# MODELING HABITAT SUITABILITY FOR AFRICAN ELEPHANTS (*Loxodonta africana*) AND THEIR PREFERRED FORAGE IN NASALOT-SOUTH TURKANA-KERIO VALLEY ECOSYSTEM, KENYA

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**A THESIS SUBMITTED TO THE SCHOOL OF ENVIRONMENTAL SCIENCES AND NATURAL RESOURCE MANAGEMENT IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF DOCTOR OF PHILOSOPHY IN ENVIRONMENTAL STUDIES (ENVIRONMENTAL BIOLOGY), UNIVERSITY OF ELDORET, KENYA**

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# DECLARATION

## Declaration by the Candidate

This thesis is my original work and has not been submitted for any academic award in any institution, and shall not be produced in part or in full, or in any form without prior written permission from the author and/or University of Eldoret.

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# DEDICATION

This work is dedicated to my family, David, Deborah, Norah, Collins, and Ethan.

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# ABSTRACT

Understanding the environmental drivers of habitat suitability for African elephants and their preferred forage plants is critical for conservation, particularly under climate change. This study focused on the Nasalot–South Turkana–Kerio Valley ecosystem in Kenya, aiming to model the current and future spatial distribution and abundance of suitable habitats for African elephants and their preferred forage plants. It also analyzed key environmental factors influencing habitat distribution and evaluated the impacts of climate change under Shared Socio-Economic Pathways (SSP) 245 and SSP585 scenarios for 2041–2060 and 2081–2100-time horizons, using the Canadian Earth System Model Version 2 (CanESM2) model from Sixth Phase of the Coupled model Intercomparison Project (CMIP6). Elephant occurrence data were sourced from previous surveys, while preferred forage plant data were systematically collected along 1 km-spaced line transects. Data on climate, topography, vegetation, soil, distance layers, and Land Use/Land Cover (LULC) were obtained from global databases, including World Climate (WorldClim), United States Geological Survey (USGS), Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM), HydroSHEDS, and OpenStreetMap. A Maximum Entropy (MaxEnt) model was employed using spatially independent occurrence data, non-correlated environmental variables, linear and quadratic feature combinations, and regularization multipliers of 1 and 3.5 for elephants and their preferred forage plants, respectively. Model performance was evaluated using the Area Under the Curve (AUC) of the Receiver Operator Curve (ROC) curve. Both models showed strong predictive performance, with mean AUC values of 0.868 ± 0.006 for elephants and 0.883 ± 0.007 for their preferred forage plants. Results indicated that African elephants and their preferred forage plants are highly susceptible to climate change, with habitat suitability and abundance exhibiting notable spatial variability. At present, suitable habitats are limited in extent, with low-suitability areas dominating central regions and highly suitable zones largely restricted to the south. Forage species exhibit similarly low habitat abundance, particularly across central and northern areas. Projections under both SSP245 and SSP585 scenarios indicate a substantial decline in the abundance of suitable habitats, with a pronounced shift toward unsuitability, especially in northern regions, including key protected areas such as Nasalot and South Turkana. Jackknife tests identified precipitation of the coldest quarter (62.5%) and LULC (14.6%) as the main factors influencing elephant habitat suitability, while precipitation seasonality, precipitation of the driest quarter, elevation, and LULC were the primary drivers for forage plant suitability. Climate change was projected to threaten the distribution and survival of both elephants and their forage plants, with suitability shifts varying by scenario and timeframe. These findings highlight the need for adaptive management strategies that incorporate future climate projections to safeguard elephant populations and their forage resources in this vulnerable dryland ecosystem.

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# ABBREVIATIONS, ACRONYMS, AND SYMBOLS

| | |
|---|---|
| A2: | High-emissions scenario from the Special Report on Emissions Scenarios (SRES) family |
| AICc: | Akaike Information Criterion corrected for small sample sizes |
| ArcGIS: | Geographic Information System for Arc/Info |
| ASTER: | Advanced Spaceborne Thermal Emission and Reflection Radiometer |
| ArcGIS: | Aeronautical Reconnaissance Coverage Geographical Information System |
| ASCII (.csv): | Comma delimited data format |
| a.s.l.: | Above Sea Level |
| AUC: | Area Under the Curve |
| AUCdiff: | Difference between the training and test areas under the Receiver Operating Characteristics Curve |
| Bioclim: | Bioclimatic modeling software programs |
| BIOMOD2: | Biological Models version 2 |
| CA: | Correlation Analysis |
| CanESM2: | Canadian Earth System Model Version 2 |
| CBD: | Convention on Biological Diversity |
| CCCMa: | Canadian Centre for Climate Modelling and Analysis |
| CIFOR: | Center for International Forestry Research |
| CITES: | Convention on International Trade in Endangered Species of Wild Fauna and Flora |
| CKC: | Choen’s Kappa Coefficient |
| CSIRO: | Commonwealth Scientific and Industrial Research Organization |
| CMIP5: | Fifth Phase of the Coupled Model Intercomparison Project |
| CMIP6: | Sixth Phase of the Coupled Model Intercomparison Project |
| DEM: | Digital Elevation Model |
| DN: | Digital Number |
| DRSRS: | Department of Resource Surveys and Remote Sensing |

| | |
|---|---|
| DSMW: | Digital Soil Map of the World |
| DSOM: | Dynamic Site Occupancy Model |
| ENVIREM: | Environmental Rasters for Ecological Modeling |
| ESRI: | Environmental Systems Research Institute |
| e.g: | For example |
| FAO: | Food & Agriculture Organization |
| FC: | Feature Combination |
| GBIF: | Global Biodiversity Information Facility |
| GCM: | General Circulation Model |
| GDP: | Gross Domestic Product |
| GLMs: | Generalized Linear Models |
| GoK: | Government of Kenya |
| GPS: | Global Positioning System |
| ha.: | Hectare |
| HydroSHEDS: | Hydrological Data and Maps based on SHuttle Elevation Derivatives at Multiple Scales |
| ICRAF: | International Centre for Research in Agroforestry |
| i. e: | In other words |
| INM-CM5-0: | Institute for Numerical Mathematics, Climate Model Version 5 |
| IUCN: | International Union of Conservation of Nature |
| $Km^2$: | Kilometer Square |
| KWS: | Kenya Wildlife Services |
| L: | Linear |
| Lat: | Latitude |
| LQ: | Linear/Quadratic |
| Long: | Longitude |
| LULC: | Land Use/Land Cover |
| LQPHT: | Linear, Quadratic, Hinge and Product |
| M: | Meters |
| MaxEnt: | Maximum Entropy |
| MAP: | Mean Annual Precipitation |

| | |
|---|---|
| MLC: | Maximum Likelihood Classification |
| MM: | Millimeters |
| MWMT: | Mean Warmest Month Temperature |
| N: | North |
| NIR: | Near Infrared |
| OA: | Overall Accuracy |
| OLI: | Operational Land Imager |
| PA: | Producer Accuracy |
| PAs: | Protected areas |
| pH: | Potential of Hydrogen |
| Q: | Quadratic |
| QGIS: | An open-source Geographic Information System |
| QSWAT: | QGIS interface (plugin) for the SWAT model |
| RGB: | Red, Green, and Blue composite |
| RCP: | Representative Concentration Pathway |
| RC: | Regularization Multiplier |
| ROC: | Receiver Operator Curve |
| SDGS: | Sustainable Development Goals |
| SNUM: | Soil Numbers |
| SSP: | Shared Socio-Economic Pathways |
| SPSS: | Statistical Package for the Social Sciences |
| SWAT: | Soil and Water Assessment Tool |
| Syn: | Synonym |
| TOR: | Top of Atmosphere Reflectance |
| TWI: | Topographic Wetness Index |
| UK-ESM1-0-LL: | United Kingdom Earth System Model Version 1.0-Low-Resolution Configuration |
| UA: | Users’ Accuracy |
| UN: | United Nations |
| UNEP: | United Nations Environmental Program |
| USGS: | United States Geological Survey |

| | |
|---|---|
| UTM: | Universal Transverse Mercator |
| VCF: | Vegetation Continuous Fields |
| WEPs: | Wild Edible Plants |
| WGS84: | World Geodetic System 1984 |
| WorldClim: | World Climate |
| WRTI: | Wildlife Research and Training Institute |
| °C: | Degrees Celsius |
| %: | Percentage |
| β: | Beta |
| ~: | Approximately |
| >: | Greater than |
| <: | Less than |
| ≥: | Equal to/greater than |
| ≤: | Equal to/less than |
| ±: | Plus/minus |

# CHAPTER ONE

# INTRODUCTION

## 1.1 Background Information

Elephants are vital mega-herbivores regarded as ecosystem engineers due to their ability to alter vegetation structure and create habitat heterogeneity (Ong *et al*., 2023; Pringle, 2008; Skarpe *et al.*, 2004), and as keystone species because of their role in seed dispersal, nutrient mobilization, and maintaining biodiversity (Campos-Arceiz & Blake, 2011; Geleta & Mengesha, 2022, McNaughton *et al.*, 1997; Polansky *et al.*, 2019). They support ecosystem functioning through habitat creation, nutrient cycling, and carbon sequestration, and offer socio-economic and cultural benefits such as tourism and spiritual value (Berzaghi *et al.*, 2019; Campos-Arceiz, 2009; Naidoo *et al.*, 2016).

Although elephants are primarily conserved in protected areas (PAs) (Correa *et al.*, 2024; Rathnayake *et al.*, 2022), a substantial proportion of populations, home ranges, core areas, and suitable habitats occur outside PAs (de la Torre *et al.*, 2022; Dejene *et al.*, 2021; Fernando *et al.*, 2010; Government of Kenya (GoK), 2012; Kshettry *et al.*, 2020; Li *et al.*, 2023; Okello *et al.*, 2011, 2015; Syombua, 2013), due to their large spatial requirements for survival and reproduction (Makati *et al.*, 2025). In Asia, 75.17% of core elephant habitats fall outside current PAs (Yang *et al.*, 2022), and in Peninsular Malaysia and Sabah, more than half of elephant home ranges lie beyond protected zones (de la Torre *et al.*, 2022). Similarly, elephants in Malaysian Borneo and northeastern India frequently use forest-agriculture mosaics and community-managed forests outside formal PAs (de la Torre *et al.*, 2022; Kshettry *et al.*, 2020).

In Africa, while protected areas are vital for African elephants, about 57.4% of their potential habitats lie outside these zones (Wall *et al.*, 2021). Elephants frequently use communal rangelands despite fragmentation and human-related risks (Bastille-Rousseau *et al.*, 2019; Graham *et al.*, 2009; Granados *et al.*, 2012; Okello *et al.*, 2015). In Kenya, over 80% of wildlife, including elephants, is often found outside protected areas, especially during the dry season (GoK, 2012; Okello *et al.*, 2011; Syombua, 2013). Also, a study focusing on the Amboseli landscape observed that elephants' home ranges encompassed various habitats outside protected areas, including woodlands and bushlands (Okello *et al.*, 2015).

Elephants exhibit remarkable ecological adaptability, occupying a wide range of habitats across Asia and Africa. Asian elephants inhabit diverse environments, including grasslands, evergreen and semi-evergreen forests, moist deciduous forests, shrublands, riparian zones, forest–grassland ecotones, floodplains, and degraded lands throughout regions such as China, India, Nepal, Indonesia, and Southeast Asia (Budhathoki *et al.*, 2023; Chen *et al.*, 2023; de Silva *et al.*, 2023; He *et al.*, 2024; Kuswanda *et al.*, 2023; Palei *et al.*, 2024; Yang *et al.*, 2022). Similarly, African elephants are distributed across varied ecosystems, from arid and semi-arid savannas to dense tropical forests, and utilize habitats such as woodlands, shrublands, grasslands, forest edges, and riverine areas in Central, Southern, and East Africa (Blake *et al.*, 2008; Chase *et al.*, 2016; Loarie *et al.*, 2009; Okello *et al.*, 2015). This broad habitat tolerance highlights the need to conserve diverse ecosystem types to support the spatial and ecological requirements of both elephant species.

Elephants are generalist, mixed feeders that consume a wide range of plant types and parts, yet exhibit selective feeding based on habitat, season, and nutritional needs (Codron *et al.*, 2011; Koirala *et al.,* 2016; Woolley *et al.,* 2011). Despite utilizing hundreds of plant species, they consistently prefer certain species (Geleta & Mengesha, 2022; Ihwagi *et al.*, 2010; Kalemera, 1989; Kuswanda *et al.*, 2023; Koirala *et al.*, 2016; Koskey, 2013, 2016; Mwambola *et al.*, 2014; Owen-Smith & Chafota, 2012; Tsegaye *et al.*, 2022; Woldegiorgis & Bekele, 2012) and plant parts, such as leaves and shoots during wet seasons and bark, roots, and stems during dry periods (Owen-Smith & Chafota, 2012; Tsegaye *et al.,* 2022), while in Indonesia, young leaves dominated their diet (Kuswanda *et al.,* 2023).

Elephants also selectively raid crops, such as maize and millet, thereby intensifying human-elephant conflict (Koskey, 2013, 2016). Nutritional analyses show a preference for forage high in protein and digestible sugars, with dietary shifts enabling adaptation to seasonal resource changes (Koskey, 2013, 2016; Staver & Hempson, 2020; Vogel *et al.,* 2020). In stable environments like Rubondo Island, diets remain consistent throughout the year (Mwambola *et al.,* 2024), whereas elephants in seasonal ecosystems diversify their diets to meet their nutritional demands. Mineral intake through bark stripping and geophagy is common, especially during periods of stress or reproduction (Codron *et al.,* 2011; Woolley *et al.,* 2011).

Elephant spatial behavior, including distribution and habitat suitability, is highly dynamic and shaped by a combination of environmental and anthropogenic factors. Key influences include precipitation, temperature, vegetation composition, forage quality and availability, proximity to water, topography, and anthropogenic factors such as road networks, fencing, agricultural expansion, and the creation of protected areas, which have further altered elephant movements and habitat use across landscapes (Akala *et al.*, 2023; Ashiagbor &

Danquah, 2017; Budhathoki *et al.*, 2023; He *et al.*, 2023; Jeza & Bekele, 2023; Kanagaraj *et al.*, 2019; Matawa *et al.*, 2012; Muposhi *et al.*, 2016; Williams *et al.*, 2018).

Beyond environmental and human factors, intrinsic ecological interactions like predation and interspecific competition also influence elephant spatial behavior. In Hwange National Park, Zimbabwe, elephants concentrated around water points earlier in the day during dry seasons, prompting other herbivores to shift their activity to avoid competition (Valeix *et al.*, 2007). Elephant-driven vegetation changes can reduce habitat heterogeneity, limiting resources for other species (Pringle, 2008; Young *et al.*, 2005), and increased elephant biomass is often negatively correlated with other browsers (Fritz *et al.*, 2002; Valeix *et al.*, 2008). Predation risk, especially to calves and juveniles, also shapes habitat use, with elephants avoiding areas of high predator presence (Power & Compion, 2009; Valeix *et al.*, 2009).

However, elephants face a range of anthropogenic threats across their ranges, largely driven by growing human populations, expanding settlements, agriculture, and infrastructure development (Chen *et al.*, 2021; Kioko & Seno, 2015; Ling *et al.*, 2016; Menon & Tiwari, 2019; Okello *et al.*, 2015; Schüßler *et al.*, 2019). Key threats include habitat loss and degradation, fragmentation of migratory corridors, poaching, land use change, and climate change (Chen *et al.*, 2021; Kioko & Seno, 2015; Ling *et al.*, 2016; Menon & Tiwari, 2019; Okello *et al.*, 2015; Schüßler *et al.*, 2019). These pressures have intensified Human-Elephant Conflicts (HECs), led to population isolation, reduced genetic diversity, increased inbreeding, local extinctions, and overall population declines (African Elephant Status Report, 2016; International Union of Conservation of Nature (IUCN), 2021; World Wildlife Fund (WWF), 2021; Lohay *et al.*, 2020).

According to the IUCN Red List of 2021, African forest elephant populations have declined by over 86% in 31 years, and African savanna elephants by at least 60% over the past 50 years (IUCN, 2021). The African Elephant Status Report (2016) estimates a loss of approximately 111,000 elephants in a decade, with around 415,000 African elephants remaining (Thouless *et al.,* 2016; Richie, 2024). In Asia, wild elephant numbers are estimated at 40,000–50,000 individuals (Richie, 2024). However, due to these declines, African forest elephants are classified as critically endangered, while African savanna and Asian elephants are listed as endangered on the IUCN Red List (IUCN, 2021).

Elephant habitats across Asia and Africa are increasingly threatened by urban expansion, infrastructure development, and land use changes, leading to significant habitat loss and degradation (Akala *et al.*, 2023; Budhathoki *et al.,* 2023; Chen *et al.*, 2023; de Silva *et al.*, 2023; Dejene *et al.,* 2021; He *et al.,* 2023; Jeza & Bekele, 2023; Palei *et al.*, 2024; Yang *et al.,* 2022). In Asia, approximately 64% (3.36 million km²) of historically suitable habitat for Asian elephants has been lost since 1700 (de Silva *et al.,* 2023), and by 2015, nearly half the area within 100 km of their current range had become unsuitable. In Nepal's Madhesh Province, only 10.89% of land was classified as highly suitable for elephants, while 37.4% was unsuitable (Budhathoki *et al.,* 2023). In Africa, just 17.1% of the continent remains highly suitable for elephants, while 56.6% is unsuitable under current climate conditions (Dejene *et al.*, 2021). In Nigeria's Omo Forest Reserve, only 332.90 km² was deemed suitable for African forest elephants, with 529.65 km² classified as unsuitable (Akala *et al.,* 2023).

Modeling studies have further predicted substantial future declines in suitable elephant habitats due to climate change and land use alterations (Abir *et al.,* 2025; Budhathoki *et al.,* 2023; Kanagaraj *et al.,* 2019; Yang *et al.,* 2022). In Nepal's Madhesh Province, projections for 2100 under Shared Socio-economic Pathway (SSP)245 show a drop in suitable habitat from 21% to 15%, with unsuitable areas rising from 39% to 49% (Budhathoki *et al.,* 2023). In Africa, highly suitable habitats are expected to decline by 51.3% under Representative Concentration Pathway (RCP) 4.5 and 67.6% under RCP 8.5 by 2050, worsening to 74.5% and 85.9% by 2070, respectively (Dejene *et al.,* 2021).

Studies on elephant feeding ecology have shown that selective feeding on specific plant species can significantly influence their spatial distribution (Ferry *et al.,* 2021; Wenborn *et al.,* 2025; Woolley *et al.,* 2011). In Hwange National Park, Zimbabwe, high elephant densities (>2 km$^{-2}$) reduced tall woody plants (>200 cm) and increased shorter vegetation (<50 cm), altering vegetation structure and prompting elephants to shift to areas with preferred forage (Ferry *et al.,* 2021). In the semi-desert highlands of northwest Namibia, the distribution of elephant-preferred forage plants such as *Sterculia africana* and *Commiphora* species, including *C. glaucescens*, influenced elephant movement from Etosha National Park into the northern highlands, where elephants actively climbed steep slopes to access them (Wenborn *et al.,* 2025). In the arid Namib Desert, elephants favored shrublands with key species like *Colophospermum mopane*, *Tamarix usneoides*, and *Combretum imberbe* to meet dietary needs (Viljoen, 1989).

Regional variation in the distribution and suitability of elephant forage plants has been widely documented, highlighting the influence of local environmental conditions on forage availability (Bio *et al.*, 2024; Bravo García *et al.*, 2024; Chérif *et al.*, 2022; Gufi *et al.*, 2023; Kuswanda *et al.*, 2023; Mechergui *et al.*, 2021; Oluoch *et al.*, 2024). For example, in Indonesia's Datuk Gedang Wildlife Corridor, 94.5% of the area supported 125 forage species (Kuswanda *et al.*, 2023). In Turkana, Kenya, *Balanites aegyptiaca* showed wide suitability, supporting elephants and local communities. In contrast, in Tigray, Ethiopia, its suitable habitat covered only 2,213 km² (3% of the area) (Gufi *et al.*, 2023).

The key environmental factors determining the spatial distribution and current suitable habitats of elephant forage plants have also been shown to vary across regions (Bio *et al.*, 2024; Bravo García *et al.*, 2024; Chérif *et al.*, 2022; Gufi *et al.*, 2023; Habou *et al.*, 2021; Kuswanda *et al.*, 2023; Mechergui *et al.*, 2021; Nkosi, 2024; Oluoch *et al.*, 2024; Seid *et al.*, 2024). For example, Kuswanda *et al.* (2023) identified land cover type, elevation, slope, and proximity to water sources as major environmental factors influencing the habitat suitability of elephant forage resources. In Tunisia, Mechergui *et al.* (2021) found that Precipitation of the Driest Quarter (bio_17) was a key variable influencing habitat suitability for *Acacia tortilis*, while in eastern Niger, Annual Precipitation (bio_12) and the Maximum Temperature of the Hottest Period (bio_5) were the most influential variables for the same species. Similarly, in Turkana County, Kenya, Oluoch *et al.* (2024) identified Mean Annual Temperature (bio_1), Temperature Seasonality (bio_4), and elevation as the most significant variables determining both current and future distributions of wild edible plants (WEPs).

Nonetheless, future projections suggest that the current distribution and habitat suitability of elephant forage plants are likely to undergo substantial changes, including complete loss of suitable habitats under various climate change scenarios (Bio *et al.*, 2024; Bravo García *et al.*, 2024; Chérif *et al.*, 2022; Gufi *et al.*, 2023; Habou *et al.*, 2021; Mechergui *et al.*, 2021; Nkosi, 2024; Oluoch *et al.*, 2024; Seid *et al.*, 2024). For instance, Gufi *et al.* (2023) projected a 65% increase in suitable habitat by 2070 under RCP4.5 in drylands of Tigray, Ethiopia, but a complete loss under RCP8.5. Oluoch *et al.* (2024) projected a total loss of suitable habitat for *B. aegyptiaca* in Turkana County, Kenya, even under the low-emission scenario, SSP126, by mid-century.

Based on the literature review, various studies have predicted the potential distribution and suitable habitats of elephants and their forage resources (Abir *et al*., 2025; Akala *et al*., 2023; Ashiagbor & Danquah, 2017; Bio *et al*., 2024; Bravo-García *et al*., 2024; Budhathoki *et al*., 2023; Chen *et al*., 2023; Chérif *et al*., 2022; Chibaye *et al*., 2021; de Silva *et al*., 2023; Dejene *et al*., 2021; Gufi *et al*., 2023; Habou *et al*., 2021; He *et al*., 2023; Jeza & Bekele, 2023; Kanagaraj *et al*., 2019; Kuswanda *et al*., 2023; Mpakairi *et al*., 2019; Muposhi *et al*., 2016; Oluoch *et al*., 2024; Palei *et al*., 2024; Seid *et al*., 2024; Williams *et al*., 2018; Yang *et al*., 2022). Nonetheless, such studies are more common within the Asian elephant ranges (Budhathoki *et al*., 2023; Chen *et al*., 2023; de Silva *et al*., 2023; He *et al*., 2023; Jeza & Bekele, 2023; Kanagaraj *et al*., 2019; Kuswanda *et al*., 2023; Palei *et al*., 2024; Yang *et al*., 2022).

In Africa, including Kenya, such studies are scarce (Akala *et al*., 2023; Ashiagbor & Danquah, 2017; Bio *et al*., 2024; Bravo-García *et al*., 2024; Chérif *et al*., 2022; Chibaye *et al*., 2021; Dejene *et al*., 2021; Gufi *et al*., 2023; Habou *et al*., 2021; Jeza & Bekele, 2023; Mpakairi *et al*., 2019; Muposhi *et al*., 2016; Oluoch *et al*., 2024; Seid *et al*., 2024; Williams *et al*., 2018). Specifically, no published research to date has focused on modeling the current and future habitat suitability for African elephants and their preferred forage plants within the Nasalot–South Turkana–Kerio Valley ecosystem. There is a distinct lack of spatial assessments that integrate ecological variables with climate change scenarios to predict habitat dynamics in this ecosystem. This study, therefore, seeks to fill this knowledge gap by modeling the current and future spatial distribution and abundance of suitable habitats for African elephants and their preferred forage plants within the Nasalot–South Turkana–Kerio Valley ecosystem, identifying and analyzing the key environmental factors influencing their habitat suitability and evaluating the potential impacts of climate change on habitat suitability for African elephants and their preferred forage plants in this ecologically important, yet understudied region.

## 1.2 Statement of the Problem

The Nasalot–South Turkana–Kerio Valley ecosystem in northeastern Kenya is ecologically diverse, with varying climate, biophysical, and edaphic conditions. It includes four national reserves: Nasalot, South Turkana, Rimoi, and Kamnarok (Kenya Wildlife Service (KWS), 2021), and features a range of habitats such as riverine forests, bushed woodlands, wooded bushlands, thickets, and grasslands (Togoch *et al*., 2018).

The ecosystem provides vital ecological services to local communities and supports the conservation of diverse wildlife, including the critically endangered giant pangolin and the endangered African elephant (IUCN, 2021; Koskey, 2013, 2016; Kuria *et al*., 2001; Togoch *et al*., 2018). It also harbors numerous plant, reptile, bird, and insect species.

Nonetheless, the ecosystem is threatened by decline and modification of wildlife habitats, losses and local extirpation of species, decline in wildlife populations, increased human–wildlife conflicts, vegetation loss, increased soil erosion, and a significant decrease in the area of Lake Kamnarok, due to sedimentation from upstream erosion, and persistently high poaching levels (Boitt *et al*., 2020; Koskey, 2016; Wildlife Research and Training Institute (WRTI), & Kenya Wildlife Service (KWS), 2021; Togoch *et al*., 2018).

The threats facing the ecosystem pose major conservation and management challenges, particularly for African elephants, their habitats, and their forage resources. These threats are largely driven by widespread LULC changes linked to agricultural expansion and population growth, which are expected to intensify in the future (Boitt *et al*., 2020; Koskey, 2016; Togoch *et al*., 2018). Infrastructure developments, including new and expanding road networks, also pose significant risks to wildlife, especially the African elephants.

The effects of multiple threats facing the ecosystem are likely to be exacerbated by climate change, evidenced by rising temperatures, erratic rainfall, prolonged droughts, flash floods, and intensified soil erosion, particularly in the semi-arid northern and northwestern Kenya, including the study area (Boitt *et al*., 2020; Huho *et al*., 2023; IPCC, 2014; Kuria, 2001; Oluoch *et al*., 2024). For example, Oluoch *et al.* (2024) found that while 64.5% (≈44,100 km²) of Turkana County is currently suitable for WEPs, future climate scenarios (2041–2100) project significant declines in habitat suitability for about half of the 23 studied species. Notably, *B. aegyptiaca*, a key wild edible plant (Oluoch *et al.*, 2024) in Turkana County and African elephants' preferred forage species (Koskey, 2013, 2016) in the study area, is expected to lose all suitable habitat even under the low-emission scenario, SSP126, by mid-century.

Nonetheless, it remains unclear how various environmental and threat factors, particularly climate change, affect the current and future distribution and habitat suitability of African elephants and their preferred forage plants in the ecosystem. However, existing studies suggest that such factors can significantly influence elephant and forage plant distributions and habitat suitability (Akala *et al*., 2023; Ashiagbor & Danquah, 2007; Bio *et al*., 2024; Bravo-García *et al*., 2024; Chérif *et al*., 2022; Chibaye *et al*., 2021; Gufi *et al*., 2023; Habou *et al*., 2021; Muposhi *et al*., 2016; Oluoch *et al*., 2024; Seid *et al*., 2024; Williams *et al.*, 2018).

Therefore, the study aimed at modeling habitat suitability of African elephants and their preferred forage plants under the influence of various environmental factors, including climate change, in the Nasalot–South Turkana–Kerio Valley ecosystem. This is vital for enhancing the conservation and management of African elephants, their preferred forage plants, and other coexisting species within the study area and in similar ecosystems globally.

## 1.3 Justification and Significance of the Study

Despite the ecological importance of the Nasalot–South Turkana–Kerio Valley ecosystem, the influence of environmental and threat factors, particularly climate change, on the current and future distribution and habitat suitability of African elephants and their preferred forage plants remains poorly understood (Akala *et al.*, 2023; Oluoch *et al.*, 2024).

Rising human population and expansion of agriculture and infrastructure in the ecosystem have led to habitat degradation, species loss, declining wildlife populations, increased human–wildlife conflicts, vegetation loss, soil erosion, and a reduction in Lake Kamnarok's area due to upstream sedimentation in the ecosystem (Boitt *et al.*, 2022; Koskey, 2016; Togoch, 2018). These threats may influence the distribution and suitability of habitats for African elephants and their forage plants. Understanding current and future habitat suitability is therefore essential for the effective conservation of elephants, their forage species, and other coexisting biodiversity in the region.

The African elephant is widely regarded as an ecosystem engineer and a keystone species due to its profound ecological impact (Campos-Arceiz & Blake, 2011; Haynes, 2012; Pringle, 2008). Through feeding and physical interactions, elephants reshape habitats, influence vegetation structure, and drive essential ecological processes (Berzaghi *et al.*, 2023; Dublin *et al.*, 1990; Holdo, 2006). By toppling trees, they limit woody encroachment, maintaining grasslands vital for biodiversity (Coverdale *et al.*, 2016; Guldemond & Van Aarde, 2010; Owen-Smith, 2010). Their access to water sources supports other species during dry periods (Ramey *et al.*, 2013), while their dung enriches soil and provides food and habitat for numerous organisms (Wolf *et al.*, 2013). Thus, conserving elephants also supports broader ecosystem integrity.

Due to widespread threats (Chen *et al.*, 2021; Kioko & Seno, 2015; Ling *et al.*, 2016; Okello *et al.*, 2014; Schüßler *et al.*, 2019), African elephants have faced global population declines, leading to their listing in Appendix I of the Convention on International Trade in Endangered Species (CITES) since 1990 and classification as endangered on the IUCN Red List (IUCN, 2021). In Kenya, they are also listed as endangered under the Fourth Schedule of the Kenya Wildlife Conservation and Management Act (WCMA) (GoK, 2013). Several global conservation frameworks support their protection, including the United Nations (UN) Sustainable Development Goals (SDGs) (UN, 2015), Kunming-

Montreal Global Biodiversity Framework [Convention on Biological Diversity (CBD), 2022], IUCN Global Species Conservation Goals (IUCN, 2021), and the UN Decade on Ecosystem Restoration (United Nations Environmental Programme (UNEP) & Food and Agriculture Organization (FAO), 2021).

At the national level, Kenya has adopted key frameworks such as the Wildlife Conservation and Management Act (WCMA) (GoK, 2013) and the National Elephant Action Plan (NEAP) 2023–2032 for Kenya (Omondi *et al*., 2022) to support the conservation and sustainable management of African elephants. This study is thus timely and relevant, contributing to both national and global conservation efforts.

In Kenya, wildlife and their habitats are vital national assets that support both local communities and the national economy. Wildlife-based tourism contributes over 10% to the country's Gross Domestic Product (GDP), more than 18% of foreign exchange earnings, and over 11% of government revenue through taxes, levies, and park fees (GoK, 2022). These habitats also provide essential resources like firewood and grazing land to surrounding communities. This study, therefore, contributes to socio-economic development at both county and national levels.

Previous vegetation studies in the study area informed the selection of preferred forage species for this study (Koskey, 2013, 2016; Kuria, 2001*)*. Koskey (2013, 2016) identified elephant preferred forage plants in Rimoi National Reserve: *Vachellia tortilis* (22.5%), *B. aegyptiaca* (14.8%), *Acacia mellifera* (9.6%), *Zizyphus mucronata* (7.5%), and *Acacia brevispica* (7.1%). Among these, *V. tortilis* (IVI = 104.0) and *A. mellifera* (IVI = 118.9) were ecologically important across the broader ecosystem (Kuria, 2001). These species were therefore selected for modeling as African elephant preferred forage plants and grouped collectively to simplify the MaxEnt analysis.

MaxEnt algorithm version 3.3.0 (Phillips *et al.*, 2006) was used to model the potential current and future distribution and suitable habitats for African elephants and their preferred forage plants. MaxEnt employs a machine learning algorithm to predict species distributions using presence-only data and environmental predictors (Phillips *et al.*, 2006). The model was selected for its strengths: (i) it does not require absence data (Elith *et al.*, 2006; Hijmans & Graham, 2006); (ii) it offers high predictive accuracy (Elith *et al.*, 2006; Phillips *et al.*, 2006); (iii) it performs well with small sample sizes (Hernandez *et al.*, 2006; Phillips *et al.*, 2006; Wisz *et al.*, 2008); (iv) it generates pseudo-absence data from presence-only input (Phillips *et al.*, 2006); and (v) it produces continuous outputs, allowing assessment of presence probabilities across the landscape (Phillips *et al.*, 2006; 2018).

The model is widely used for predicting habitat suitability for elephants and forage plants (Akala *et al.*, 2023; Bio *et al.*, 2024; Bravo–García *et al.*, 2024; Budhathoki *et al.*, 2023; Chen *et al.*, 2023; Chérif *et al.*, 2022; de Silva *et al.*, 2023; Dejene *et al.*, 2021; Gufi *et al.*, 2023; Habou *et al.*, 2021; He *et al.*, 2023; Jeza & Bekele, 2023; Kuswanda *et al.*, 2023; Mechergui *et al.*, 2021; Nkosi, 2024; Oluoch *et al.*, 2024; Palei *et al.*, 2024; Seid *et al.*, 2024; Williams *et al.*, 2018; Yang *et al.*, 2022).

The influence of environmental factors, particularly climate change, on the spatial distribution and habitat suitability of African elephants and their forage plants has been emphasized by several studies (Akala *et al.*, 2023; Bio *et al.*, 2024; Bravo-García *et al.*, 2024; Budhathoki *et al.*, 2023; Chen *et al.*, 2023; Chérif *et al.*, 2022; de Silva *et al.*, 2023; Dejene *et al.*, 2021; Gufi *et al.*, 2023; Habou *et al.*, 2021; He *et al.*, 2023; Jeza & Bekele, 2023; Kuswanda *et al.*, 2023; Mechergui *et al.*, 2021; Nkosi, 2024; Oluoch *et al.*, 2024; Palei *et al.*, 2024; Seid *et al.*, 2024; Williams *et al.*, 2018; Yang *et al.*, 2022). These scientists have argued that such studies are essential for understanding how environmental factors affect the habitat suitability of African elephants and their forage plants. They contribute to existing knowledge, support academic research, and offer insights into current and future habitat dynamics. This information is crucial for informed decision-making and the formulation of effective conservation strategies targeting elephants, their forage species, and coexisting wildlife. The study is particularly relevant to the Government of Kenya, policymakers, conservation managers, researchers, students, and other stakeholders.

## 1.4 Objectives of the Study

### 1.4.1 General Objective

To model the habitat suitability for African elephants and their preferred forage plants in the Nasalot–South Turkana–Kerio Valley ecosystem, Kenya.

### 1.4.2 Specific Objectives

1. To model the current and future spatial distribution and abundance of suitable habitats for African elephants and their preferred forage plants within the Nasalot–South Turkana–Kerio Valley ecosystem.
2. To assess the influence of key environmental variables on the current and projected distribution and abundance of suitable habitats for African elephants and their preferred forage plants.

3. To evaluate the potential impacts of climate change on habitat suitability for African elephants and their preferred forage plants under different climate scenarios (SSP245 and SSP585) across future time horizons (2041–2060 and 2081–2100).

