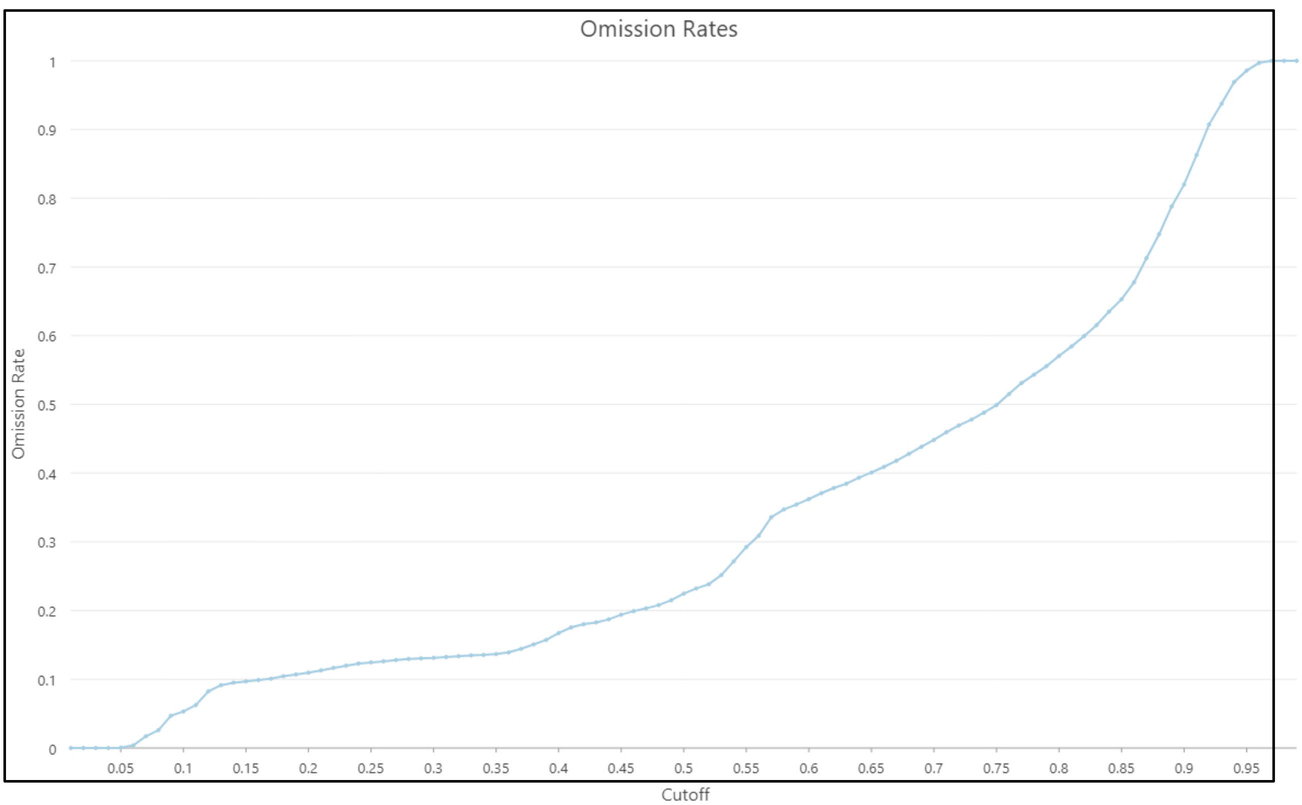

Figure 10. Omission Rates for Continuous Variables.

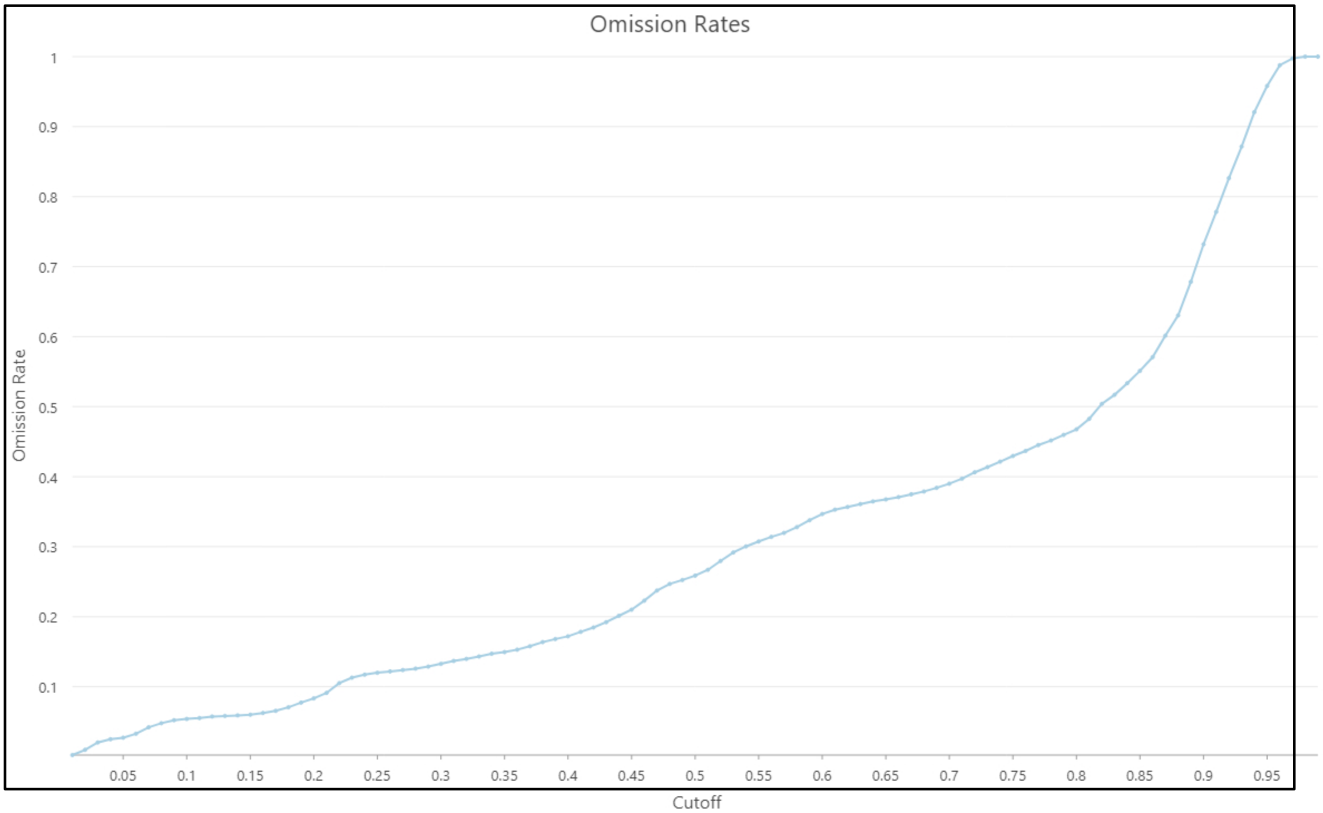

Figure 11. Omission Rates for Categorical Variables.

To evaluate how different cut-off values impact the rate of background points being classified as presence, the Receiver Operating Characteristic Curve (ROC) Plot can be used (Esri,2022). This information can be helpful in determining the optimal cut-off value for balancing false positives and false negatives (Esri, 2022). It also provides a visual representation of the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) at different classification thresholds (Esri, 2022).

By plotting the true positive rate against the false positive rate, the ROC Plot allows us to assess the model's ability to distinguish between presence and absence points. A good model will have a curve closer to the plot's top-left corner, indicating a higher true positive rate and a lower false positive rate. This is the case of both models obtained using continuous variables (Figure 12) and the land use categorical variable (Figure 13).

In addition to the ROC Plot, the omission rate graph provides insights into the model's performance at different presence probability cut-off values. Both the ROC Plot and the omission rate graph are essential tools for evaluating and fine-tuning models, and they should be observed together to find a balanced cut-off value.

Finally, the Area Under the Curve (AUC) gave us information about how well the model can accurately classify known presence and background locations. The higher AUC in both Figures 12 and Figure 13 suggest that the model has been effective in predicting presence. By considering these metrics, an optimal cut-off value can be determined in future efforts to minimize false positives (ensuring that predicted presence is likely to be true presence) or false negatives (ensuring that predicted non-presence is likely to be true absence). The ideal balance is represented by the ROC plot value that is closest to the upper left corner of the chart (Esri, 2022).

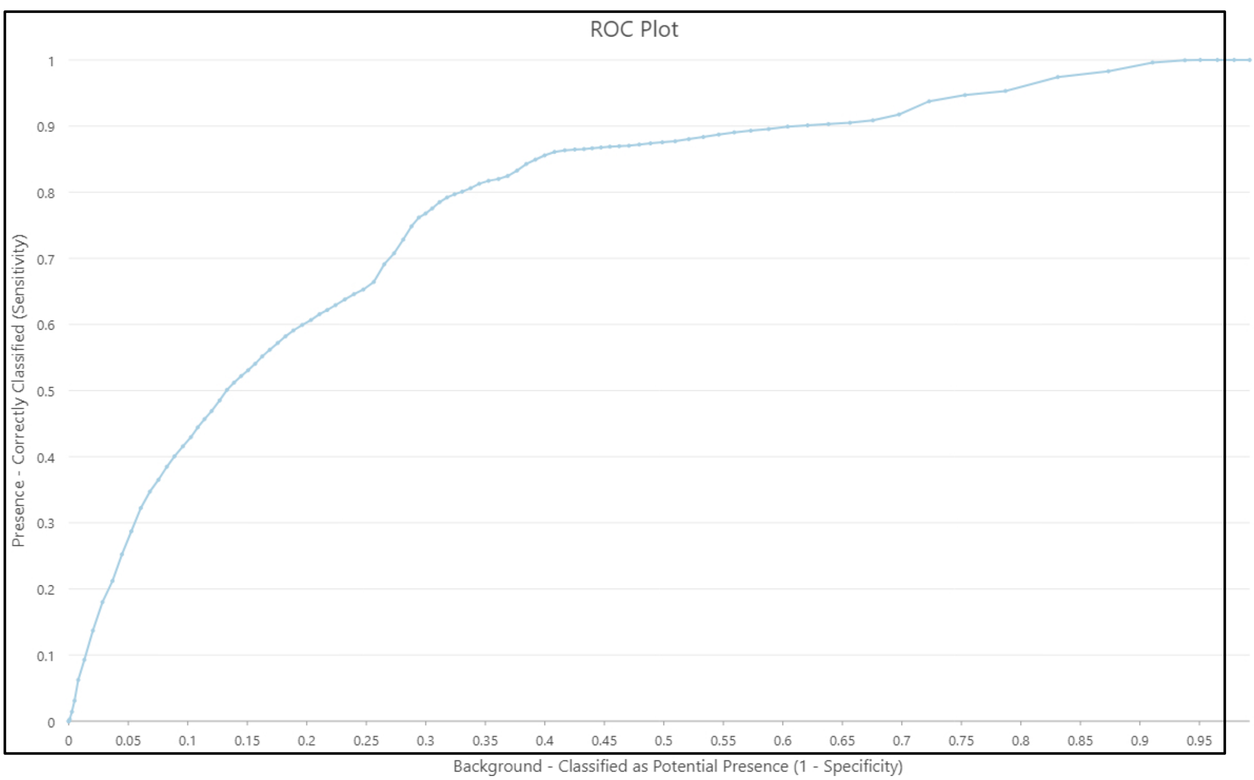

Figure 12. ROC Continuous Variables.