### 1.4.3 Research Questions

1. What are the current and projected future spatial distributions and abundances of suitable habitats for African elephants and their preferred forage plants in the Nasalot–South Turkana–Kerio Valley ecosystem?
2. Which environmental variables most significantly influence the current and future distributions and abundances of suitable habitats for African elephants and their preferred forage plants in the study area?
3. How do different climate change scenarios (SSP245 and SSP585) affect the habitat suitability for African elephants and their preferred forage plants across the future time horizons of 2041–2060 and 2081–2100?

## 1.5 Scope and Limitations of the Study

In Kenya's key conservation areas, including the Nasalot–South Turkana–Kerio Valley ecosystem, studies on the potential distribution and suitable habitats of African elephants and their preferred forage plants remain scarce. This study, therefore, modeled their potential habitat suitability within this ecosystem.

In this study, 28 predictor environmental variables were selected based on availability and prior use in modeling habitat suitability and distribution of African elephants and their forage plants (Akala *et al.*, 2023; Bio *et al.*, 2024; Bravo-García *et al.*, 2024; Chérif *et al.*, 2022; Gufi *et al.*, 2023; Habou *et al.*, 2021; Jeza & Bekele, 2023; Kuswanda *et al.*, 2023;

Mechergui *et al.*, 2021; Nkosi, 2024; Oluoch *et al.*, 2024; Williams *et al.*, 2018). These comprised 19 bioclimatic, 3 topographic (elevation, slope, aspect), 3 distance-based (to roads, waterbodies, human settlements), 1 vegetation [Normalized Difference Vegetation Index (NDVI)], 1 edaphic (soil type), and 1 LULC variable. Intrinsic factors like predation and interspecific competition were not considered (Vailex *et al.*, 2007).

Climate change studies identify vulnerable species as those with restricted ranges, specialized resource needs, low physiological tolerance, slow reproduction, and poor dispersal (Chirima *et al.*, 2018). Such species are often rare or endangered (Hetem *et al.*, 2014; Kupika & Nhamo, 2016). Key large herbivores like giraffe (*Giraffa camelopardalis*), hippopotamus (*Hippopotamus amphibius*), and African elephant are listed as endangered or vulnerable by the IUCN (2021). As a result, these species are frequently the focus of climate impact studies. For instance, Kupika & Nhamo (2016) studied elephants and hippos in Zimbabwe due to their broad range needs, while Kiria (2018) used elephants in Kenya's Meru Conservation Area for their visibility, mobility, and conflict potential. This study, therefore, adopts the African elephant as a representative case study species.

Previous vegetation studies in the area informed the selection of plant species for this study (Koskey, 2013, 2016; Kuria, 2001). Koskey (2013, 2016) identified *V. tortilis* (syn. *Acacia tortilis*), *B.aegyptiaca*, *A.mellifera*, *Z. mucronata*, and *A. brevispica* as key forage species for African elephants in Rimoi National Reserve. Among these, *V. tortilis* (IVI = 104.0) and *A. mellifera* (IVI = 118.9) were also ecologically dominant (Kuria, 2001). These species were thus selected and collectively referred to as African elephant preferred forage plants.

Previous climate change risk assessments have attempted to quantify the effects of three main components of climate change risk: sensitivity, exposure, and adaptive capacity, as well as extinction risks (Dawson *et al.*, 2011; Williams *et al.*, 2008). Sensitivity risk due to climate change is typically assessed using life history traits, physiological tolerances, species interactions, or dependence on specific habitat types (Pacifici *et al.*, 2017; Shoo *et al.*, 2013). Adaptive risk is measured using intrinsic factors such as genetic diversity, phenotypic plasticity, and life history traits. Exposure risk is commonly evaluated using bioclimatic envelope models, projected changes in temperature or precipitation within a species' range, and projected habitat shifts (Dawson *et al.*, 2011; Foden & Young, 2016).

Among these, exposure risk is the most commonly assessed component in many climate change studies. This study focused on evaluating the exposure risk of climate change on African elephants in the Nasalot–South Turkana–Kerio Valley ecosystem. However, it did not assess the sensitivity, adaptive, or extinction risks associated with climate change.

One limitation of MaxEnt modeling is reliance on coarse-resolution environmental data (e.g., 1 km$^2$), which, while widely available and suitable for broad-scale analyses, often fail to capture fine-scale habitat and microhabitat variability, especially in heterogeneous landscapes (Guisan *et al.*, 2017; Merow *et al.*, 2013). Many layers come from free databases such as WorldClim and SoilGrids, which, despite being accessible and standardized, may have issues with accuracy, regional relevance, or update frequency (Fick & Hijmans, 2017; Poggio *et al.*, 2021). Climatic data, for instance, are often interpolated from sparse weather stations, limiting local accuracy in data-poor regions (Deblauwe *et al.*, 2016). Variations in temporal coverage, spatial resolution, and quality across sources can create inconsistencies when combined, reducing model reliability.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Spatial Distribution Patterns of Elephants

The African savanna elephant, African forest elephant (*Loxodonta cyclotis*), and Asian elephant (*Elephas maximus*) are the three species of elephants that exist on earth today. Globally, they are distributed in the tropical and subtropical regions of Asia and the African continents (Menon & Tiwari, 2019). The Asian elephant is distributed in the tropical and subtropical regions of Asia, and is native to 13 Asian countries, including Bangladesh, Bhutan, Cambodia, China, India, Indonesia, Laos, Malaysia, Myanmar, Nepal, Sri Lanka, Thailand, and Vietnam (Menon & Tiwari, 2019).

The African savanna elephant is distributed in sub-Saharan Africa, primarily in the eastern and southern regions, but also in a wider range of countries, including those in West Africa and the Sahel (Riddle *et al.*, 2010). The largest populations are found in southern and eastern African countries like Botswana, Zimbabwe, Tanzania, Kenya, Namibia, Zambia, and South Africa (Riddle *et al.*, 2010).

The African forest elephant is primarily distributed across the dense tropical rainforests of Central and West Africa, with major populations found in Gabon, which holds the largest remaining numbers, as well as the Republic of the Congo, Cameroon, the Central African Republic, Equatorial Guinea, the Democratic Republic of the Congo, Liberia, Ivory Coast, and Sierra Leone (Riddle *et al.*, 2010). Their habitats have become increasingly fragmented due to human pressures such as deforestation and poaching (Kouakou *et al*., 2020; Laguardia *et al*., 2021).

**Figure 1: A herd of African savanna elephants. Source: Save the Elephants (https://savetheelephants.org).**

## 2.2 Elephant Habitats

Elephants exhibit broad ecological adaptability, occupying diverse habitats across their ranges. Asian elephants occur in grasslands, rainforests, evergreen and mixed forests, shrublands, and riparian corridors in regions such as China's Yunnan Province (Chen *et al.,* 2023; de Silva *et al.,* 2023; He *et al.,* 2023). In South and Southeast Asia, they inhabit tropical and subtropical forests, ecotones, scrublands, secondary woodlands, floodplains, and seasonal grasslands (Yang *et al.,* 2022). In Nepal and eastern India, they use forest–grassland mosaics, shrublands, and moist deciduous to semi-evergreen forests (Budhathoki *et al.,* 2023; Palei *et al.,* 2024). In Indonesia, their range includes forests, plantations, agricultural lands, and degraded corridors (Kuswanda *et al.,* 2023).

Likewise, African elephants show extensive habitat tolerance, from arid savannas and dense Central African forests (Blake *et al.,* 2008) to woodland, shrubland, and grassland mosaics in southern and East Africa (Chase *et al.,* 2016; Loarie *et al.,* 2009; Okello *et al.,* 2015). These studies highlight the ecological flexibility of both species and the need to conserve varied ecosystems that support their spatial and ecological needs.

## 2.3 Current Habitat Suitability of Elephants

Current habitat suitability for elephants is shaped by ecological resources such as forage, water, cover, and space as well as human influences (Akala *et al.*, 2023; Budhathoki *et al.*, 2023; Chen *et al.*, 2023; He *et al.*, 2023; Jeza & Bekele, 2023; Kanagaraj *et al.*, 2019; Matawa *et al.*, 2012; Williams *et al.*, 2018; Yang *et al.*, 2022; Zhang *et al.*, 2024). Studies increasingly show that elephant habitats occupy a limited portion of the landscape. In South and Southeast Asia, Yang *et al.* (2022) estimated 516,753 km² of potential habitat for Asian elephants, mainly in southern and northeastern India, southern Nepal, Sri Lanka, and southern Thailand. The current core habitats cover 491,455 km², while protected areas categorized as suitable span 627,367 km² - 21.4% larger than the modeled potential habitat.

In Nepal’s Madhesh Province, Budhathoki *et al.* (2023) reported that 1,037.3 km² (10.89%) was highly suitable, 1,965.5 km² (20.6%) suitable, 2,960.3 km² (31.07%) marginally suitable, and 3,563.6 km² (37.4%) unsuitable, with Rautahat and Bara having the most highly suitable areas. In Yunnan Province, China, Chen *et al.* (2023) identified 29,765 km² (7.5% of the province) as suitable, including 12,335 km² of poor-quality habitat and

17,430 km² of higher suitability, subdivided into 5,522 km² of excellent and 11,907 km² of good habitat. He *et al.* (2023), in Sipsongpanna Prefecture, Yunnan, found that under non-anthropogenic conditions, 9,342.86 km² (51.23%) was suitable, with 4,711.43 km² (25.34%) low, 2,456.77 km² (11.82%) medium, and 1,998.75 km² (11.6%) high suitability. Under anthropogenic influences, suitable area declined to 9,023.41 km² (46.35%), with 4,796.32 km² (25.64%) low, 2,437.83 km² (14.78%) medium, and 1,804.56 km² (13.23%) high suitability. In Odisha, India, Palei *et al.* (2024) modeled 14.6% (22,442.73 km²) of the state as highly suitable, 13.3% (20,464 km²) moderately high, 11.34% (17,436.44 km²) moderately suitable, and 15.14% (23,273.95 km²) as moderately low potential.

In Africa, Dejene *et al.* (2021) found 17.1% of the continent highly suitable and 56.6% unsuitable for African elephants under current climate conditions, with key determinants being temperature, precipitation, and land cover. In Hwange National Park, Zimbabwe, Mpakairi *et al.* (2019) estimated 146.76 km² of potential habitat, driven by proximity to park boundary, Temperature Seasonality (bio_4), and rainfall variables. In Ethiopia's Omo National Park, Jeza & Bekele (2023) reported that elephants ranged over 1,999 km² (39% of the study area), with 365 km² (7.2%) optimal, 748 km² (14.7%) suitable, and 886 km² (17.5%) moderately suitable habitat.

Seasonal changes also influence habitat suitability. Akala *et al.* (2023) found that in Nigeria's Omo Forest Reserve, 332.90 km² was mapped as high potential during the dry season, 564.22 km² moderate, and 421.67 km² unsuitable. During the wet season, 376.43 km² was suitable, 495.08 km² moderate, and 447.28 km² unsuitable.

## 2.4 Environmental Determinants of Spatial Distribution and Habitat Suitability of Elephants

Several studies using diverse methodologies such as the Dynamic Site Occupancy Model (DSOM), correlation analyses, home range estimation, ensemble models, and MaxEnt have demonstrated that a range of environmental factors influence elephant occurrence, spatial distribution, habitat suitability, and other spatial behaviors. These include climatic variables (e.g., precipitation and temperature), biophysical factors (e.g., vegetation, forage quality and quantity, proximity to surface water, and topography), and anthropogenic elements (e.g., roads, fences, agriculture, and protected areas) (Bohrer *et al.*, 2014; Martin *et al.*, 2010; Muposhi *et al.*, 2016). However, the relative importance of these factors varies depending on the elephant species, landscape context, season, and study year.

Studies by Martin *et al.* (2010) in Hwange National Park, Zimbabwe, using the DSOM, identified rainfall and proximity to waterholes as key environmental factors influencing the habitat suitability, distribution, and abundance of African elephants. The study emphasized that habitat suitability and its driving factors directly affect species distribution and abundance.

Studies by Mpakairi *et al.* (2019), which used an ensemble modeling approach integrating multiple candidate models, found that African elephant habitat suitability in the Sebungwe Region of northwestern Zimbabwe was mainly influenced by proximity to the park boundary, Temperature Seasonality (bio_4), precipitation of the wettest quarter (bio_16), Annual Precipitation (bio_12), and land cover type, together accounting for over 99% of the model's predictive power. Other variables, including elevation, slope, NDVI, distance to rivers and roads, and population density, had minimal influence and were excluded from the final model.

Benitez *et al.* (2022) estimated the home range size of African elephants across four sites in Namibia, along gradients of precipitation and human impact. Precipitation and vegetation were the strongest overall predictors, explaining 53% of the observed variation. However, predictor importance varied by site: in the drier western regions, precipitation accounted for up to 74% of variation (n = 66), while in the Kavango-Zambezi Transfrontier Conservation Area, human impact explained 71% (n = 10).

In the Marsabit Protected Area, Kenya, Ngene *et al.* (2009), using correlation analysis, identified distance from drinking water (24%), elevation (15%), shrubland (10%), forest (9%), distance from settlements (8%), and distance from minor roads (7%) as key predictors, explaining 73% of the variation in elephant distribution. In the same area, Bohrer *et al.* (2014) found that elevation and precipitation-driven vegetation changes significantly influenced habitat use and migration patterns. During the dry season, optimal habitats occurred at elevations between 650–1100 m above sea level (a.s.l.) due to the availability of green forage and permanent water, while in the wet season, elephants shifted to lower elevations where forage and water were more widely distributed. This seasonal variability in habitat conditions shaped elephant migration between high and low elevations.

Palei *et al.* (2024), using an ensemble model in Biological Models version 2 (BIOMOD2) to assess Asian elephant habitat suitability in Odisha, India, found NDVI (42%), terrain ruggedness (19%), elevation (17%), and distance to protected areas (13%) to be the most influential variables, while annual precipitation (bio_12) contributed minimally (8%).

Recent MaxEnt studies using variable importance tests such as percentage contribution, permutation importance, and Jackknife tests of regularized training gain and AUC have identified key environmental factors influencing elephant spatial distribution and habitat suitability. These include climatic factors (e.g., precipitation, temperature), biophysical variables (e.g., vegetation, forage quality and quantity, proximity to surface water, topography), and anthropogenic factors (e.g., roads, fences, agriculture, and protected areas) (Akala *et al.*, 2023; Budhathoki *et al.*, 2023; Chen *et al.*, 2023; He *et al.*, 2023; Jeza & Bekele, 2023; Kanagaraj *et al.*, 2019; Matawa *et al.*, 2012; Williams *et al.*, 2018; Yang *et al.*, 2022; Zhang *et al.*, 2024).

In China’s Sipsongpanna Prefecture, Yunnan Province, MaxEnt modeling identified altitude, Mean Annual Precipitation (MAP), and Mean Warmest Month Temperature (MWMT) as key predictors of Asian elephant habitat suitability under both non-anthropogenic and anthropogenic conditions (He *et al.*, 2023). Under non-anthropogenic influence, altitude, MAP, and MWMT contributed 37.2%, 22.4%, and 22.4% respectively, while under anthropogenic influence, their contributions were 44.5%, 23.7%, and 14.9% (He *et al.*, 2023).

Another study in Yunnan Province, southwestern China, found forest fragmentation (59.9%) and elevation (26.3%) to be the most influential factors determining suitable habitats for Asian elephants. In contrast, rubber plantations (6.1%), forest cover (4.1%), cropland extent (1.9%), and road density (1.7%) contributed minimally to the model (Chen *et al.*, 2023).

A recent study in Jiangcheng County, Yunnan Province, China, by Zhang *et al.* (2024) identified annual average rainfall (50.1%), distance to rivers (17.1%), and distance to roads (12.7%) as the primary factors influencing elephant distribution, collectively accounting for 79.9% of the variance in the MaxEnt model. Secondary factors including land use, altitude, distance to residential areas, average temperature, and habitat quality, contributed 19.4%, while variables like vegetation type, distance to farmland and forest, slope, and NDVI had minimal impact (0.6%).

In South and Southeast Asia, Yang *et al.* (2022) identified key variables influencing Asian elephant distribution and habitat suitability, including Precipitation of the Coldest Quarter (bio_19) (25.1%), population density (22.9%), Aridity Index (13.4%), and LULC (5.4%). Less influential variables included distance to urban areas (4.9%), elevation (4%), slope (4%), Vegetation Continuous Fields (VCF) (3.7%), Precipitation of the Coldest Quarter (bio_19) (3.7%), Temperature Seasonality (bio_4) (3.5%), and several others, each contributing less than 3%, with the least important being Annual precipitation from Environmental Rasters for Ecological Modeling (ENVIREM) (1.3%), Mean Diurnal Range (bio_2) (1.3%), and Precipitation of the Driest Quarter (bio_17) (1.1%).

In Madhesh Province, southern central-eastern Nepal, Budhathoki *et al.* (2023) used the Jackknife test of regularized training gain to identify elevation, slope, Precipitation Seasonality (bio_15), Precipitation of the Driest Quarter (bio_17), and Temperature Seasonality as key variables influencing Asian elephant habitat suitability. Each of these variables, when used in isolation, contributed more than 0.15 to the model, and their exclusion resulted in the greatest reduction in model gain, highlighting their importance.

Williams *et al.* (2018), in a study on African elephant habitat suitability in the Kasigau Wildlife Corridor, southeastern Kenya, identified waterholes (46.5%), precipitation (26.7%), elevation (5.9%), and mean temperature (5.2%) as the most influential factors. Less important variables included Terrain Ruggedness Index (4.5%), distance to Tsavo National Parks (3%), distance to farms (2.8%), carcasses (2.8%), and vegetation (1.5%).

In the Sioma Ngwezi landscape, Zambia, Chibeya *et al.* (2021) found elevation (64%), land cover (13.5%), and NDVI (10.2%) to be the most influential variables, while proximity to settlements (6.7%), dirt roads (5.3%), and Topographic Wetness Index (TWI) (0.4%) were the least important.

However, other studies have reported seasonal variation in rainfall as an important environmental factor influencing elephant spatial distribution and habitat suitability (Akala *et al.*, 2023; Jeza & Bekele, 2023). In Omo Forest Reserve, Nigeria, Akala *et al.* (2023) reported that during the dry season, the most influential variables were distance to rivers (53.3%), roads (16.4%), Mean Diurnal Range (bio_2) (13.6%), and Precipitation Seasonality (bio_15) (5.2%). In the wet season, distance to farmland (48.2%), rivers (24.9%), Mean Diurnal Range (15.1%), and NDVI (11.2%) were most important. Least influential variables in the dry season included distance to farmland (4.6%), NDVI (0%), Mean Temperature of Warmest Quarter (bio_11) (3.3%), and Temperature Seasonality (bio_4) (2.6%), while in the wet season they included distance to roads (0.2%), Precipitation Seasonality (bio_15) (0.1%), Mean Temperature of Warmest Quarter (bio_11) (0%), and Temperature Seasonality (bio_4) (0%).

In Omo National Park, Ethiopia, Jeza & Bekele (2023) found that during the dry season, distance to rivers (49.2%), LULC (28.7%), and distance to canals (16.3%) were the most influential variables affecting African elephant distribution. Variables such as Temperature Seasonality (bio_4), elevation, distance to roads, Isothermality (bio_3), slope, Mean Diurnal Range (bio_2), distance to cultivated land, and aspect each contributed less than 10%. In the wet season, distance to canals (40.1%), LULC (33.8%), and distance to rivers (10%) remained key factors, while variables like Temperature Seasonality (0%), elevation (5.0%), Mean Diurnal Range (7.2%), and others contributed minimally to the model.

Matawa *et al.* (2012) concluded that habitat heterogeneity influences habitat selection by wild herbivores and demonstrated year-to-year variation in the importance of environmental variables for elephant habitat suitability in the Zambezi Valley, Zimbabwe. In 2006, elephant occurrence was primarily explained by distance to rivers (81.5%) and roads (16.2%), while NDVI (1.7%) and distance to artificial water (0.6%) were least important. However, in 2010, these variables no longer explained variability in elephant distribution.

## 2.5 Effects of Environmental Variables on Spatial Distribution and Habitat Suitability of Elephants

Previous research has shown that elephant abundance, distribution, movement, and habitat suitability are influenced by various environmental factors, including climatic variables (e.g., precipitation and temperature), biophysical elements (e.g., vegetation cover, forage quality, proximity to water, and topography), and anthropogenic influences (e.g., roads, fences, agriculture, and protected areas) (Akala *et al.*, 2023; Budhathoki *et al.*, 2023; Chen *et al.*, 2023; He *et al.*, 2023; Jeza & Bekele, 2023; Kanagaraj *et al.*, 2019; Matawa *et al.*, 2012; Williams *et al.*, 2018; Yang *et al.*, 2022; Zhang *et al.*, 2024). These factors, individually or interactively, shape how elephants utilize habitats across different landscapes.

### 2.5.1 Climatic Factors

#### 2.5.1.1 Precipitation

Precipitation strongly influences elephant distribution and movement by affecting the availability and distribution of forage and water (Ashiagbor & Danquah, 2017; Benitez *et al.*, 2022; Bohrer *et al.*, 2014; Chamaillé-Jammes *et al.*, 2007; Kuria *et al.*, 2024; Makati *et al.*, 2025; Maseka *et al.*, 2024; Purdon *et al.*, 2018). In seasonal environments, home range size is driven by rainfall-induced changes in resource availability. Studies across southern Africa show that in wetter savannas, elephants maintain smaller, seasonally overlapping ranges, while in drier regions with variable rainfall, they range more widely to access forage (Young & van Aarde, 2010).

Benitez *et al.* (2022) found that African elephant home range sizes across four Namibian sites varied with precipitation and human impact. In drier regions, elephants had larger ranges to access scattered resources, while in wetter areas, smaller ranges were maintained due to more abundant forage and water.

In Zambia’s Kabompo Landscape, elephants had the largest home range (1,720.8 km$^2$) during the wet season, dominated by grassland, due to increased vegetation and habitat availability. In contrast, ranges were smaller (931.8 km²) in the cold dry season, likely due to limited resources and increased threats like human activity and wildfires (Maseka *et al.*, 2024).

Similarly, studies show that rainfall seasonality strongly influences elephant habitat preference, causing shifts between wet and dry seasons. In Mole National Park, Ghana, suitable habitat expanded to 856 km² in the wet season due to abundant water and forage, but contracted to 547.68 km² in the dry season, with elephants favoring areas near waterholes and saltlicks (Ashiagbor & Danquah, 2017).

Studies have also shown that elephants adjust their movements based on precipitation-driven vegetation changes. For instance, Purdon *et al.* (2018) observed partial migration among southern African elephant populations, with individuals shifting between dry and wet season ranges. Wet season migrations coincided with rainfall onset and the greening of forage.

In the Marsabit Protected Area, Kenya, elephants expanded their range to lower elevations with more abundant vegetation during periods of increased rainfall. In contrast, during drier periods, they retreated to higher elevations for access to evergreen forests and reliable water sources (Bohrer *et al.*, 2014). Similarly, in the Greater Mapungubwe Transfrontier Conservation Area spanning Botswana, South Africa, and Zimbabwe, elephants used natural areas with ample forage during the wet season but shifted into agricultural lands during the dry season to exploit irrigated crops as high-quality forage (Branco *et al.*, 2019).

The influence of precipitation on elephant distribution is closely linked to surface water availability across various landscapes (Chamaillé-Jammes *et al.*, 2007; Makati *et al.*, 2025). In Hwange National Park, Zimbabwe, elephant distribution during the dry season was concentrated around areas with high densities of artificial waterholes, which were unevenly spread across the park (Chamaillé-Jammes *et al.*, 2007). However, in years with higher annual rainfall, elephants dispersed more widely. Persistent clustering around waterholes has been associated with overgrazing and habitat degradation (Chamaillé-Jammes *et al.*, 2007; Kuria *et al.*, 2024; Mukwashi, 2012; Shannon *et al.*, 2009; Wilson *et al.*, 2021).

Studies by Makati *et al.* (2025) in the Eastern Okavango Panhandle, Botswana, found that during the wet season, elephants dispersed widely due to the availability of ephemeral water sources. However, as these sources dried up in the early dry season, elephants moved closer to permanent water bodies like the Okavango River, often near human settlements. In Omo National Park, Ethiopia, African elephants showed a strong year-round preference for areas near rivers, with this reliance intensifying during the dry season due to dependence on permanent water sources (Jeza & Bekele, 2023).

Studies by Bastille-Rousseau *et al.* (2020) in Kenya’s Samburu–Laikipia ecosystem found that elephants contracted their ranges during dry periods to stay near permanent water sources and expanded them during wetter seasons to access dispersed vegetation. The study highlights how rainfall-driven resource availability shapes elephant movements, while human land-use pressures further limit access to seasonal forage.

Studies by Kuria *et al.* (2024) in the Laikipia–Samburu ecosystem, northern Kenya, reported sex-based differences in elephant responses to seasonal surface water availability. On average, core area centroids were 17 km from the nearest river, with females and males occupying areas 13.5 km and 27.5 km away, respectively. Females ranged farther from rivers in the wet season, while males did so in the dry season.

Recent modeling studies have highlighted the influence of precipitation-related bioclimatic variables on elephant distribution and habitat suitability. For example, He *et al.* (2023) found that in Sipsongpanna Prefecture, southern Yunnan, China, Asian elephants preferred areas with MAP between 1400–1600 mm under both non-anthropogenic and anthropogenic conditions. Habitat suitability declined in both drier (<1200 mm) and wetter (>1800 mm) areas.

In southwest Myanmar, Thant *et al.* (2023) found that MAP, elevation, and distance to water sources significantly influenced elephant habitat suitability. The MaxEnt response curve for MAP showed that suitability increased sharply with rising rainfall, peaking at moderate to high levels before plateauing or slightly declining, indicating a preference for areas with moderate to high annual precipitation.

Studies by Jeza & Bekele (2023) in Omo National Park, Ethiopia, using MaxEnt models, found that distance to rivers and LULC were key drivers of elephant habitat suitability, with precipitation indirectly influencing both. Elephants favored areas farther from rivers during the wet season but depended more on proximity to water in the dry season.

Polansky *et al.* (2019) tested the “green-wave surfing” hypothesis in savanna elephants in Etosha National Park, Namibia, using Global Positioning System (GPS), NDVI, and rainfall data. They found that elephants adjusted their movements to follow vegetation green-up after rainfall, effectively “surfing” the green wave to access high-quality forage.

This behavior was strongest during and after rain events, highlighting that rainfall and vegetation greenness are key drivers of elephant movement and foraging strategies.

#### 2.5.1.2 Temperature

Kinahan *et al.* (2007) suggested that elephants may select habitats based on temperature fluctuations and shade availability. However, elephants are highly adaptable and can inhabit areas with extreme temperatures by employing behavioral strategies to manage heat stress. Mole *et al.* (2016) found that in environments with sufficient forage, water, and shade, elephants maintained homeothermy even at temperatures above 40 °C by seeking shade and increasing water-related behaviors.

Recent studies highlight the importance of temperature-related variables in shaping elephant habitat suitability and movement. In Sipsongpanna Prefecture, Yunnan, China, He *et al.* (2023) found that Mean Warmest Month Temperature (MWMT) significantly influenced Asian elephant habitat suitability. Under non-anthropogenic conditions, suitability peaked at 24–26 °C, while in human-impacted areas, it peaked at 23–24 °C before declining sharply. This suggests elephants are more sensitive to high temperatures in disturbed habitats, emphasizing the role of thermal conditions in habitat use.

In Madhesh Province, Nepal, Budhathoki *et al.* (2023) identified Temperature Seasonality as a key factor influencing Asian elephant habitat suitability. The Jackknife test showed that using this variable alone yielded a gain above 0.15, while its exclusion significantly reduced model performance, indicating strong predictive power. The response curve revealed that suitability increased with moderate temperature seasonality but declined at higher levels, suggesting elephants favor areas with moderate thermal variation.

In Nigeria’s Omo Forest Reserve, Akala *et al.* (2023) found that the optimal Mean Diurnal Range (bio_2) for African forest elephants was between 7.66 °C and 7.70 °C during both dry and wet seasons, with habitat suitability declining as values increased beyond 7.70 °C to 9.20 °C. In the Kasigau Wildlife Corridor, southeastern Kenya, Williams *et al.* (2018) identified Mean Temperature as a key variable influencing African elephant distribution, contributing 5.2% to the overall habitat suitability model.

### 2.5.2 Biophysical Factors

Important biophysical factors that determine elephant presence and potential suitable habitats include topography, vegetation, forage quality and quantity and proximity to surface water.

#### 2.5.2.1 Topographic Features

While the TWI, which measures water accumulation potential, has minimal influence on elephant distribution (Chibeya *et al.*, 2021), elevation, slope, and aspect significantly affect elephant presence, shaping spatial behavior and habitat suitability (Bohrer *et al.*, 2014; Chibeya *et al.*, 2021). Elephants occur across a range of elevations, with high presence typically between 50–1100 m a.s.l., depending on vegetation heterogeneity and resource availability (Bohrer *et al.*, 2014; Chibeya *et al.*, 2021; Htet *et al.*, 2021).

A study in Cambodia’s Phnom Kulen Wildlife Sanctuary found that most Asian elephant herds occupied elevations between 700–900 m a.s.l., mainly in dry evergreen forests, while solitary males and female groups were typically found between 400–700 m a.s.l. (Htet *et al.*, 2021). In eastern India, Palei *et al.* (2024) identified elevations between 400–600 m a.s.l. as optimal habitats for Asian elephants, typically associated with forest cover and mountain valleys. Elephants favored rugged terrain within this range due to the availability of large forested areas, water sources and conversion of lower flatter areas to settlements and agriculture.

Bohrer *et al.* (2014) found that seasonal variation influenced elephant movement in Marsabit Protected Area, Kenya, with migrations occurring between 650–1100 m a.s.l. During the dry season, elephants moved to higher elevations for access to permanent water and green forage, while in the wet season, they shifted to lower elevations where water and food were more abundant.

Despite, studies have shown that elephants exhibit distinct elevation-based habitat preferences. In Thailand’s Phu Khieo Wildlife Sanctuary, Asian elephants preferred higher elevations on the plateau, while solitary males were observed in high-elevation dry evergreen forests, likely to avoid conflict with dominant males in the lowlands (Htet *et al.*, 2021).

In Parsa National Park, Nepal, Sharma *et al.* (2020) reported that Asian elephants were mostly found between 150–350 m a.s.l., with suitability declining at higher elevations. Similarly, in Yunnan Province, China, elephants primarily occupied areas below 1000 m a.s.l., favoring regions with abundant food, water, and cover such as tropical and seasonal rainforests, valleys, bamboo forests, and gentle slopes. Habitat suitability declined sharply above 1000 m, indicating sensitivity to higher altitudes (Jiang *et al.*, 2023).

He *et al.* (2023) found altitude to be a key predictor of Asian elephant habitat suitability in Sipsongpanna Prefecture, Yunnan, China. Under non-anthropogenic conditions, optimal habitats occurred between 800–1200 m a.s.l., with suitability declining beyond 1300 m.

When anthropogenic factors were included, the optimal elevation range narrowed to 900–1100 m a.s.l. Chen *et al.* (2023) found that peak habitat suitability for elephants in Yunnan, southwestern China, occurred at mid-elevations between 800–1030 m a.s.l., where the predicted probability of presence was ≥ 0.5; beyond 1030 m, suitability declined sharply.

Chibeya *et al.* (2021) reported that in Zambia's Sioma Ngwezi landscape, steep slopes acted as barriers to elephant movement, influencing their distribution and habitat selection. Elephants preferred gentle gradients between 990–1020 m a.s.l., likely due to easier access to resources and reduced energy expenditure.

In Ghana's Mole National Park, Ashiagbor & Danquah, (2007) reported that African elephants mainly occupied the park's southern region, characterized by elevations of 121.9–192.2 m a.s.l. and flat terrain with slopes under 4°. In contrast, Palei *et al.* (2024) found that in Odisha, India, Asian elephants preferred rugged terrain between 400–600 m a.s.l., where forest cover and natural water sources were abundant, while lower, flatter areas had been converted to settlements and agriculture.

Although studies on the influence of aspect on elephant distribution are limited, Okello *et al.* (2015) found that in Kenya's Amboseli landscape, habitat selection was influenced by vegetation heterogeneity and resource availability, which varied with aspect. Elephants preferred bushland habitats occurring on specific terrain aspects.

Bohrer *et al.* (2014) reported that in Kenya's Marsabit Protected Area, seasonal changes in vegetation and water availability influenced elephant movements across elevation zones. During the rainy season, elephants moved to lower elevations (650–1100 m a.s.l.) with peak vegetation activity, while in the dry season, they retreated to higher elevations with evergreen forests offering reliable forage and water.

#### 2.5.2.2 Vegetation Aspects

Previous studies consistently emphasize the pivotal role of landscape heterogeneity, particularly vegetation structure and composition, in shaping elephant spatial distribution. For example, Polansky *et al.* (2019) demonstrated that in Namibia’s Etosha National Park, elephants tracked increases in NDVI following rainfall, an adaptive foraging behavior known as “green-wave surfing”, highlighting their reliance on NDVI as a proxy for forage quality. Similarly, Chen *et al.* (2022) reported that in Myanmar, Asian elephants adjusted their range size in response to fragmentation in agricultural and natural landscapes.

In Kruger National Park, South Africa, de Knegt *et al.* (2011) found that forage characteristics influenced elephant distribution at broad spatial scales, whereas proximity to water played a greater role at finer scales. The study also noted sexual differences in habitat use. In Kenya’s Greater Mara ecosystem, elephants showed a strong preference for densely canopied areas and adjusted habitat selection based on land management zones and human activity (Wall *et al.*, 2024). Comparable trends were observed in Cameroon, where elephants favored wooded savannas and gallery forests while avoiding agriculture and human settlements (Granados *et al.*, 2012), and in Amboseli, Kenya, where woodlands and bushlands were preferred due to higher resource availability and vegetation heterogeneity (Okello *et al.*, 2015).

Fine-scale habitat heterogeneity also plays a significant role. At Mpala, Kenya, Kimuyu *et al.* (2020) observed that elephants preferred plateau and valley habitats with accessible vegetation, avoiding steep, densely vegetated slopes. Other studies have shown that vegetation interacts with environmental variables such as soil type and water availability to influence elephant movements. For instance, Abraham *et al.* (2021) found bull elephants in Kruger preferred basaltic soils with sparse trees near artificial waterholes, while mixed herds clustered around rivers. In Marsabit, Kenya, elephants shifted seasonally from high-elevation forests in the dry season to lowland shrublands in the wet season, following vegetation dynamics captured by NDVI (Bohrer *et al.,* 2014). Conversely, elephants tended to avoid bare lands with limited forage and shelter, which offer lower habitat quality (Harris *et al.,* 2008; Wall *et al.,* 2024).

Modeling algorithms such as the MaxEnt model have reinforced importance of vegetation aspects in predicting elephant habitat suitability. Studies in India (Palei *et al.,* 2024) and Zambia (Chibeya *et al.,* 2021) reported strong positive correlations between NDVI and elephant presence, reflecting a clear preference for dense, green vegetation.

Studies on elephant feeding ecology have shown that foraging requirements play a significant role in shaping elephant spatial distribution and habitat preference. In Hwange National Park, Zimbabwe, high elephant densities reduced tall woody vegetation, shifting the landscape structure and driving elephants toward areas with preferred forage (Ferry *et al.,* 2021). In the mountainous regions of Namibia, elephants actively sought out favored forage species such as *Sterculia africana* (African star chestnut) and *Commiphora glaucescens* (blue-leaved corkwood), even navigating steep slopes to access them (Wenborn *et al.,* 2025). In the arid Namib Desert, elephants favored shrublands with key species like *Colophospermum mopane, Tamarix usneoides,* and *Combretum imberbe* to meet dietary needs (Viljoen, 1989).

### 2.5.2.3 Surface Water Resource

Surface water availability is a key determinant of elephant distribution, as they require drinking water every 1–3 days (Makati *et al.*, 2025; Western, 1975). In times of drought, elephants have been observed digging into dry riverbeds to access subsurface water. In Tanzania’s Ruaha National Park, for instance, they engaged in well-digging when surface water dried up and bacterial loads increased during the dry season (Stommel *et al.*, 2016).

Elephants exhibit uniform spatial distribution in areas with evenly distributed water but tend to concentrate near permanent water sources in drier regions, particularly during the dry season (Makati *et al.*, 2025). In southwestern Myanmar, elephant presence declined with increasing distance from water bodies, with areas beyond 8 km rarely used (Thant *et al.*, 2023). Similarly, in Nigeria’s Omo Forest Reserve, elephants frequently moved toward riverine habitats (Akala *et al.*, 2023).

Rainfall seasonality influences surface water availability and thus elephant distribution. In Hwange National Park, Zimbabwe, elephants clustered around artificial waterholes during dry seasons, especially in low-rainfall years, but dispersed more widely during wetter periods (Chamaillé-Jammes *et al.*, 2007). These aggregations led to overgrazing and habitat degradation (Chamaillé-Jammes *et al.*, 2007). In Botswana’s Eastern Okavango Panhandle, elephants were evenly distributed during the wet season when ephemeral water sources were abundant but shifted toward permanent sources like the Okavango River as temporary waters dried up (Makati *et al.*, 2025).

In Ethiopia’s Omo National Park, elephants consistently preferred areas near rivers year-round, with this preference intensifying in the dry season (Jeza & Bekele, 2023). Similarly, in Kenya’s Tsavo East National Park, about 66.6% of elephants stayed within 1 km of water during the dry season, causing increased browsing pressure near water points as numbers declined with distance (Ngatia, 2015).

In Zimbabwe’s Matetsi Safari Area, elephant distribution varied annually in response to artificial water points. In 2006, presence probability was highest near these points and declined with distance, while in 2010, the opposite pattern was observed. However, distance to rivers was not a significant predictor in either year (Muposhi *et al.*, 2016).

In Kenya’s Laikipia–Samburu ecosystem, elephants showed sex-specific responses to seasonal water availability, with core areas averaging 17 km from rivers (range: 0.2–50.3 km). Females ranged farther from rivers in the wet season, while males did so in the dry season (Kuria *et al.*, 2024).

Although elephants are generally water-dependent, they can occupy areas far from water. In Gonarezhou National Park, Zimbabwe, elephant occurrence peaked within 9 km of water and again beyond 50 km, likely due to factors like forage availability or reduced competition for resources (Ndaimani *et al.*, 2017).

#### 2.5.2.4 Anthropogenic Factors

Human activities such as cultivation, settlement expansion, infrastructure development, overgrazing, and road construction significantly influence elephant spatial behavior. Elephants generally avoid areas with high human presence to reduce conflict. For instance, in the Sebungwe Region, Zimbabwe, elephants avoided settlements and agricultural fields during the wet season, remaining over 4.5 km away (Mpakairi *et al.*, 2019). Similarly, in

Botswana’s Okavango Panhandle, elephants avoided pathways near larger settlements and cultivated areas but occasionally adopted group movement strategies for safety (Songhurst *et al.*, 2015). In Congo’s Nouabalé-Ndoki region, elephants rerouted travel paths to avoid villages and agricultural zones, leading to smaller and more fragmented home ranges (Blake *et al.*, 2008).

In southeast Angola, elephants kept a distance of at least 6 km from roads and settlements (Schlossberg *et al.*, 2018), while in northern Kenya’s Samburu and Buffalo Springs reserves, they moved away from areas with seismic human-generated white noise (Mortimer *et al.*, 2021). Elephants also alter activity timing to minimize human encounters. In Gorongosa National Park, Mozambique, they restricted movement to nocturnal and crepuscular hours near roads and park boundaries (Gaynor *et al.*, 2018). Similar behavior was recorded in Kenya’s Laikipia-Samburu ecosystem and Greater Mara ecosystem, where elephants increased nighttime activity in human-dominated areas (Duporge *et al.*, 2022; Wall *et al.*, 2024). Conversely, in Botswana’s Chobe District, elephants exhibited more daytime than nighttime movement (Adams *et al.*, 2021).

Elephants also adjust home range size and movement behavior in response to human disturbance. For example, forest elephants in West Africa exhibited shorter movement distances and smaller home ranges in disturbed areas (Bairne *et al.*, 2021). In the Greater Mara, elephants preferred closed-canopy habitats for food and cover, avoiding open grasslands, particularly in unprotected zones (Wall *et al.*, 2024).

Land use changes such as agriculture and deforestation also drive elephant habitat fragmentation. In Asia, over 64% (3.36 million km$^2$) of suitable elephant habitats have been lost since 1700 due to land conversion, resulting in 83% reduction in patch sizes and increased fragmentation (de Silva *et al.*, 2023). In Botswana’s Chobe District, elephant movement varied across agricultural, protected, and multi-use zones, with relatively small home ranges of ~450–1,750 km² (Adams *et al.*, 2021). In Kenya’s Amboseli ecosystem, human expansion reduced elephant home ranges to 5,360–37,167 km² (Ngene *et al.*, 2017). In Laikipia, conversion of forests to farmland disrupted migration routes and increased human-elephant conflict (Mumu *et al.*, 2010; Gara *et al.*, 2017). Land cover changes led to a 16.3% loss of woodlands and bushlands, narrowing key corridors (Schüßler *et al.*, 2018).

Despite the risks, elephants sometimes remain near human areas when essential resources like water and forage are concentrated there. In Gorongosa, they used agricultural areas for food and water and roads for travel (Gaynor *et al.*, 2018). In Zimbabwe and Angola, elephants frequented agricultural fields and communal lands during dry seasons and sometimes preferred areas within 6–40 km of humans (Mpakairi *et al.*, 2019; Schlossberg *et al.*, 2018). In Marsabit, Kenya, elephants stayed close to settlements and roads, with average distances of 3.1 km and 3.5 km, respectively (Ngene *et al.*, 2009).

Proximity to human activity increases risks of conflict and poaching. For instance, elephants frequently raided farms near Katavi National Park, Tanzania, during dry periods, causing economic losses (Kashaigili, 2014). In Tsavo East National Park, Kenya, poaching incidents were more common near roads and rivers (Kiyale *et al.*, 2011).

Habitat suitability modeling further supports these patterns. In China’s Sipsongpanna Prefecture, MaxEnt modeling revealed that human disturbances altered preferred elevation ranges of Asian elephants, narrowing optimal habitat from 800–1,200 m to 900–1,100 m a.s.l. (He *et al.*, 2023). In the same region, for example, habitat suitability decreased with increased rubber plantation coverage and forest fragmentation, though suitability stabilized once forest patches exceeded a certain threshold (Chen *et al.*, 2023). These findings illustrate how agricultural expansion and fragmentation diminish suitable habitats and complicate elephant conservation.

### 2.5.3 Competition and Predation

In addition to anthropogenic and environmental drivers, intrinsic ecological factors such as interspecific competition and predation also influence elephant spatial distribution. Studies have shown that elephants, due to their large body size and resource dominance, can alter access to key resources for other herbivores. For instance, in Hwange National Park, Zimbabwe, elephants dominated waterhole use during the early to mid-afternoon, causing other species such as zebras, impalas, and kudus to adjust their activity to mornings or late afternoons to reduce competition (Valeix *et al.*, 2007). However, overall temporal overlap remained stable, suggesting behavioral adaptations that allow coexistence (Valeix *et al.*, 2007).

Size-based competitive dominance has been observed across African savannas, where elephants and buffaloes often outcompete smaller herbivores through non-lethal interference, particularly under resource-limited conditions. Although facilitative interactions such as habitat opening, occasionally benefit smaller grazers, competitive effects generally prevail (Young *et al.*, 2005). Similarly, across multiple savanna ecosystems, including Hwange, Kruger, and Serengeti, high elephant biomass was associated with reduced populations of browser species. This pattern suggests strong competition and habitat modification by elephants (Fritz *et al.*, 2002). While grazers became more dominant, overall herbivore biomass remained relatively stable, indicating a guild-level shift in community structure.

Long-term monitoring in Hwange National Park showed inverse trends between elephant populations and browsers such as kudu (*Tragelaphus strepsiceros*) and giraffe, particularly during dry years. Increasing elephant densities and declining rainfall intensified competition and habitat degradation, especially around artificial waterholes (Valeix *et al.*, 2008).

Predation, particularly by lions, also plays a significant role in influencing elephant behavior. In Chobe National Park, Botswana, coordinated lion hunts during the dry season resulted in the predation of juvenile elephants mainly between 4 and 11 years of age, especially at night and near waterholes (Joubert, 2006; Power & Shem Compion, 2009). These events, driven by prey scarcity and large lion pride sizes, may influence elephant spatial behavior, movement patterns, and group cohesion.

Additionally, elephants with calves in Hwange were observed to alter their timing of waterhole visits to midday, when lions are less active, as a predator avoidance strategy. Similar behavior was noted in other herbivores in response to predation pressure (Valeix *et al.*, 2009). These findings underscore the importance of both competitive interactions and predation in shaping the spatial ecology and behavior of elephants in savanna ecosystems.

## 2.6 Habitat Suitability of Elephants Under Future Climate Change Scenarios

Climate change poses a growing threat to elephant conservation by altering habitat suitability through shifts in temperature, precipitation patterns, and the frequency of extreme weather events. These changes are expected to impact vegetation productivity, water availability, and overall landscape conditions.

One of the most direct impacts of climate change is the projected shift in suitable elephant habitat ranges. Rising temperatures and reduced rainfall may lead to habitat contractions in some areas and expansions into new regions, influenced by climate and land-use changes. In India and Nepal, Kanagaraj *et al.* (2019) estimated a current suitable area of 486,800 km² for Asian elephants, projecting a 17.1% loss under climate-only scenarios and up to 41.8% loss under combined climate and land-use change by 2070 (RCP 8.5), with potential gains of up to 42% in more northern and elevated areas.

In South and Southeast Asia, Yang *et al.* (2022) projected a decline in core elephant habitats from 491,455 km² to 332,544 km² by 2090 under SSP585, though protected areas are expected to remain stable at around 219,545 km² for conservation. In Nepal's Madhesh Province, Budhathoki *et al.* (2023) predicted that under SSP245, highly suitable habitats will cover only 14% of the landscape by 2100, with unsuitable areas rising to 49%. Under SSP585, unsuitable habitats are expected to increase further, with a decrease in moderately suitable areas and a slight rise in highly suitable ones.

At a broader regional scale, Abir *et al.* (2025) projected extensive habitat loss across Tropical Asia under future scenarios. Under SSP245, northern areas may lose 588 km² annually between 2061–2080, while under SSP370, the western zone could lose up to 1,799 km² annually. The eastern zone, currently the most favorable may lose 148,000 km² of habitat by 2080. Increasing habitat fragmentation is expected to severely affect elephant movement and survival.

For African elephants, Dejene *et al.* (2021) projected a 51.3% reduction in highly suitable habitats by 2050 under RCP 4.5 and 67.6% under RCP 8.5. By 2070, reductions could reach 74.5% and 85.9%, respectively, with a corresponding rise in unsuitable areas. Similarly, in Hwange National Park, Zimbabwe, Mpakairi *et al.* (2019) projected a 40% decline in suitable habitat by 2050 under RCP 8.5, shrinking from 146.8 km² to 88 km².

## 2.7 Foraging Behavior and Forage Preferences of Elephants

Elephants are generalist, mixed feeders that consume a wide variety of plant types and parts, including grasses, browse, bark, fruit, and bulbs (Codron *et al.*, 2011; Koirala *et al.*, 2016; Seloana *et al.*, 2018; Tsegaye *et al.*, 2022; Woolley *et al.*, 2011). Their foraging strategies vary depending on season, habitat, body size, nutritional demands, and social dynamics (Anoop *et al.*, 2023; Codron *et al.*, 2011; Kalemera, 1989; Koirala *et al.*, 2016; Mwambola *et al.*, 2024; Staver & Hempson, 2020; Woolley *et al.*, 2011).

Seasonal dietary flexibility is a key ecological adaptation. Staver and Hempson (2020) found that many savanna herbivores, particularly large mixed feeders such as elephants and buffalo, shift between grazing and browsing based on resource availability. This flexibility allows them to exploit a broader range of food sources throughout the year, supporting larger populations and reducing interspecific competition. Ecosystems with such adaptable species tend to maintain higher herbivore biomass, emphasizing the ecological importance of dietary flexibility in sustaining resilient populations.

Regional studies further support these patterns. In Lake Manyara National Park, Tanzania, Kalemera (1989) observed a strong feeding preference for *A. tortilis*, particularly during the dry season when alternative forage was scarce. In Kruger National Park, South Africa, Codron *et al.* (2011) found that African elephant diets consisted of approximately 35% grass overall, with higher grass consumption (~40%) in the north and lower (~10%) in the south during the dry season. During the wet season, grass intake increased to about 50% across all regions.

In Atherstone Collaborative Nature Reserve, elephants favored grasses and herbs during the wet season, but shifted to woody vegetation, especially bark and branches, in the dry season (Seloana *et al.*, 2018). In Pilanesberg National Park, Woolley *et al.* (2011) reported that family groups used both grass and browse consistently across seasons. Calves prioritized softer, high-quality plant parts, while adult females consumed tougher vegetation such as roots and branches. Adults also adjusted their foraging height to accommodate calves.

In Nepal's Parsa Wildlife Reserve and Chitwan National Park, Koirala *et al.* (2016) found that browse was preferred during the dry season, while both grasses and browse were important in the rainy season. In Babile Elephant Sanctuary, Ethiopia, Geleta & Mengesha (2022) reported greater browsing on woody species in the wet season, attributed to the availability of growing shoots, leaves, and fruits. Similarly, Tsegaye *et al.* (2022) in

Chebera Churchura National Park, Ethiopia, observed that most plant species consumed in the dry season were also eaten in the wet season.

In southern India, Anoop *et al.* (2023) noted that Asian elephants primarily browsed in forested habitats with sparse grasses but grazed in adjacent savannas with higher grass abundance, highlighting habitat-based dietary plasticity. In contrast, elephants in Rubondo Island National Park, Tanzania, showed no variation in species composition between wet and dry seasons, suggesting stable year-round food availability (Mwambola *et al.*, 2024).

Numerous studies have documented the wide range of plant species utilized as forage by elephants, yet evidence consistently shows that elephants are selective feeders at the species level, with preferences varying across landscapes and seasons (Geleta & Mengesha, 2022; Ihwagi *et al.*, 2010; Kalemera, 1989; Kuswanda *et al.*, 2023; Koirala *et al.*, 2016; Koskey, 2013, 2016; Mwambola *et al.*, 2014; Owen-Smith & Chafota, 2012; Tsegaye *et al.*, 2022; Woldegiorgis & Bekele, 2012). In Indonesia's Datuk Gedang Wildlife Corridor, Asian elephants utilized 125 plant species, mainly from Moraceae, Euphorbiaceae, and Aracaceae families (Kuswanda *et al.*, 2023). Similarly, in Nepal's Parsa Wildlife Reserve and Chitwan National Park, elephants consumed 57 species, with *Spatholobus parviflorus*, *Saccharum spontaneum*, and *Shorea robusta* among the most preferred (Koirala *et al.*, 2016).

In African landscapes, seasonal and species-specific preferences have been widely observed. In Botswana's Chobe National Park, *Croton gratissimus* and *Terminalia sericea* were heavily browsed, particularly during the dry season, while some species were consistently avoided (Owen-Smith & Chafota, 2012). In the arid Namib Desert, elephants preferred *Colophospermum mopane, Tamarix usneoides,* and *Combretum imberbe* (Viljoen, 1989).

In Ethiopia's Babile Elephant Sanctuary, elephants showed strong preferences for *Acacia albida*, *Acacia seyal*, and *Opuntia ficus-indica*, while avoiding species such as *Combretum molle* (Geleta & Mengesha, 2022; Woldegiorgis & Bekele, 2012). In Chebera Churchura National Park, 109 plant species were recorded in the elephant diet, with *Phoenix reclinata* and *Oxytenanthera abyssinica* among the most consumed species (Tsegeya *et al.*, 2022). Other notable preferences include *A. tortilis* in Tanzania's Lake Manyara National Park and Kenya's Samburu and Buffalo Springs Reserves (Ihwagi *et al.*, 2010; Kalemera, 1989), and *Phoenix reclinata* in Rubondo Island National Park (Mwambola *et al.*, 2014). In the Rimoi Conservation Area, Kenya, elephants foraged on 19 plant species, but favored *A. tortilis*, *B. aegyptiaca*, *A. mellifera*, *Z. mucronata*, and *A. brevispica*, which accounted for the highest proportion of feeding records (Koskey, 2013, 2016).

Studies have also indicated that in addition to wild plants, elephants consume various cultivated crops and are equally selective, preferring specific crop species over others (Kosgey, 2013, 2016; Woldegiorgis & Bekele, 2012). For example, in the Babile Elephant Sanctuary, Ethiopia, Biru & Bekele (2012) recorded elephants consuming 14 cultivated plant species from 10 families. In the Rimoi Conservation Area, Kenya, Koskey (2013, 2016) observed that elephants preferred several crops, with the most raided being maize (86.5%), millet (51.4%), and green grams (34.8%), while the least raided were cowpeas (16.8%) and sorghum (7.3%). This selective crop consumption has contributed to human-elephant conflict in various landscapes.

Elephants may consume all parts of a plant, especially herbs and shrubs. For instance, in the Datuk Gedang Wildlife Corridor, Indonesia, elephants consumed entire plants in 14.4% of observations (Kuswanda *et al.*, 2023). However, they are selective at the plant-part level, with preferences varying by species, season, and nutritional content (Geleta & Mengesha, 2022; Kalemera, 1989; Koirala *et al.*, 2016; Kuswanda *et al.*, 2023; Mwambola *et al.*, 2014; Owen-Smith & Chafota, 2012; Seloana *et al.*, 2018; Tsegaye *et al.*, 2022; Woolley *et al.*, 2011).

In Nepal's Parsa Wildlife Reserve and Chitwan National Park, Asian elephants consumed leaves and twigs significantly more than other plant parts (Koirala *et al.*, 2016). In Pilanesberg National Park, South Africa, African elephant calves selected less fibrous and more nutritious parts, such as stripped leaves, while adult females predominantly consumed branches, bark, and roots (Woolley *et al.*, 2011).

In the Kalahari Sandveld region of Chobe National Park, Botswana, elephants fed mainly on leaves and shoots during the wet season, which comprised about 80% of their woody plant diet. This reliance dropped to 45% during the cool dry season, with increased consumption of stems, bark, and roots (~ 50%), surging to 94% during the hot dry season (Owen-Smith & Chafota, 2012).

In the Babile Elephant Sanctuary, Ethiopia, elephants fed on growing shoots, leaves, and fruits during the wet season but switched to bark and other available materials during the dry season (Biru & Bekele, 2012). In Antherstone Collaborative Nature Reserve, elephants consumed more bark and branches in the dry season, with leaves, branches, and bark making up the bulk of their diet (Seloana *et al.*, 2018).

Tsegaye *et al.* (2022) reported that African elephants in Chebera Churchura National Park, Ethiopia, preferred leaves of woody plants over bark/stem and fruits. Whole parts of grasses and herbaceous plants contributed significantly to their total feeding score, followed by fruit, which was least consumed. Similarly, in Datuk Gedang Wildlife Corridor, Indonesia, elephants primarily consumed young leaves (41.6%), and a combination of leaves and bark (15.2%) (Kuswanda *et al.*, 2023). In Lake Manyara National Park, Tanzania, elephants showed a strong preference for *Acacia tortilis* leaves, branches, and fruits (Kalemera, 1989), while in Rubondo Island National Park (RINP), Tanzania, their feeding was dominated by leaves (72%), followed by bark/stem (18%) and fruits (10%) (Mwambola *et al.*, 2014).

The distribution of preferred forage species shapes elephant spatial patterns and habitat use. In Hwange National Park, Zimbabwe, high elephant densities (>2/km²) reduced tall woody vegetation (>200 cm) and increased short plants (<50 cm), prompting movement toward areas with preferred forage (Ferry *et al*., 2021). In northwest Namibia, species such as *Sterculia africana* and *Commiphora glaucescens* drew elephants from Etosha National Park into mountain slopes for forage (Wenborn *et al*., 2025). In the arid Namib Desert, elephants favored shrublands with key species like *Colophospermum mopane, Tamarix usneoides,* and *Combretum imberbe* to meet dietary needs (Viljoen, 1989).

## 2.8 Environmental Determinants of Distribution and Habitat Suitability of Selected Preferred Forage Plants

Understanding the distribution and habitat suitability of elephants' preferred forage plants is vital for effective conservation of both elephants and other coexisting species. However, there is limited scientific literature that systematically examines these aspects for African elephant forage plants. A notable contribution is the study by Kuswanda *et al.* (2023) in the Datuk Gedang Wildlife Corridor, Indonesia, where habitat fragmentation threatens the endangered Sumatran elephant (*Elephas maximus sumatranus*). The study identified forage species and assessed habitat suitability using strip-transect surveys across six land cover types, applying the Importance Value Index (IVI) and MaxEnt modeling to guide conservation and restoration efforts.

In the study by Kuswanda *et al.* (2023), 94.5% of the Datuk Gedang Wildlife Corridor was found suitable for the growth of 125 elephant forage species, with *Phrynium pubinerve* Blume, *Miconia crenata* (Vahl) Michelang, and *Beilschmiedia kunstleri* Gamble showing over 50% suitability. Key environmental factors included land cover, elevation, slope, and proximity to water. The study also provided valuable insights into the spatial distribution, soil preferences, and ecological associations of forage species, highlighting the role of habitat quality in sustaining wildlife populations.

Despite its significance, the study by Kuswanda *et al.* (2023) remains one of the few comprehensive assessments of forage plant habitat suitability in relation to elephant ecology, highlighting a critical knowledge gap. This is especially important given elephants' selective feeding behavior at the species level, with preferences varying across landscapes (Geleta & Mengesha, 2022; Ihwagi *et al.*, 2010; Kalemera, 1989; Koirala *et al.*, 2016; Koskey, 2013, 2016; Kuswanda *et al.*, 2023; Mwambola *et al.*, 2014; Owen-Smith & Chafota, 2012; Tsegaye *et al.*, 2022; Woldegiorgis & Bekele, 2012).

Given the limited studies on environmental influences affecting the distribution and suitability of elephant forage plants, relevant botanical and ecological literature will be synthesized from previous research on individual species identified by Koskey (2013, 2016) in the study area: *A. tortilis*, *A. mellifera*, *A. brevispica*, *B. aegyptiaca*, and *Z. mucronata*. While limited research exists on *A. brevispica* and *Z. mucronata*, the other three species are well-studied in terms of their distribution, habitat suitability, and responses to environmental factors, including climate change.

### 2.8.1 *Vachellia tortilis* (Forssk.) Galasso & Banfi (syn. *Acacia tortilis*) – Umbrella Thorn Acacia

*Vachellia tortilis*, commonly known as the umbrella thorn acacia, is a pod-bearing tree in the family Fabaceae, subfamily Mimosoideae (Cheruto *et al*., 2025) (Figure 2). *Vachellia tortilis* is a keystone species in arid and semi-arid ecosystems across Africa, the Arabian Peninsula, and Australia, occurring from subtropical deserts to very dry tropical forests (Cheruto *et al*., 2025; Kennenni, 1991; Yadav *et al*., 2013). Native to dry, tropical, southern, and northern Africa, as well as the Middle East, it grows widely across these regions (Cheruto *et al*., 2025). It occurs in pure or mixed stands within dry bushland, grasslands, riverine vegetation, and arid scrub (Maundu & Tengnäs, 2005), and may also be found in homesteads, croplands, and on soil conservation structures such as contours (Kuria *et al*., 2018).

The distribution of *V. tortilis* is influenced by rainfall, temperature, topography, and soil (Kebbas *et al*., 2015; Kennenni, 1991; Yadav *et al*., 2013). Precipitation is particularly critical, shaping its dominance in riparian zones and affecting canopy cover (Coughenour

& Ellis, 1993). The species grows in areas with 100–1,000 mm annual rainfall, optimally at 300–600 mm (Cheruto *et al*., 2025; Maundu & Tengnäs, 2005), and can tolerate as little as 10 mm (Yadav *et al*., 2013). Most populations of *V. tortilis* occur at 0–1,000 m a.s.l., occasionally up to 1,500 m, and on slopes of 0–5% (Orwa *et al*., 2009; Jaouadi *et al*., 2013).

Other precipitation variables, such as Precipitation of the Driest Quarter (bio_17) and Annual Precipitation (bio_12), strongly influence the distribution of *V. tortilis*, with MaxEnt models consistently identifying them as key predictors (Bio *et al.,* 2024; Mechergui *et al.*, 2021; Nkosi, 2024). In Tunisia, bio_17 contributed 31.9% to model performance (Mechergui *et al.*, 2021); in eastern Niger, bio_12 contributed 56.5% (Bio *et al.*, 2024); and in South Africa, bio_17 accounted for 65.3% of the model gain (Nkosi, 2024).

*Vachellia tortilis* thrives at an annual mean temperature of 18–28 °C but can withstand extremes ranging from 5 °C in winter to 50 °C in summer (Cheruto *et al.*, 2025; Yadav *et al.*, 2013). In eastern Niger, Bio *et al*. (2024) found that the Maximum Temperature of the Hottest Period (bio_5) contributed 13.4% to model performance. This broad tolerance to temperature and rainfall reflects its drought-resistant traits, including deep rooting systems and high water-use efficiency.

It thrives in sandy, loam, sandy loam, and rocky soils with good drainage, often in low-lying areas, gentle slopes, and sandy dunes (Coughenour & Ellis, 1993; Orwa *et al*., 2009), preferring alkaline soils with a pH of 6.5–8.5 (Cheruto *et al*., 2025; Orwa *et al.*, 2009; Yadav *et al*., 2013), and can also grow in alluvial soils that support riparian vegetation (MacGregor & O'Connor, 2004). In Venetia-Limpopo Nature Reserve, Limpopo Province, South Africa, this species occupied about 102 ha, primarily on Prismacutanic, Pedocutanic B-horizons, and Glenrosa and Mispah soils, known for their moisture retention and ecological value (Nkosi, 2024).

Climate change is anticipated to significantly influence the distribution and habitat suitability of *V. tortilis* across its range, with shifts largely driven by changing temperature and precipitation patterns. Projections from different regions consistently indicate that this drought-tolerant species may experience considerable range expansion under future climate scenarios, particularly in arid and semi-arid landscapes. For instance, Bio *et al.* (2024) projected that in Eastern Niger, the current favourable range of *V. tortilis* could increase from approximately 19.8% to over 30.33% under RCP4.5 and 32.85% under RCP8.5 by 2055, primarily within the Sahelo-Saharan and Sahelian zones. Similarly, Mechergui *et al.* (2021) found that in Tunisia, highly suitable habitats (>0.6 suitability) covering about 1,142.5 km² under current conditions could expand markedly under both low- and high-emission scenarios, reaching up to 14,684.9 km² by 2070 under RCP8.5.

**Figure 2: Growth Habit of *V. tortilis* (Forssk.) Hayne (syn. *A. tortilis*) (Source: Cheruto *et al.*, 2025).**

### 2.8.2 *Acacia mellifera* (M.Vahl) Benth. (syn. *S. mellifera*) – Blackthorn Acacia

*Acacia mellifera*, commonly known as the blackthorn acacia (Figure 3), is a resilient woody species prevalent in arid and semi-arid regions of Africa, with its distribution shaped by a combination of climatic, edaphic, and anthropogenic factors. *Acacia mellifera* thrives in areas with mean annual rainfall ranging from 150 mm to 1,200 mm, favoring regions with 2 to 10 consecutive dry months. It tolerates mean annual temperatures between 15°C and 30°C, withstanding extremes from 2°C to 40°C. These adaptations enable its survival in diverse climates, including tropical savannas and desert margins. It occurs from 30 to 1,850 m a.s.l., showing broad altitudinal adaptability.

*Acacia mellifera* thrives in diverse soils, preferring loamy types but also occurring in black cotton, sandy, and heavy clay soils. In the Northern Cape, South Africa, Britz (2004) found it favored loamy-sand and clay-mix soils, which balance drainage and moisture retention, over pure sand or clay. Pure sands drain too quickly, while pure clays risk waterlogging and poor aeration. The species was absent from clay pans and scarce on other clay and sandy soils, highlighting the influence of soil texture and water regimes on its distribution.

In the Northern Cape, South Africa, Britz and Ward (2007) reported that *A. mellifera* was absent from clay pans and scarce on other clay and sandy soils, a pattern linked to soil texture, water regimes, and heavy utilization. They identified soil rockiness as a key factor supporting its long-term presence, likely due to improved moisture conditions.

**Figure 3: Growth Habit of *A. mellifera* (M. Vahl) Benth. (syn. *S. mellifera*) (Source: https://www.cifor-icraf.org/knowledge/photo/53707249969/)**

Predictive modeling by Bravo-García *et al.* (2024) identified key climatic drivers of *S. mellifera* distribution in southern Africa. The Mean Temperature of the Wettest Quarter (bio_8) was most influential (50.9%), followed by Annual Mean Temperature (bio_1, 27.4%) and Annual Precipitation (bio_12, 11.1%). These findings highlight the species' sensitivity to thermal and moisture conditions, particularly during wet periods, explaining its broad yet selective distribution across central southern Africa.

Under current climate conditions, *Senegalia mellifera* occupies 56% of the study area (~1,460,353 km²), reflecting its broad tolerance and adaptability (Bravo García *et al.*, 2024). It is the most habitat-adapted of the modeled bush encroacher species, widespread across central southern Africa, but absent from Namibia’s arid west coast and the wetter southern zones, indicating distribution limits set by precipitation and soil moisture.

Future projections show that *S. mellifera* will expand its habitat suitability across all climate scenarios (Bravo-García *et al.,* 2024), with the largest increase (29.4%) predicted for 2061–2080 under the SSP585 high-emission pathway using the UK-ESM1.0-LL model. The smallest gain (8%) is expected in 2024–2060 under SSP245 with the INM-CM5-0 model.

### 2.8.3 *Balanites aegyptiaca* (L.) Delile – Desert Date

*Balanites aegyptiaca* (L.) Delile., also known as the Desert date, is a dicotyledonous, evergreen flowering plant (Thakkar *et al.,* 2025), classified in either Zygophyllaceae or Balanitaceae (Chothani & Vaghasiya, 2011; Dubey *et al.,* 2011). It is widespread in dryland areas of the Sahel–Saharan regions, the Middle East, and South India (Chothani & Vaghasiya, 2011; Dubey *et al.,* 2011; Hall *et al.,* 1992; Sagna *et al.,* 2014 a or b), and is native to all drylands south of the Sahara, extending to Malawi in the Rift Valley and the Arabian Peninsula (Chothani & Vaghasiya, 2011; Dubey *et al.,* 2011; Rojas-Sandoval, 2016; Thakkar *et al.,* 2025).

*Balanites aegyptiaca* is among the most widely distributed African trees, extending over 50° of latitude from Israel to southern Zimbabwe and across Africa from Senegal to Somalia (Hall & Walker, 1991; Rojas-Sandoval, 2016; Thakkar *et al.,* 2025). . It is common in Senegal (Sagna *et al.,* 2014) and also occurs in Iran, Palestine, Jordan, India, Oman, Yemen, Saudi Arabia, and Myanmar (Murthy *et al.,* 2021).

*Balanites aegyptiaca* occurs in diverse habitats, ranging from savanna woodland, deciduous bushland, and thicket to desert wadis (Hall & Walker, 1991; Orwa *et al.*, 2009; Sagna *et al.*, 2014). In Kenya, it inhabits dry bushland, bushed and wooded grasslands, woodland, and riverine areas or luggas (Beentje, 1994).

Natural formations of *B. aegyptiaca* consist of well-spaced individuals with full crown exposure, though pure stands occur as trees are often spared during felling for their value (Rojas-Sandoval, 2016). It is listed as invasive in Curaçao, where it spreads into ruderal areas despite free-ranging goats (Burg *et al.,* 2012), and in Palestine and Sudan, where it can form dense thorny thickets that hinder native biodiversity (Zohary, 1973; Miehe, 1986; PROTA, 2016). In Sudan's Jebel Marra, it invades degraded areas (Miehe, 1986).

The natural distribution of *B. aegyptiaca* is obscured by cultivation, with introductions in Latin America, the West Indies, Cape Verde Islands, the Azores, and India (Chothani & Vaghasiya, 2011; Govaerts, 2016). In India, it is common in Rajasthan, Gujarat, Madhya Pradesh, and the Deccan (Dubey *et al.,* 2011; Rojas-Sandoval, 2016; Thakkar *et al.,* 2025). Introduced to Curaçao in 1885, it now spreads from the east to the west, and is also found in Bonaire, the Dominican Republic, and Puerto Rico (Burg *et al.,* 2012). It is widely planted across Africa, with small plantations in Niger, Chad, and northern Nigeria (Rojas-Sandoval, 2016).

*Balanites aegyptiaca* has a wide ecological amplitude (Sagna *et al.,* 2014), tolerating wet and dry conditions. It is drought-resistant, requiring 250–800 mm of rainfall annually (Bhardwaj *et al.*, 2024). Hall and Walker (1991) suggest a 1000 mm annual mean rainfall isohyet as its natural limit in Sudan, with wetter-area occurrences often linked to disturbance or introduction. Reports from areas with up to 1300 mm rainfall (e.g., Guinea Bissau, Central African Republic) reflect secondary vegetation or introductions.

It tolerates high temperatures up to 40 °C and generally occurs in areas with 20–30 °C mean annual temperatures, supporting a tropical origin (Bhardwaj *et al.*, 2024; Rojas-Sandoval, 2016). In West Africa, low elevations experience ~24 °C, while elevated areas in Eastern and Southern Africa range from 20–25 °C (Hall & Walker, 1991). Coastal zones show declines, with <19 °C only in the Ethiopian Mountains.

*Balanitis aegyptiaca* grows from 300–1500 m, occasionally up to 2000 m (Hall & Walker, 1991; Bhardwaj *et al.*, 2024). It occurs on diverse soils; sandy, stony, clayey, alluvial, volcanic, old crystalline, sandstone, sandy plains, black clays, and tolerates heavy clays (Orwa *et al.*, 2009; Teel, 1984).

Overgrazing is a significant factor affecting the distribution and survival of *B. aegyptiaca* in dryland ecosystems. Gaisberger *et al.* (2017) identified it as the fourth most prevalent threat in the Sahelian zone, particularly in northern Burkina Faso, and ranked it as the second most important threat to *B. aegyptiaca*, impacting 20.7% of its range after climate change. High-threat areas included the Sahel, Centre, Plateau-Central, northern Est, Centre-Est, and parts of Centre-Ouest and Hauts-Bassins.