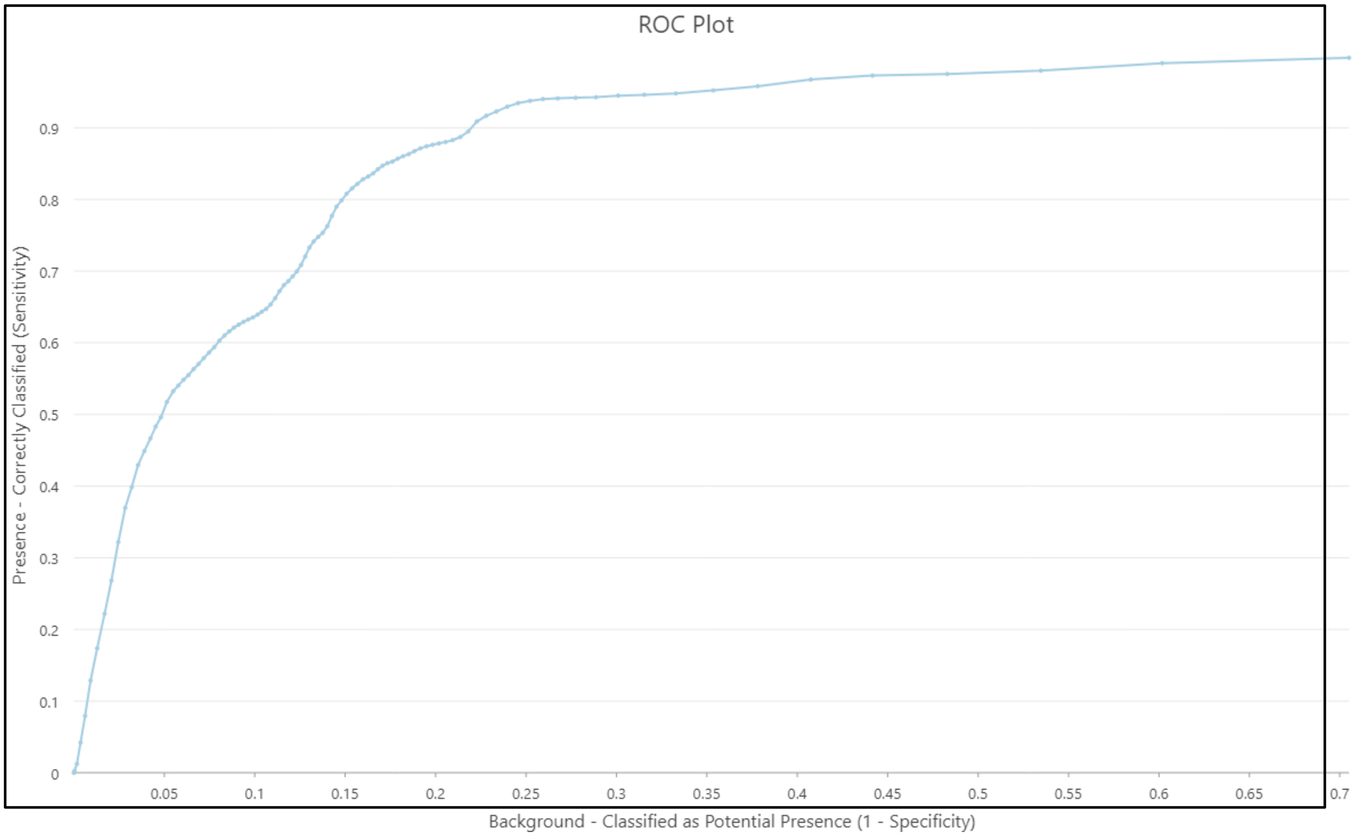

Figure 13. ROC Categorical Variable, Land Use.

The MaxEnt tool in ArcGIS Pro also provided an output-trained raster that represents spatially the distribution of elephant presence (Figure 14). This raster classified the probability of presence at each cell in the extent of the input training data into four categories. The extent of the output-trained raster corresponds to the intersection of the explanatory training raster in the study area. The cell size of this raster is 30 m. The elephant's presence rages from 0 to 1. Values close to 0 represent no presence and values close to 1 are very high elephant presence. In this sense, areas shown in dark purple fall into the range of 0.6-0.7 which represents a high probability of elephant presence. These areas coincide with the location of the built-up area and closeness to communal lands, and water bodies.

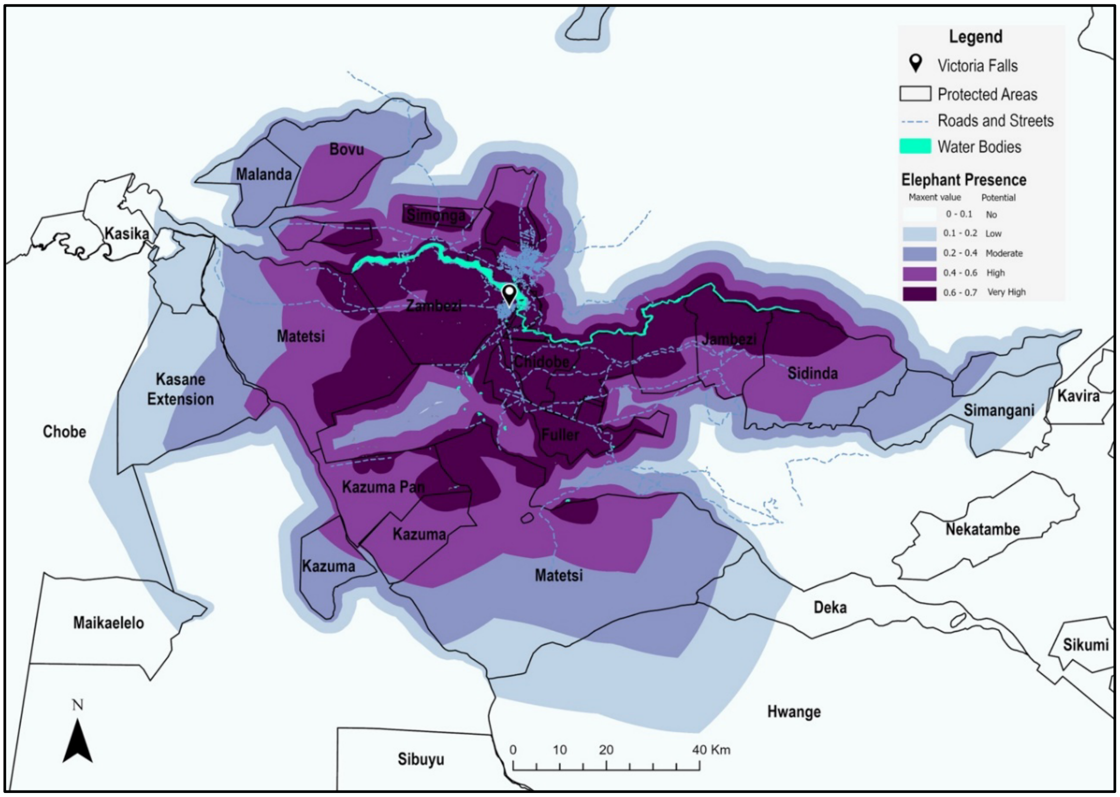

Figure 14. Probability of Elephant Presence in Victoria Falls Using Explanatory Training Distance Features.

The partial response of continuous variables is composed of multiple charts: each chart visualizes the effect of changing values in each explanatory variable on presence probability while keeping all other factors the same.

The results show that the probability of elephant presence increases the further away from the roads but increases closer to the built-up area. Likewise, a greater presence is reported inside and near protected areas, at a cumulative distance of 20 km there is no greater increase in elephant presence. This is similar with reference to water bodies where there is a higher probability of elephant presence in the vicinity of water bodies, and it remains constant from values of 50 km onwards. In summary, there is a higher probability of the presence of elephants in the range of 150 km of accumulated distance from the explanatory variables (Figure 15).

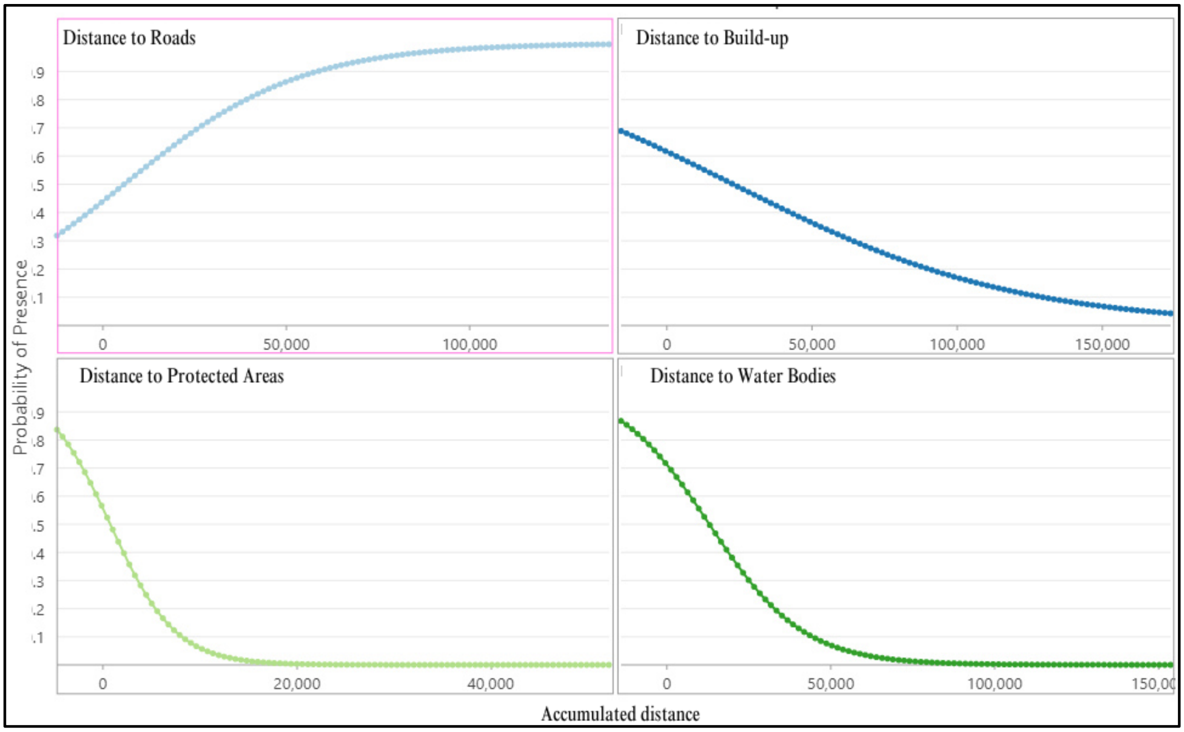

Figure 15. Partial Response of Continuous Variables, Distance to Roads, Distance to Built-up, Distance to Protected Areas, and Distance to Water Bodies.

Similarly, the trained raster for categorical variables groups the raster values in four categories. In this model we also obtained potential locations of elephant presence from background points, and this allowed the whole land use raster to show information of potential elephant presence. Figure 16 shows that there is a very high probability of elephant presence in the built-up areas and water bodies located mostly in the central area of Victoria Falls.