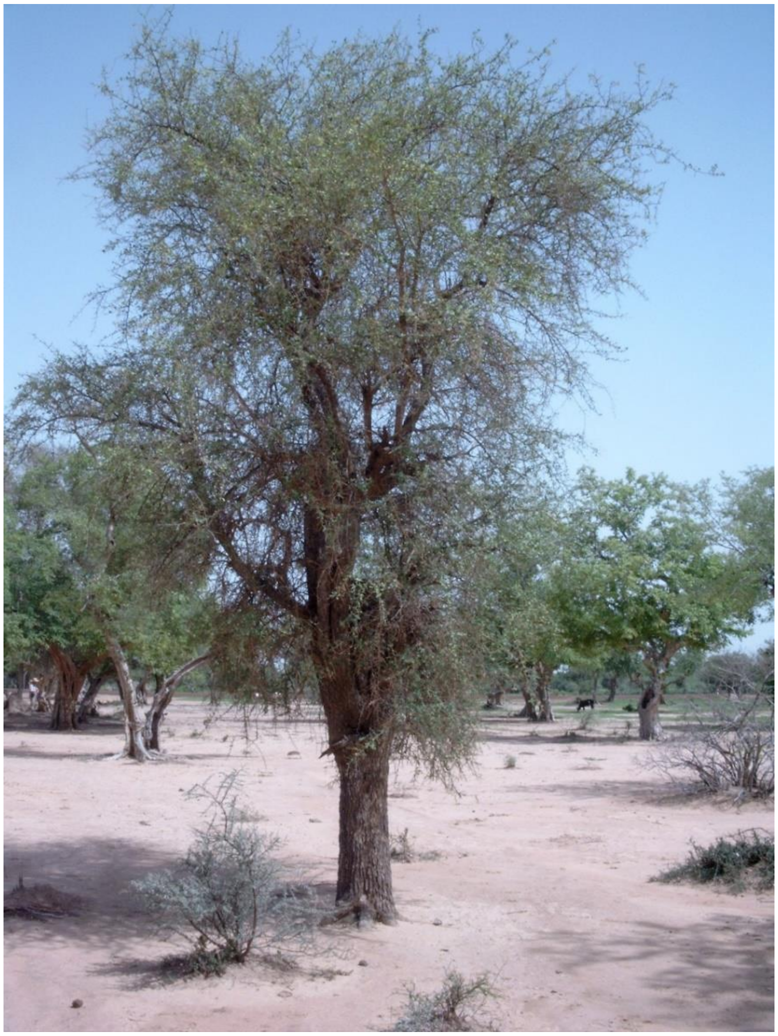


**Figure 4: Growth Habit of *B. aegyptiaca* (L.) Delile (Source: Thakkar *et al.* 2025)**

Ecological modeling studies highlight *Balanites aegyptiaca* is sensitivity to bioclimatic and edaphic variables, with notable regional variation. In Chad, Chérif *et al*. (2022) found highly suitable habitats concentrated in the central and southern Sahelian zone, covering ~46% of the country. Precipitation of the Wettest Month (bio_13, 31.5%) and dry month duration (28.2%) were top predictors, together explaining nearly two-thirds of habitat suitability, followed by temperature seasonality (16.7%) and soil factors (13.8%). In Niger, Habou *et al.* (2021) reported that 67.7% of the territory is currently very favorable for *B.*

*aegyptiaca*, driven mainly by bio_19 and bio_13. In Ethiopia, Seid et *al.* (2024) identified the Central Rift Valley as the core habitat (114,517 km² highly suitable), with bio_7 and bio_15 as key drivers, while in Tigray, Gufi *et al.* (2023) found suitability covering 2,213 km² (3% of the area), strongly influenced by bio_15, bio_2, and bio_1. In Turkana County, Kenya, Oluoch *et al.* (2024) reported suitability over 25% of the county, with bio_1, bio_12, and elevation as main predictors.

Projections indicate significant shifts in habitat suitability across regions. In Niger, Habou *et al.* (2021) projected a decline from highly suitable to moderately suitable habitats by 2050 under the A2 emissions scenario, though reserves such as Tamou and Gadbédji are expected to retain high suitability. In Ethiopia, Seid *et al.* (2024) projected modest expansion under SSP245 (+2.1%) and greater gains under SSP585 (+7.5%). In Tigray, Gufi *et al.* (2023) projected a 65% expansion under RCP4.5 by 2070, but a complete contraction under RCP8.5. In Turkana, Oluoch *et al.* (2024) predicted complete local habitat loss under all future climate scenarios.

### 2.8.4 *Ziziphus mucronata* Willd. – Buffalo Thorn

*Ziziphus mucronata,* also known as the buffalo thorn, is a tree in the family Rhamnaceae (Figure 5). It is deciduous, and may grow up to 15 m tall (Beentje, 1994). It is native to Angola, Botswana, Eritrea, Ethiopia, Ghana, Kenya, Lesotho, Mozambique, Namibia, Niger, Senegal, Somalia, South Africa, Sudan, Swaziland, Tanzania, Uganda, Zimbabwe (Orwa *et al.,* 2009). but it is widely distributed through the summer rainfall areas of Sub-Saharan Africa, Yemen, and Arabian Peninsula (Adebayo & Mosoko, 2019; Maier *et al.,* 2006; Mongalo *et al.*, 2020). It grows in all types of soil and standing intense heat and cold equally well (Mongalo *et al.*, 2020; Orwa *et al.*, 2009).

The distribution of *Z. mucronata* across landscapes is influenced by a range of factors, including climate, soil properties, topography, and land-use practices. Precipitation is a primary determinant of *Z. mucronata* distribution, as it thrives in both temperate and tropical climates in semi-arid to sub-humid regions. It typically occurs in areas receiving Mean Annual Rainfall between 250 mm and 1200 mm (Orwa *et al.*2009). This species can tolerate drought (Maier *et al.,* 2006). Temperature also plays a role, with the species adapted to warm climates, often with Mean Annual Temperatures of between 8 $^{o}$C and 36 $^{o}$C (Orwa *et al.*2009), but it can tolerate high seasonal variations, heat, and cold frost (Maier *et al.*, 2006).

*Ziziphus mucronata* grows in altitude up to 2000 m a.s.l. (Orwa *et al.*2009), and show a preference for well drained soils, including loamy sands, sandy clay loams, and alluvial soils, but it can survive in a wide variety of soil types, often Fluvisols and a variety of soil conditions such as fine texture soils (Adebayo & Mosoko, 2019; Maier *et al.*, 2006; Orwa *et al.*2009), but it can tolerate shallow soils, seasonal waterlogging, salt spray, moderate soil salinity, on soils deposited by rivers, and rocky soils, but grows frequently on termite mounds (Adebayo & Mosoko, 2019; Maier *et al.*, 2006; Orwa *et al.*2009).

The species often occupies lower slopes, Brackish flats, valleys, along laggas, streams, and riparian zones where moisture retention is higher (Beentje, 1994; Orwa *et al.*, 2009; Schemid *et al.*, 1998). However, it can also colonize open woodlands, bushlands, wooded grassland, and savanna plains, particularly where disturbances reduce competition (Orwa *et al.,* 2009). They are also associated with areas dominated by thorny vegetation (Maier *et al.,* 2006; Orwa *et al.,* 2009).

**Figure 5: Growth habit *Z. mucronata* Willd. Source: Wikipedia (en.wikipedia.org)**

### 2.8.5 *Acacia brevispica* Harms (syn. *S. brevispica* Harms) – Honeybee / Honey Locust

*Senegalia brevispica,* formerly *Acacia brevispica* (Figure 6) and commonly known as honey bee or honey locust, is native to Eastern Africa, occurring across Sudan, Ethiopia, Somalia, Kenya, Zaire, Angola, Natal, Cape Province, and South Africa (Royal Botanic Gardens, Kew, n.d.). It thrives in both dry and semi-humid areas (Azene Bekele-Tesemma & World Agroforestry Centre, 2007). In Ethiopia, it grows between 400–2000 m a.s.l. in the Borana Plateau rangelands (Coppock, 1994). In Kenya, it occurs in Acacia woodland, wooded grassland, and forest edges (Beentje, 1994), often forming dense thickets on well-drained slopes at 1600–2000 m a.s.l. in deep, fertile red soils (Skerman, 1982).

**Figure 6: Growth habit *A. brevispica* Harms (syn. *S. brevispica* Harms). Source: Center for International Forestry Research (CIFOR)-International Centre for Research in Agroforestry (ICRAF)** (https://www.cifor-icraf.org)

### 2.9 Scientific Studies in Nasalot-South Turkana-Kerio Valley Ecosystem

The Nasalot-South Turkana-Kerio Valley ecosystem has increasingly attracted scientific attention due to its ecological diversity, vulnerability to climate change, and the socio-economic importance of its natural resources. Several studies have been conducted across this landscape, addressing themes such as forage preference for African elephants (Koskey (2013, 2016), vegetation ecology (Kuria, 2001), LULC change (Togoch, 2018), indigenous knowledge systems (Kipkorir & Kareithi, 2013), soil erosion (Boitt *et al*., 2020) climate variability, and climate change (Boitt *et al*., 2020; Huho *et al.*, 2023); Imana, 2023; Muragijimana *et al.*, 2024; Oluoch *et al.*, 2024.

Kuria (2001) conducted a comprehensive study on various vegetation parameters in the region, including vegetation composition and structure, distribution of plant associations, and their relationship with selected soil factors, namely calcium, sodium, phosphorus, and potassium. This study provided valuable insights into how soil chemistry influences plant community distribution and ecosystem structure in semi-arid environments.

Focusing on wildlife-vegetation interactions, Koskey (2013, 2016) investigated important forage resources utilized by African elephants in Rimoi National Reserve. The study identified *V. tortilis* (22.5%), *B. aegyptiaca* (14.8%), *A. mellifera* (9.6%), *Z. mucronata* (7.5%), and *A. brevispica* (7.1%) as the dominant forage species, highlighting the ecological significance of these woody plants in elephant dietary preferences.

Kipkorir & Kareithi (2013) investigated indigenous irrigation systems, and their role in enhancing food security in Tot Division, Kerio Valley. Their study highlighted the value of traditional ecological knowledge in sustaining agricultural production under semi-arid conditions. In a related environmental context, Boitt *et al.* (2020) assessed the effects of soil erosion and climate variability within the Kerio Valley Basin, revealing significant challenges for sustainable land management due to accelerated degradation processes.

Changes in land use and cover have also been a focal point of research. Togoch (2018) analyzed LULC change in and around Rimoi National Reserve, evaluating how human-induced transformations affect wildlife habitats and protected areas.

In Turkana County, numerous studies have examined the intersection of climate change, livelihoods, and development. Huho *et al.* (2023) explored how local communities are adapting to climate change, documenting various coping mechanisms and resilience strategies in semi-arid regions. Muragijimana *et al.* (2024) investigated the cultural and health dimensions of climate change, with a focus on indigenous resilience practices while Imana & Zenda (2023) analyzed the impacts of climate change on pastoral livelihoods in Loima Sub-County, Turkana County, revealing the vulnerability and fragility of pastoral systems amid growing climatic uncertainty. Complementing this, Akall (2021) evaluated the effects of development interventions on pastoral communities, highlighting both the opportunities and disruptions brought about by externally driven projects.

In terms of ecological impacts, Oluoch *et al.* (2024) assessed the current and future distribution of 23 WEPs species in Turkana County. The study found that, on average, 64.5% of the county, approximately 44,100 km$^2$ is currently suitable for WEPs growth. However, projections under future climate scenarios SSP126, SSP370, and SSP585 across time horizons (2041–2070 and 2071–2100) indicate that about half of these species are likely to experience significant declines in habitat suitability. Of particular concern is *B. aegyptiaca*, a key WEPs and an important forage plant for elephants in the region (Koskey, 2013, 2016), which is projected to lose all of its suitable habitat under these future climate scenarios.

Collectively, these studies underscore the dynamic nature of socio-ecological interactions in the Nasalot-South Turkana-Kerio Valley ecosystem. They also point to the need for integrated approaches to research and management that consider ecological, cultural, and institutional dimensions of sustainability.

## 2.10 The MaxEnt Algorithm

The MaxEnt model is a widely used machine learning algorithm for species distribution modeling with presence-only data (Phillips *et al.,* 2006). Based on the principle of maximum entropy, it estimates the most uniform species distribution constrained by environmental conditions at occurrence points (Elith *et al.*, 2011). MaxEnt often outperforms other presence-only and presence–absence methods, such as Bioclim, Genetic Algorithm for Rule-set Production (GARP), and Generalized Linear Models (GLMs), particularly with limited data (Elith *et al.*, 2006; Phillips & Dudík, 2008).

Due to its accuracy, flexibility, and ease of use, MaxEnt is widely adopted in ecological and conservation modeling. It has been used to model potential distributions of diverse species, including threatened and elusive taxa like the African elephant, aiding habitat suitability assessments for conservation planning under current and future conditions (Dejene *et al.*, 2021; Mpakairi *et al.,* 2019).

MaxEnt assumes that presence records reflect the species' true distribution and that the species is in equilibrium with its environment (Yackulic *et al.,* 2013). It requires ecologically relevant, non-collinear predictors, representative background points, and minimal or corrected spatial/sampling bias through methods like spatial filtering or bias files (Merow *et al.*, 2013; Phillips *et al.*, 2009).

MaxEnt performs well with small sample sizes, accommodates complex predictor interactions, produces continuous habitat suitability maps, estimates variable contributions, and provides interpretable response curves, making it valuable for conservation in data-poor regions (Elith *et al.,* 2006; Phillips & Dudík, 2008). However, it is sensitive to sampling bias and spatial autocorrelation, lacks explicit consideration of biotic interactions, dispersal barriers, and temporal dynamics, and its predictions depend heavily on the quality of environmental layers, background extent, and careful parameter calibration (Fourcade *et al*., 2014; Merow *et al.,* 2013; Yackulic *et al.,* 2013).

Many studies have used the default settings of the MaxEnt software (Merow *et al.*, 2013; Phillips and Dudík, 2008; Phillips *et al.*, 2018). The initial default settings in MaxEnt were based on the experimental work of Phillips and Dudík (2008), who used presence-only data to determine appropriate feature types and regularization parameters for modeling 225 species across six regions worldwide.

The MaxEnt model, however, has undergone subsequent improvements to its default setting with an objective of improving its performance (Bald *et al.,* 2023; Phillip *et al.,* 2018). Philip *et al.,* (2018) improved the MaxEnt software by introducing a future combination of Linear, Quadratic, Hinge and Product (LQPHT) and Regularization Multiplier (RM) of 1 as default setting of MaxEnt.

Despite, recent studies have optimized settings for the MaxEnt model through selection of Feature Combination (FC) and Regularization Multiplier (RM) (β values), which is considered important for accurate modeling of geographical distribution of species because it reduces model overfitting (Philip and Dudík, 2008). Consequently, the MaxEnt model in this study was optimized through selection of feature combination and regularization multiplier using the R software.

## 2.11 Knowledge Gap

A substantial body of literature provides evidence that various environmental factors significantly influence the current and future spatial distribution and habitat suitability of African elephants and their preferred forage plant species (Abir *et al*., 2025; Akala *et al*., 2023; Ashiagbor & Danquah, 2017; Bio *et al*., 2024; Bravo-García *et al*., 2024; Budhathoki *et al*., 2023; Chen *et al*., 2023; Chérif *et al*., 2022; Chibaye *et al*., 2021; de Silva *et al*., 2023; Dejene *et al*., 2021; Gufi *et al*., 2023; Habou *et al*., 2021; He *et al*., 2023; Jeza & Bekele, 2023; Kanagaraj *et al*., 2019; Kuswanda *et al*., 2023; Mpakairi *et al*., 2019; Muposhi *et al*., 2016; Oluoch *et al*., 2024; Palei *et al*., 2024; Seid *et al*., 2024; Williams *et al.*, 2018; Yang *et al*., 2022).

However, such studies remain relatively scarce within the African context, particularly in Kenya (Akala *et al*., 2023; Ashagbor *et al*., 2017; Bio *et al*., 2024; Bravo-García *et al*., 2024; Chérif *et al*., 2022; Chibaye *et al*., 2021; Dejene *et al*., 2021; Gufi *et al*., 2023; Habou *et al*., 2021; Jeza & Bekele, 2023; Mpakairi *et al*., 2019; Muposhi *et al*., 2016; Oluoch *et al*., 2024; Seid *et al*., 2024; Williams *et al*., 201).

To date, no study has comprehensively predicted the current and future spatial distribution and habitat suitability of African elephants and their preferred forage plants under the influence of environmental variables, including climate change within the Nasalot-South Turkana-Kerio Valley ecosystem. In particular, there is a lack of studies that have modeled and mapped the existing suitable habitats, identified and analyzed key environmental drivers, and projected future habitat shifts under climate change scenarios. This study, therefore, aimed at addressing existing critical knowledge gap by providing a spatially explicit assessment of habitat suitability for African elephants and their forage species in this understudied landscape.

## 2.12 Theoretical Framework of the Study

The theoretical framework of the study draws upon ecological niche theory (Grinnell, 1917) to guide a comprehensive study of the habitat suitability of African elephants and their preferred forage plants. This theory was originally defined as the suite of ecological conditions within which a species is capable of surviving and reproducing without immigration subsidy (Grinnell, 1917).

The term species niche was later used to refer to the functional role that a species plays in a community (Elton, 1927). Hutchinson, (1957) further defined ecological niche theory as an n-dimensional hypervolume of environmental conditions under which a species can survive and reproduce, and further subdivided the species niche into fundamental niche and realized niche. Fundamental niche is the set of abiotic environmental conditions under which a species can persist indefinitely, and realized niche is the part of the fundamental niche that is constrained by interactions with other species (Hutchinson, 1957).

The theory supports predictive modeling that integrates current environmental variables with feature scenarios, aiming to inform biodiversity conservation, land use planning, and climate adaptation strategies in landscapes. Therefore, the framework provided the basis for understanding the habitat suitability of the African elephant and their preferred forage plants.

## 2.13 Conceptual Framework of the Study

The conceptual framework of species habitat suitability is shown in Figure 7. The flow diagram illustrates a conceptual framework grounded in ecological niche theory (Grinnell, 1917), emphasizing the complex interplay of factors that determine species habitat suitability. At the top of this framework is the outcome variable: species habitat suitability, which emerges from the interaction between either the African elephant or their preferred forage plants and the various abiotic factors of the environment.

Abiotic factors in the study included climatic factors such as precipitation, temperatures, and climate change, the physical factors such as topography, soil, vegetation productivity, and proximity to waterbodies, anthropogenic factors such as land use/land cover, and proximity to roads and human settlements. Ultimately, the diagram emphasizes that species habitat suitability is a dynamic outcome shaped by multi-scalar interactions between environmental gradients, and anthropogenic influences. This integrated perspective is essential for modeling habitat suitability of the African elephants and their preferred forage plants in the study.

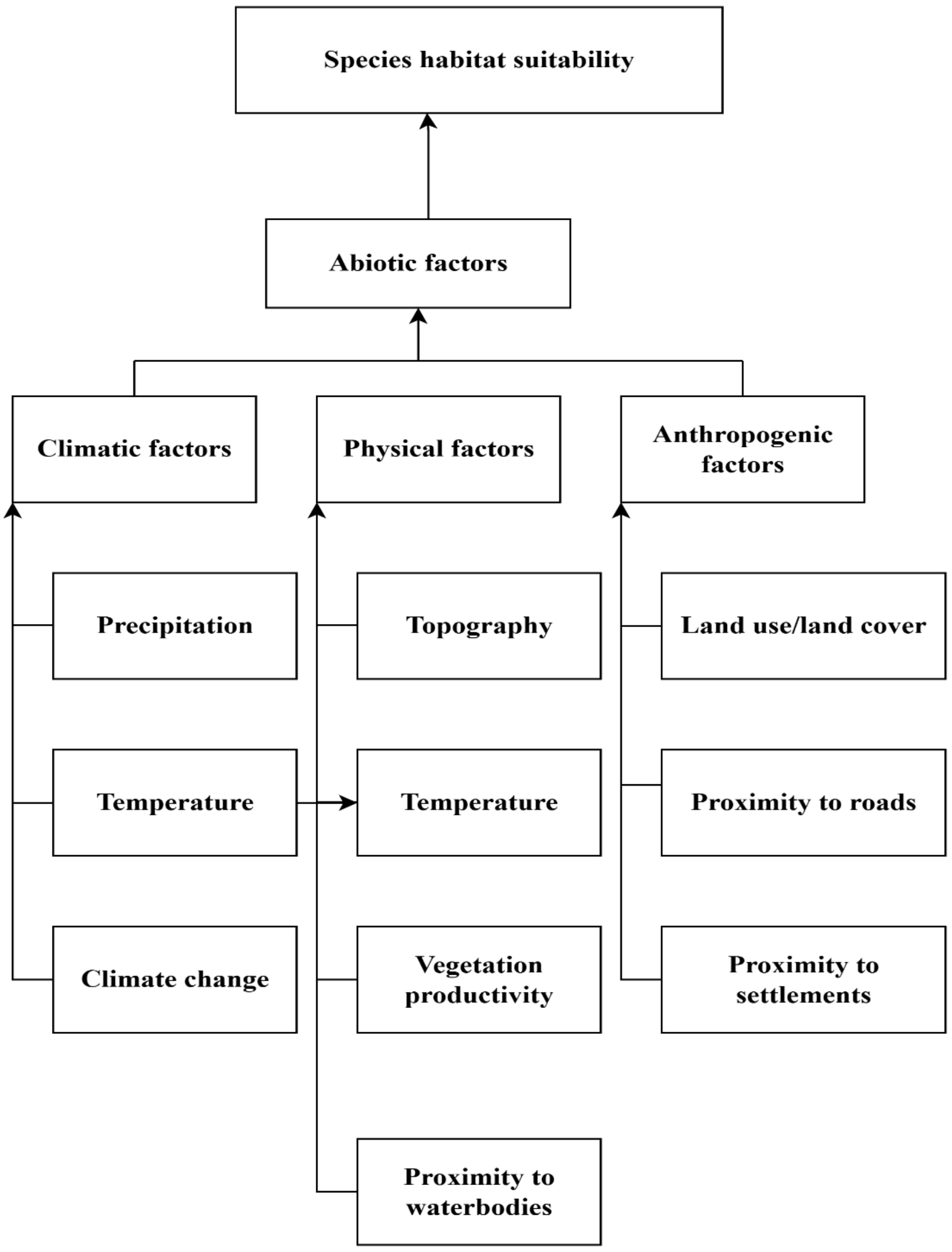


**Figure 7: A conceptual model explaining mechanisms prompting species habitat suitability in the study**

# CHAPTER THREE

# METHODOLOGY

## 3.1 The Study Area

### 3.1.1 Location and Size

The study area is located in the northwestern part of Kenya, within the counties of Elgeyo Marakwet, Baringo, West Pokot, and Turkana, between latitude 0º 61′ 18″ N and 2º 17′ 59″ N and Longitude 35º 33′ 16″ E and 35º 79′ 11″ E as shown in Figure 8. The total land area of the study area is 4700.37km$^2$.

### 3.1.2 Climatic Conditions

Based on the amount and reliability of rainfall and ecological potential, Kenya has been divided into seven (7) eco-climatic zones (Pratt & Gwynne, 1977). This ecosystem is found within the region categorized as eco-climatic zone IV (Pratt & Gwynne, 1977). The climatic condition of the region is typical of semi-arid regions of Kenya, characterized by high mean annual temperatures (33 ºC), low mean annual rainfall (≤ 508 mm), erratic rainfall patterns, and frequent droughts (Kuria, 2001).

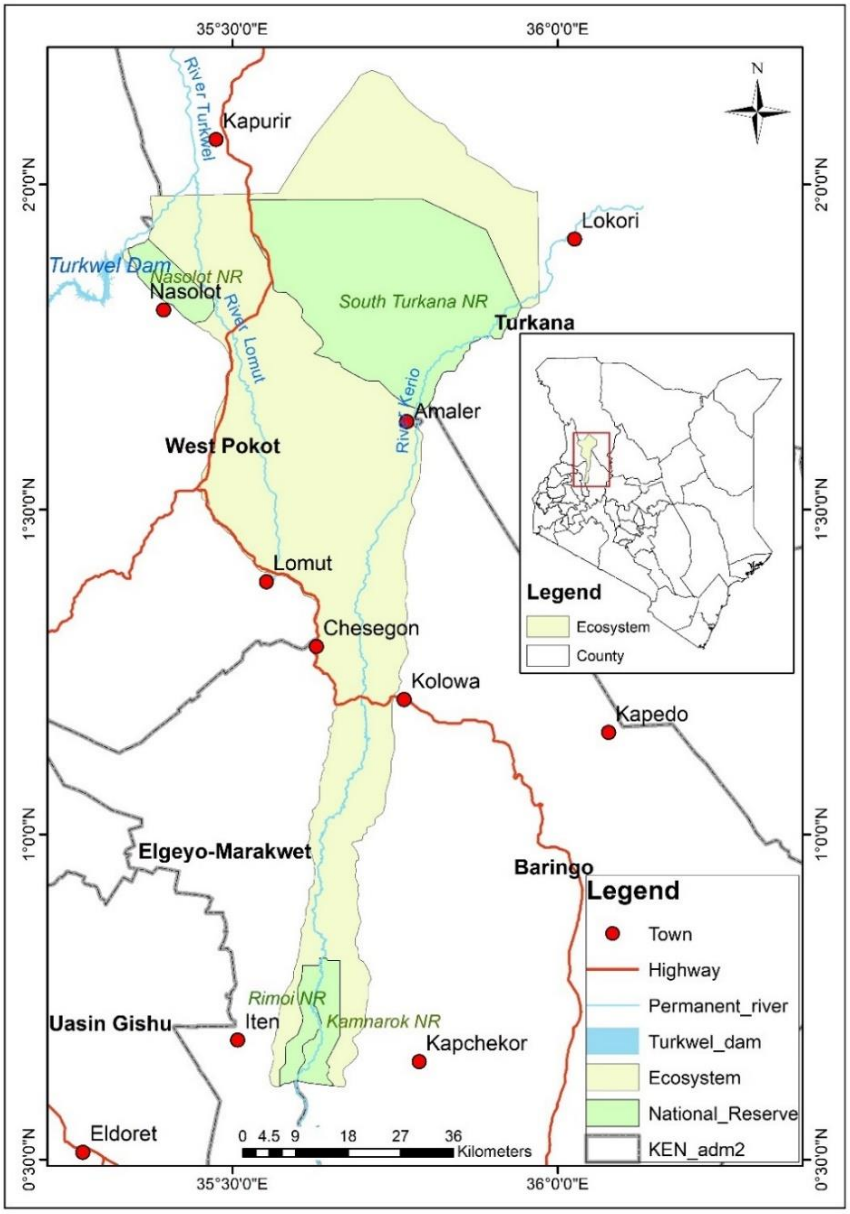


**Figure 8: Map of the Nasalot–South Turkana–Kerio Valley ecosystem. Source: Prepared by the researcher (2024)**

### 3.1.3 Topographic Features

Elevation, slope, aspect, and soil map of the study area are shown in Figure 9. These maps were created from the Digital Elevation Model (DEM) of the study area downloaded from the United States Geological Survey (USGS) website (http://ned.usgs.gov). According to the map, the elevation values of the study area range from 644 m to 1,916 m above sea level (a.s.l.); the slope values range from 0° to 48°, and the aspect values range from 0° to 359°.

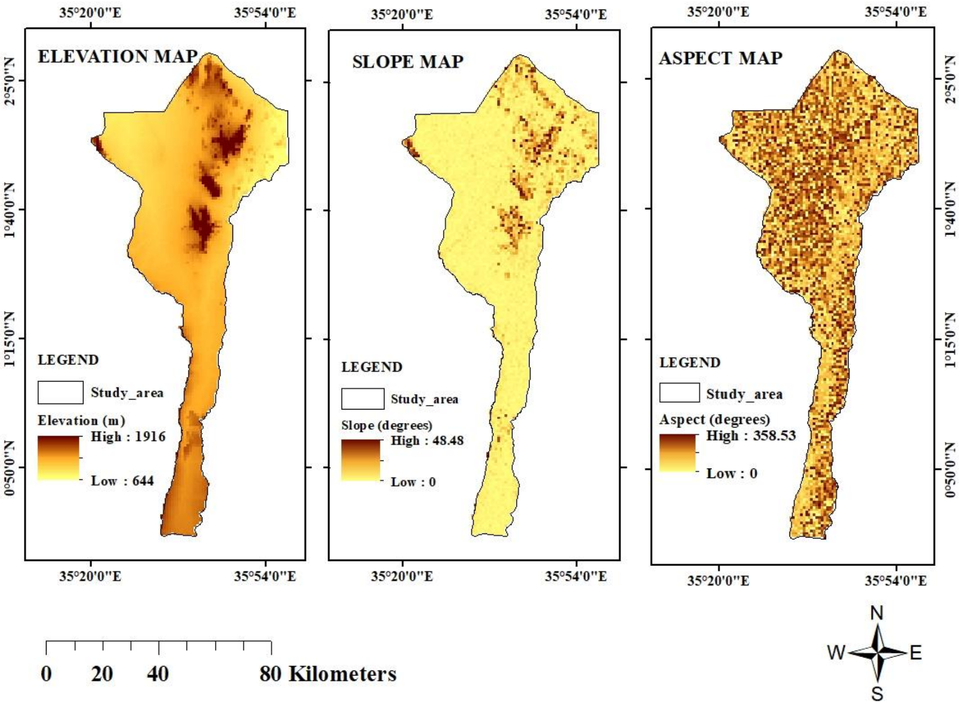


**Figure 9: Map showing elevation, slope, and aspect (Source: USGS, http://ned.usgs.gov: Year of access: 2024).**

### 3.1.4 Soil Types

The soil map of the study area is shown in Figure 10. The soil map created from the Food and Agriculture Organization (FAO) Digital Soil Map of the World (DSMW) (https://www.fao.org/) shows that the study area is characterized by loam and clay-loam soils. Most parts of the study area were dominated by loam soils, but a small area of clay-loam soils was found in the north-eastern part of the study area. However, a previous study shows that soils in Rimoi National Reserve range from sandy to clay (Kuria, 2001).

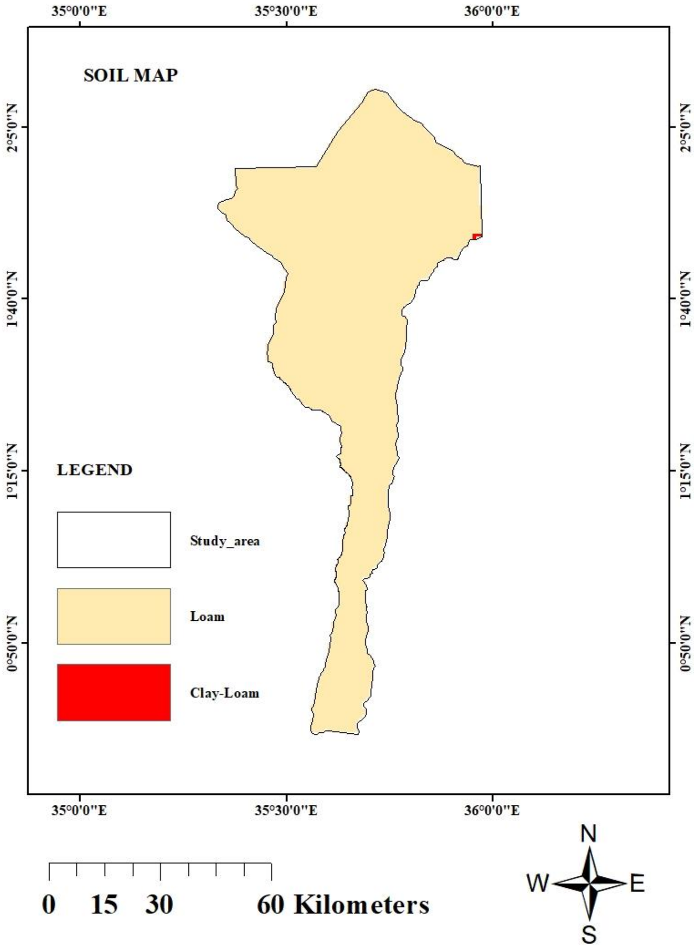


**Figure 10: Map showing soil types in the study area (Source: FAO Soils Portal, http://www.fao.org)**

### 3.1.5 Protected Areas

To achieve in-situ protection of its fauna and flora, the ecosystem hosts four National Reserves: Rimoi, Kamnarok, Nasalot, and South Turkana, as shown in Figure 8. Rimoi and

Kamnarok National Reserves lie adjacent to each other in the Kerio Valley region between Tugen hills in the east and Elgeyo escarpment in the west, but separated by the Kerio River (Kuria, 2001). Rimoi National Reserve lies between longitudes 35º 51' and 35º 38' East, latitudes 0° 36' and 0° 42' North, and an altitude of 1060 meters above sea level (Kuria, 2001) (Figure 8). The reserve was gazetted as a trust land in January 1985 and covers an area of 66km$^2$ (Kuria, 2001). Rimoi National Reserve is currently managed by the County Government of Elgeyo Marakwet, while Kamnarok National Reserve is managed by the County Government of Baringo.

South Turkana National Reserve is found in the southern part of Turkana County, while Nasalot National Reserve is located in West Pokot County, and lies in the western part of South Turkana National Reserve. South Turkana National Reserve and Nasalot National Reserve are currently managed by the County Governments of Turkana and West Pokot respectively.

### 3.1.6 Flora and Fauna

A previous study in Rimoi National Reserve has shown vegetation to be composed of riverine forest, bushed woodland, wooded bushland, bushed thicket, and grassland, which serve as important wildlife habitats (Kuria, 2001; Togoch, 2018). Plant species in the reserve belong to various life-forms; trees, shrubs, herbs, forbs, graminoids, but trees and lianas are the most dominant plant life-forms. Most of the plant species belong to Poaceae, Mimosaceae, Acanthaceae, Capparaceae, Labiatae, and Euphorbiaceae families (Kuria, 2001).

Based on the Importance Value Index, important plant species in Rimoi National Reserve include *A. tortilis* (IVI=104.0), *A. melifera* (IVI=118.9), *Cynodon nlemfluencis* (IVI=188.1), *Acacia Sayel* (IVI=162), *Ficus sycomorus* (IVI=141), and *Acacia fruticosa* (IVI=139.2) (Kuria, 2001).

The vegetation in Rimoi National Reserve is influenced by various factors, including rainfall seasonality and changes in land/use land cover (Togoch, 2018). Togoch (2018) reported drastic changes in vegetation cover in various habitat types over a period of 20 years (1986-2006) due to increased agricultural activities and increasing human population growth.

Historically, the ecosystem has been a home to several mammals, including African elephants, buffaloes (*Syncerus caffer* Sparman), leopards (*Panthera pardus* L.) waterbucks (*Kobus defassa* Rüppell), bushbucks (*Tragelaphus scriptus* Pallas), dikdik (*Modoqua kirkii* Günther), bushpigs (*Potamochoerus porcus* L.), African warthogs (*Potamochoerus aethiopicus* Pallas), cavet cats (*Viverra civetta* Schreber), impalas (*Aepyceros melampus* Lichtenstein), giraffes, baboons (*Papio anubis* J.P. Fisher) and various species of monkeys (Kuria, 2001). The population of African elephants in the ecosystem is the largest in northwestern Kenya (Chase *et al.,* 2015), having remained relatively stable from 1999 to 2021 (KWS, 2021). The current population is estimated at 493 individuals (Kenya Wildlife Services (KWS), 2021).