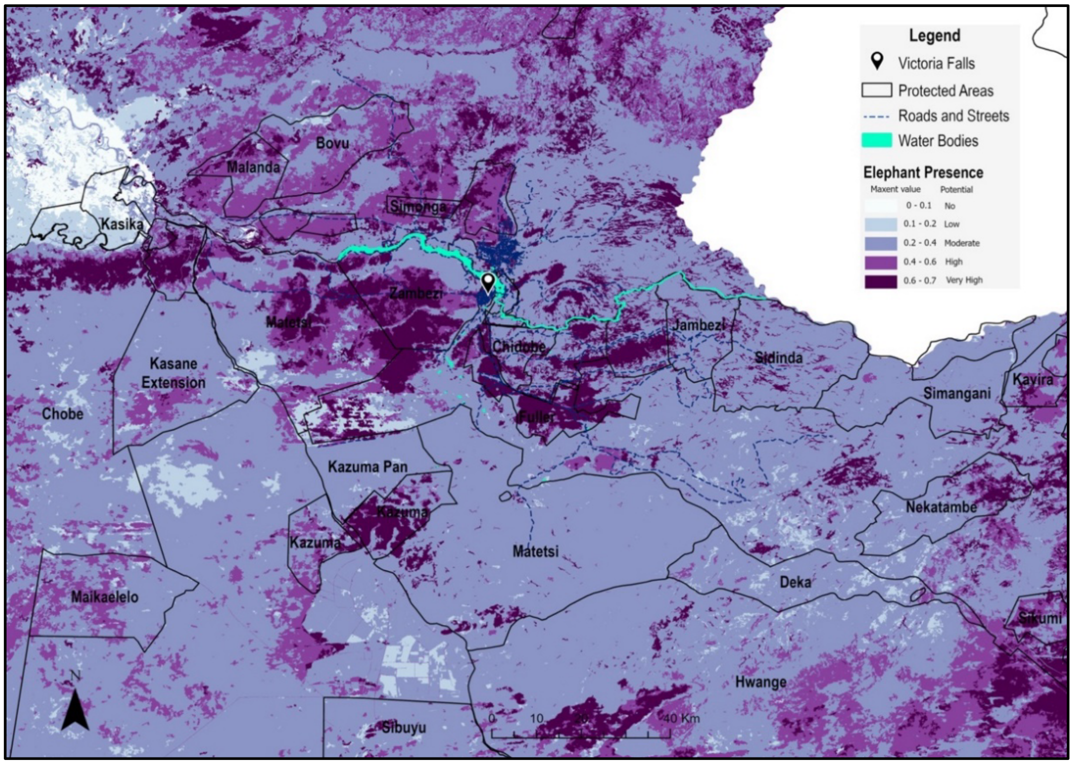

Figure 16. Probability of Elephant Presence in Victoria Falls Using Land Use as a Predictor Variable.

Table 5.Land Cover Classification Scheme for The Study Areas. Adapted from KAZA Land Cover (Gebhardt, 2021).

Code	Land Use Description	Code	Land Use Description
31	Open Herbaceous Vegetation	91	Sparse Herbaceous Wetland
32	Bare Floodplain Area	92	Open Herbaceous Wetland
61	Open Herbaceous Floodplain	120	Closed Woodland
40	Cropland	130	Closed Bushland
50	Built Up	210	Sparse Forest Woodland
80	Water Bodies Permanent	222	Sparse/ Open Bushland/ Shrubs
81	Water Bodies Seasonal	231	Open Woodland/Bushland
90	Closed Herbaceous Wetlands	232	Open Bushland/Shrubs

The partial response of categorical variables chart is a single bar chart displaying the marginal response of presence for the land use explanatory variable category (Figure 17).

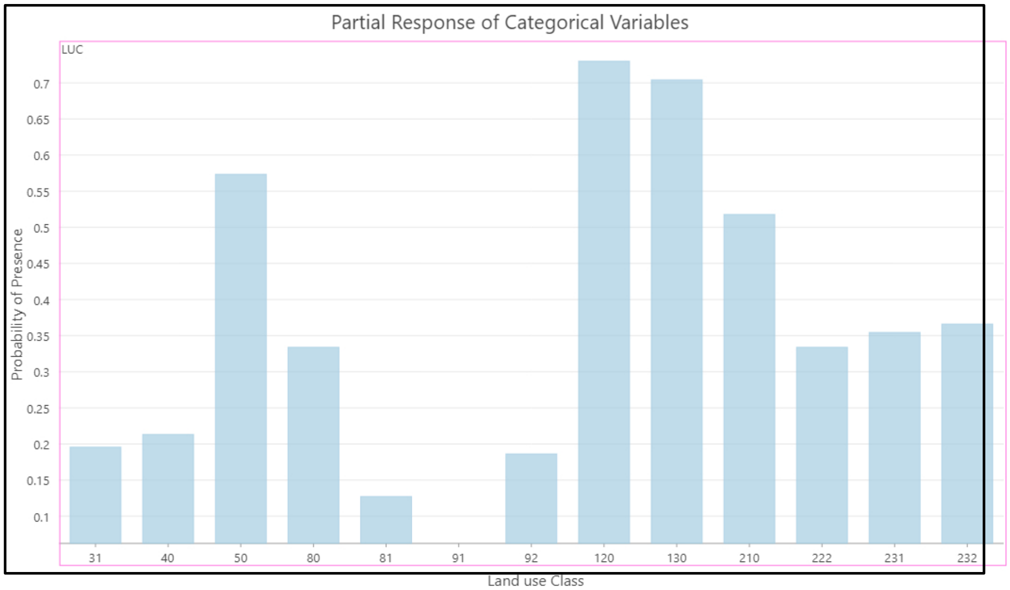

Figure 17. Partial Response of Categorical Variable, Land Use

Table 6. Explanatory Variable Category Diagnostics.

Training						
Variable	Feature (after thinning)			Raster		
	Categories	Count	(%)	Categories	Count	(%)
LUC	Open Herbaceous vegetation	927718	1.74	31	927717	1.74
	Open Herbaceous/Floodplain	37276	0.07	32	37276	0.07
	Cropland	2304482	4.33	40	2304476	4.33
	Built-up	113139	0.21	50	113126	0.21
	Bare Floodplain Area	14671	0.03	61	14671	0.03
	Water Bodies Permanent	200022	0.38	80	200029	0.38
	Water Bodies Seasonal	824591	1.55	81	824578	1.55
	Closed Herbaceous Wetland	66106	0.12	90	66106	0.12
	Sparse Herbaceous Wetland	765825	1.44	91	765825	1.44
	Open Herbaceous Wetland	1255941	2.36	92	1255935	2.36
	Closed Woodland	319746	0.6	120	319717	0.6
	Closed Bushland	5378234	10.11	130	5377731	10.11
	Sparse Forest /Woodland	9148882	17.19	210	9148450	17.19
	Sparse/Open Bushland/Shrubs	17992602	33.81	222	17992324	33.81
	Open Woodland/Bushland	3420525	6.43	231	3420477	6.43
	Open Bushland/Shrubs	10 441242	19.62	232	10 441098	19.62

Figure 17 shows the vegetation cover with the highest probability of elephant presence is closed woodlands, followed by closed bushlands and sparse forest/woodlands, with probability ranges above 0.5, representing a very high probability of elephant presence. Permanent water bodies recorded a probability of presence above 0.3, which is considered a moderate presence. On the other hand, the urbanization category obtained elephant presence probability ranges above 0.55, which is considered a high probability of elephant presence. Table 5 shows a complete description of the land cover scheme for the study area. It can be used as a guide to explore in detail the probability of elephant presence for each land cover analyzed.

Suitability Analysis

Suitable Areas for Agriculture

The highest zones suitable for agriculture are in the east and southeast of the study area, within the territory of local communities and access roads (Figure 18). These zones are historically human-influenced areas and depend on the Zambezi River as a water source, as well as other subsurface water sources such as boreholes (or wells). Many of these areas border areas of strict protection for biodiversity and crop raiding is common not only by elephants but also by other species (Markham, 2021). Some medium priority areas for agriculture are areas close to safari lands that do not have a strict protection status and may be considered more suitable for subsistence farming activities due to their proximity to roads and water sources as well as the predominant vegetation type. The areas closer to woodlands and wetlands would be the least suitable because they are also preferred by elephants and farmers do not see the benefit of planting crops in these areas because of their high probability of being raided by elephants.

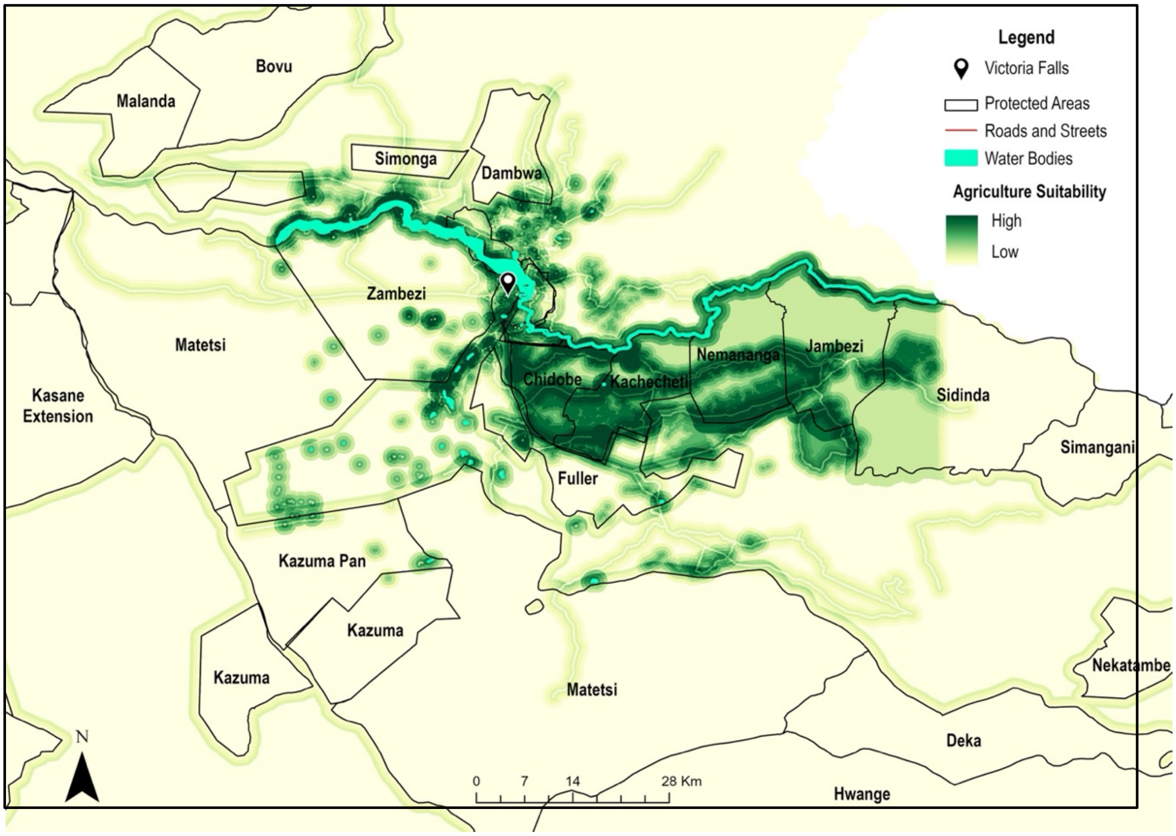

Figure 18. Suitable Areas for Agriculture. The Areas in Intense Green Represent Current and Potential Farming Areas Located on Communal Property. This Type of Agriculture is Subsistence and is Dependent on Subsurface Water Sources and Climatic Conditions.

Suitable Areas for Urban/Commercial Development

Areas with high suitability for urban/commercial use are located close to the current urban area. The evenly suitable zones are related to tourist attractions such as Victoria Falls and the location of hotel infrastructure on the banks of the Zambezi River near Victoria Falls and Livingstone (Figure 19). The medium suitability zones are close to other zones along the Zambezi River and are highly influenced by the land use change vulnerability layer included in the modeling. The location of other subsurface water sources such as wells is also shown as attractive sites for urban development in the area, as well as communal property areas where natural resource management for subsistence purposes is allowed. These areas correspond to communal territories located in the southern part of the study area. Many of these areas are associated with existing urban land use, water bodies and communal lands where the combined use of natural resources for subsistence purposes is permitted.

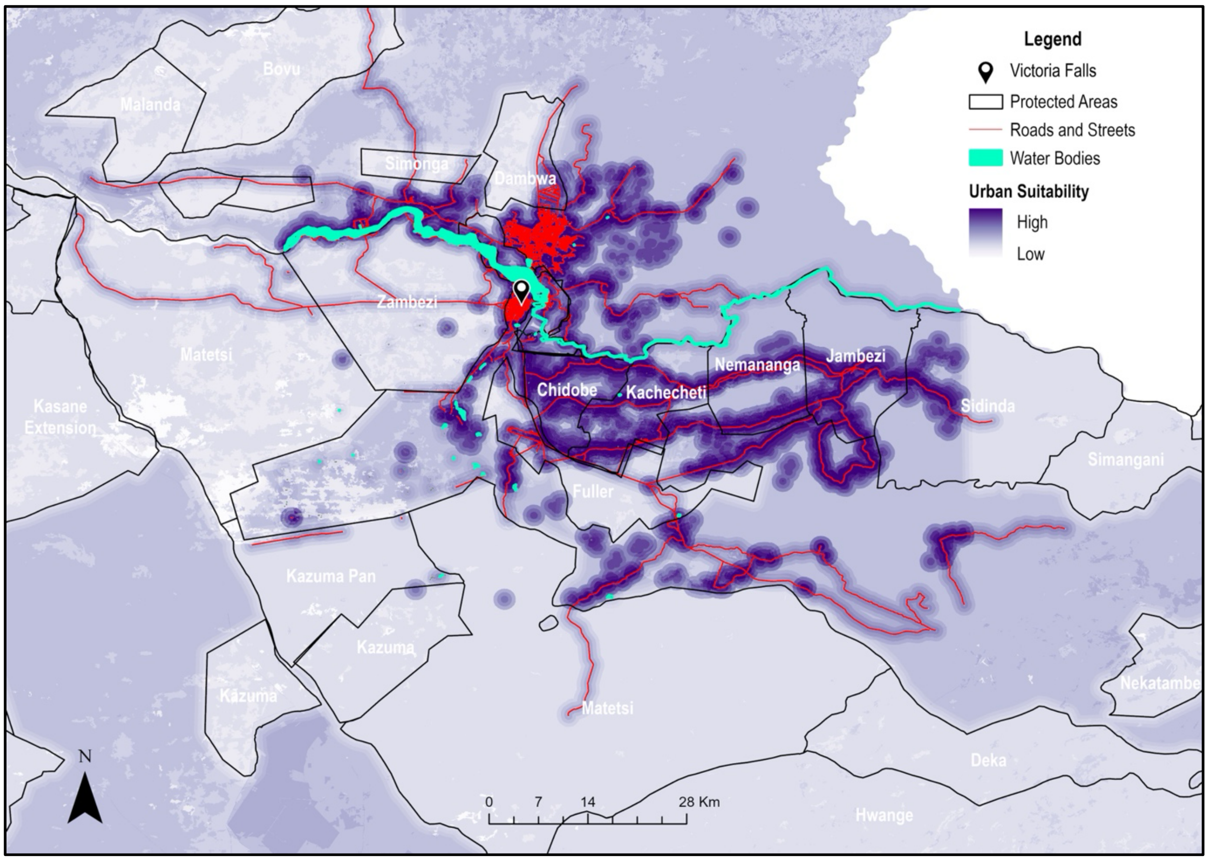

Figure 19. Suitable Areas for Urban Development. Shown in Red are the Areas with the Highest Suitability for Urban Development.

Suitable Areas for Elephant Conservation

The areas suitable for elephant conservation are distributed throughout the study area, as the zone is located throughout the elephant range. However, according to the MaxEnt results, there are certain areas of higher interest. The high level shown in blue is located around water bodies and built-up areas (crops and urban areas) (Figure 20). The medium level is represented by cultivated areas and some urban areas shown in green. In addition, we realized that the northern zone of the Zambezi River near Victoria Falls presents the greatest confluence of elephants, which is precisely the most urbanized area of our study area.

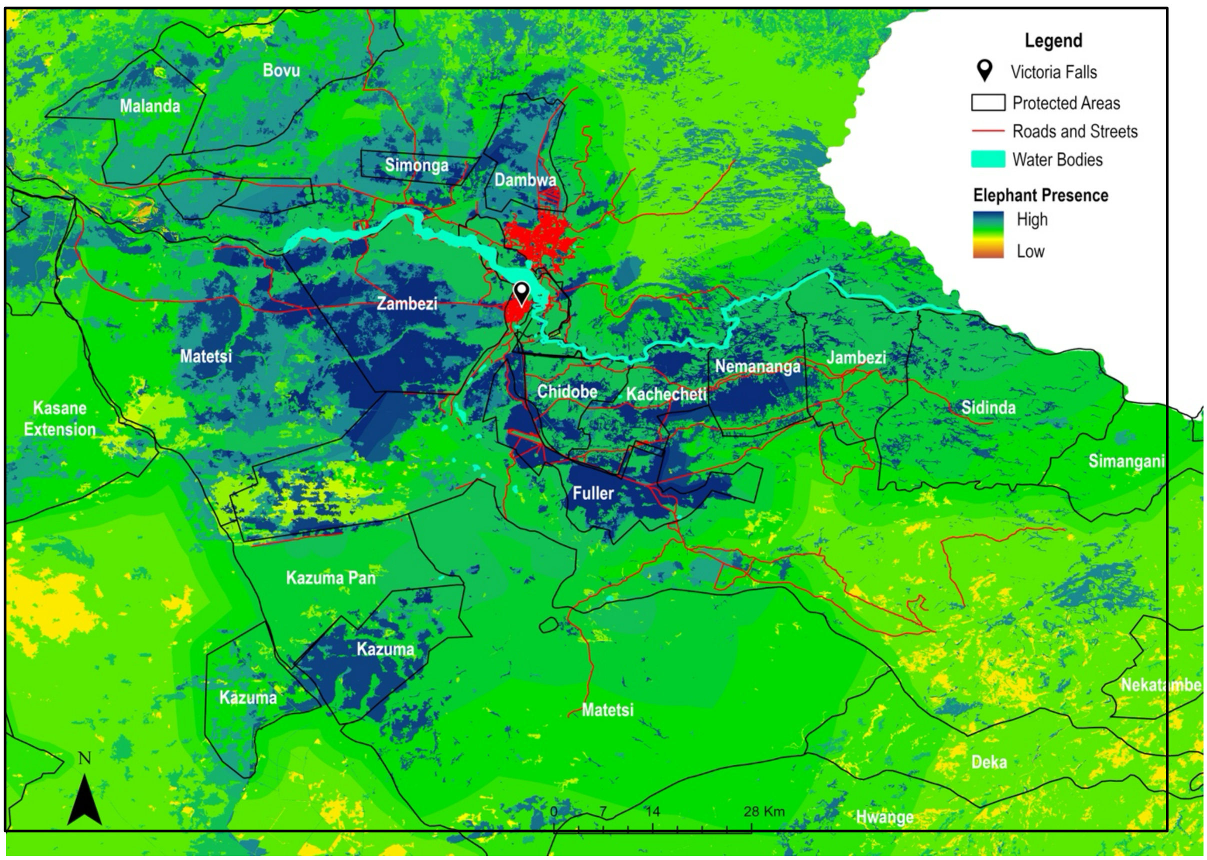

Figure 20.Suitable Areas for Elephant Habitat Conservation.

Land Use Conflict Identification Strategy Model

The LUCIS model overlays the three suitability maps from three perspectives to create an overall map of areas of conflict (i.e., areas most suitable for all three stakeholders), moderate conflict areas suitable for two of the stakeholders, and low conflict or areas suitable for one or none of the stakeholders. The regions likely to experience major human-elephant interactions include around the Zambezi River area, near the urban/commercial zone of Victoria Falls, and to the southeast in the communal farming areas in Chidobe, Kachecheti, Nemananga and Jambezi. In the urban zone, the areas with the most conflict are related to water bodies, agricultural crops, urban areas and near Victoria Falls areas covered by bushlands, woodlands, and seasonal water bodies near Victoria Falls. In general, current, and potential urbanized and agricultural areas have the greatest potential for conflict.

Different suitability map overlays were created to find areas of specific potential conflict between elephant habitat conservation and urban areas, elephant habitat conservation and agriculture, and agriculture and urban areas for the 2020 wet season. Table 7 and Figure 21 present a summary of the percentage of conflict by intensity for each pair of map overlays and the total combination of the three suitability maps.

Table 7. Percentage of study area coverage by type of conflict.

Type of Conflict	Reclass	Intensity	Pixel Count	Area (km2)	%
Elephant-Urban	1	No	748755	6.4	1.41
	2	Low	13238662	11334.4	24.88
	3	Moderate	33080273	28322.1	62.17
	4	High	5009520	4289.0	9.41
	5	Very high	1132846	969.9	2.13
Elephant-Agriculture	1	No	704691	603.3	1.32
	2	Low	46914678	40166.5	88.17
	3	Moderate	4282314	3666.4	8.05
	4	High	1308373	1120.2	2.46
Agriculture-Urban	2	Low	46632578	39925.0	87.64
	3	Moderate	4526982	3875.8	8.51
	4	High	1197221	1025.0	2.25
	5	Very high	853275	730.5	1.60
Elephant-Urban-Agriculture	1	No	694793	594.9	1.31
	2	Low	25080031	21472.6	47.13
	3	Moderate	24544317	21013.9	46.13
	4	High	2402307	2056.8	4.51
	5	Very high	488608	418.3	0.92

Overall, 62% of the study area held a moderate-intensity elephant-urban conflict. There was88% low conflict observed between elephant habitat conservation and agricultural uses, and 87% low conflict between agricultural and urban land uses. Combining the three-suitability models resulted in 47% of the study area being likely to experience low conflict for elephant, urban and agricultural land uses, 46% likely to experience moderate combined conflict in the wet season and 4.5% high conflict Table 7.