Nonetheless, most of the mammals have become extirpated from the reserve due to unknown causes, and today, a few species, including African elephants, African warthogs, dikdiks, duikers, impalas, and baboons are found in this ecosystem. In addition, the ecosystem is known for the conservation of various species of reptiles, birds, and insects (Kuria, 2001).

Restoration of Rimoi National Reserve through restocking and reintroduction of some extirpated species began two decades ago and is still ongoing. The first restocking involved Rothschild's giraffes, which were relocated from Soy in Uasin Gishu. To date, only a few species have been restocked. Additionally, due to changes in LULC in parts of the ecosystem, biodiversity has continued to decline, and the frequency of human–wildlife conflicts has increased over time (Togoch, 2018).

### 3.1.7 Land Use/Land Cover

The study area is heterogeneous, comprising five LULC classes, which include: built-up areas, waterbodies, agriculture, woodland, shrubland, and bareland.

### 3.1.8 Socio-Economic Activities

Historically, communities living in the ecosystem, including Keiyos, Marakwets, Tagens, Pokots, and Turkanas, have been practicing pastoralism. However, their socio-economic activities are changing into sedentary farming and livestock keeping. The ecosystem has been classified in terms of security as a disturbed region in the northern part of Kenya (Ernest *et al.*, 2024).

## 3.2 Research Design

This study adopted an exploratory research design to identify and evaluate the key environmental factors influencing the potential habitat suitability of African elephants and their preferred forage plant species. Exploratory designs are particularly suitable for studies involving complex ecological systems where prior hypotheses may be limited or absent (Creswell, 2014). Such a design allows for the flexible assessment of spatial patterns, variable interactions, and species–environment relationships, making it ideal for species distribution modeling using presence-only data (Clark *et al.*, 2017; Guisan & Zimmermann, 2000). The approach facilitated the use of MaxEnt modeling to explore the contribution and influence of multiple biophysical and climatic variables without presupposing specific outcomes.

## 3.3 Data Types, Sources, and Descriptions

In the MaxEnt model, species occurrence data are combined with predictor environmental variables to model potential distribution and suitable habitats of targeted species (Philips *et al.*, 2006). Therefore, in this study, three types of datasets were used: occurrence points of African elephants and their preferred forage plants, and datasets of various predictor environmental variables.

### 3.3.1 Data for African Elephants

In Kenya, secondary data on the population and distribution of various large herbivore species, including African elephants, are typically available through several key sources. These include the Global Biodiversity Information Facility (GBIF) (http://www.gbif.org) (Jenkins, 2010), GoK annual reports, especially those from the WRTI and the KWS (WRTI & KWS, 2021), as well as KWS technical reports (Chase *et al*., 2015; Litoroh *et al*., 2010; Mwangi *et al*., 2007; Ngene *et al*., 2013), and reports from the Department of Resource Surveys and Remote Sensing (DRSRS). The secondary data have been collected annually since 1977, primarily through large-scale aerial census techniques, as described in detail by Northon-Griffiths (1978).

However, aerial census surveys do not cover all conservation areas or all wildlife species in the country. As a result, surveys of some large herbivores in smaller conservation areas and dispersal zones are often conducted through foot and vehicle patrols (WRTI & KWS, 2021). Therefore, species occurrence data for African elephants were obtained secondarily from previously conducted field surveys. These surveys, conducted between 2011 and 2022, included both foot and vehicle patrols and were based on direct sightings and indirect evidence of elephant presence, such as footprints (tracks), dung, feeding marks, and other signs of herbivory. Such surveys are often designed to detect presence-only data, not absence. Therefore, the dataset comprises presence-only records, suitable for MaxEnt modeling approach, which is designed to handle such data limitations.

To enhance spatial and temporal coverage in the current research, data from the 11 years were pooled and compiled into a single dataset for use in species habitat suitability modeling. Over 200 occurrence points were targeted during sampling to ensure sufficient data for reliable habitat suitability modeling using MaxEnt. This sample size falls within the range recommended by Pearson *et al.* (2007) and Wisz *et al.* (2008), who demonstrated that models based on larger numbers of presence records, typically over 100, produce more robust and reliable outputs. Such a sample size is considered ideal for enhancing model performance, evaluating the contribution of environmental predictors, and supporting accurate spatial and temporal projections (Wisz *et al.*, 2008).

### 3.3.2 Data for African Elephants' Preferred Forage Plants

Systematic sampling was employed to collect occurrence data for modeling plant species distribution and habitat suitability using the MaxEnt algorithm. Sampling was conducted along predefined road transects, with data points targeted at 1 km intervals to ensure even spatial coverage and reduce spatial autocorrelation. At each 1 km interval, a quadrat measuring 20 m × 20 m was laid alternately on either side of the road. Within each quadrat, the targeted plant species for the study were identified and classified in the field according to Agnew and Agnew (1994), Beentje (1994), Schmid *et al.* (1998), and Noad and Birnie (1994). In addition, important information, including species identification codes, taxonomic names of individual plants, and the latitude and longitude coordinates of each species' exact location, was recorded in the field (Scheldeman *et al.*, 2010). The geographical coordinates of all occurrence points were geo-referenced using a handheld GPS device (Phillips *et al.*, 2006). More than 200 occurrence points were targeted during sampling to meet the minimum threshold recommended for robust species distribution modeling using MaxEnt (Pearson *et al.*, 2007; Wisz *et al.*, 2008). Systematic sampling along road transects has been effectively applied in previous studies modeling plant species distribution and habitat suitability, particularly in areas with limited off-road accessibility (Elith *et al.*, 2011; Shrestha & Bawa, 2014).

### 3.3.3 Predictor Environmental Variable Datasets

Twenty-eight (28) environmental predictor variables were preliminarily identified and selected for use in the study. These consisted of 19 bioclimatic variables, three topographic variables (elevation, slope, and aspect), three distance variables (Euclidean distance to roads, Euclidean distance to waterbodies, and Euclidean distance to human settlements), one vegetation variable (NDVI), one edaphic variable (soil type), and one LULC variable.

The selection of these variables was based on their previous use and relevance in modeling the spatial distribution and habitat suitability of African elephants (Akala *et al.,* 2023; Jeza & Bekele, 2023; Williams *et al.,* 2018), as well as of plant species documented as their preferred forage in the study area (Koskey, 2013, 2016). Selection was also informed by the availability of data from various sources, including the WorldClim version 2 global climate database (http://www.worldclim.org/), United States Geological Survey (USGS) (http://earthexplorer.usgs.gov), ASTER Global DEM (http://gdem.ersdac.jspacesystems.or.jp/), Digital Soil Map of the World (DSMW) (https://www.fao.org/) HydroSHEDS (https://www.hydrosheds.org/), and OpenStreetMap (https://www.openstreetmap.org/).

### 3.3.3.1 Bioclimatic Variables

In this study, 19 bioclimatic variables from WorldClim version 2, covering the period from 1970 to 2000 (Table 1) (Fick & Hijmans, 2017; http://www.worldclim.org), were used as the basis for predicting potential current and future suitable habitats for African elephants and their preferred forage plants. For future projections, the study used downscaled and calibrated bioclimatic data from the CMIP6 General Circulation Models (GCMs), specifically from the Canadian Earth System Model version 5 (CanESM5). This model is a coupled Earth system climate model developed by the Canadian Centre for Climate Modelling and Analysis (CCCma), part of Environment and Climate Change Canada (Fick & Hijmans, 2017; https://www.worldclim.org/).

Two Shared Socioeconomic Pathways (SSPs), SSP245, representing a "middle of the road" scenario, and SSP585, representing a fossil fuel–driven development scenario, along with averages of monthly data values for the periods 2041–2060 and 2081–2100 (Fick & Hijmans, 2017; http://www.worldclim.org), were used to project the potential future distribution and suitable habitats of African elephants and their preferred forage plants. The selection of bioclimatic variables for future projections was based on their demonstrated importance in modeling the current habitat suitability for African elephants and their preferred forage plants. Present and future bioclimatic variables with a 30 arc-second (~1 km) spatial resolution were downloaded as GeoTIFF files from the WorldClim version 2 global climate database (http://www.worldclim.org/) (Fick & Hijmans, 2017). This resolution was preferred because it allowed for the integration of other datasets with similar or lower spatial resolution available for use in the study.

The 19 bioclimatic variables have been used in previous studies to predict potential current and future distributions and suitable habitats of African elephants in various landscapes (Akala *et al.*, 2023; Dejene *et al.*, 2021; Jeza & Bekele, 2023; Williams *et al.*, 2018). Similarly, these variables have been used to model potential current and future suitable habitats of various plant species, including the preferred forage plants of elephants in South Africa (Bio *et al.*, 2024; Bravo-García *et al.*, 2024; Chérif *et al.*, 2022; Gufi *et al.*, 2023; Habou *et al.*, 2021; Kuswanda *et al.*, 2023; Mechergui *et al.*, 2021; Nkosi, 2024; Oluoch *et al.*, 2024; Seid *et al.*, 2024).

**Table 1: Bioclimatic variables and their specifications**

| Code | Bioclimatic Variable and Description | Unit |
|---|---|---|
| bio_1 | Annual Mean Temperature | °C |
| bio_2 | Mean Diurnal Range (Mean of monthly (max temp – min temp)) | °C |
| bio_3 | Isothermality (bio_2/bio_7) (100) | % |
| bio_4 | Temperature Seasonality (standard deviationx100) | °C |
| bio_5 | Max Temperature of Warmest Month | °C |
| bio_6 | Min Temperature of Coldest Month | °C |
| bio_7 | Temperature Annual Range (P5-P6) | °C |
| bio_8 | Mean Temperature of Wettest Quarter | °C |
| bio_9 | Mean Temperature of Driest Quarter | °C |
| bio_10 | Mean Temperature of Warmest Quarter | °C |
| bio_11 | Mean Temperature of Coldest Quarter | °C |
| bio_12 | Annual Precipitation | mm |
| bio_13 | Precipitation of Wettest Month | mm |
| bio_14 | Precipitation of Driest Month | mm |
| bio_15 | Precipitation of Seasonality (Coefficient of Variation) | % |
| bio_16 | Precipitation of Wettest Quarter | mm |
| bio_17 | Precipitation of Driest Quarter | mm |
| bio_18 | Precipitation of Warmest Quarter | mm |
| bio_19 | Precipitation of Coldest Quarter | mm |

#### 3.3.2.2 Remote Sensing Imagery Datasets

Multispectral remote sensing images, USGS Landsat-8 Operation Land Imager (OLI) Collection 2, level 1 for the year 2024, were used to generate current LULC categories and to calculate current spectral indices for NDVI. Bands 1–11 of the Landsat 8 Operational Land Imager (OLI), with spatial resolutions ranging from 15 m to 100 m, were acquired from the USGS Earth Explorer website (https://earthexplorer.usgs.gov) (Table 2; Table 3). Landsat-8 OLI imagery has high spectral resolution and temporal resolution, but moderate spatial resolution (Lillesand *et al.*, 2004) and a revisit period of 16 days (Schowengerdt, 2007).

In-scene components such as clouds, smoke, and haze are contaminants that can degrade or mask the true ground brightness value of each pixel and manifest during data collection and transmission as line dropouts, striping, and banding (Bruce & Hibert, 2006). To minimize the presence of such contaminants as well as errors in the data retrieval and transmission process, Landsat datasets sensed during the dry season, in January through March 2024, were thoroughly examined, and available images displaying a high-quality index of 9 and less than 10% cloud cover were acquired for use. In addition, datasets acquired at the same time of the year can help minimize radiometric differences between dates due to differences in Earth-sun distance and solar illumination angles (Bruce & Hibert, 2006).

**Table 2: Details of the acquired Landsat 8 OLI-TIRS Imagery**

| Landsat ID | Date of acquisition | Row/ Path | UTM Zone | Cloud cover | Spatial Resolution |
|---|---|---|---|---|---|
| LC09_L1TP_169059_20240317_02_T1 | 17/03/2024 | 169/059 | 37 | 0.10% | 30m |
| LC09_L1TP_169060_20240317_02_T1 | 17/03/2024 | 169/060 | 36 | 0.01% | 30m |
| LC08_L1TP_170059_20240316_02_T1 | 16/03/2024 | 170/059 | 36 | 0.05% | 30m |

**Table 3: Specifications of bands 1-11 of the acquired Landsat 8 OLI_TIRS Imagery**

| Spectral Bands | Description | Wavelength | Spatial Resolution |
|---|---|---|---|
| Band 1 | Costal | 0.433-0. 453µm | 30m |
| Band 2 | Blue | 0. 450-0. 515µm | 30m |
| Band 3 | Green | 0. 525-0. 600µm | 30m |
| Band 4 | Red | 0. 630-0. 680µm | 30m |
| Band 5 | NIR | 0. 845-0. 885µm | 30m |
| Band 6 | SWIR-1 | 1. 560-1. 660µm | 30m |
| Band 7 | SWIR-2 | 2. 100-2. 300µm | 30m |
| Band 8 | Pan | 0. 500-0. 680µm | 15m |
| Band 9 | Cirrus | 1. 360-1. 390µm | 30m |
| Band 10 | TIR-1 | 10. 6-11. 2µm | 100m |
| Band 11 | TIR-2 | 11. 5-12. 5µm | 100m |

Nonetheless, further examination and rectification of datasets were achieved during pre-processing stages.

### 3.3.2.4 Sources and Descriptions of Other Geospatial Datasets

In addition to bioclimatic data and remote sensing data, other geospatial data essential for the study included the following: topographic data (elevation, slope, and aspect), distance layers (Waterbodies data, road network data, human settlement data), and ground truthing data. The datasets were obtained from various sources as shown in Table 4.

**Table 4: Data type, source, and description**

| Data type | Source | Description |
|---|---|---|
| **Topographic data** | ASTER Global DEM website (http://gdem.ersdac.jspacesystems.or.jp/) | –Shapefile<br>–Elevation measured in meters; slope in degrees; aspect in degrees clockwise from north, 0 to 360<br>–Spatial resolution of 30m |
| **Waterbodies network data** | HydroSHEDS website (https://www.hydrosheds.org/) | –Shapefile<br>–Distance in meters to waterbodies |
| **Soil map** | FAO website (https://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026564/) | –SoilGrids |
| **Road network data** | OpenStreetMap website (https://www.openstreetmap.org/) | –Shapefile<br>–Distance in meters to road networks |
| **Human settlement data** | OpenStreetMap website (https://www.openstreetmap.org/ | –Shapefile<br>–Distance in meters to settlements |
| **Ground truthing data** | Field Surveys/Google Earth Pro | –Point locations (latitudes, longitudes) |

## 3.4 Pre-processing of Species Occurrence Datasets

### 3.4.1. A Preliminary Data Quality Analysis and Cleaning

To improve the accuracy of prediction, a preliminary data quality check was performed on the collected location data and duplicate points and redundant data with inaccurate geographic location information were eliminated.

### 3.4.2 Organization of Species Occurrence Data in Excel File

Species occurrence datasets of African elephants collected from both primary and secondary data sources were organized first in an Excel file. These occurrence data were reported using a latitude/longitude (lat/long) coordinate system and presented in Decimal Degrees (DD) format (DD. DDDD), with DD points having a precision of at least four decimals (Scheldeman *et al*., 2010). The latitude/longitude system (in DD formats) was preferred as it was more likely to be compatible with the other available thematic layers (administrative unit information, climate change data, and projected land use cover change data) (Scheldeman *et al*., 2010).

### 3.4.3 Analysis of Sampling Biases in Species Occurrence Datasets

The spatial autocorrelation, Global Moran's Index (Moran's I) (Moran 1950) in ArcGIS version 10.8 [Environmental Systems Research Institute (ESRI), 2020]. was performed on the collected species occurrence datasets before and after correcting for sampling biases using the spatial filtering method. Moran's I method is commonly used to measure spatial autocorrelation in species occurrence datasets, as it quantifies the overall clustering of datasets across a study area (Grase *et al.,* 2012; Mathur, 2015).

Moran's, I range between −1 and +1, with a score of 0 indicating the null hypothesis of no clustering, a positive score indicating clustering of species occurrence points, and a negative value showing that neighbouring areas are characterized by dissimilar points. Nonetheless, Moran's I value can be transformed to a z-score for statistical hypothesis testing, in which values greater than 1.96 or smaller than -1.96 indicate spatial autocorrelation that is significant at the 5% level.

However, before spatial autocorrelation analysis, species location datasets were aggregated and coincident points merged using the 'integrate' tool and 'collect event' tools, respectively, in ArcGIS version 10.8. The x, y tolerance values for aggregation of points were set at the default.

### 3.4.4 Correction of Sampling Biases in Species Occurrence Datasets

The MaxEnt model can correct for sampling biases by removing redundant records that occur within a single cell and by generating 'background'/'pseudo-absence' sample points. However, sampling biases in species occurrence datasets were corrected before the datasets were used in modeling species distribution using the MaxEnt model. Spatial filtration, selection of background points, and selection of suitable environmental variables for modeling using Pearson's Correlation Analysis (CA) and a preliminary MaxEnt model were used to correct for sampling biases in species occurrence datasets. The methods have been recommended for the correction of sampling biases of species occurrence datasets for MaxEnt models (Elith *et al.,* 2011; Phillips *et al.,* 2006).

### 3.4.5 Spatial Filtration of Species Occurrence Datasets

In this study, species occurrence datasets were spatially filtered using the ‘remove identical’ tool in ArcGIS version 10.8. The ‘remove identical’ tool helps to reduce spatial clustering of species occurrence datasets by removing duplicate records and by reducing records to a single point within a specified area. The x, y tolerance of the species occurrence datasets was set to start at a distance of 0.5 km, and was increased at intervals of 0.5 km until a non-clustered dataset was obtained based on Moran’s I results. Species occurrence datasets with a minimum distance from each other and showing no clustering were selected for further analyses.

### 3.4.6 Selection of Background Points

In the study, the datasets collected were species presence data, but not species absence data; hence, ten thousand (10,000) background points were generated randomly within the study area using the default settings in the MaxEnt software.

### 3.4.7 Partitioning of Species Occurrence Data

Species occurrence data were randomly divided into two sets: 70% as training data (for calibrating the species models) and 30% as testing data (for evaluating the models) (Budhathoki *et al.*, 2023; Jeza & Bekele, 2023; Phillips *et al.*, 2006). Accordingly, the random test percentage was set at 30% in the MaxEnt software.

### 3.4.8 Conversion of Species Occurrence Points from Excel into Comma Delimited (.csv) Format

The organized species occurrence data were converted into Excel comma-delimited (.csv) format, then into a raster layer in ArcGIS software, and finally into ASCII format for spatial analysis and modeling using the MaxEnt model (Phillips *et al.*, 2006; Scheldeman *et al.*, 2010).

## 3.5 Pre-processing of Predictor Environmental Variables

### 3.5.1 Bioclimatic Variables

The bioclimatic variables did not require extensive processing for use in the study. However, they were processed alongside other variables using the procedure described in Sub-section 3.5.7.

### 3.5.2 Current LULC Categories

The LULC map of the study area for the year 2024 was considered the current LULC dataset

#### 3.5.2.1 Pre-processing of Landsat-8 OLI Imagery

Satellite images acquired by Landsat sensors are subject to distortions caused by sensor, solar, atmospheric, and topographic effects (Young *et al.*, 2017). Pre-processing procedures aim to reduce or eliminate these undesired artifacts, enhance the quality of key image features, and establish a direct relationship between the data and biophysical phenomena (Young *et al.*, 2017). Therefore, the downloaded Landsat images were preprocessed through several steps, including image projection, atmospheric correction, geometric correction, image enhancement, layer stacking, mosaicking, and masking, as recommended by Young *et al.* (2017).

### 3.5.2.2 Landsat-8 OLI Imagery Projection

The downloaded Landsat images were projected to the Universal Transverse Mercator (UTM) coordinate system, using the World Geodetic System 1984 (WGS84) datum, specifically Zone 37N, in ArcGIS software.

### 3.5.2.3 Atmospheric & Radiometric Correction of the Landsat-8 OLI Imagery

Conversion to Top of Atmosphere Reflectance (TOR) units is one of the radiometric corrections that can help remove variations due to differences in Earth-Sun distance and solar zenith angle caused by different scene dates, overpass time, and latitude differences. Firstly, the measured DN were converted into radiance using in-flight sensor calibration parameters, which are supplied with absolute radiance values. The exact radiometric response function for each band was determined and applied to normalize temporal radiometric differences between sensors. The equation of the response function for each ban is as shown in the equation below;

$L = \text{Gain} \times DN + \text{Bias}$

Where;

L = spectral radiance measured over the spectral bandwidth of a channel,

DN = digital number value recorded,

Gain = $(L_{max} - L_{min}) / 255$,

= slope of response function

Bias = Lmin

= intercept of response function

Lmax = radiance measured at detector saturation in mWcm-2sr-1

Lmin = lowest radiance measured by detector in mWcm-2sr-1

In the second step, TOA were calculated for each band as per the equation below. This helped correct for illumination variations (sun angle and Earth-sun distance) within and between scenes. This correction was applied on a pixel-by-pixel basis for each scene.

$\rho\lambda = \pi d2L\lambda$

$E0\lambda \cos\theta s$

Where;

$\rho\lambda$ = reflectance as a function of bandwidth,

d = Earth-sun distance correction,

$L\lambda$ = radiance as a function of bandwidth,

$E0\lambda$ = exoatmospheric irradiance,

$\theta s$ = solar zenith angle.

Radiometric correction procedures account for errors that affect the brightness value of pixels due to both a sensor system detector error and an environmental attenuation error (e.g. changes in scene illumination, atmospheric conditions, and viewing geometry (Lillesand and Kiefer 1994).

### 3.5.2.4 Layer Stacking of the Landsat-8 OLI Imagery

Individual bands of Landsat images were stacked sequentially from bands 1 to 7 to create a composite image/band using the ‘raster processing tool’ of the ‘Data Management Tool’ in ArcGIS software.

### 3.5.2.5 Layer Mosaicking of the Landsat-8 OLI Imagery

Composite images from different paths and rows, obtained through layer stacking of individual bands, were mosaicked to create a new raster using the ‘Mosaic to New Raster’ tool in the Data Management Tools toolbox in ArcGIS software.

### 3.5.2.6 Layer Sub-Setting of the Landsat-8 OLI Imagery

The mosaicked image was clipped to the full extent of the study area using the 'Extract by Mask' tool in ArcGIS software. Image extraction involved removing irrelevant portions of the image and focusing on the region of interest. This process helps reduce the image file size by limiting it to the Area of Interest (AoI), eliminating extraneous data, and increasing data processing efficiency.

### 3.5.2.7 Classification of LULC of the Study Area

The mosaiced Landsat satellite imagery was used for image classification. Pixel-based supervised image classification, with Maximum Likelihood Classification (MLC) algorithm in ArcGIS version 10.8 was used to classify LULC of the study area for the year 2024 into six categories. This classification algorithm is the widely used method in LULC studies. The method requires a prior knowledge of LULC types of the study area, knowledge concerning statistical aspects of the classes (Lillesand *et al.*, 2015), and a prior knowledge of visual interpretation using Google Earth historical function (Aniah *et al.*, 2023).

Different band combinations for Landsat 8 OLI imagery are shown in Table 5. However, composite bands such as RGB (Red, Green, and Blue) composite, Natural colour, False colour (Urban), Colour infrared (vegetation), Agriculture, Health Vegetation, and Land/Water were used for identification and classification of different LULC categories. Areas of visually homogeneous spectral response that were well distributed all over the image, as Area of Interest (AoI) were chosen as training sites (10-12 training set per class) and added to the spectral signature editor.

Training sites were defined using ground truth data, and signature separability functions in ArcGIS software were used to examine the quality of training sites and class signatures (Aniah *et al.,* 2023). For LULC categories indicating different spectral signatures in different areas of the study area, several spectral signatures were created for the different areas and later merged into one spectral signature for a specific LULC category.

Land use/land cover categories were identified based on previous studies in the study area and the surrounding landscapes (Kanda *et al.*, 2023; Kipkulei *et al.*, 2025; Togoch, 2018), while land cover types (woodland, shrubland, and bareland) were classified according to the physiognomic characteristics of vegetation, as described by Pratt and Gwynne (1977) and illustrated in Table 6.

**Table 5: Band combinations for Landsat 8 OLI imagery**

| Composite Name | Bands |
|---|---|
| Natural colour | 4,3,2 |
| False colour (Urban) | 7,6,4 |
| Colour infrared (vegetation) | 5,4,3 |
| Agriculture | 6,5,2 |
| Health Vegetation | 5,6,2 |
| Land/Water | 5,6,4 |
| Natural with Atmospheric removal | 7,5,3 |
| Short-wave Infrared | 7,5,4 |
| Vegetation Analysis | 6,5,4 |

**Table 6: Land use/land cover categories**

| LULC Category | Description |
|---|---|
| Built -up | Areas with buildings and other artificial infrastructure occupying the land |
| Waterbodies | Areas of surface water, either impounded in ponds, lakes, or reservoirs, or flowing as streams, rivers, or other water bodies |
| Agriculture | Areas under cultivation with temporary crops, followed by harvest and a period of bare soil |
| Woodlands | Areas with trees 5 to 10 meters tall, a broken canopy cover of 20% to 80%, and shrubs and grasses growing underneath |
| Shrubland | Areas with little vegetation, mainly scattered shrubs and short-lived herbs, and tree cover below 5% |
| Bareland | Areas with very little vegetation, a few drought-tolerant plants, and mostly bare soil. |

### 3.5.2.8 Accuracy Assessment of the Classified LULC Classes

Accuracy assessment was done using a confusion matrix table (Congalton, 1991). The matrix table has the ability to identify the nature of the classification errors and quantities, to compare the classification to geographical data that are assumed to be true, to determine the accuracy of the classification process.

Accuracy assessment for the classified LULC image involved the use of the collected ground truth data and was supplemented using points generated using a stratified random sample in ArcGIS. The Google Earth Pro image (https://earth.google.com/web/) used for accuracy assessment corresponded to the LULC classes for the reference year, 2024. A total of three hundred (300) points were used in the assessment, of which 140 were ground truthing points.

Accuracy assessment of the classified LULC was done using various measures of accuracy assessment, such as Overall Accuracy (OA), Producer’s Accuracy (PA), User’s Accuracy (UA), and Cohen’s Kappa Coefficient (CKC) (Congalton, 1991; Foody 2002; Foody,2008; Jensen, 2016; Lillesand *et al.*, 2015; Olofsoon *et al.,* 2013; Olofsoon *et al.,* 2014).

Overall Accuracy (OA), which is the measure of the total number of correctly classified samples relative to the total number of samples, was calculated using the following equation:

Overall Accuracy (OA) = (Total number of correctly classified samples) / (Total number of samples) × 100

Producer's Accuracy (PA), which is a measure of how much of the land in each LULC category is correctly classified, was assessed using the following equation:

Producer's Accuracy (PA) = (Correctly classified samples for a class) / (Total reference samples for that class) × 100

User’s Accuracy (UA), which is a measure of how many of the samples classified into a particular class actually match the reference data, was determined using the following equation:

User's Accuracy (UA) = (Correctly classified samples for a class) / (Total samples classified as that class) × 100

Cohen’s Kappa Coefficient (measures the degree of agreement between the classified remote sensing image and the reference data. A Kappa value of 1 indicates perfect agreement, while a value of 0 indicates no agreement beyond what would be expected by random chance (Congalton, 1991). Cohen’s Kappa is expressed using the following equation:

Kappa ($\kappa$) = (Po - Pe) / (1 - Pe)

Where:

Po = Observed Accuracy (correct classifications / total samples)

Pe = Expected Accuracy (chance agreement)

Choen’s Kappa Coefficient (CKC) was classified into six categories according to Kumar & Viraji (2021), as shown in Table 7.

**Table 7: Classification of Choen’s Kappa Coefficient (CKC)**

| **Choen's Kappa coefficient** | **Degree of agreement** |
|---|---|
| <0.00 | Poor |
| 0.00-0.20 | Slight |
| 0.20-0.40 | Fair |
| 0.41-0.60 | Moderate |
| 0.61-0.80 | Substantial |
| 0.81-1.00 | Almost perfect |

### 3.5.3 Topographic Features

Topographic features; elevation, slope and aspect elevation, slope, and aspect were considered as predictor environmental variables in this study. Elevation is a measure of height a.s.l. in meters, slope represents the steepness of an area in degrees, and aspect indicates the direction of the slope in compass degrees, ranging from 0° to 360°, with 0° representing north. These topographic features were derived from the DEM using the Spatial Analyst extension in ArcGIS software.

### 3.5.4 Normalized Difference Vegetation Index (NDVI)

The NDVI (Tucker, 1979) is a widely used remote sensing metric for assessing vegetation health and density. Normalized Difference Vegetation Index (NDVI) was calculated using two bands: Band 4 (Red) and Band 5 (Near-Infrared, NIR) of the Landsat 8 OLI imagery for the year 2024, using the formula provided below:

NDVI = (NIR - RED) / (NIR + RED) (Rabatel *et al.*, 2014)

Where;
NDVI = Natural Difference Vegetation Index

NIR = Near Infrared band of the Landsat 8 OLI imagery

The NDVI values range between -1 and +1, and a value close to -1 indicates areas of water and a value close to +1 indicates areas of vegetation.

### 3.5.5 Soil Types

The soil map of Kenya was extracted from the FAO-DSMW using the ‘extract by mask tool’ in ArcGIS software. The Soil Numbers (SNUM) for the soils of Kenya were generated, and a shapefile of the study area was used to extract the soils of the study area from the soils of Kenya. The SNUM extracted were used to generate the soil map of the study area.

The SNUM were 57, 76, 248, 392, 660, and 848. These SNUM were counterchecked for the soil type in the QSWAT 2012, and the corresponding soil types were loam for all the numbers, with varying soil properties except for SNUM 392, which corresponded to a clay-loam soil type. All loam soil types with varying soil properties were merged into one soil type, the loam soil type, and the soil map of the study area was extracted using the shapefile of the study area.

### 3.5.6 Distance Layers

Three distance layers, Euclidean distances to roads, waterbodies, and human settlements were prepared in meters using ArcGIS software.

### 3.5.7 Other Preparations for the Predictor Environmental Variables

#### 3.5.7.1 Extraction of Predictor Environmental Variable Values at Species Occurrence Points

In the study, all predictor environmental variables were extracted at occurrence points for each study species using the Spatial Analyst tool in ArcGIS. The resultant data was used to perform Pearson’s CA on the predictor environmental variables.

#### 3.5.7.2 Re-Projection of Predictor Environmental Variables to An Equal Area Projection

All the spatial layers for the study were projected into an equal area projection, WGS84, using ArcGIS version 10.8 for subsequent analyses and modeling.

#### 3.5.7.3 Extraction of Predictor Environmental Variables to the Extent of the Study Area

The predictor environmental variables for the study were extracted to the extent of the study area using the “extract by mask tool” in ArcGIS.

#### 3.5.7.4 Resampling of Predictor Environmental Variables

Most of the predictor environmental variables, including the bioclimatic data, LULC data, NDVI data, and topographic data, were in 30m (~ 1 km) spatial resolution. However, other types of data having a different spatial resolution were resampled into a 30m spatial resolution using the ‘environment’ in ArcGIS.

#### 3.5.7.5 Conversion of Predictor Environmental Variables from Raster to ASCII Formats

All the preselected environmental variables were converted from raster format to ASCII format using “conversion tools” in ArcGIS version 10.8 software.

### 3.5.7.6 Evaluation and Preselection of Important Environmental Variables for Analyses and Modeling

Identification and exclusion of highly correlated and less important predictor environmental variables from the modeling study can help to minimize potential issues with spatial biases, model complexity, and overfitting of modeling results, which can help increase the accuracy of modeling results. In this study, therefore, the selection of suitable predictor environmental variables for use in analysis and modeling was based on Pearson's Correlations and percentage contribution following the procedure described by Zhou *et al.* (2020).

### 3.5.7.7 The Pearson's Correlation Analysis

The CA in the Statistical Package for the Social Sciences (SPSS) version 20.0 was used to test for collinearity among pairs of all preselected predictor environmental variables, except LULC and soil types, which were treated as categorical datasets. The correlation coefficient values (r) range between -1 and 1; a positive r value indicates a positive correlation, a negative r value indicates a negative correlation, and a zero (0) r value indicates no correlation.

Pairs of predictor environmental variables showing a correlation coefficient value of less than 0.8 (<0.8) (Bravo-García *et al.*, 2024; Zhou *et al.*, 2020) were considered suitable for further analyses and modeling. However, for pairs of predictor environmental variables involved in collinearity, one of the pairs was removed as described in sub-section 3.5.7.8. This step is important in eliminating multicollinearity between pairs of variables and in reducing the number of variables used in the final modeling.

### 3.5.7.8 Evaluation of Percentage Contribution of the Predictor Environmental Variables

The selection of suitable predictor environmental variables followed a procedure described by Zhou *et al.* (2020). This procedure involves building preliminary MaxEnt models using the current 'default' settings of the MaxEnt software version 3.3.0 (Phillips *et al.,* 2018), with the regularization multiplier (RM) set at 1 and the features combination of Linear, Quadratic, Hinge, and Product (LQHP) (Phillips *et al.,* 2018). The software was set to perform Jackknife tests of variable importance.

All the predictor environmental variables were used to run 10 replicates of preliminary MaxEnt models and a set of predictor variables contributing the highest AUC value to the generated models were identified and evaluated based on their contribution to the model and their correlation coefficient values.

The predictor environmental variables contributing less than 0.3% (Bravo-García *et al.,* 2024; Zhou *et al.,* 2020) to the identified model were excluded from any further selection process. Also, all variables showing a correlation coefficient value of more than 0.8 (>0.8) (Bravo-García *et al.,* 2024; Zhou *et al,*.2020) with the variable contributing the highest percentage to the first generated model were excluded from the selection process. This selection procedure was repeated several times until a set of predictor environmental variables that contribute a percentage of above 0.3% and are non-correlated was identified for optimization of the final MaxEnt model and further analyses and modeling.

## 3.6 Modeling of Potential Suitable Habitats of African Elephants and Their Preferred Forage Plants Using the Maxent Software

### 3.6.1 Evaluation and Selection of Feature Combination (FC) and Regularization Multiplier (RM) for Analyses and Modeling

The evaluation and selection of feature combinations and regularization multipliers for optimizing the MaxEnt model were conducted using the ENMeval package in R software (Muscarella *et al.,* 2014). The ENMeval package incorporates the findings of Radosavljevic and Anderson (2014) to offer a range of training and testing partition methods and tuning options. It evaluates model complexity by calculating the Akaike Information Criterion (AIC) corrected for small sample sizes under different MaxEnt parameter settings (Gao *et al.,* 2023). The Akaike Information Criterion correction (AICc) is a standard metric used to evaluate the goodness of fit of statistical models. It generally favors models with lower AICc values, indicating a better balance between model fit and complexity (Gao *et al.,* 2023).

The ENMeval package in R (R Core Team, 2021) was used with 133 African elephant occurrence points and 12 preselected environmental predictor variables to generate Regularization Multiplier (RM) (β) values. The 'default' settings of the MaxEnt software version 3.3.3 (FC = LQHPT, RM = 1) served as the control model for comparison with all other generated models (Phillips *et al.,* 2018). For tuning in ENMeval, the Block partitioning method (k = 4), as described by Valavi *et al.* (2018), was used to spatially partition the data based on longitude and latitude. This method also facilitated the calculation of the Akaike Information Criterion corrected for small sample sizes (AICc) (Muscarella *et al.*, 2014; Valavi *et al.*, 2018).