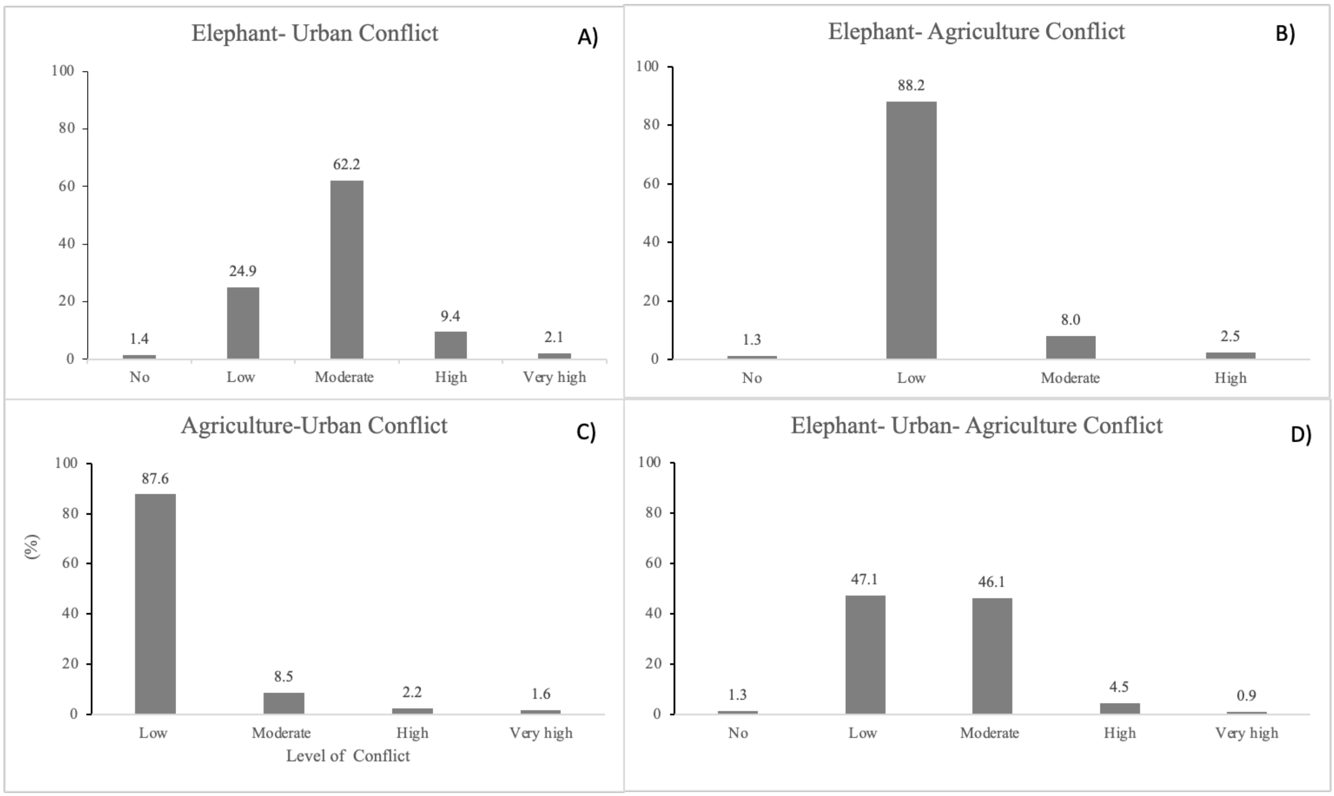

Figure 21. Percentage of Conflict Areas by Intensity in the Wet Season, 2020 in Victoria Falls. Percentage of Areas of Elephant- Urban Conflict, B) Percentage of Areas of Elephant- Agriculture Conflict, C) Percentage of Areas of Agriculture- Urban Conflict, D) Percentage of Areas of Elephant- Urban- Agriculture Conflict.

As can be seen in Figure 21A, about 60% of the elephant-urban conflict is of the moderate type and 25% of low intensity. These zones are distributed throughout the study area as most of the area is of interest to elephants and with potential for future urbanization. Only 11.5% of the area is considered high- and very high-conflict zones that are in existing urban areas, cultivated areas, and in the vicinity of roads (Figure 22).

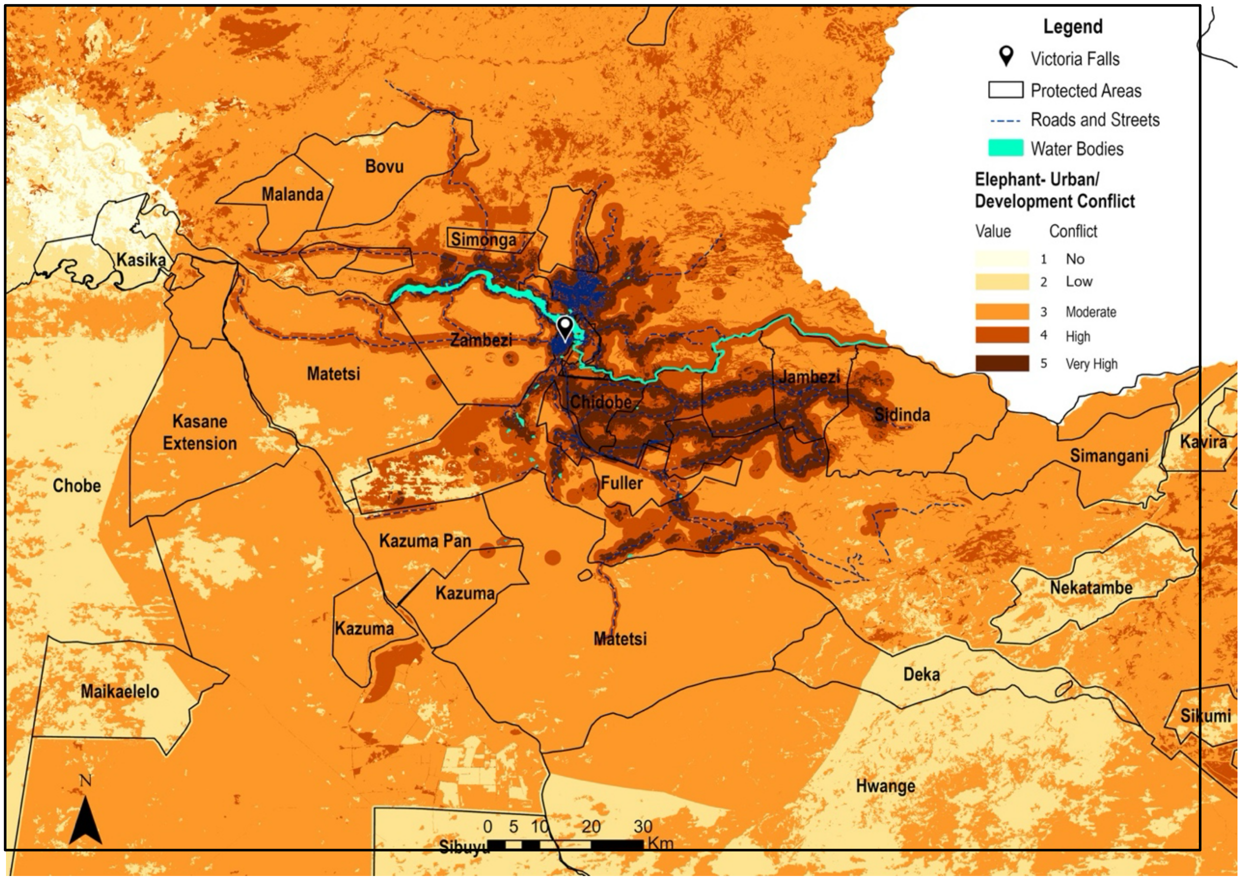

Figure 22. Areas of Potential Elephant- Urban Conflict. Brown and dark Orange Areas Represent High and Very High Potential Conflict, and most of these Areas are Related to Existing Developed Areas (i.e., Crops and Urban Settlements).

The Elephant-Agriculture overlap (Figures 21B and 23) shows 88% of the area with low conflict between elephants and agriculture is in the vicinity of communal lands, roads, and existing construction zones, while 8% of the area expresses moderate conflict, and 2.5% of the study area expresses high conflict. High conflict zones are concentrated in the agricultural zones, urbanized areas, and water bodies (Figure 23).

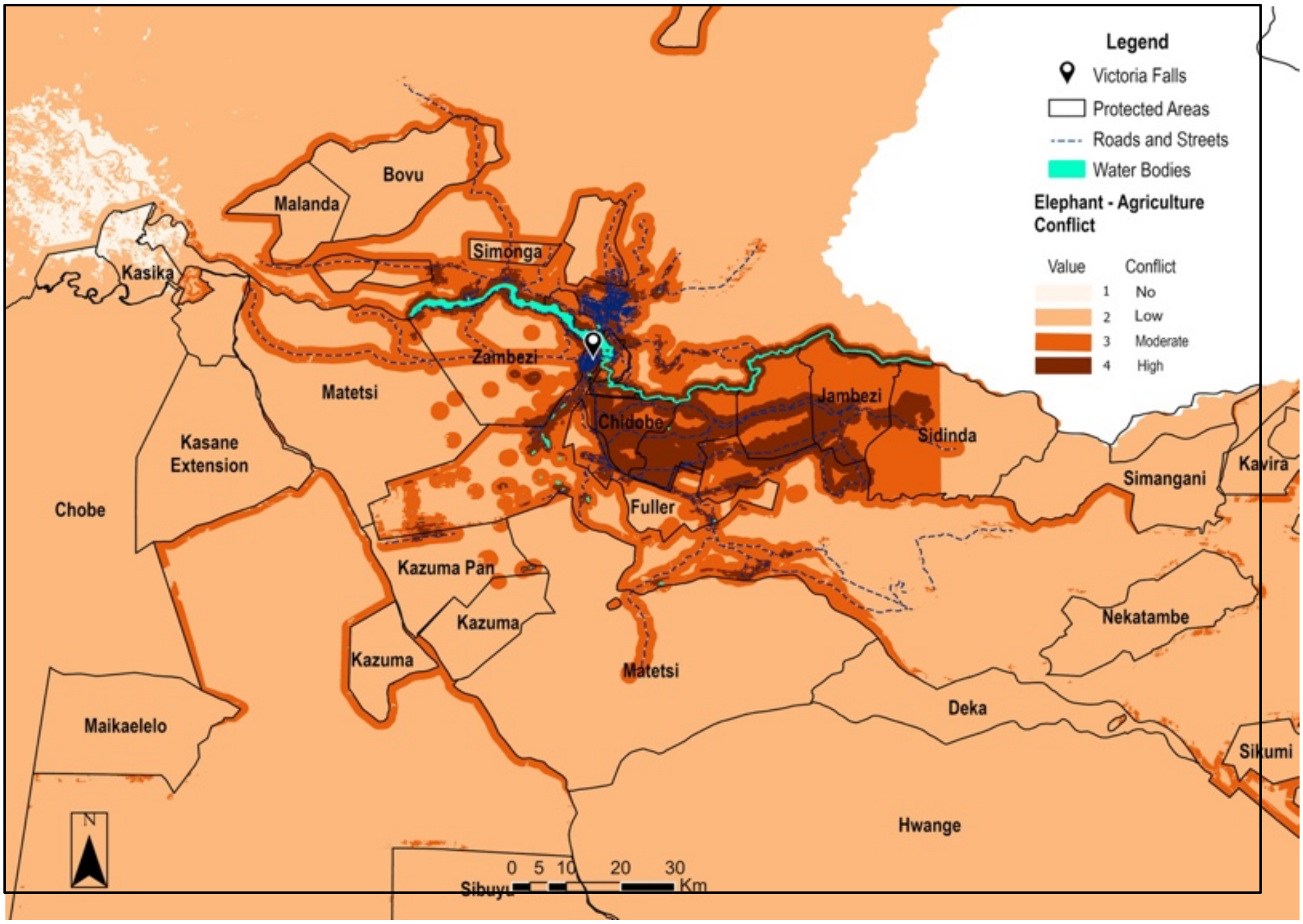

Figure 23. Areas of Potential Elephant-Agriculture Conflict.

The Urban-Agricultural Conflict is low in 87% of the study area, 8% is moderate and 2.2% and 1.6 is high and very high (Figures 21C and 24). As in the previous cases, most of this intense conflict is found in the core of the urbanized and cultivated areas and near water bodies (Figure 24).

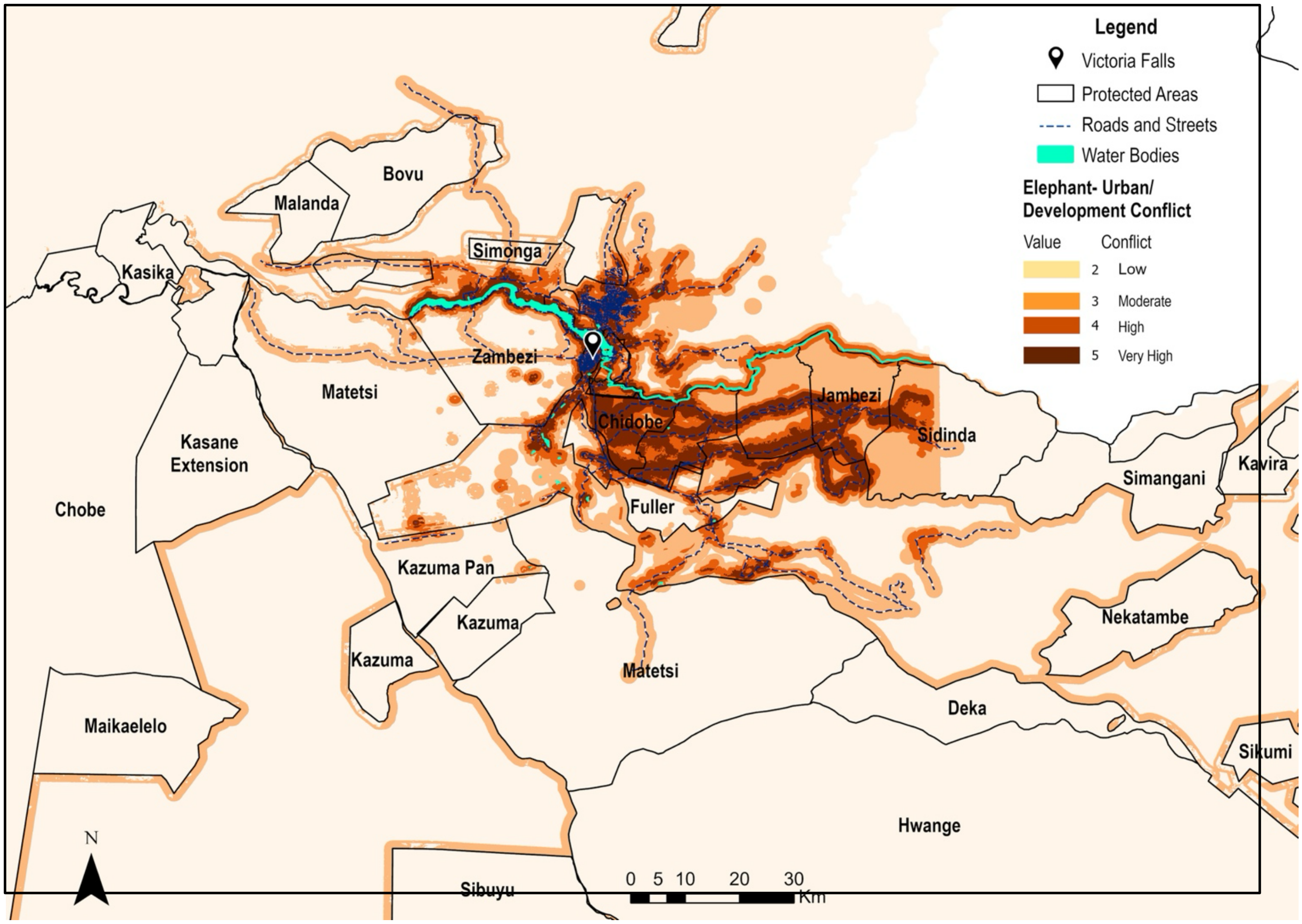

Figure 24. Areas of Potential Urban/ Development- Agriculture Conflict. Areas in Brown and Dark Orange Represent Very High- and High-Conflict. They are Represented in Existing Crop Areas and Residential/Developed Areas.

The overlay of the three suitable maps Elephant-Urbanization-Agriculture classifies 47% of the area as low conflict for all three stakeholders. These low-conflict areas are outside the 1,500-meter radius of distance features (i.e., distance to water bodies, roads, protected areas, and crops); while 46% of the area shows moderate-conflict and is within protected areas and communal lands. Only 4.5% of the study area expresses high conflict within 500 to 1500 meters of urbanized areas, roads, and important bodies of water (Figures 21D and 25). These zones are covered by terrain such as open herbaceous wetlands, closed bushlands, and bare floodplains. Only 0.9% of the study area was identified as very high-conflict zones. Those are areas within 100 and 500 m of the existing built-up area, water bodies, and roads.

The yellow areas located in the center and east of Victoria Falls represent very high conflict areas. They underlie mainly existing built-up areas (residential and hotel) and cultivation. Most of the cultivated area is located within the communal lands of Chidobe, Jambezi and Sisinda. As can be seen, most of the existing development is strongly related to the location of water bodies such as the Zambezi River, groundwater wells depicted in bright light blue, and major roads and streets shown in flattened blue lines Figure 25.

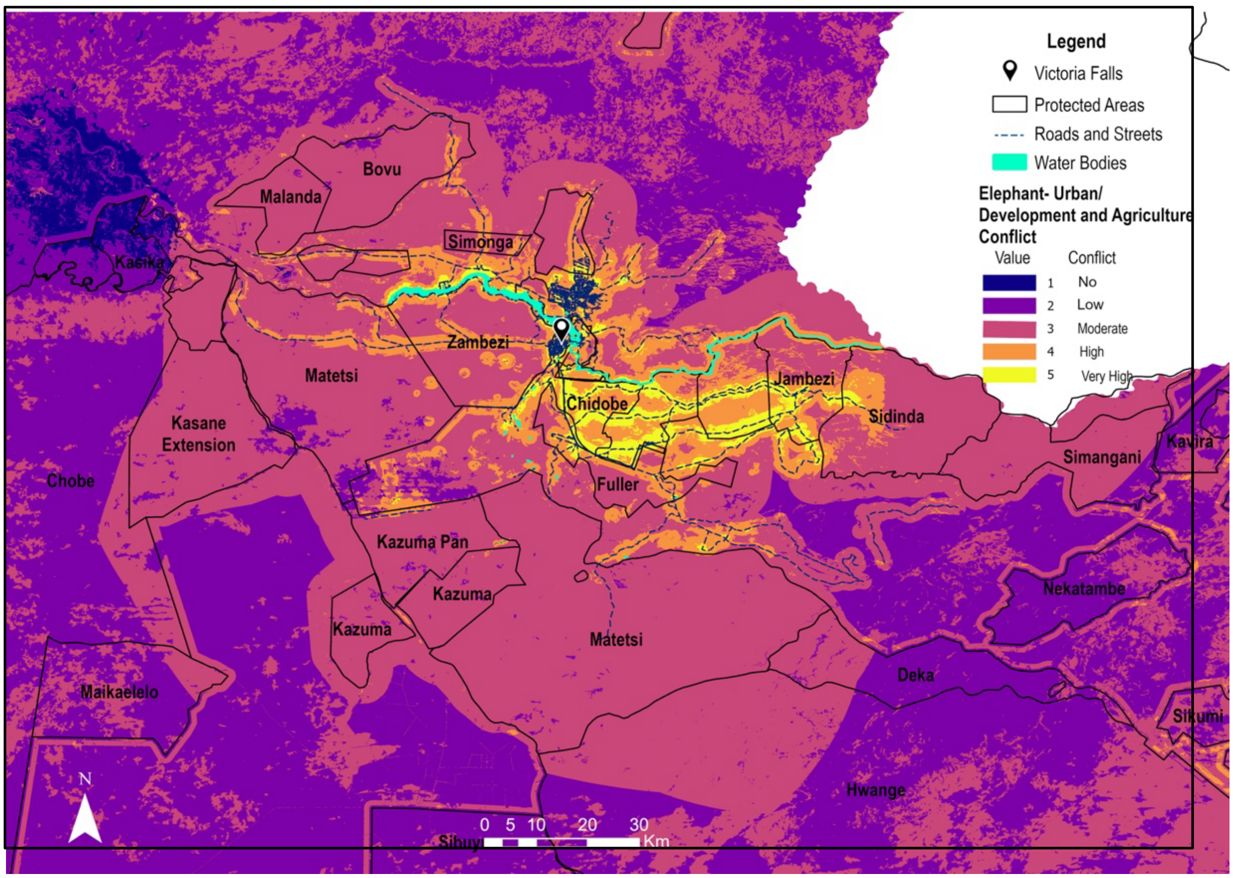

Figure 25. Areas of Potential Human-Elephant Conflict. Yellow Areas Represent Very High Potential Conflict, with most of these Areas Related to Water Bodies, Urban/Agricultural Areas and Land Cover such Woodlands, Shrubs, and Crops.

CHAPTER 6

SUMMARY AND CONCLUSIONS

This study had three objectives. The first covered the environmental factors that determine elephant use of space, the second focused on studying human land use preferences for agriculture and urban development. The third objective used the results of the human-elephant land use suitability analysis to identify areas of potential human-elephant conflict (HEC) for Victoria Falls. The results of the three objectives are summarized below.

To prepare the model of potential human-elephant conflict areas in Victoria Falls, the Land Use Conflict Identification Strategy (LUCIS) modeling framework was used. This framework allowed the inclusion of the perspective of three stakeholders regarding the use of space in a flexible manner. The implementation of this model involved the combination of spatial information on current land use generated by the KAZA project (Gebhardt, 2021) and spatial references of infrastructure downloaded from OpenStreetMap. The perspective of local stakeholders regarding their land use preferences were determined through conversation with experts with knowledge of the local reality. Expert knowledge was also input for the elephant presence prediction model which was combined with GPS data of elephant movements.

We first prepared suitability models for elephant habitat conservation, agricultural development, and urban development. To determinate the suitable areas for elephant habitat conservation, we implemented a MaxEnt presence only model based on GPS tracking data for bull elephants. For this we evaluated the likelihood of elephant presence in two models using continuous variables (distance to water bodies, distance to protected areas, distance to roads and distance to build area) and categorical variables (land use). The result of the continuous variables showed that there is a higher probability of elephant presence near water bodies and protected areas, especially the built-up area. Regarding the categorical variables, there is an over 50% probability of elephant presence in the built-up area. The land covers also of interest for elephants that are shown as very high probability represent closed woodlands, followed by closed bushlands and sparse forest/woodlands, with probability ranges between 50 and 70%. Interestingly, elephant presence in croplands was predicted to be only 20%. Presence at permanent water bodies was predicted to be nearly 35%, while seasonal water bodies and seasonal wetlands were less than 15% and 1%, respectively.

The second objective was to determine elephant conflict with human land use. The data sets used to determine areas suitable for agriculture and urban use included: 1) current land use; 2) proximity to water bodies; 3) proximity to existing crops; 4) proximity to communal lands; 5) proximity to water bodies; 6) proximity to protected areas; and 7) proximity to existing urban areas. Each of these variables represented factors that contribute to the socio-economic development of the people of Victoria Falls.

In creating the data layers on socio-economic factors, accessibility, the prohibited factors, and physical attributes for the Victoria Falls HEC potential area as model inputs, it was found that proximity to currently disturbed areas are the most preferred areas by local stakeholders for the implementation of crops or urban infrastructure. The percentage of land devoted to agriculture was highly concentrated in the area southeast of Victoria Falls within the communal land jurisdiction, while urban areas were concentrated along the banks of the Zambezi River near Victoria Falls. The agricultural zones are mostly represented by maize crops. It is a subsistence agriculture with a high dependence on boreholes (i.e., wells), seasonal water bodies and wetlands. It was observed that the variable, proximity to communal lands, defined the zones with medium interest for the development of agriculture. This is reasonable since in Victoria Falls, it is the forest reserve category where the direct use of resources is allowed, which implies the development of sustainable agriculture. The least suitable areas for agriculture are shown within the reserve zones as these areas have government regulations restricting land use for activities other than conservation. However, it is the edges of the protected areas that would appear to be moderately attractive for agricultural and urban development. This land use variable also had an influence on the delimitation of areas of medium interest for urban development and agriculture, especially the bushland class. This could be because it is a cover that is easily cleared and transformed to developed land, and it is also the most abundant.