The MaxEnt software includes five feature types: L = Linear, Q = Quadratic, H = Hinge, P = Product, and T = Threshold (Phillips *et al.*, 2006). For the evaluation and selection of feature combinations (FC) and regularization multipliers (RM), the feature combinations tested included: L, LQ, H, LQH, LQHP, and LQHPT (Gao *et al.*, 2023). The RM values were set to range from 0.5 to 5.0, in increments of 0.5.

The difference between the training and test areas under the Receiver Operating Characteristic Curve (AUCdiff), along with the Akaike Information Criterion corrected for small sample sizes (AICc), was used to select the optimal parameter combination for the MaxEnt model (Gao *et al.*, 2023). The parameter combination with an AUCdiff of zero (0) and the lowest AICc value was selected for configuring the final MaxEnt model. The same procedure was used to select the optimal feature combination and regularization multiplier for modeling suitable habitats of African elephants' preferred forage plants, based on 152 occurrence points and 8 preselected environmental predictor variables.

### 3.6.2 Building of Optimized MaxEnt Models

Optimized MaxEnt models in the study were built using spatially independent occurrence records for both the African elephant and its preferred forage plants, along with various sets of preselected predictor environmental variables (Figure 11). The selected Feature Combination (FC) of and Regularization Multiplier (RM) values were appropriately configured to generate separate MaxEnt models for the study species and their preferred forage plants.

The MaxEnt software was configured to generate response curves and perform Jackknife tests of variable importance. The response curves illustrated how each preselected predictor environmental variable affected the MaxEnt model results and how the predicted probability of presence changed as each variable was varied, while all other variables were held at their average sample values. The output format for the response curves was set to cloglog.

The Jackknife test of variable importance was useful in identifying the contribution of each predictor variable to the generated MaxEnt models and in detecting variables that significantly improved predictions of the study species' occurrences (Phillips *et al.*, 2006). The Jackknife test provided results on percentage contribution, permutation importance, Jackknife of regularized training gain, Jackknife of regularized test gain, and Jackknife of AUC, for the 12 and eight sets of the preselected predictor environmental variables for modeling habitat suitability of the African elephants and their preferred forage plants respectively.

The red bars in the Jackknife of regularized training gain, test gain, and AUC figures represented the combined contribution of all preselected predictor environmental variables and served as the control group. Dark blue bars represented the Jackknife results (regularized training gain, test gain, and AUC for each predictor variable, while light blue bars indicated the contribution (or specificity) of each predictor variable when used in isolation.

The longer the dark blue bar, the more important the bioclimatic variable is in predicting the current and future distribution and suitable habitats of the study species and its preferred forage plants. Conversely, the shorter the green bar, the more unique information the predictor variable provides that is not present in other variables. A short green bar indicates that removing the variable leads to the greatest decrease in Jackknife regularized training gain, test gain, and AUC, highlighting its critical role in the model.

Other basic features of the MaxEnt software, such as ‘Random seed’ and ‘Skip when outputs exist’, were enabled during the modeling process. However, options such as ‘Write clamp grid when projecting’ and ‘Do MESS analysis when projecting’ were excluded in modeling the current potential distribution and habitat suitability of African elephants and their preferred forage plants.

Species occurrence data were randomly divided into two sets: 70% as training data (for calibrating the species models) and 30% as testing data (for evaluating the models) (Budhathoki *et al.,* 2023; Jeza & Bekele, 2023; Phillips *et al.,* 2006). The model replicate was 10-fold, and the replicate run type was bootstrap. All other MaxEnt settings, including those without explicit values, were left at their default configurations as provided in the MaxEnt software (Phillips *et al.*, 2006, 2018).

However, when projecting under future climatic scenarios, the same predictor environmental variables used to model the current potential distribution and suitable habitats of the study species and its preferred forage plants were also considered. Additionally, the ‘Do MESS analysis when projecting’ feature was enabled during the modeling of future habitat suitability for the study species and their preferred forage plants.

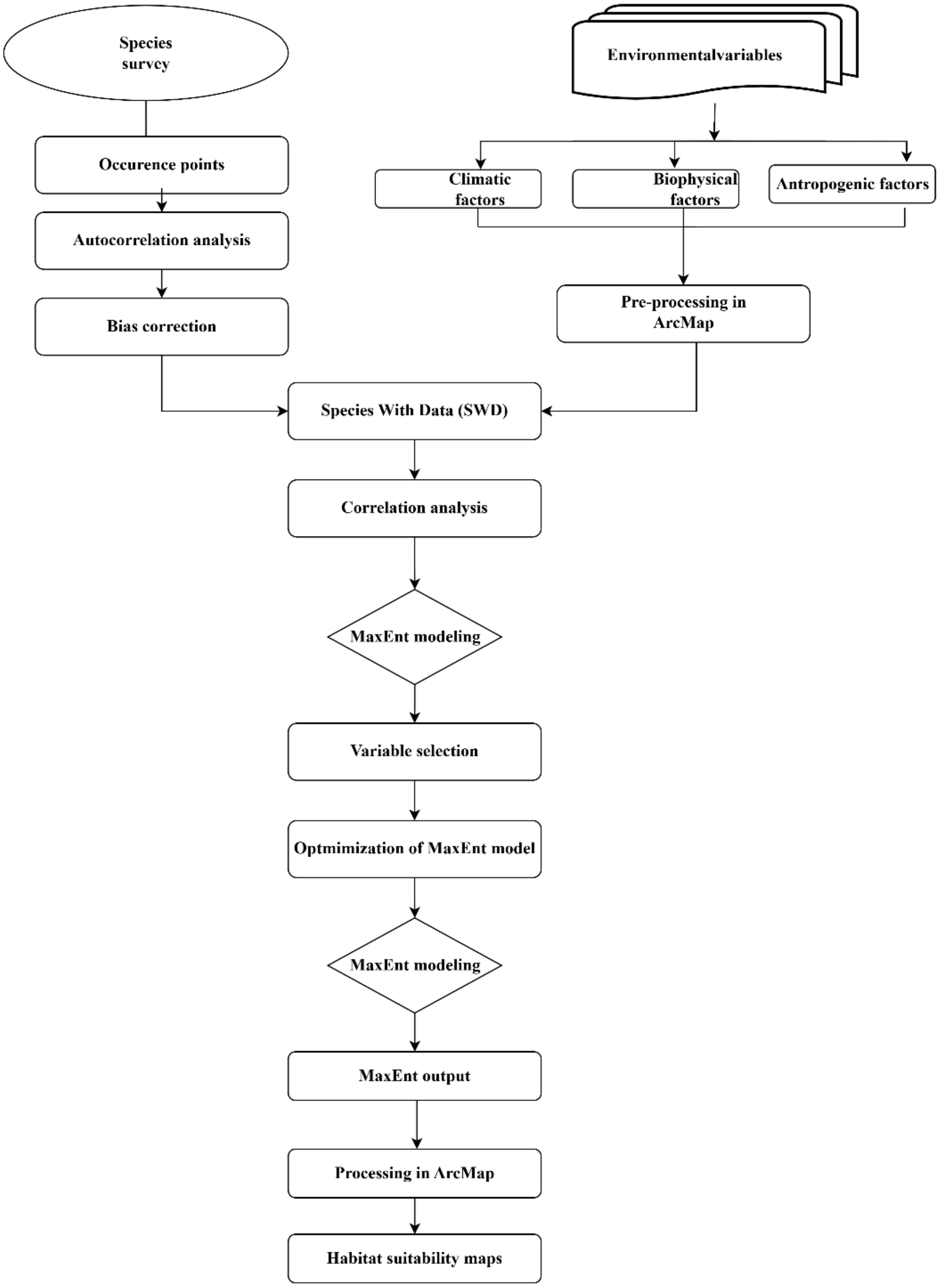


**Figure 11: Flowchart illustrating the methodology used in predicting potential habitat suitability for African elephants and their preferred forage plants**

### 3.6.3 Accuracy Evaluation of MaxEnt Models

The MaxEnt models were evaluated using a threshold-independent analysis of the AUC provided by the ROC (Phillips *et al*., 2006). These sensitivity tests model accuracy by calculating the proportion of true positives versus false positives. In general, AUC values range from 0 to 1, with higher values indicating better predictive performance of the model. In this study, AUC values were classified into five categories following previous studies (Duan *et al.,* 2014; Elbahi *et al.,* 2024; Mouafo *et al.,* 2023; Swets, 1988), as shown in Table 8.

**Table 8: Classification of AUC**

| AUC Category | AUC value |
|---|---|
| Fail | 0-0.6 |
| Poor | 0.6-0.7 |
| Fair | 0.7-0.8 |
| Good | 0.8-0.9 |
| Excellent | 0.9-1.0 |

### 3.6.4 Classification of Current and Future Potential Suitable Habitats for African Elephants and their Preferred Forage Plants

Cloglog outputs of the MaxEnt software were used in the classification of suitable habitats for African elephants and their preferred forage plants. The mapped predictions produced in an ASCII (.asc) format were imported into ArcGIS version 10.8 software and converted into a raster format. The raster data was projected to WGS1984, multiplied by ten thousand (10,000) using the raster calculator tool to convert into integer using the Spatial analyst tool. Unsuitable habitats were identified using the 10th percentile training presence cloglog threshold. The continuous MaxEnt prediction rasters were imported into ArcGIS software and classified based on the 10th percentile training presence cloglog threshold method and further refined using the manual method. The raster was further classified and visualized into four habitat categories in ArcGIS as follows;

**Table 9: Classification of habitats**

| Suitability class | Prediction value range |
|---|---|
| Unsuitable | < 10th percentile threshold |
| Low suitability | ≥ 10th percentile threshold < 0.4 |
| Moderate suitability | ≥ 0.4 < 0.6 |
| High suitability | ≥ 0.6 ≤ 1 |

### 3.6.5 Estimation of Abundance of Potential Current and Future Suitable Habitat Categories for African Elephants and their Preferred Forage Plants

The abundance of potential current and future suitable habitat categories for African elephants and their preferred forage plants in the study was estimated by calculating areas (km$^2$) and proportions (%) of area occupied by each of the classified habitat categories of African elephants and their preferred forage plants. To ensure accuracy, the raster files of current and future climate change scenarios were converted into a projected coordinate system, WGS 1984 UTM Zone 37N, and then converted into a polygon file using the raster-to-polygon conversion tool in ArcGIS version 10.8 software. Areas (km$^2$) and proportions (%) of area occupied by each of the classified potential current and future suitable habitat categories of African elephants and their preferred forage plants were determined using the calculation function in ArcGIS.

### 3.6.6 Change Analyses Between Current and Future Potential Suitable Habitats for African Elephant and their Preferred Forage Plants

Change analysis was conducted to assess spatial shifts in habitat suitability for African elephants and their preferred forage plants between the current scenario (1970–2000) and SSP245 and SSP585 climate change scenarios for the period 2041– 2060, and 2081–2100. This analysis was based on classified habitat suitability maps derived from MaxEnt model outputs for both periods and was done by comparing the differences in areas (km²) and proportions (%) of area occupied by each of the classified habitat categories.

Change analysis was done by converting the raster files of classified habitat suitability maps for both current and future climatic scenarios into polygons using the conversion tool in ArcGIS. Intersection analysis was performed for the polygon data to calculate the difference in abundance between current and future climate change scenarios using the 'Calculate Geometry' function in ArcGIS.

# CHAPTER FOUR

# RESULTS

## 4.1 MaxEnt Model Performance and Validation for Prediction of Potential Suitable Habitats for African Elephants and Their Preferred Forage Plants

### 4.4.1 Results of Omission and Commission Rate Analysis

The test omission rate and predicted habitat suitability for African elephants, plotted against the cumulative threshold and averaged over ten MaxEnt replicate runs, are illustrated in Figure 12. The omission rate (green line) closely aligned with the predicted omission (black line), reflecting the definition of the cumulative threshold. Variability in mean area and mean omission was depicted by blue and orange lines, respectively, indicating consistency in model predictions.

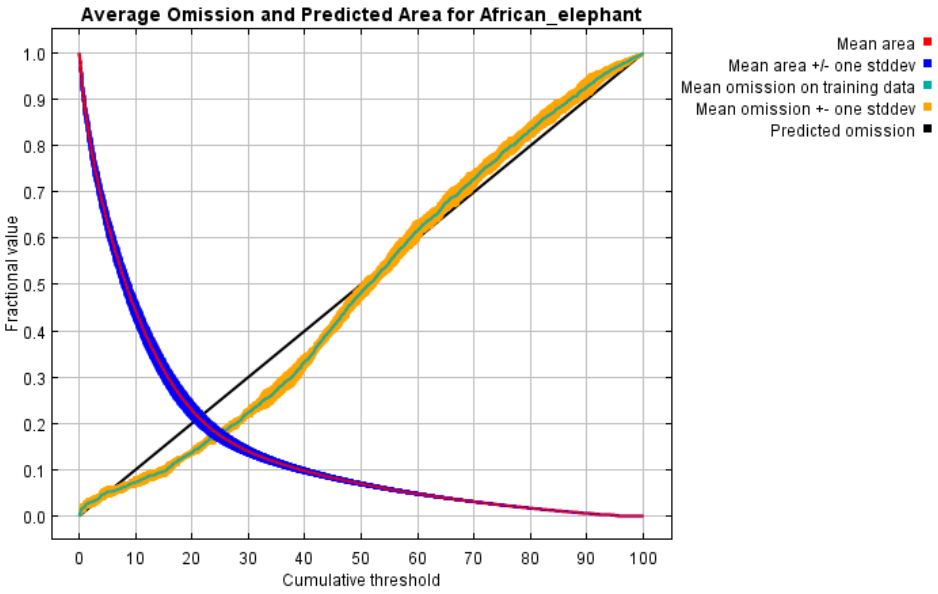


**Figure 12: Test omission rate and predicted habitat suitability for African elephants**

The test omission rate and predicted distribution area of African elephants' preferred forage plants are shown as a function of cumulative threshold, averaged over ten MaxEnt replicate runs, as illustrated in Figure 13. The observed omission rate (green line) closely aligned with the predicted omission (black line), consistent with the cumulative threshold definition. Variability in mean area and mean omission was indicated by blue and orange lines, respectively.

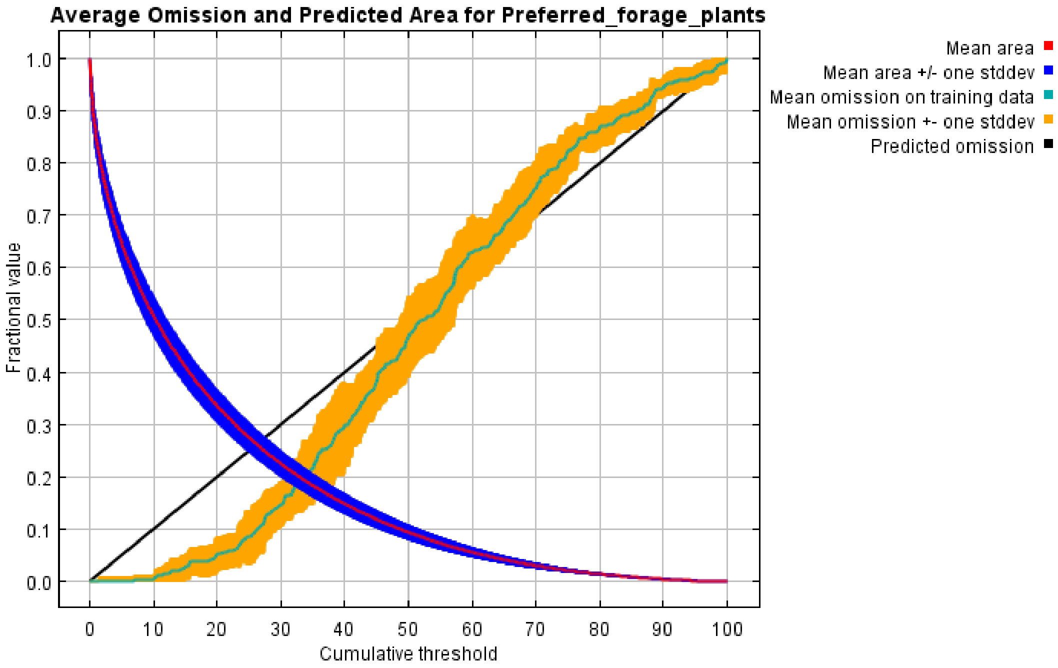


**Figure 13: Test omission rate and predicted habitat suitability for African elephants' preferred forage plants**

### 4.4.2 Results of the Receiver Operating Characteristic (ROC) Analysis

The ROC curve illustrating the predicted suitable habitat of African elephants is shown in Figure 14. The model achieved an average test AUC of 0.868 ± 0.006 across 10 MaxEnt replicates, demonstrating excellent discriminatory ability between suitable and unsuitable habitats, well above the random prediction value of 0.5.

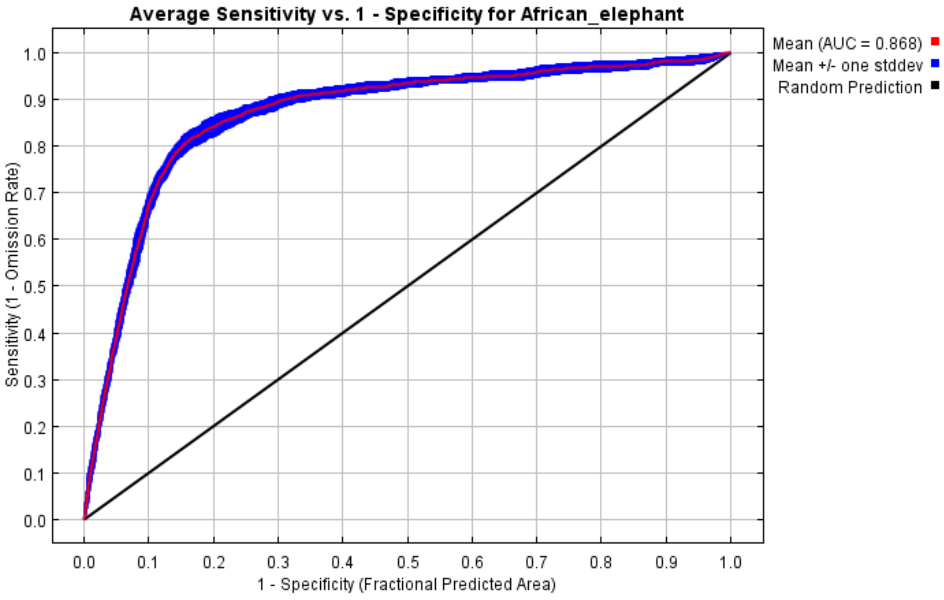


**Figure 14: Receiver Operating Characteristic (ROC) curve for predicted habitat suitability for African elephants**

The ROC curve for the predicted suitable habitats of African elephants' preferred forage plants under current environmental conditions is presented in Figure 15. The curve shows an average test AUC of 0.883 ± 0.007, across 10 replicate MaxEnt model runs, indicating strong model performance relative to a random prediction (AUC = 0.5).

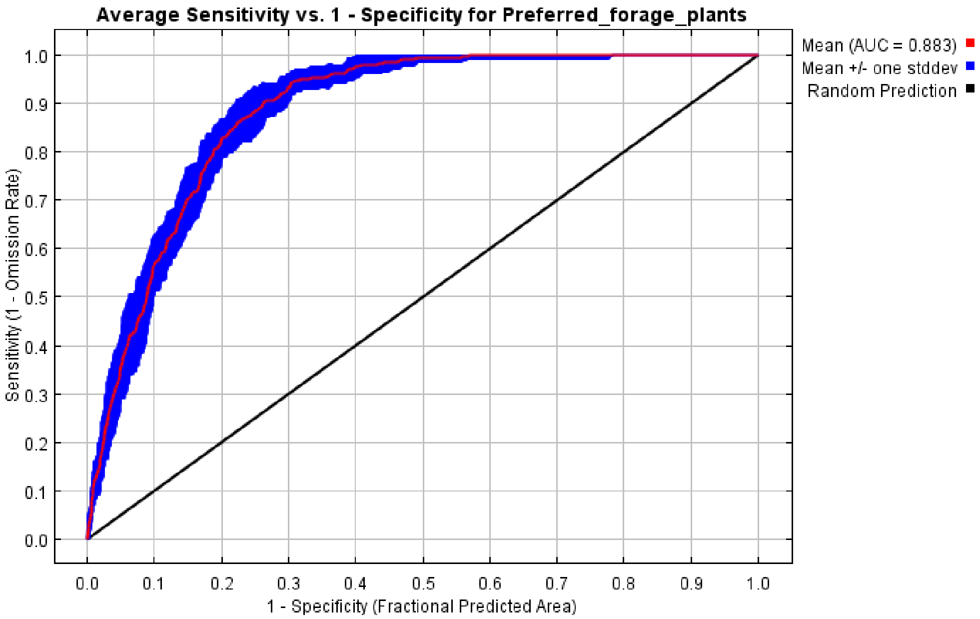


**Figure 15: Receiver Operating Characteristic (ROC) curve for predicted habitat suitability of African elephants' preferred forage plants**

## 4.2 Spatial Distribution and Abundance of Potential Current and Future Suitable Habitats for African Elephants and their Preferred Forage Plants within the Nasalot–South Turkana–Kerio Valley ecosystem.

### 4.2.1 Spatial Distribution and Abundance of Potential Current Suitable Habitats for African Elephants

The current habitat suitability map for African elephants, derived from MaxEnt model outputs and classified into four categories using the 10th percentile training presence based on a cloglog threshold of 0.1532, is shown in Figure 16. The categories include unsuitable (<0.1532), low (≥0.1532–<0.4), moderate (≥0.4–<0.6), and high (≥0.6–≤1.0) suitability (Appendix XXII). The spatial distribution of suitability categories varied across the study area. Highly suitable habitats were concentrated in the southwestern region, particularly within Rimoi and Kamnarok National Reserves. Moderate suitability areas occurred adjacent to highly suitable habitats, primarily in the southeastern region. Low suitability habitats were located centrally, forming a transitional zone between southern suitable areas and the northern unsuitable zones. Unsuitable habitats dominated the northern region, including Nasalot and South Turkana National Reserves.

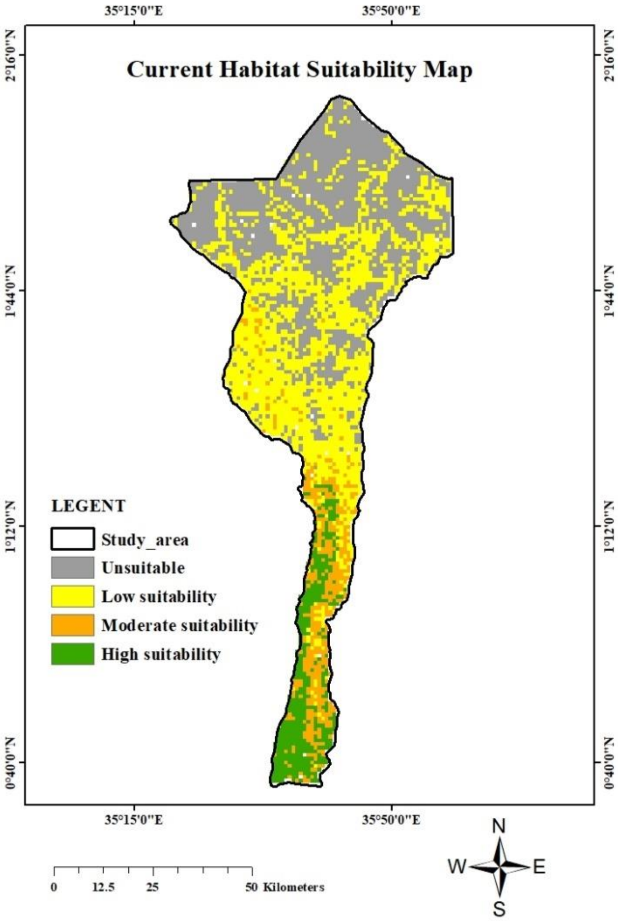


**Figure 16: A map showing current habitat suitability for African elephants**

The area (km²) and proportion (%) of land occupied by various habitat suitability categories for African elephants under the current scenario are presented in Table 10. Low suitability habitats occupied the largest share, covering 1,931.59 km² (41.09%) of the total area. The remaining categories, unsuitable, moderate, and highly suitable habitats, each occupied between 409.37 km² and 1931.59 km².

**Table 10: Area (km²) and proportion (%) of land occupied by various habitat suitability categories for African elephants under current conditions**

| Suitability category | Area ($km^2$) | Proportion (%) |
|---|---|---|
| Unsuitable habitats | 1918.68 | 40.82 |
| Low suitability | 1931.59 | 41.10 |
| Moderate suitability | 440.37 | 9.37 |
| High suitability | 409.37 | 8.71 |
| **TOTAL** | **4700.36** | **100** |

### 4.2.2 Spatial Distribution and Abundance of Potential Current Suitable Habitats for African Elephants' Preferred Forage Plants

The current habitat suitability map for African elephants' preferred forage plants, based on MaxEnt model output classified into four categories using the 10th percentile training presence cloglog threshold (0.3349), is shown in Figure 17. The categories include unsuitable ($< 0.3349$), low ($\geq 0.3349$ to $< 0.4$), moderate ($\geq 0.4$ to $< 0.6$), and high suitability ($\geq 0.6$ to $\leq 1.0$) (Appendix XXIII). The map reveals spatial variation in habitat suitability, with highly suitable areas concentrated in the south, particularly around Rimoi and Kamnarok National Reserves. Moderate and low suitability zones are found as fragments in the southern, northeastern and northwestern regions of the ecosystem, while unsuitable habitats dominate the central and northern regions.

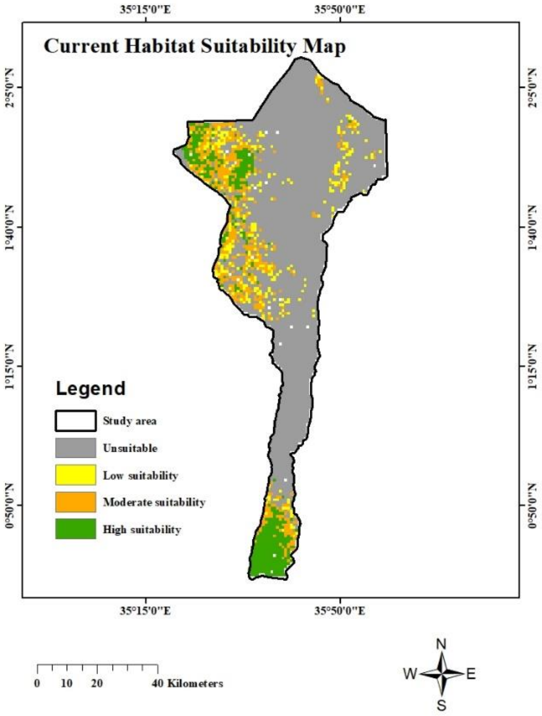


**Figure 17: Map showing current habitat suitability of African elephants' preferred forage plants**

The area (km²) and proportion (%) of land occupied by habitat suitability categories for African elephants' preferred forage plants under the current scenario are presented in Table 11. Unsuitable habitats dominated, covering 3,451.05 km² (73.42%) of the total area. In contrast, low, moderate, and high suitability habitats each occupied between 300 km² and 600 km².

**Table 11: Area (km²) and proportion (%) of land occupied by various habitat suitability categories for African elephants' preferred forage plants under current conditions**

| Suitability category | Area (km$^2$) | Proportion (%) |
|---|---|---|
| Unsuitable | 3451.05 | 73.42 |
| Low suitability | 306.10 | 6.51 |
| Moderate suitability | 508.02 | 10.81 |
| High suitability | 435.18 | 9.26 |
| **TOTAL** | **4700.37** | **100** |

### 4.2.3 Spatial Distribution and Abundance of Potential Future Suitable Habitats for African Elephants

Habitat suitability maps for African elephants under future climate scenarios (SSP245 and SSP585) for the periods 2041–2060 and 2081–2100 are displayed in Figure 18. The maps, derived from MaxEnt model outputs and classified into four categories using the 10th percentile training presence cloglog threshold, show spatial variation in habitat suitability across the study area.

Highly suitable habitats were concentrated in the southwestern region, particularly in areas of both Rimoi and Kamnarok National Reserves. In contrast, unsuitable habitats dominated the northern areas, including Nasalot and South Turkana National Reserves. Moderate and low suitability areas were primarily distributed between these zones of high and low habitat suitability, indicating transitional habitat conditions.

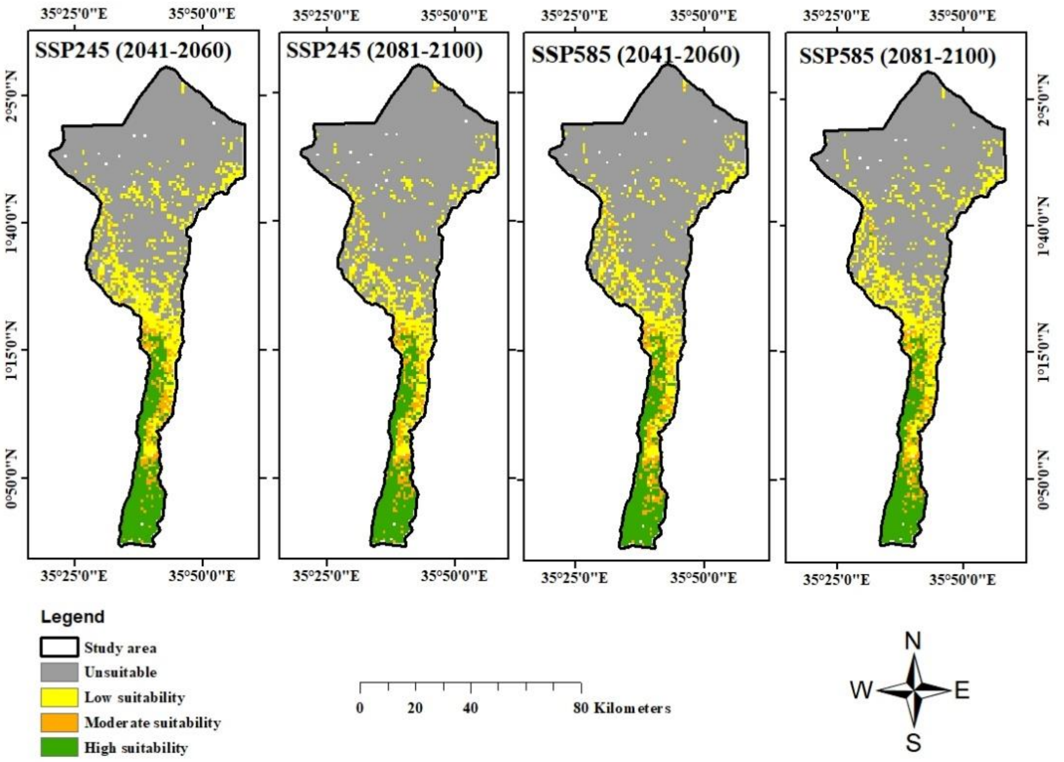


**Figure 18: Maps showing future habitat suitability for African elephants under various climate change scenarios.**

The projected area (km²) and proportion (%) of land occupied by different habitat suitability categories for African elephants under future climate scenarios (SSP245 and SSP585) for the periods 2041–2060 and 2081–2100 are presented in Table 12. The results show a consistent trend toward increasing habitat unsuitability, with unsuitable habitats occupying the largest share of the landscape across all scenarios, ranging from 67.09% to 70.93%. In contrast, low, moderate, and high suitability habitats each covered between 4.34% and 16.32% of the total area, indicating a projected significant reduction in suitable habitat availability over time.

**Table 12: Area (km$^2$) and proportion (%) of land occupied by each habitat suitability category for African elephants under future climate change scenarios**

| | | **Suitability category** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Unsuitable** | | **Low** | | **Moderate** | | **High** | | **Total** | |
| **Scenario** | **Period** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** |
| Current | 1995—2000 | 1918.68 | 40.82 | 1931.59 | 41.10 | 440.37 | 9.37 | 409.37 | 8.71 | 4700.36 | 100.00 |
| SSP245 | 2041—2060 | **3153.24** | **67.09** | 767.10 | 16.32 | **203.76** | **4.34** | 576.25 | 12.26 | 4700.36 | 100.00 |
| SSP245 | 2081—2100 | **3333.95** | **70.93** | 614.05 | 13.06 | **210.16** | **4.47** | 542.12 | 11.53 | 4700.30 | 100.00 |
| SSP585 | 2041—2060 | **3303.53** | **70.28** | 638.95 | 13.59 | **221.28** | **4.71** | 536.61 | 11.42 | 4700.36 | 100.00 |
| SSP585 | 2081—2100 | **3195.65** | **67.99** | 747.74 | 15.91 | **212.98** | **4.53** | 543.98 | 11.57 | 4700.36 | 100.00 |

### 4.2.4 Spatial Distribution Pattern and Abundance of Potential Future Suitable Habitat for African Elephants' Preferred Forage Plants

Habitat suitability maps for African elephants' preferred forage plants under future climate scenarios, based on MaxEnt model outputs classified into four categories: unsuitable, low, moderate, and high suitability, are shown in Figure 19. The classification was based on the 10th percentile training presence cloglog threshold averaged over 10 MaxEnt runs. Under SSP245 and SSP585 scenarios for 2041–2060 and 2081–2100, habitat suitability varied across the study area. Highly suitable habitats were concentrated in the southwest, particularly within Rimoi and Kamnarok National Reserves, with moderate and low suitable habitats scattered, mainly in the southern, northeastern, and northwestern regions, while unsuitable habitats dominated the central and northern parts.

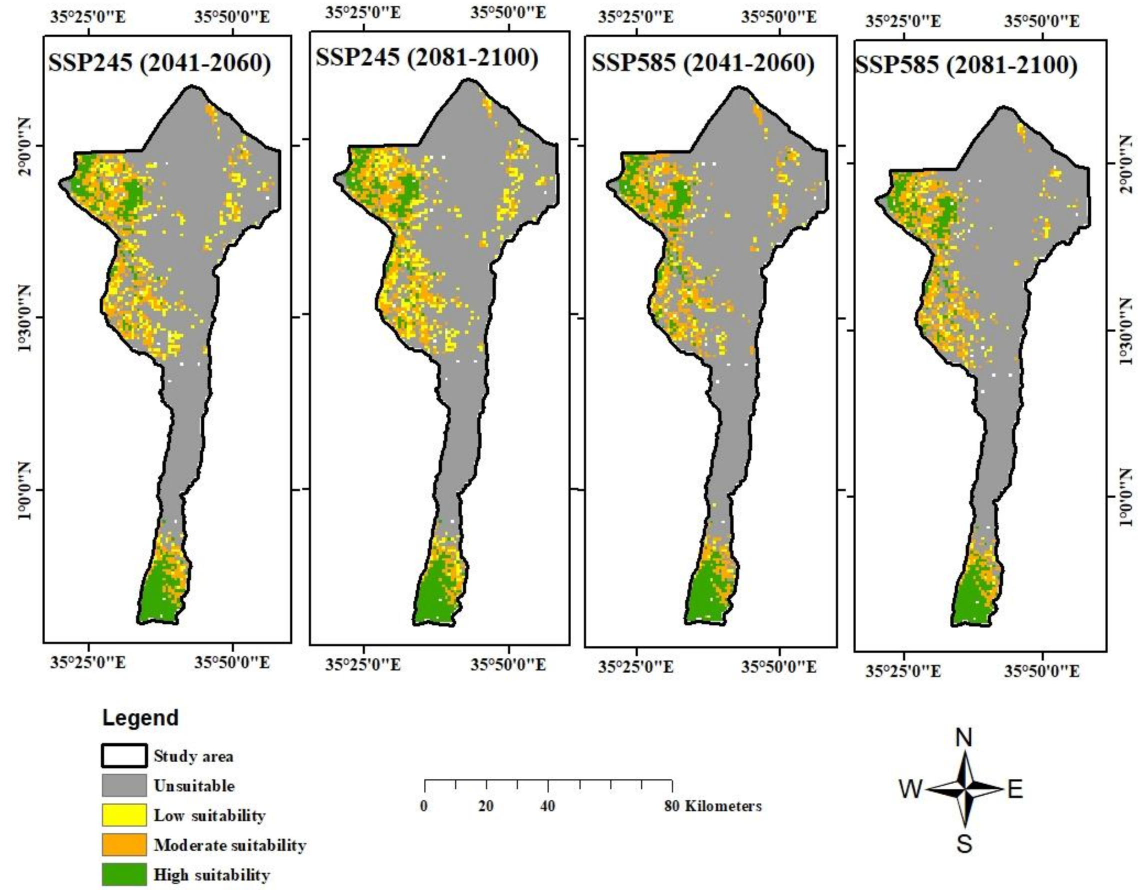


**Figure 19: Maps showing future habitat suitability of African elephants' preferred forage plants under various climate change scenarios.**

The area (km²) and proportion (%) of land occupied by different habitat suitability categories for African elephants' preferred forage plants under future climate scenarios are presented in Table 13. Unsuitable habitats consistently dominated, covering 3,320.12–3,568.14 km² (70.11%–75.91%) of the total area. In contrast, low, moderate, and high suitability habitats each occupied smaller areas, ranging between 190.85 km² and 554.12 km².