The final objective was to use the results of the first two objectives, as well as map algebra, to develop a model showing the areas of potential conflict between humans and elephants. To do this, map algebra was used with a final cartographic output. There was a total of three input variables, each of which represented areas of interest for spatial use in agriculture, human development, and elephant habitat conservation. This model achieved its purpose of identifying low-, medium-, and high-conflict zones.

The application of the model determined that the zones with the highest potential for conflict are located near the crop and urban areas of Victoria Falls and around permanent and seasonal water bodies. The medium-conflict zones are defined by the coincidence of the extent of the spatial distribution range of elephant movement in reference to the training distance features, i.e., distance to water bodies and built-up areas.

Future Model Testing and Applications

Further research should be devoted to testing the LUCIS model by sensitivity analysis of the chosen variables and their relative weights for different years and seasons. Although noted as an important and necessary step in modeling, due to time constraints, sensitivity analysis was not carried out in this study for the areas suitable for agriculture and development. It is also important to verify the model. This could be done through field testing or in-depth discussion with NGOs currently working in the area as well as local jurisdictional and governmental agencies. The results of this study indicate that the model can be improved by incorporating more stakeholder feedback. Repeated and timely human-to-elephant encounter/conflict location data in the area would help to test the accuracy of the model and could be used to monitor any changes in the location of potential conflicts according to seasonality and resource availability.

Since this model is comprehensive and incorporates many factors, it has numerous applications. It includes social, ecological, and physical components that can serve as a reference for future studies on local community life development, other local wildlife with elephant-like ecological cycles and wildlife in other parts of the world. Many countries deal with human-wildlife conflicts because of land cover change, environmental degradation, political or natural shocks, or an unstable economy. For example, countries in Latin America, Africa, and Asia could use this model to help identify regions with higher occurrences of human-wildlife conflict and assist with resource management, protection of agricultural lands and urban planning decisions.

The fact that a similar model is not already being applied may be due to the lack of spatial data, especially concerning the use of space by wildlife. It should be noted that the elephant data used in this study tracked only bull elephants, rather than cows and family groups. Problems arise in measuring short-term versus long-term disturbances and the scale of the spatial data related to human use of space. Another deficiency lies in the accessibility and difficulty of collecting data firsthand and with the necessary frequency, as it involves financial support and training.

The LUCIS model implemented in Victoria Falls could also influence the distribution of aid from both NGOs and internal and international conservation programs. It could be used by decision makers to determine new government policies, as well as educational programs in human-elephant conflict management. Visual analysis of the results of this study indicates that the distribution of areas of potential human-elephant conflict is focused near water bodies, the urban/agricultural area and certain vegetation cover such as shrubs and trees.

Conclusions

Although the unique geography, flora and fauna of Victoria Falls are world-renowned, the subject of this study is the under-explored relationship of its population with wildlife, particularly human-elephant conflict. Specifically, this research aimed to create a spatial model to examine the relationships between social factors, environmental factors, elephant movements and areas of potential human-elephant conflict by examining elephant distributions and spatial patterns. Objective 1 was to identify landscape-scale elephant land-use preferences using GPS tracking data from 22 elephants collected between 2017 and 2021, elephant behavior in response to environmental variables and human characteristics using the presence only Maxent model. The results were used to identify critical areas for elephant conservation. Objective 2 was to model areas suitable for human development and sustainable agriculture using raster and vector data, as well as stakeholder preferences and create maps suitable for development of human activities (i.e., urban/residential development and sustainable subsistence agriculture). And the Objective 3 was to apply the LUCIS model to identify areas of potential conflict between different stakeholders (i.e., urban/residential development subsistence agriculture, and elephants) that can be used to mitigate human-elephant conflict and assist in the implementation of a GeoDesign for future development, agriculture and wildlife conservation in Victoria Falls, Zimbabwe.

The variables chosen for this model were appropriate and reasonable in terms of their influence on both human and elephant use of space. The results of the LUCIS model for Victoria Falls indicated that the areas most likely to experience human-elephant conflict in the wet season are those near water bodies, the built-up area of Victoria Falls and the cropping area. This information provided by the model results can be used to inform public policy and social programs, allowing them to address the more complicated issues related to human-elephant conflict. This integrated analysis of spatial and ecological variables associated with HEC using a GIS approach demonstrated the application of geospatial ecology, GeoAI and spatial statistics to broad domains and contributed to research methodological tools that bridge the traditional fields of human geography, ecology, and geospatial techniques. The incorporation of ecological and GeoAI factors to apply the LUCIS model has been little used in human-wildlife conflict studies. The Victoria Falls LUCIS model contains aspects of social, physical, and ecological phenomena that intersect in geographic space to produce information on areas of potential human-elephant conflict. The nature of HEC varies from casual to permanent according to climatic conditions and availability of natural resources. Although each of the five levels of potential conflict (from low to high) occurred over approximately 20% of the land area, statistical analysis of the spatial pattern of conflict revealed that the highest levels were significantly clustered in the vicinity of the Zambezi River and in the urban area of Victoria Falls. The LUCIS model results of this study show low-conflict zones within the protected areas but intensifying at the edges of the protected areas due to gradual land degradation and loss (e.g., the deforested periphery, especially the central and eastern parts of the study area near the agricultural area, and the decrease of available food due to the inadequacy of the road network).

The identification of potential human-elephant conflict hotspots is expected to help guide conflict prevention and management efforts in times of climate crisis and natural resource availability. Suitability maps can be used in participatory workshops with stakeholders from different interest groups (i.e., conservation, agriculture sustainability, and urban development). The maps will provide the participants a spatial perspective of their areas of interest and allow for an understanding of current land use and its potential impacts on wildlife and the development of local communities' livelihoods. This is a starting point to negotiate for current and future spatial use and develop agreements and regulations. By bringing stakeholders together, interactive exercises can be developed to validate the results and make the necessary adjustments to the model, which will increase the accuracy of the model of potential current conflicts. These validated results can also serve as a starting point for long-term projections and monitoring of potential conflict zones and be applied to natural resource management with an adaptive approach. Future scenarios can also be developed by assigning different weights to each use according to the priorities of local agencies/governments (with interests, for example, in elephant habitat conservation, commercial/urban and agriculture) to the designed model in model builder. This will allow stakeholders to visualize the potential outcomes of certain spatial use decisions, which may be reflected in an increase or decrease in conflict. Areas of potential conflict can also be analyzed as areas of opportunity for human-elephant cooperation that can be of benefit to local communities. The models can be important information for feasibility studies of eco-projects such as the development of conservation tourism activities or other sustainable productive activities.

Another aspect to consider is that this model was only applied for the 2020 wet season. Future studies could analyze suitable areas for elephant habitat during the dry season under normal and drought conditions. This multi-temporal modeling could help stakeholders identify conflict areas in advance of seasonal changes and predicted climate changes to establish conflict management strategies. This would be possible through a training program for local entities to make use of the proposed model with different data sets of elephant movements for each season. This would be possible through the socialization of basic GIS techniques and the manipulation of the proposed model. That would open the opportunity to initiate a monitoring program of human-wildlife conflict and spatial interaction, as this methodology can even be extended to the analysis of movement data of other wildlife species in the area.

This study is a unique and valuable contribution to the literature because it incorporates a set of ecological and socio-economic variables towards understanding human-elephant conflict and uses spatial statistics rather than classical statistics to examine the importance of apparent spatial patterns. The usefulness of this model derives from the nature of human-wildlife conflict as a problem that is not only social but also strongly influenced by the physical environment and ecological processes of wildlife space use. At the regional scale, the results of the human-elephant land use conflict identification model in Victoria Falls reflect the general trends produced by cumulative human use of space; however, these patterns may change according to the availability of resources in each season (wet and dry). Because this model includes social as well as physical and ecological factors, the Victoria Falls LUCIS model is more robust and provides a more complete picture of the spatial distribution of human-elephant land-use conflict in Victoria Falls.

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APPENDICES

Appendix 1Reclassification Schema for Suitable Analysis and LUCIS Model

1.1.Reclassification Schema for Modelling Suitable Areas for Agriculture

Distance to Protected Areas	Weight
Reclass	
0-100	1
100-500	2
500-1000	3
1000-1500	4
1500- >	5
Land Use	**Weight**
Reclass	
Built-Up/ Cropland	5
Water Bodies	3
Herbaceous Wetland	2
Woodland	3
Bushland	4
Distance to Existing Crops	**Weight**
Reclass	
0-100	5
100-500	4
500-1000	3
1000-1500	2
1500- >	1
Communal Lands	**Weight**
Reclass	
0-100	5
100-500	4
500-1000	3
1000-1500	2
1500-+	1
Distance To Water Bodies	**Weight**
Reclass	
0-100	1
100-500	5
500-1000	4
1000-1500	3
1500- >	1

Distance to Roads	Weight
Reclass	
0-100	1
100-500	5
500-1000	4
1000-1500	3
1500- >	2

Layer Weights	
Distance to Protected Areas	10
Land Use	30
Distance to Existing Crops	20
Distance to Communal Lands	10
Distance to Water Bodies	20
Distance to Roads	10

1.1. Reclassification Schema for Modelling Suitable Areas for Urban/ Development

Distance to Protected Areas	Weight
Reclass	
0-100	1
100-500	2
500-1000	3
1000-1500	4
1500- >	5
Land Use	**Weight**
Reclass	
Build-up/ cropland	5
Water bodies	1
Herbaceous Wetland	1
Woodland	3
Bushland	4
Distance to Existing Built Area	**Weight**
Reclass	
0-100	5
100-500	5
500-1000	4
1000-1500	3
1500- >	1

Communal Lands	Weight
Reclass	
0-100	5
100-500	4
500-1000	3
1000-1500	2
1500-+	1
Distance to Water Bodies	**Weight**
Reclass	
0-100	1
100-500	5
500-1000	4
1000-1500	3
1500- >	1
Distance to Toads	**Weight**
Reclass	
0-100	1
100-500	5
500-1000	4
1000-1500	3
1500- >	2

Weights of Elephant Conservation	
Layers	**Weights**
Distance to Protected Areas	10
Land Use	20
Distance to Existing Urban	30
Distance to Communal Lands	10
Distance to Water Bodies	20
Distance to Roads	10

1.2.Reclassification Schema for Modelling Suitable Areas for Elephant Habitat Conservation

Probability of Occurrence of Land Use Layer	Weight
Reclass	
0.1	1
0.1-0.2	2
0.2-0.4	3
0.4-0.6	4
0.6-0.7	5

Probability of Occurrence of Distance Layers	Weight
Reclass	
0.1	1
0.1-0.2	2
0.2-0.4	3
0.4-0.6	4
0.6-0.7	5

Layer Weights Elephant Conservation	
Layers	**Weight**
Distance variables	1
Land Use	2

1.3.Influential Weights of Suitability Maps for LUCIS Model

Suitability Maps	Weights
Suitable Areas for Elephant Conservation	40
Suitable Areas for Agriculture Sustainability	30
Suitable Areas for Urban/Development	30
Total	100