**Table 13: Area (km²) and proportion (%) of land occupied by each habitat suitability category for African elephants' preferred forage plants under different future climate change scenarios**

| | | **Habitat suitability category** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Unsuitable** | | **Low** | | **Moderate** | | **High** | | **Total** | |
| **Scenario** | **Period** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** |
| Current | 1970–2000 | 3451.05 | 73.42 | 306.10 | 6.51 | 508.02 | 10.81 | 435.18 | 9.26 | 4700.36 | 100.00 |
| SSP245 | 2041–2060 | **3406.79** | **72.48** | **357.74** | **7.61** | 519.09 | 11.04 | 416.74 | 8.87 | 4700.36 | 100.00 |
| SSP245 | 2081–2100 | **3320.12** | **70.11** | **406.60** | **8.65** | 537.53 | 11.44 | 436.11 | 9.27 | 4700.36 | 100.00 |
| SSP585 | 2041–2060 | **3517.43** | **74.83** | **190.85** | **4.06** | 554.12 | 11.79 | 437.95 | 9.32 | 4700.36 | 100.00 |
| SSP585 | 2081–2100 | **3568.14** | **75.91** | **193.62** | **4.12** | 508.94 | 10.83 | 429.65 | 9.14 | 4700.36 | 100.00 |

## 4.3 Key Environmental Determinants of the Current and Projected Distribution and Abundance of Suitable Habitats for African Elephants and their Preferred Forage Plants.

### 4.3.1 Percentage Contribution and Permutation Importance

The relative importance of environmental variables used in the MaxEnt model to predict suitable habitats for African elephants, expressed as percentage contribution and permutation importance, is summarized in Table 14. Precipitation of the Coldest Quarter (bio_19) was the most influential variable, with the highest percentage contribution (62.5%) and permutation importance (53.3%). Land Use/Land Cover (LULC) was the second most important, contributing 14.6% by percentage and less than 10% by permutation. Combined, bio_19 and LULC accounted for 77.1% of the model's predictive contribution. All remaining variables individually contributed less than 10%, highlighting the dominant role of a few key predictors in shaping habitat suitability.

**Table 14: Predictor environmental variables and their contributions to the MaxEnt model for African elephants**

| **Predictor Variable** | **Percentage contribution (%)** | **Cumulative contribution (%)** | **Permutation importance (%)** |
|---|---|---|---|
| Precipitation of the Coldest Quarter (bio_19) | **62.5*** | 62.5 | **53.3*** |
| Land use/land cover (LULC) | **14.6*** | 77.1 | 4.4 |
| Euclidean distance to waterbodies (waterbodies) | 6.2 | 83.3 | 6.2 |
| Mean Diurnal Range (bio_2) | 5.2 | 88.5 | 0 |
| Temperature Seasonality (bio_4) | 4.0 | 92.5 | **18.1*** |
| Normalized Difference Vegetation Index (NDVI) | 2.6 | 95.1 | 1.8 |
| Aspect | 2.3 | 97.4 | 5.7 |
| Euclidean distance to roads (roads) | 1.5 | 98.9 | 0.6 |
| Isothermality (bio_3) | 0.8 | 99.7 | 8.0 |
| Elevation | 0.1 | 99.8 | 1.8 |
| Precipitation Seasonality (bio_15) | 0.1 | 99.9 | 0.1 |
| Slope | 0.1 | 100 | 0 |

The relative importance of environmental predictor variables used to model the current suitable habitats for African elephants’ preferred forage plants, based on the MaxEnt model, is presented in Table 15. The percentage contribution of variables ranged from 1.4% to 34.6%, with Precipitation Seasonality (bio_15) contributing the most (34.6%), followed by Precipitation of the Driest Quarter (bio_17) at 26.7%, Elevation at 19.7%, and LULC at 10.0%. Collectively, these four variables accounted for approximately 91% of the total model contribution.

Aspect exhibited the lowest contribution at 1.4%. A similar trend was observed in permutation importance, where bio_15 and Elevation were the most influential variables (33.4% and 25.9%, respectively), while Aspect remained the least important (1.4%).

**Table 15: Predictor environmental variables and their contributions to the MaxEnt model for African elephants' preferred forage plants**

| Predictor Variable | Percentage contribution (%) | Cumulative contribution (%) | Permutation importance (%) |
|---|---|---|---|
| Precipitation Seasonality (bio_15) | **34.6*** | 34.6 | **33.4*** |
| Precipitation of Driest Quarter (bio_17) | **26.7*** | 61.3 | 7.5 |
| Elevation | **19.7*** | 81 | **25.9*** |
| Land use/land cover (LULC) | **10.0*** | 91 | 3.9 |
| Normalized Difference Vegetation Index (NDVI) | 3.2 | 94.2 | 6.2 |
| Euclidean distance to waterbodies | 2.6 | 96.8 | 3.7 |
| Precipitation of the Wettest Quarter (bio_18) | 1.8 | 98.6 | 1.8 |
| Aspect | 1.4 | 100 | 1.4 |

### 4.3.2 Jackknife Analysis of Regularized Training Gain for African Elephants and their Preferred Forage Plants

The Jackknife analysis of regularized training gain for environmental variables used in the MaxEnt model to predict current suitable habitats for African elephants is presented in Figure 20. The regularized training gain using all variables was approximately 1.1 (red bar), serving as a baseline for comparison. When used individually (blue bars), Precipitation of the Coldest Quarter (bio_19) yielded the highest gain (~0.73), followed by Mean Diurnal Range (bio_2) at ~0.45, while other variables, individually contributed less than 0.3. Omitting bio_19 from the model (green bar) reduced the gain to ~0.92, more than the exclusion of any other variable.

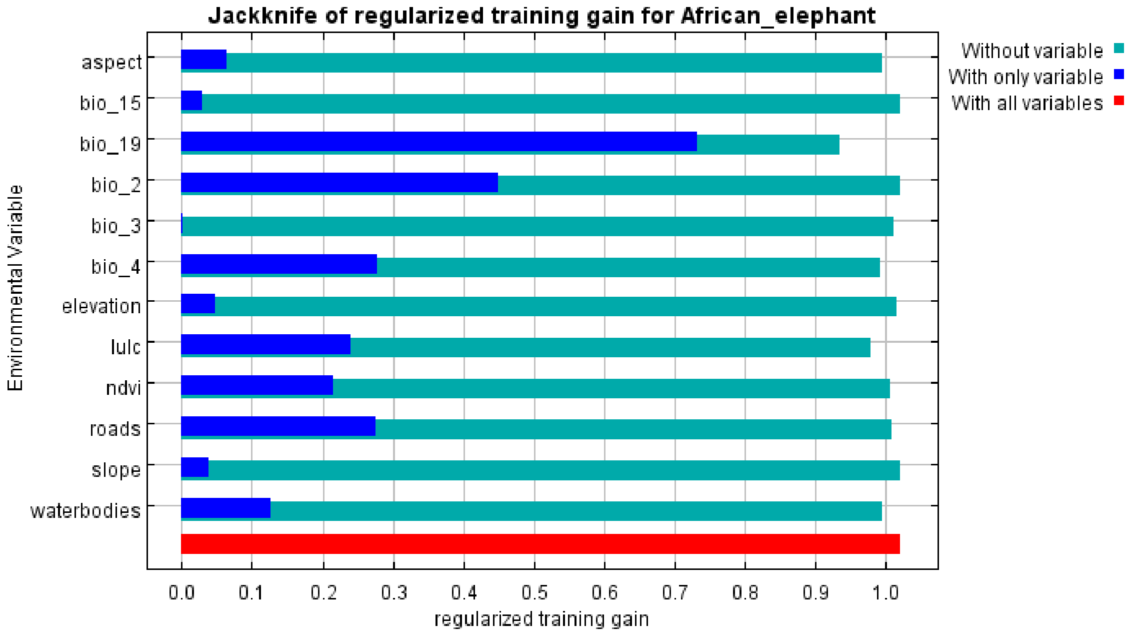


**Figure 20: Jackknife analysis of regularized training gain for African elephants**

The Jackknife test results of regularized training gain for environmental variables used in the MaxEnt model to predict current suitable habitats for African elephants' preferred forage plants are presented in Figure 21. The training gain with all variables was ~0.85. When used individually, Precipitation Seasonality (bio_15) produced the highest gain (~0.47), indicating it was the most informative variable. Elevation had the lowest individual gain (~0.0), but its omission reduced the overall gain to ~0.61, suggesting it provided unique information not captured by other variables, and was therefore also an important predictor.

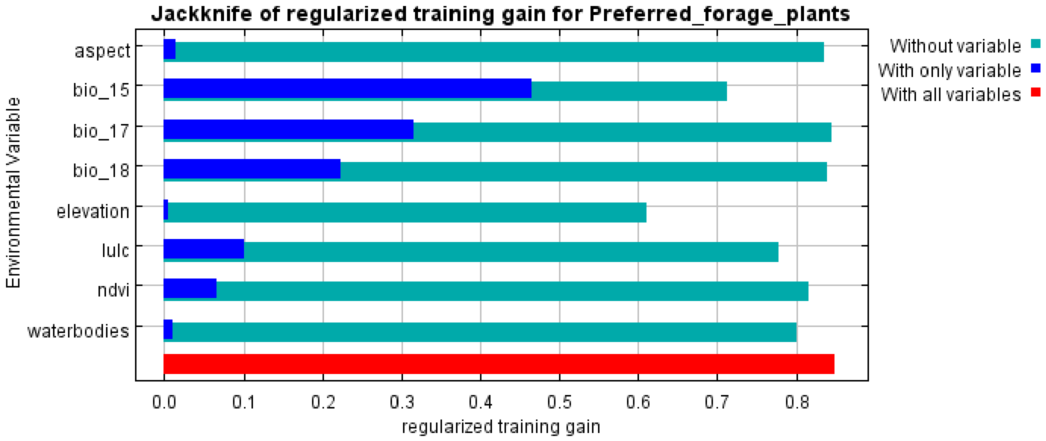


**Figure 21: Jackknife test of regularized training gain for African elephants' preferred forage plants.**

### 4.3.3 Jackknife Analysis of Test Gain for African Elephants and their Preferred Forage Plants

The results of the Jackknife analysis of regularized test gain for environmental variables used in the MaxEnt model to predict suitable habitats for African elephants are presented in Figure 22. The analysis compared the test gain using all variables (1.09; red bar), with each variable individually (blue bars), and with each variable omitted (green bars). When used in isolation, Precipitation of the Coldest Quarter (bio_19) yielded the highest test gain (~0.70), followed by Mean Diurnal Range (bio_2) at 0.48. All other variables contributed less than 0.30. Excluding bio_19 reduced the test gain to approximately 0.99, more than the exclusion of any other variable.

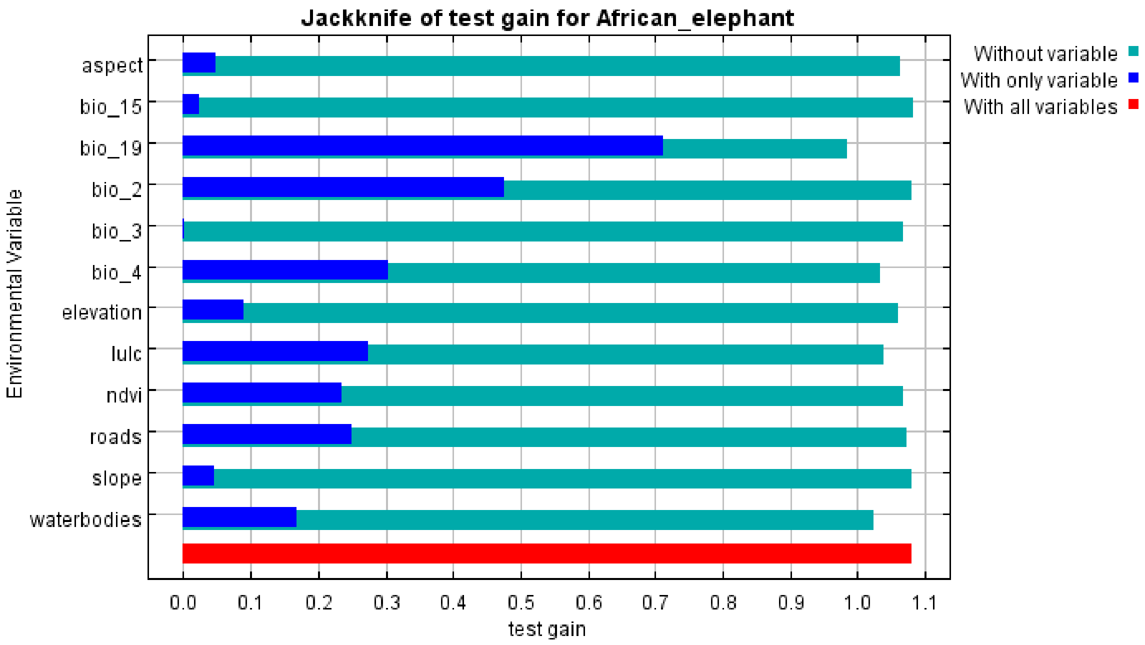


**Figure 22: Jackknife analysis of test gain for African elephants**

The Jackknife test results of regularized test gain for environmental variables used in the MaxEnt model to predict habitat suitability for African elephants’ preferred forage plants are presented in Figure 23. The test gain with all variables was ~0.89. When used individually, Precipitation Seasonality (bio_15) had the highest gain (~0.42), indicating it was the most informative predictor. In contrast, Aspect, Elevation, and Distance to Waterbodies contributed the least, with gains near 0.0. Omitting Elevation from the model reduced the test gain to ~0.53, suggesting it contained unique information essential for accurate habitat prediction.

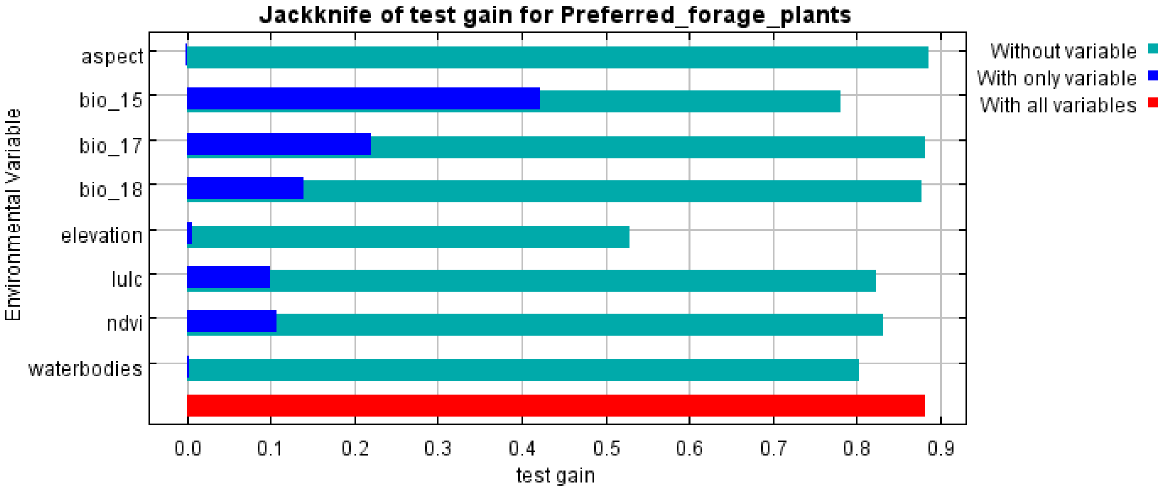


**Figure 23: Jackknife test of test gain for African elephants preferred forage plants**

### 4.3.4 Jackknife Analysis of AUC Test for African Elephants and their Preferred Forage Plants

The Jackknife analysis of the AUC test for environmental variables used in the MaxEnt model to predict suitable habitats for African elephants is presented in Figure 24. The analysis included three tests: using all variables (AUC = 0.87; red bar), using each variable in isolation (blue bars), and excluding each variable individually (green bars). When used alone, Precipitation of the Coldest Quarter (bio_19) produced the highest AUC (~0.80), followed by Mean Diurnal Range (bio_2) at ~0.77, indicating bio_19 was the most informative predictor. In contrast, excluding Euclidean distance to waterbodies reduced the AUC to ~0.85, suggesting this variable contributed unique spatial information not captured by others, thus underscoring its importance in predicting suitable elephant habitats.

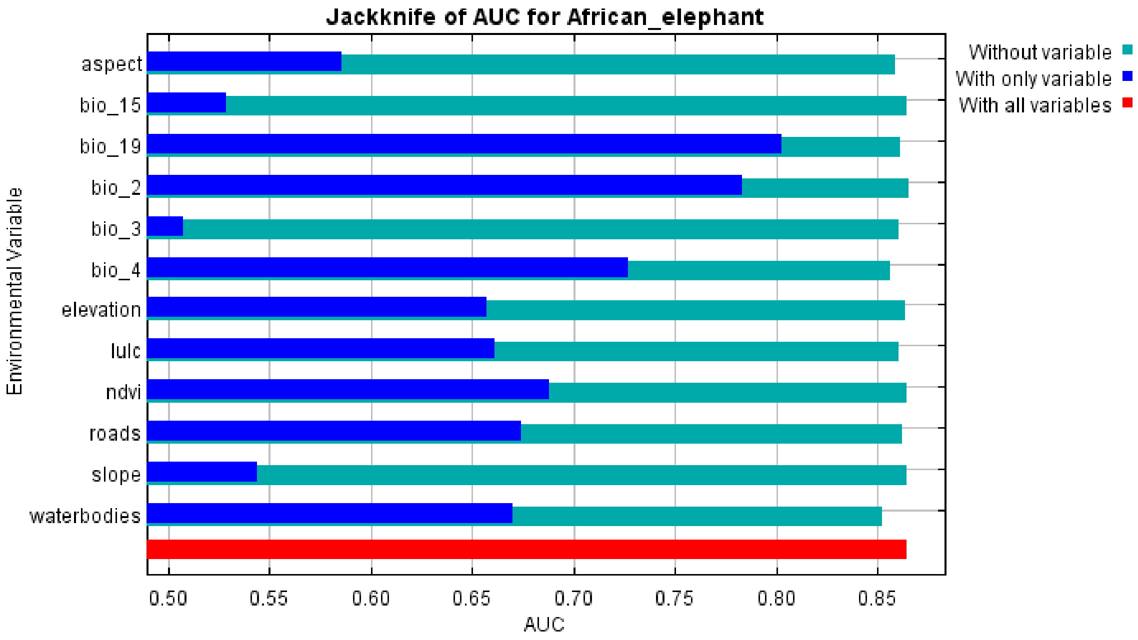


**Figure 24: Jackknife analysis of the AUC test for African elephants**

The Jackknife test of AUC results for environmental variables used to model habitat suitability for African elephants' preferred forage plants is shown in Figure 25. The AUC with all variables was ~0.87. When used alone, Precipitation Seasonality (bio_15) produced the highest AUC (~0.76), indicating bio_15 was the most informative variable. Excluding Elevation from the model reduced the AUC to ~0.85, suggesting it provided unique information not shared with other predictors, making it a key variable in habitat suitability prediction.

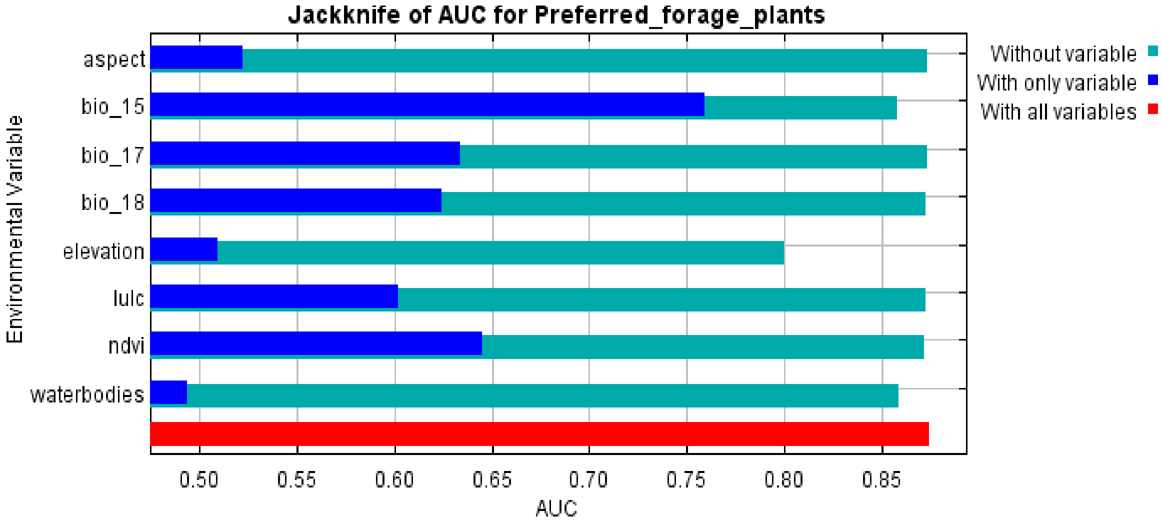
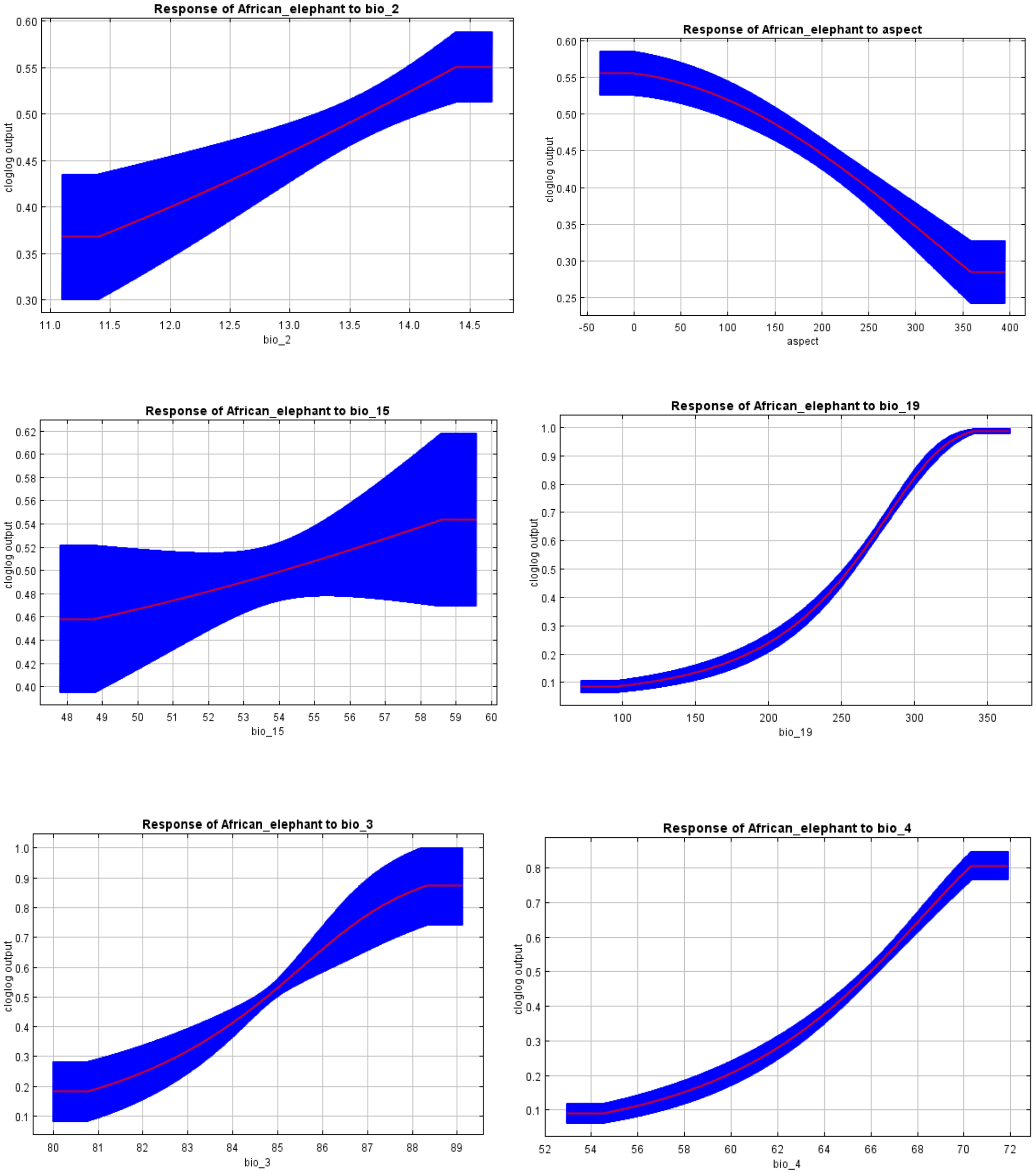


**Figure 25: Jackknife test of AUC for African elephants' preferred forage plants**

### 4.3.5 MaxEnt Marginal Response Curves for the Selected Predictor Environmental Variables

MaxEnt marginal response curves showing the probability of suitable habitat for African elephants with selected environmental predictor variables, based on cloglog output averaged over 10 MaxEnt runs, are presented in Figure 26. The probability varied with each variable, with Precipitation of the Coldest Quarter (bio_19), the most influential predictor, exhibiting a sigmoidal response. Habitat suitability increased with bio_19, peaking at approximately 350 mm, after which further increases did not enhance suitability.

Suitability also varied across LULC types, with the highest probabilities observed in woodland (0.85), followed by built-up areas and shrubland (both 0.64), waterbodies and agricultural areas (both 0.62), while bareland showed a moderate suitability probability of 0.40.



Response of African_elephant to bio_2

Response of African_elephant to aspect

Response of African_elephant to bio_15

Response of African_elephant to bio_19

Response of African_elephant to bio_3

Response of African_elephant to bio_4

**Figure 26: MaxEnt marginal response curves for the selected predictor environmental variables for African Elephants**

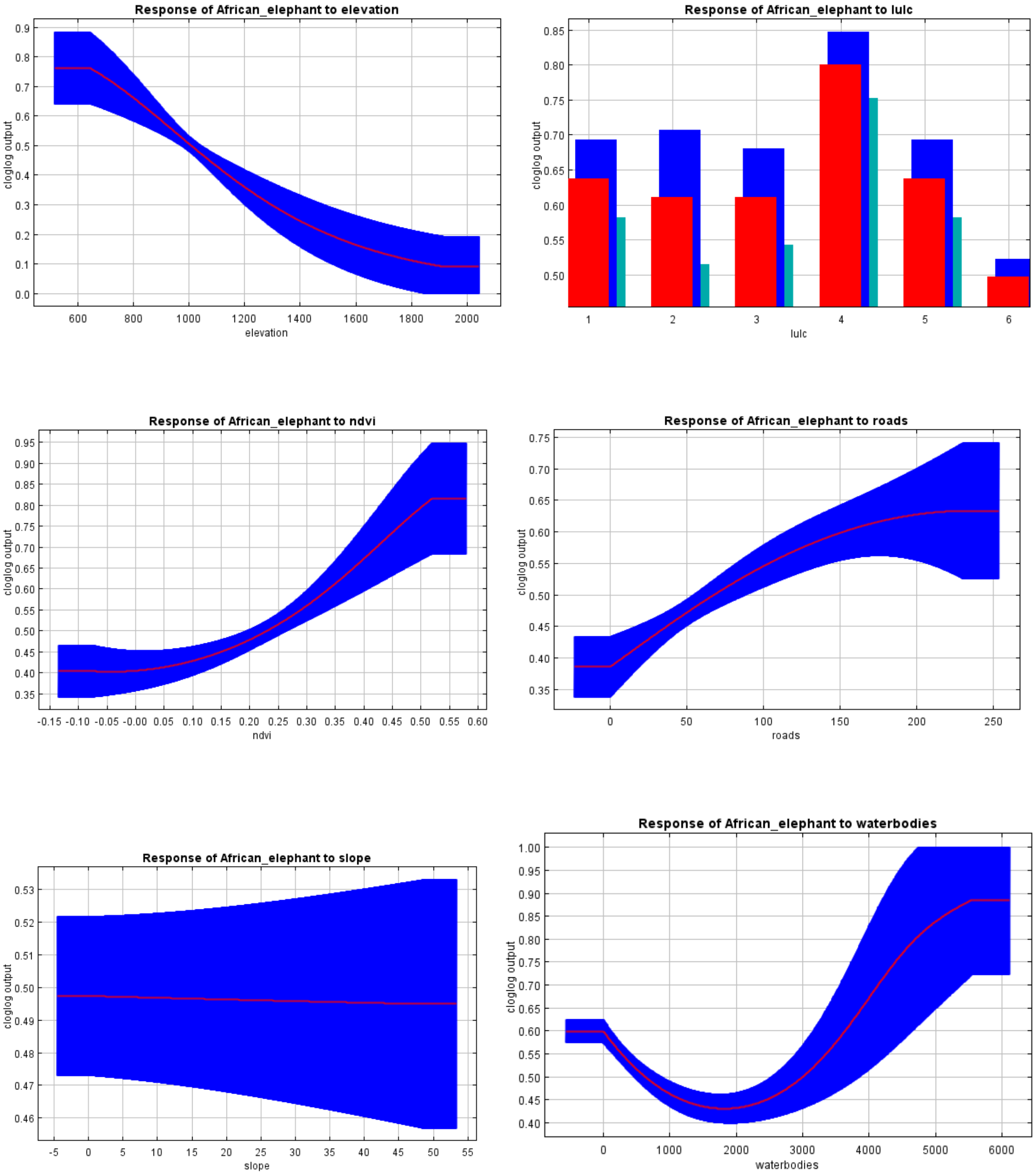


**Figure 26: MaxEnt marginal response curves for the selected predictor environmental variables for African elephants (Continued)**

NB: LULC categories: Built-up Area (1), Waterbody (2), Agriculture (3), Woodland (4), Shrubland (5), and Bareland (6).

MaxEnt marginal response curves showing the probability of suitable habitats for African elephants' preferred forage plants in relation to selected environmental variables, using the cloglog output averaged over ten runs, are presented in Figure 27. The probability declined with increasing Precipitation Seasonality (bio_15), the most important predictor, reaching zero around a value of 58. Similarly, suitability decreased with Elevation, with the highest probability between 600–1,000 m a.s.l., declining up to 1,400 m a.s.l and stabilizing thereafter. In contrast, Precipitation of the Driest Quarter (bio_17) showed a sigmoidal increase in suitability as values rose. Habitat suitability also varied by LULC type, with highest probabilities in shrubland (0.85), built-up areas (0.70), and bareland (0.65), while waterbodies, agricultural land, and woodland showed moderate probabilities (~0.43).

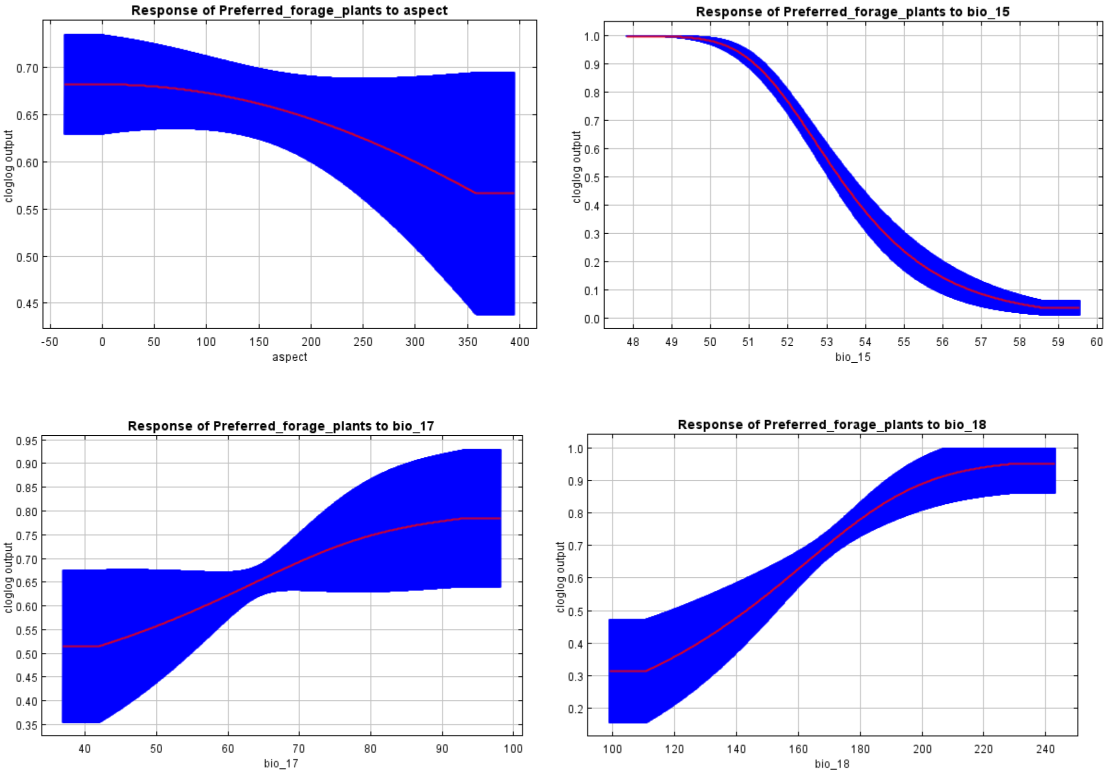


**Figure 27: MaxEnt marginal response curves for the preselected predictor environmental variables for African Elephants' preferred forage plants.**

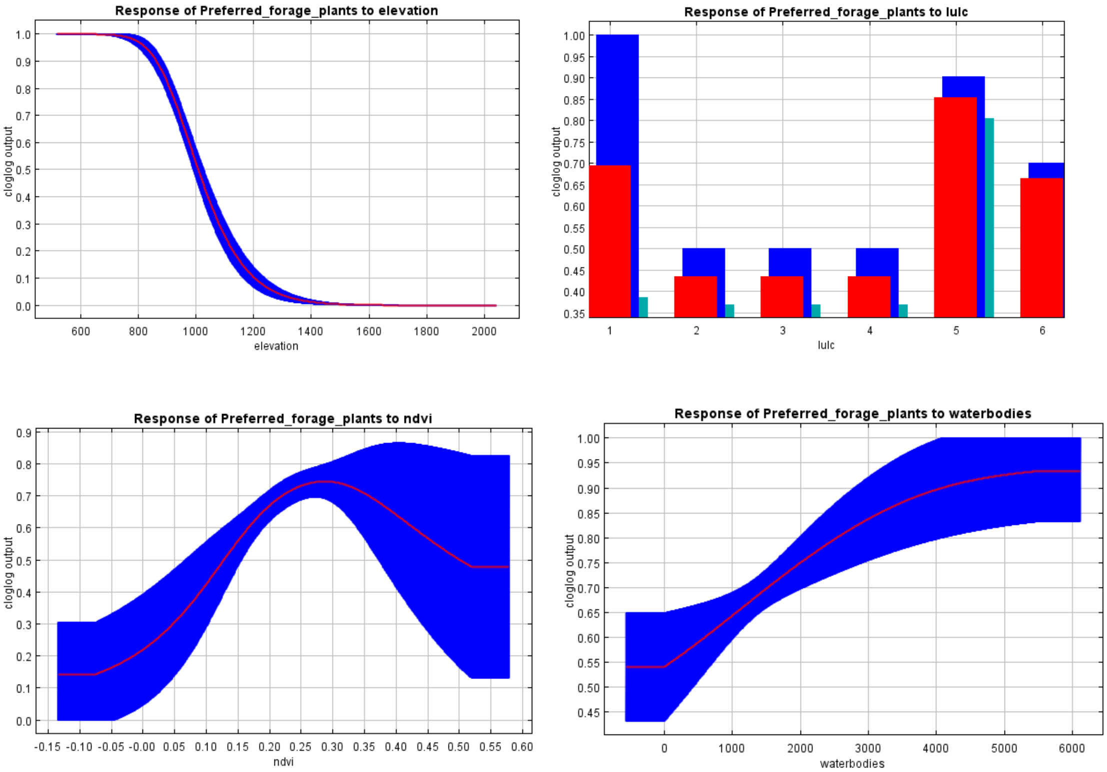


**Figure 27: MaxEnt marginal response curves for the preselected predictor environmental variables for African Elephants' preferred forage plants (Continued).**

NB: LULC categories: Built-up Area (1), Waterbody (2), Agriculture (3), Woodland (4), Shrubland (5), and Bareland (6).