Appendix 2. Geoprocessing Workflow for the LUCIS model implementation in Model Builder in ArcGIS Pro.

```
# -*- coding: utf-8 -*-"""Generated by ArcGIS ModelBuilder on : 2023-07-16 19:03:16"""import arcpydef Model7():

# Model7    # To allow overwriting outputs change overwriteOutput option to True.
arcpy.env.overwriteOutput = False    Reclass_LUC_1 = arcpy.Raster("Reclass_LUC_1")
Elephant_probability_of_occurrance_distance_variables_ = arcpy.Raster("Trained rasters \\Elephant probability of occurrance distance variables ")
Elephant_probability_of_occurrance_LUC_wet = arcpy.Raster("Trained rasters \\Elephant probability of occurrance LUC wet")    Dist_protected_areas_3_ = arcpy.Raster("ModelBuilder\\Dist_protected_areas")    Reclass_LUC_1_3_ = arcpy.Raster("Reclass_LUC_1")    Dist_Build = arcpy.Raster("ModelBuilder\\Dist_Build")
Dist_communal_lands_3_ = arcpy.Raster("ModelBuilder\\Dist_communal_lands")
Dist_roads_3_ = arcpy.Raster("ModelBuilder\\Dist_roads")    Dist_water_bodies_3_ = arcpy.Raster("ModelBuilder\\Dist_water_bodies")    Dist_protected_areas =
```

```
arcpy.Raster("ModelBuilder\\Dist_protected_areas")    EucDist_crop =
arcpy.Raster("ModelBuilder\\EucDist_crop")    Dist_communal_lands =
arcpy.Raster("ModelBuilder\\Dist_communal_lands")    Dist_water_bodies =
arcpy.Raster("ModelBuilder\\Dist_water_bodies")    Dist_roads =
arcpy.Raster("ModelBuilder\\Dist_roads")

  # Process: Reclassify (Reclassify) (sa)    Reclass_LUC =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_LUC"    Reclassify = Reclass_LUC    Reclass_LUC = arcpy.sa.Reclassify(in_raster=Reclass_LUC_1,
reclass_field="CLASS", remap="Buildup/Cropland 5;Bushland 4;'Herbaceous Wetlands'
2;'Water Bodies' 3;Woodland 3", missing_values="DATA")    Reclass_LUC.save(Reclassify)

# Process: Reclassify (13) (Reclassify) (sa)    Reclass_VA =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_VA"    Reclassify_13_ = Reclass_VA    Reclass_VA =
arcpy.sa.Reclassify(in_raster=Elephant_probability_of_occurrance_distance_variables_,
reclass_field="VALUE", remap="0.000000082 0.100000000 1;0.100000000 0.200000000
2;0.200000000 0.400000000 3;0.400000000 0.600000000 4;0.600000000 0.790083029 5",
missing_values="DATA")    Reclass_VA.save(Reclassify_13_)

# Process: Reclassify (14) (Reclassify) (sa)    Reclass_LUC_2_ =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_LUC"    Reclassify_14_ = Reclass_LUC_2_    Reclass_LUC_2_ =
arcpy.sa.Reclassify(in_raster=Elephant_probability_of_occurrance_LUC_wet,
reclass_field="VALUE", remap="0.062364798 0.100000000 1;0.100000000 0.200000000
2;0.200000000 0.400000000 3;0.400000000 0.600000000 4;0.600000000 0.730064058 5",
missing_values="DATA")    Reclass_LUC_2_.save(Reclassify_14_)

# Process: Weighted Sum (3) (Weighted Sum) (sa)    Elephant_ok =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Elepha
nt_ok"    Weighted_Sum_3_ = Elephant_ok    Elephant_ok =
arcpy.sa.WeightedSum(in_rasters=[[Reclass_VA, "VALUE", 20], [Reclass_LUC_2_, "VALUE", 80]])
Elephant_ok.save(Weighted_Sum_3_)

  # Process: Reclassify (7) (Reclassify) (sa)    Reclass_PA2 =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_PA2"    Reclassify_7_ = Reclass_PA2    Reclass_PA2 =
arcpy.sa.Reclassify(in_raster=Dist_protected_areas_3_, reclass_field="VALUE", remap="0 100
1;100 500 2;500 1000 3;1000 1500 4;1500 47370.007812 5", missing_values="DATA")
Reclass_PA2.save(Reclassify_7_)
```

```
# Process: Reclassify (8) (Reclassify) (sa)    Reclass_LUC2 =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_LUC2"    Reclassify_8_ = Reclass_LUC2    Reclass_LUC2 =
arcpy.sa.Reclassify(in_raster=Reclass_LUC_1_3_, reclass_field="CLASS",
remap="Buildup/Cropland 5;Bushland 4;'Herbaceous Wetlands' 1;'Water Bodies' 1;Woodland
3", missing_values="DATA")    Reclass_LUC2.save(Reclassify_8_)

# Process: Reclassify (9) (Reclassify) (sa)    Reclass_Build2 =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_Build2"    Reclassify_9_ = Reclass_Build2    Reclass_Build2 =
arcpy.sa.Reclassify(in_raster=Dist_Build, reclass_field="VALUE", remap="0 100 5;100 500 5;500
1000 4;1000 1500 3;1500 147326.375000 1", missing_values="DATA")
Reclass_Build2.save(Reclassify_9_)

# Process: Reclassify (10) (Reclassify) (sa)    Reclass_CL2_2_ =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_CL2"    Reclassify_10_ = Reclass_CL2_2_    Reclass_CL2_2_ =
arcpy.sa.Reclassify(in_raster=Dist_communal_lands_3_, reclass_field="VALUE", remap="0 100
5;100 500 4;500 1000 3;1000 1500 2;1500 179209.515625 1", missing_values="DATA")
Reclass_CL2_2_.save(Reclassify_10_)

# Process: Reclassify (11) (Reclassify) (sa)    Reclass_RO2 =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_RO2"    Reclassify_11_ = Reclass_RO2    Reclass_RO2 =
arcpy.sa.Reclassify(in_raster=Dist_roads_3_, reclass_field="VALUE", remap="0 100 1;100 500
5;500 1000 4;1000 1500 3;1500 140802 2", missing_values="DATA")
Reclass_RO2.save(Reclassify_11_)

# Process: Reclassify (12) (Reclassify) (sa)    Reclass_WB2 =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_WB2"    Reclassify_12_ = Reclass_WB2    Reclass_WB2 =
arcpy.sa.Reclassify(in_raster=Dist_water_bodies_3_, reclass_field="VALUE", remap="0 100
1;100 500 5;500 1000 4;1000 1500 3;1500 151958.156250 2", missing_values="DATA")
Reclass_WB2.save(Reclassify_12_)

# Process: Weighted Sum (2) (Weighted Sum) (sa)    URBAN =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\URBA
N"    Weighted_Sum_2_ = URBAN    URBAN =
arcpy.sa.WeightedSum(in_rasters=[[Reclass_PA2, "VALUE", 10], [Reclass_LUC2, "VALUE", 20],
[Reclass_Build2, "VALUE", 30], [Reclass_CL2_2_, "VALUE", 10], [Reclass_RO2, "VALUE", 20],
[Reclass_WB2, "VALUE", 10]])    URBAN.save(Weighted_Sum_2_)
```

```
# Process: Reclassify (2) (Reclassify) (sa)    Reclass_PA =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_PA"    Reclassify_2_ = Reclass_PA    Reclass_PA =
arcpy.sa.Reclassify(in_raster=Dist_protected_areas, reclass_field="VALUE", remap="0 100 1;100
500 2;500 1000 3;1000 1500 4;1500 47370.007812 1", missing_values="DATA")
Reclass_PA.save(Reclassify_2_)

# Process: Reclassify (3) (Reclassify) (sa)    Reclass_Crops =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_Crops"    Reclassify_3_ = Reclass_Crops    Reclass_Crops =
arcpy.sa.Reclassify(in_raster=EucDist_crop, reclass_field="VALUE", remap="0 100 5;100 500
4;500 1000 3;1000 1500 2;1500 150481.921875 1", missing_values="DATA")
Reclass_Crops.save(Reclassify_3_)

# Process: Reclassify (4) (Reclassify) (sa)    Reclass_CL =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_CL"    Reclassify_4_ = Reclass_CL    Reclass_CL =
arcpy.sa.Reclassify(in_raster=Dist_communal_lands, reclass_field="VALUE", remap="0 100
5;100 500 4;500 1000 3;1000 1500 2;1500 179209.515625 1", missing_values="DATA")
Reclass_CL.save(Reclassify_4_)

# Process: Reclassify (5) (Reclassify) (sa)    Reclass_WB =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_WB"    Reclassify_5_ = Reclass_WB    Reclass_WB =
arcpy.sa.Reclassify(in_raster=Dist_water_bodies, reclass_field="VALUE", remap="0 100 1;100
500 5;500 1000 4;1000 1500 3;1500 151958.156250 1", missing_values="DATA")
Reclass_WB.save(Reclassify_5_)

# Process: Reclassify (6) (Reclassify) (sa)    Reclass_Roads =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Reclass
_Roads"    Reclassify_6_ = Reclass_Roads    Reclass_Roads =
arcpy.sa.Reclassify(in_raster=Dist_roads, reclass_field="VALUE", remap="0 100 1;100 500 5;500
1000 4;1000 1500 3;1500 140802 2", missing_values="DATA")
Reclass_Roads.save(Reclassify_6_)

# Process: Weighted Sum (Weighted Sum) (sa)    Agriculture =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Agricul
ture"    Weighted_Sum = Agriculture    Agriculture =
arcpy.sa.WeightedSum(in_rasters=[[Reclass_PA, "VALUE", 10], [Reclass_Crops, "VALUE", 20],
```

```
[Reclass_CL, "VALUE", 10], [Reclass_WB, "VALUE", 20], [Reclass_Roads, "VALUE", 10]])
Agriculture.save(Weighted_Sum)

# Process: Weighted Sum (4) (Weighted Sum) (sa)    Weighte_Elep1 =
"C:\\Users\\ecd43902\\Documents\\ArcGIS\\Projects\\VictoriaF_SA\\VictoriaF_SA.gdb\\Weight
e_Elep1"    Weighted_Sum_4_ = Weighte_Elep1    Weighte_Elep1 =
arcpy.sa.WeightedSum(in_rasters=[[Elephant_ok, "VALUE", 2], [URBAN, "VALUE", 1],
[Agriculture, "VALUE", 1]])    Weighte_Elep1.save(Weighted_Sum_4_)if __name__ == '__main__':

# Global Environment settings    with
arcpy.EnvManager(cellSize=r"C:\Users\ecd43902\Documents\ELLEN\Spring 2023\spatial
analysis_ thesis\NDVI_ROI\wet2017", cellSizeProjectionMethod="PRESERVE_RESOLUTION",
outputCoordinateSystem="PROJCS["WGS_1984_UTM_Zone_34S",GEOGCS["GCS_WGS_1984",
DATUM["D_WGS_1984",SPHEROID["WGS_1984",6378137.0,298.257223563]],PRIMEM["Greenw
ich",0.0],UNIT["Degree",0.0174532925199433]],PROJECTION["Transverse_Mercator"],PARAMET
ER["False_Easting",500000.0],PARAMETER["False_Northing",10000000.0],PARAMETER["Central_
Meridian",21.0],PARAMETER["Scale_Factor",0.9996],PARAMETER["Latitude_Of_Origin",0.0],UNI
T["Meter",1.0]]",
scratchWorkspace=r"C:\Users\ecd43902\Documents\ArcGIS\Projects\VictoriaF_SA\VictoriaF_S
A.gdb",
workspace=r"C:\Users\ecd43902\Documents\ArcGIS\Projects\VictoriaF_SA\VictoriaF_SA.gdb"):
Model7()
```