## 4.4 Potential Impacts of Climate Change on Habitat Suitability for African Elephants and their Preferred Forage Plants under (SSP245 and SSP585) across Future Time Horizons (2041–2060 and 2081–2100).

The projected changes in area (km²) and proportion (%) of suitable habitats for African elephants under future climate scenarios are presented in Table 16. The results reveal significant shifts, particularly in unsuitable and low-suitability habitats, with unsuitable habitats increasing by 64.34% to 73.76% and low suitable habitats decreasing by 60.29% to 68.21%.

**Table 16: Area (km²) and proportion (%) of change in potential future suitable habitats for African elephants under climate change scenarios**

| | | **Suitability category** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Unsuitable** | | **Low** | | **Moderate** | | **High** | |
| **Scenario** | **Period** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** |
| Current | 1995–2000 | 1918.68 | 40.82 | 1931.59 | 41.10 | 440.37 | 9.37 | 409.37 | 8.71 |
| SSP245 | 2041–2060 | **1234.56** | **64.34** | **-1164.49** | **60.29** | -236.61 | 53.73 | 166.88 | 40.77 |
| SSP245 | 2081–2100 | **1415.27** | **73.76** | **-1317.54** | **68.21** | -230.21 | 52.28 | 132.75 | 32.43 |
| SSP585 | 2041–2060 | **1384.85** | **72.18** | **-1292.61** | **66.92** | -219.09 | 49.75 | 127.24 | 31.08 |
| SSP585 | 2081–2100 | **1276.97** | **66.55** | **-747.74** | **61.29** | -213.07 | 51.64 | 134.61 | 32.88 |

The area (km²) and percentage (%) changes in habitat suitability categories for African elephants’ preferred forage plants under SSP245 and SSP585 future climate scenarios for the periods 2041–2060 and 2081–2100, compared to the current scenario, are shown in Table 17. The results reveal significant shifts, particularly in low suitability habitats, which showed the largest changes, ranging from a decrease of 115.25 km² (−37.65%) to an increase of 100.50 km² (32.83%) depending on the scenario. In contrast, changes in unsuitable, moderately suitable, and highly suitable habitats were relatively minor, with area changes ranging between 0.92 km² (0.18%) and 130.92 km² (−3.79%).

**Table 17: Area (km²) and proportion (%) of changes in the abundance of potential future suitable habitats for African elephants' preferred forage plants under climate change scenarios**

| | | Habitat suitability category | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Unsuitable | | Low | | Moderate | | High | |
| **Scenario** | **Period** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** | **km$^2$** | **%** |
| Current | 1970–2000 | 3451.05 | 74.42 | 306.10 | 6.51 | 508.02 | 10.80 | 435.18 | 9.26 |
| SSP245 | 2041–2060 | -44.27 | 1.28 | 51.63 | 16.87 | 11.03 | 2.17 | -18.44 | 4.24 |
| SSP245 | 2081–2100 | -130.92 | 3.79 | 100.50 | 32.83 | 29.50 | 5.81 | 0.92 | 0.21 |
| SSP585 | 2041–2060 | 66.38 | 1.92 | -115.25 | 37.65 | 46.10 | 9.07 | 2.77 | 0.64 |
| SSP585 | 2081–2100 | 117.09 | 3.39 | -112.48 | 36.72 | 0.92 | 0.18 | -5.53 | 1.27 |

# CHAPTER FIVE

# DISCUSSIONS

## 5.1 MaxEnt Model Performance and Validation for Prediction of Potential Suitable Habitats for African Elephants and Their Preferred Forage Plants

The high AUC values obtained during model validation, 0.868 ± 0.006 for African elephants and 0.883 ± 0.007 for their preferred forage plants, indicate strong model performance and reliable predictive accuracy. These results suggest that the MaxEnt models effectively captured the environmental factors that influenced habitat suitability, with values well above random prediction (AUC = 0.5).

The strong performance of the models is attributed to the use of spatially filtered, independent occurrence data and the selection of uncorrelated, high-contribution environmental variables. Variables were filtered through pairwise correlation analysis and importance testing to remove redundancy and optimize model efficiency. For both models, the MaxEnt algorithm was fine-tuned using a Linear-Quadratic (LQ) feature combination with regularization multipliers of 3.5 for elephants and 1 for forage plants, enhancing predictive accuracy while minimizing overfitting.

These model performances for the African elephants is consistent with similar elephant habitat modeling studies across Asia and Africa. For elephants, He *et al.* (2023) and Yang *et al.* (2022) reported high predictive accuracy in China, while Budhathoki *et al.* (2023) demonstrated reliable results in Nepal under both current and future scenarios. Similarly, Htet *et al.* (2021) and Jeza & Bekele (*2023*) documented moderate to strong seasonal performance in Myanmar and Ethiopia, respectively, and Akala *et al.* (2023) showed reliable seasonal predictions in Nigeria.

Similar findings for African elephants' preferred forage plants have been reported in other species distribution modeling studies. Bio *et al.* (2024) predicted habitat suitability for *V. tortilis* in eastern Niger with high model performance. Nkosi (2024) achieved strong accuracy in mapping suitable habitats for *V. tortilis* and *V. stuhlmannii* in South Africa, and Kuswanda *et al.* (2023) successfully modeled 152 forage plant species in Indonesia's Datuk Gedang Wildlife Corridor.

## 5.2 Spatial Distribution and Abundance of Potential Current and Future Suitable Habitats for African Elephants and their Preferred Forage Plants within the Nasalot–South Turkana–Kerio Valley ecosystem.

Under current conditions, habitat suitability for African elephants varied across the study area, with low-suitability habitats dominating the landscape, and were primarily concentrated in the central transitional region. In contrast, highly suitable habitats occupied a smaller area and proportion of the landscape, with their distribution largely restricted to the southern region, particularly within Rimoi and Kamnarok National Reserves.

This result suggests that, under current conditions, the majority of the study area offers only marginally suitable environments for African elephants, with optimal habitats being limited in both extent and location. The concentration of low-suitability habitats in the central transitional region may indicate suboptimal conditions due to factors such as limited precipitation during the coldest quarter or LULC, which were identified as key drivers of habitat suitability for African elephants in the study.

The confinement of highly suitable habitats to the southern region, particularly within protected areas like Rimoi and Kamnarok National Reserves, highlights the critical role these reserves play in providing refuge for African elephants in the ecosystem. It also implies that outside these protected zones, the broader landscape may lack the necessary ecological conditions, such as adequate water, forage, or low human disturbance to support elephants effectively. This spatial disparity could influence elephant movement patterns, increase pressure on limited high-quality habitats, and raise concerns about habitat connectivity and long-term population viability.

The spatial distribution pattern of potential current suitable habitats for African elephants observed in this study is consistent with findings from previous research. He *et al.* (2022) found that suitable habitats in China's Sipsongpanna Prefecture were unevenly distributed, linked to high precipitation and the intact forest cover. Similarly, Yang *et al.* (2022) reported variation across South and Southeast China, driven by land use change, elevation, and climate. In Nepal, Budhathoki *et al.* (2023) attributed habitat differences to land cover, topography, and water proximity, while Htet *et al.* (2021) observed similar patterns in Myanmar influenced by slope, elevation, and forest density.

The result on the abundance of potential current suitable habitats aligns with previous research showing that suitable habitats for elephants typically occupy a small portion of the landscape, while large areas are classified as low suitability or unsuitable (Budhathoki *et al*., 2023; Chen *et al*., 2023). Similar patterns have been reported in Nepal, China, India, and various parts of Africa, where anthropogenic pressures and environmental factors have significantly influenced habitat quality (Dejene *et al*., 2021; He *et al*., 2022; Palei *et al*., 2024). Studies in Ethiopia and Nigeria have also highlighted seasonal variation in habitat suitability, with optimal areas remaining limited (Akala *et al*., 2023; Jeza & Bekele, 2023). Collectively, these findings underscore the widespread scarcity of high-quality elephant habitats across diverse regions

Habitat suitability for African elephants' preferred forage plants varied across the study area under current conditions, with unsuitable habitats dominating the study area, and mostly distributed in the central and northern regions. However, low suitable habitats were the least dominant and were distributed as fragments in the southern, northeastern, and northwestern regions.

The result could imply spatial heterogeneity in habitat suitability of African elephants preferred forage plants, likely due to impacts of various environmental factors on their potential habitats, particularly, environmental variables that were reported as key in influencing habitat suitability of African elephants' preferred forage plants such as Precipitation Seasonality (bio_15), Precipitation of the Driest Quarter (bio_17), LULC and elevation, which could make various parts of the study area to differ widely in their ability to support growth and development of African elephant preferred forage plants.

The pattern of widespread habitat unsuitability observed in this study is consistent with findings from previous research conducted in similar semi-arid and arid landscapes, where habitat suitability for key forage species is often spatially limited and fragmented. Mechergui *et al.* (2021) reported that *V. tortilis* in Tunisia is confined to specific arid zones such as Bled Talah, where dry-season precipitation plays a dominant role in defining suitable habitats. Likewise, Bio *et al.* (2024) found that suitable habitats for *V. tortilis* in eastern Niger are largely restricted to the Sahelo-Saharan and Sahelian zones, with unsuitable areas dominating the broader landscape due to climatic limitations. In South Africa, Nkosi (2024) observed that *V. tortilis* occupies only localized areas within the Venetia-Limpopo Nature Reserve, where distribution is strongly influenced by specific soil types, further reflecting the narrow environmental requirements of this species.

Similarly, for *S. mellifera*, Bravo-García *et al.* (2024) noted that although the species is broadly distributed in southern Africa, highly suitable habitats occur in isolated pockets where temperature and precipitation align closely with the species' physiological needs. For *B. aegyptiaca*, studies by Seid *et al.* (2024) and Gufi *et al.* (2023) in Ethiopia revealed a fragmented distribution pattern, particularly in dryland areas, which is shaped by topographic complexity and land degradation. Chérif *et al.* (2022) also reported that in Chad, high and moderate suitability zones for *B. aegyptiaca* are concentrated in regions with favorable rainfall regimes and shorter dry seasons. In Kenya, Oluoch *et al.* (2024) documented a highly constrained distribution of suitable habitats for *B. aegyptiaca* and other wild forage species in Turkana County, underlining the severity of environmental limitations in arid northern Kenya.

In contrast to these arid and semi-arid contexts, Kuswanda *et al.* (2023) reported a markedly different pattern in the Datuk Gedang Wildlife Corridor in Indonesia, where most of the landscape was found suitable for Asian elephant forage plant species. This difference is likely driven by the region's more humid climate, higher rainfall, and relatively undisturbed environmental conditions.

Future climate projections under SSP245 and SSP585 (2041–2060 and 2081–2100) indicate a substantial decline in suitable habitats for African elephants, with a clear shift toward unsuitability, particularly in the northern zones of the study area, including areas of South Turkana and Nasalot National Reserves. Areas currently considered moderately suitable are projected to become the least abundant and widely distributed in the southern region, between zones of high and low habitat suitability.

The results suggest projected spatial heterogeneity in habitat suitability for African elephants in the future, likely driven by future climate change impacts, particularly changes in Precipitation of the Coldest Quarter (bio_19) and land use/land cover, which were identified as key environmental variables. This spatial variation may lead to differing capacities across the landscape to meet the ecological and biological needs of elephants (Akala *et al*., 2023; Jeza & Bekele, 2023; Makati *et al*., 2025; Owen-Smith & Chafota, 2009; Western, 1975). The result also suggests that climate change will cause habitat contraction and range shifts for African elephants, reducing access to key resources and increasing competition in remaining areas. As northern habitats become unsuitable, elephants may shift southward, but fragmentation could restrict movement and disrupt their keystone role in maintaining ecosystem balance. Overall, these changes indicate intensified ecological pressure and rising HECs.

Projections of future climate change show a consistent trend of declining habitat suitability for elephants across both Africa and Asia. In Africa, researchers such as Dejene *et al.* (2021) and Mpakairi *et al.* (2019) report significant loss of suitable habitats due to climate impacts. Similarly, Asian elephant habitats are expected to shrink substantially under future climate and land use scenarios. Research by Abir *et al.* (2025), Budhathoki *et al.* (2023), Kanagaraj *et al.* (2019), and Yang *et al.* (2022) projects widespread reductions across South and Southeast Asia, including key strongholds like India, Nepal, and Tropical Asia.

Under the SSP245 and SSP585 climate scenarios for the period 2041–2060 and 2081–2100, the spatial distribution of African elephants' preferred forage plants is projected to vary across the study area. Unsuitable habitats are projected to dominate in the central and northern parts of the study area, while low suitable habitats are the least dominant in the southern, northeastern, and northwestern regions.

These results suggest that under SSP245 and SSP585 scenarios for the period 2041–2060 and 2081–2100, habitats of African elephants' preferred forage plants will likely become increasingly spatially heterogeneous due to effects of climate change, which is expected to alter local environmental conditions, leading to varied habitat suitability across the landscape.

This aligns with growing research by Bravo-García *et al.* (2024), Bio *et al.* (2024), Gufi *et al.* (2023), Mechergui *et al.* (2021), Oluoch *et al.* (2024), and Seid *et al.* (2024), showing that climate change will reshape the distribution of dryland woody species in arid and semi-arid regions. Depending on species-specific tolerances to heat, precipitation variability, and soil conditions, some species are projected to expand their ranges, while others may experience contraction or complete habitat loss. For example, *V. tortilis* is projected to undergo significant habitat expansion under future climate scenarios (Bio *et al.*, 2024; Mechergui *et al.*, 2021). In Tunisia, Mechergui *et al.* (2021) reported an increasing trend in the extent of highly suitable habitats under both moderate and high emission scenarios, accompanied by a directional shift toward the east and northeast. Similarly, Bio *et al.*

(2024) projected a notable increase in the suitable habitat area for *V. tortilis* in Eastern Niger under future climate conditions, emphasizing the species’ resilience in arid and warming environments.

For *S. mellifera*, Bravo-García *et al.* (2024) projected a 29.4% increase in suitable habitat under SSP585 for 2061–2080, and an 8% gain under SSP245 for 2024–2060 in southern Africa. The species is expected to expand across central and southern Africa, favored by rising wet-season temperatures and adequate moisture, similar to other woody encroachers like *Terminalia sericea*.

In contrast, projections for *B. aegyptiaca* are mixed. In Ethiopia, Seid *et al.* (2024) forecasted modest but stable expansion in central and northern areas. Gufi *et al.* (2023) predicted a 65% increase in suitable habitat in Tigray under RCP4.5 by 2070, but complete habitat loss under RCP8.5. Similarly, Oluoch *et al.* (2024) reported total loss of suitable habitat in Turkana County, Kenya, under all scenarios, including the low-emission SSP126, highlighting the species' vulnerability to extreme climatic conditions.

### 5.3 Key Environmental Determinants of the Potential Current and Projected Spatial Distribution and Abundance of Suitable Habitats for African Elephants and their Preferred Forage Plants.

The 12 preselected, non-correlated environmental variables contributed to the MaxEnt model, though to varying degrees. Precipitation of the Coldest Quarter (bio_19) and LULC were the most influential environmental variables.

The observed variations in the importance of the predictor environmental variables in the MaxEnt model reflect the diverse physiological and ecological requirements of African elephants, such as high water intake, substantial forage demand, sensitivity to temperature extremes, avoidance of human disturbance, and a preference for habitats with high precipitation, diverse vegetation types, dense vegetation cover, proximity to permanent water sources, and gentle elevation and slope (Chen *et al*., 2023; Chibeya *et al*., 2021; Gaynor *et al*., 2018; Loarie *et al*., 2009; Makati *et al*., 2025; Mlambo *et al*., 2024; Mpakairi *et al*., 2019; Owen-Smith, 1988; Owen-Smith & Chafota, 2009; Schlossberg *et al*., 2018; Western, 1975; Yang *et al*., 2022).

The significance of Precipitation of the Coldest Quarter (bio_19) in this study aligns with findings by Yang *et al.* (2022), who identified it as a key predictor of elephant habitat suitability in Asia. This is further supported by studies from Africa demonstrating that precipitation strongly influences elephant habitat selection, migration behavior, and home range size (Bohrer *et al*., 2014; Benítez *et al*., 2022; Williams *et al.*, 2018).

The importance of LULC in this study is consistent with findings from other regions, where vegetation structure, fragmentation, and anthropogenic land-use patterns significantly influence elephant distribution. In Zimbabwe, Mpakairi *et al.* (2019) found LULC to be a key predictor of habitat suitability, while in Kenya, Ngene *et al.* (2009) highlighted the role of shrubland and forest in supporting elephant presence. In China, Chen *et al.* (2023) identified forest fragmentation as the most influential factor. Seasonal variations in LULC importance, as reported by Jeza & Bekele (2023) in Ethiopia, further demonstrate elephants' adaptive habitat use. Similar trends were noted by Budhathoki *et al.* (2023) in

Nepal and Yang *et al.* (2022) in Asia, where LULC influence was stronger under anthropogenic pressure.

Marginal response curves indicated that habitat suitability increased with higher values of Precipitation of the Coldest Quarter (bio_19), with an optimal range of 250–350 mm. This underscores the importance of seasonal water availability in sustaining browse species during the coldest, driest months, suggesting that elephants preferentially occupy areas with higher Precipitation of the Coldest Quarter (bio_19) while avoiding low-precipitation regions during this critical period. The observed variation highlights precipitation as a key determinant of elephant habitat suitability, influencing both forage and water availability (Akala *et al.*, 2023; Bohrer *et al.*, 2014). Consequently, conservation efforts should focus on areas with moderate to high precipitation during the coldest quarter, which provide essential water and forage resources that sustain elephants through dry months and enhance long-term habitat suitability.

This finding aligns with the known habitat preferences of African elephants, which tend to favor areas with higher precipitation, dense and diverse vegetation, and reliable water sources (Akala *et al.*, 2023; Bohrer *et al.*, 2014; Loarie *et al.*, 2009). For instance, Bohrer *et al.* (2014) reported that in Marsabit, Kenya, elephants occupied lower elevations during periods of high precipitation due to increased vegetation activity, but retreated to higher-elevation evergreen forests during the dry season. Similarly, in Omo Forest Reserve, areas with dense vegetation, often driven by higher rainfall, were more frequently utilized by forest elephants (Akala *et al.*, 2023). Loarie *et al.* (2009) also observed that elephants preferred areas with dense vegetation during the wet season, reflecting increased forage and water availability.

The optimum range of Precipitation of the Coldest Quarter (bio_19) in this study (250–350 mm) is considerably lower than that reported in other regions. Yang *et al.* (2023) found the highest probability of species occurrence at around 1000 mm of bio_19 in South and Southeast Asia, where this variable ranges from 0 to 6000 mm. In contrast, the present study area in Kenya's ASALs recorded much lower values (96–341 mm), highlighting regional climatic differences that likely influence elephant habitat preferences.

The response curve for LULC indicated that the probability of African elephant presence varied notably across different LULC categories. High probabilities of presence were observed in areas classified as waterbodies, woodlands, agriculture, built-up areas, and shrubland. In contrast, bareland exhibited a lower probability of presence, suggesting moderate habitat suitability. These results suggest that African elephants exhibit a preference for habitats associated with higher vegetation cover, water availability, and even human-modified landscapes such as agricultural and built-up areas, possibly due to the availability of forage or water resources. Conversely, the lower suitability in bareland areas may reflect limited forage or cover, reducing their attractiveness to elephants.

African elephants are known to exhibit flexible habitat use and may utilize areas with either dense or sparse vegetation for foraging, depending on the availability of critical resources such as water and forage (Loarie *et al.*, 2009; Wall *et al.*, 2013). The high preference exhibited by African elephants for woodlands and shrublands may be attributed to the availability of essential ecological resources, including food, water, and cover, which can provide cooler microclimates and protection from human disturbance (Blake *et al.*, 2008; Loarie *et al.*, 2009).

These findings are consistent with previous research indicating that African elephants prefer natural habitats such as forested areas, woodlands, shrublands, and grasslands, which offer a combination of forage, cover, and space for movement. In the Amboseli ecosystem, elephants exhibited a strong preference for bushland and woodland habitats due to their superior patchiness and heterogeneity (Okello *et al.,* 2015). In the arid Namib Desert, elephants preferred habitats dominated by shrublands containing key forage species, such as *Colophospermum mopane*, *Tamarix usneoides*, and *Combretum imberbe*, which met their dietary needs (Viljoen, 1989).

Across southern Africa, GPS tracking and aerial surveys revealed that elephants utilize large tracts of savanna, forest edges, and grasslands, with selection influenced by resource availability (Chase *et al.*, 2016). Seasonal variation in habitat use has also been documented; for example, in southern Africa, elephants shifted preference to woodlands, shrublands, and grasslands during the wet season when fresh vegetation was more abundant and movement was easier (Loarie *et al.*, 2009).

Bareland in the study area formed part of the African elephant migratory corridor and was characterized by sparse vegetation, particularly grasses and herbs, which are often important forage resources for elephants, especially during the wet season (Geleta & Mengesha, 2022; Koirala *et al.*, 2016). The moderate probability of elephant presence in this land cover type may be attributed to the species' ecological adaptability to utilize diverse habitats, including those with sparse vegetation (de Boer *et al.*, 2000; Loarie *et al.*, 2009; Schmitt *et al.*, 2024; Wall *et al.*, 2013). Additionally, the availability of alternative resources within this land cover, such as specific food types, and its role as a migratory corridor connecting woodlands, shrublands, and waterbodies, may further support its seasonal use by elephants.

The moderate probability of African elephant presence in bareland aligns with findings from previous studies, which have reported that elephants often utilize areas of sparse vegetation for foraging, particularly during the wet season when such areas offer abundant forage and water resources (de Boer *et al.*, 2000; Loarie *et al.*, 2009; Wall *et al.*, 2013). For instance, in southern Africa's arid savannas, elephants frequently visited sparsely vegetated areas, especially those near permanent water sources (de Beer & Van Aarde, 2008). In Kruger National Park, South Africa, elephants were observed using sparsely vegetated areas during the dry months, as these often support key foraging opportunities (Grainger *et al.*, 2005). Similarly, Loarie *et al.* (2009) noted frequent elephant use of sparsely vegetated open savannahs in Kruger National Park, particularly in areas with nearby water. In the Gourma region of Mali, elephants utilized sparsely vegetated transition zones during long-distance movements, with proximity to water sources being a key factor influencing their movement, especially during the dry season (Wall *et al.*, 2013).

The high probability of suitable habitat presence in areas with anthropogenic activities, such as built-up and agricultural areas, could be attributed to the movement of African elephants along their traditional migratory routes, which have been disrupted by human developments. These routes now intersect with infrastructure such as roads, farmlands, and human settlements, including villages, hospitals, and schools, leading to increased instances of human-elephant interactions and conflict in the study area (Togoch, 2018).

However, the high probability of suitable habitats in agricultural areas could also be attributed to the availability of preferred, nutritious, high-calorie, and palatable crops such as maize, millet, and green grams (Graham *et al.*, 2009; Koskey, 2013; Sitati *et al.*, 2005), as well as the overlap between agricultural lands and African elephant ranges (Hoare & Du Toit, 1999). This overlap may be influenced by resource scarcity, particularly during the dry season and in fragmentation habitats (Chiyo *et al.*, 2005). The results may also suggest shared resource use between humans and African elephants, which can increase the likelihood of resource-use conflict (Blake *et al.*, 2008; Graham *et al.*, 2009; Hoare & Du Toit, 1999; Sitati *et al.*, 2005).

The observed high probability of African elephant presence in built-up and agricultural areas is further supported by findings from other regions where elephants have been reported to utilize human-modified landscapes. In southwest Zimbabwe, elephants showed moderate to high preference for agricultural zones during the dry season due to natural forage scarcity (Hoare & Du Toit, 1999). Similar patterns were observed in Gorongosa National Park, Mozambique, where elephants used agricultural areas for food and water and roads as corridors (Gaynor *et al.*, 2018), and in the Sebungwe Region, Zimbabwe, where they were frequently seen near riverside agricultural fields during the dry season (Mpakairi *et al.*, 2019).

In southeast Angola, Schlossberg *et al.* (2018) documented elephant preferences for areas near human settlements. Similarly, in Nigeria’s Omo Forest Reserve, Akala *et al.* (2023) reported frequent elephant movements through agricultural areas. Studies by Chiyo *et al.* (2005) in Kibale National Park, Uganda, have shown that elephants utilize agricultural lands during the dry season, particularly in relation to nearby water sources and protected areas. In Marsabit, Kenya, Ngene *et al.* (2009) highlighted the proximity of elephants to human settlements and infrastructure. Williams (2018) also found that elephants in the Kasigau Wildlife Corridor, southeastern Kenya, often occurred near agricultural areas.

Furthermore, the raiding of agricultural fields by African elephants has been shown to correlate with the high suitability of such areas for elephant use. For example, Sitati *et al.* (2005) found that African elephants were attracted to crops in agricultural areas due to their higher nutritional value compared to native vegetation, particularly during the dry season. In the Laikipia region of Kenya, elephants raided farms located near protected areas, where high-calorie crops were readily available. Elephants demonstrated a marked preference for crops such as maize, which provided more nutrition than natural forage during periods of resource scarcity (Graham *et al.*, 2009).

This result contrasts with previous studies showing that African elephants tend to avoid areas with high human activity and presence. For example, in the Sebungwe Region of Zimbabwe, elephants avoided settlements and agricultural fields during the wet season (Mpakairi *et al.*, 2019). Similar avoidance behavior was reported in the Okavango Panhandle, Botswana, where elephants avoided pathways near settlements and cultivated land, often adopting a safety-in-numbers strategy when moving through human-dominated areas (Songhurst *et al.*, 2015). In southeast Angola, satellite-collared elephants showed avoidance of areas associated with human presence (Schlossberg *et al.*, 2018). Mortimer *et al.* (2021) also observed that elephants moved away from locations where human-generated seismic vibrations (white noise) were introduced. These findings suggest that elephants in the study area may eventually alter their habitat use patterns in response to increasing human activity.

The high probability of suitable habitats for African elephants in areas classified as waterbodies could be attributed to their strong dependence on water and forage resources for survival (Akala *et al.*, 2023; Owen-Smith & Chafota, 2012; Jeza & Bekele, 2023; Makati *et al.*, 2025; Western, 1975) and their known preference for habitats near water sources (Akala *et al.*, 2023). For instance, in the Omo Forest Reserve, Nigeria, elephants frequently moved towards riverine areas, indicating a strong preference for habitats near water (Akala *et al.*, 2023). In Hwange National Park, Zimbabwe, elephants congregated in areas with a high density of artificial waterholes, which were unevenly distributed across the park (Chamaillé-Jammes *et al.*, 2007). Similarly, in the Eastern Okavango Panhandle, Botswana, elephants moved closer to permanent water bodies, such as the Okavango River, particularly during the dry season (Makati *et al.*, 2025).

In Omo National Park, Ethiopia, elephants exhibited a consistent preference for areas near rivers throughout the year, with this preference intensifying during the dry season due to increased reliance on permanent water sources (Jeza & Bekele, 2023). Muposhi *et al.* (2016) also reported a high probability of elephant presence near artificial water points, with decreasing probability as the distance from these points increased. In Tsavo East National Park, Kenya, Ngatia (2014) observed that approximately 66.6% of elephants remained within 1 km of water sources during the dry season, with their numbers declining at greater distances. In the Marsabit protected area, Kenya, Ngene *et al.* (2009) found that elephants were commonly located near permanent water points during the dry season and near seasonal rivers during the wet season.

The MaxEnt model results showed that all eight preselected, non-correlated environmental variables contributed to habitat suitability predictions of African elephants' preferred forage plants, though to varying degrees. Precipitation Seasonality (bio_15) was the most influential, followed by Precipitation of the Driest Quarter (bio_17), Elevation, and LULC. The result could suggest that much of the variations among the environmental variables in predicting suitable habitats of African elephant preferred forage plants in the MaxEnt model could be explained by the four most important variables: Precipitation of Seasonality (bio_15), Precipitation of the Driest Quarter (bio_17), elevation, and LULC.

Several previous studies support the findings of this research by emphasizing the importance of climatic and biophysical variables in determining the habitat suitability of plants. Mechergui *et al.* (2021) and Nkosi (2024) both identified Precipitation of the Driest Quarter (bio_17) as the most influential predictor for *V. tortilis* and *V. stuhlmannii* in Tunisia and South Africa, respectively. Bravo-García *et al.* (2024) found temperature-related variables, particularly Mean Temperature of the Wettest Quarter (bio_8), Annual Mean Temperature (bio_1), and Annual Precipitation (bio_12), to be key for *S. mellifera* in southern Africa.

Bio *et al.* (2024) reported Annual Precipitation and Maximum Temperature of the Hottest Period as primary drivers of *V. tortilis* distribution in eastern Niger. For *Balanites aegyptiaca*, Chérif *et al.* (2022) and Habou *et al.* (2021) highlighted precipitation-related factors, including the Wettest Month, Coldest Quarter, and Dry Season duration, as important predictors in Chad and Niger.

In Ethiopia, Seid *et al.* (2024) and Gufi *et al.* (2023) found that temperature and precipitation seasonality strongly influence the distribution of *B. aegyptiaca* in drylands, with Gufi *et al.* (2023) emphasizing the importance of temperature variability. In Indonesia, Kuswanda *et al.* (2023) identified land cover, elevation, slope, and proximity to water as key predictors of habitat suitability for elephant forage plants in more humid landscapes.

The response curve for Precipitation Seasonality (bio_15) showed a unimodal trend, with habitat suitability peaking at moderate levels of precipitation variability and declining at both lower and higher extremes. Specifically, the marginal response curves indicated a higher probability of suitable habitats for African elephants' preferred forage plants in areas with moderate precipitation seasonality, typically between 49% and 53%. However, suitability declined as precipitation seasonality increased beyond this range.

This result suggests that African elephants' preferred forage plants are adapted to environments with moderate fluctuations in monthly rainfall. The importance of Precipitation Seasonality (bio_15) as a key climatic filter indicates that these species thrive where water availability is neither too sparse nor highly erratic, emphasizing the conservation value of such regions under current and future climate scenarios.

This level of seasonality reflects environments with a distinct wet season and a manageable dry period, which support key plant life stages such as germination, seedling establishment, and growth (Botha, 2006; D'Onofrio *et al.*, 2014; Gignoux *et al.*, 1997; Keya, 1997; Larson *et al.*, 2015; Staver *et al.*, 2011; Wilson & Witkowski, 1998). Plant species often thrive under such conditions by synchronizing their biological cycles with seasonal moisture availability, while avoiding stress associated with highly erratic or overly uniform rainfall patterns (Dahlin *et al.*, 2017; Falkenmark & Rockström, 2008; Patrick *et al.*, 2009; Proud & Rasmussen, 2011; Rodríguez-Iturbe *et al.*, 2001; Schwinning & Kelly, 2013; Zeppel *et al.*, 2014).

This finding aligns with studies from other landscapes where precipitation seasonality strongly influences plant distribution. For example, modeling by Mechergui *et al.* (2021) in Tunisia identified Precipitation Seasonality (bio_15) as the key predictor of *V. tortilis* subsp. *raddiana* distribution, with habitat suitability peaking at intermediate to high levels of rainfall seasonality, indicating the species' preference for environments with distinct wet and dry seasons.

Studies by Seid *et al.* (2024) and Gufi *et al.* (2023) underscore the importance of Precipitation Seasonality (bio_15) in shaping the habitat suitability of *Balanites aegyptiaca* in Ethiopia. Seid *et al.* (2024) reported increased suitability under moderate to high rainfall seasonality in the Central Rift Valley, reflecting the species’ adaptation to distinct wet and dry seasons. Similarly, Gufi *et al.*2023 observed a positive response to Precipitation Seasonality (bio_15) in Tigray’s drylands, with suitability rising at intermediate to high seasonality levels. These findings highlight seasonal rainfall variability as a key driver of *B. aegyptiaca* distribution under current climate conditions.

The marginal response curve for Precipitation of the Driest Quarter (bio_17) showed moderate habitat suitability at 40–50 mm, with suitability increasing up to 60 mm. This trend indicates that African elephants’ preferred forage plants are sensitive to dry-season moisture thresholds. Below 40 mm, conditions may be too arid to support essential physiological functions such as growth, water retention, and root maintenance. As bio_17 values increase, conditions become more favorable, supporting plant persistence. While these species are drought-tolerant, they still require a minimum moisture level to maintain metabolic activity. This underscores the role of dry-season precipitation as a key limiting factor in determining forage plant distribution in arid and semi-arid ecosystems.

This result aligns with findings from other studies on forage species. For example, *V. tortilis* subsp. *raddiana* distribution in Tunisia was primarily influenced by the Precipitation of the Driest Quarter (bio_17), highlighting its adaptation to prolonged dry spells (Mechergui *et al.*, 2021). Similarly, Nkosi (2023) identified bio_17 as the most significant variable for *V. tortilis* in semi-arid savannas, contributing the highest model gain (65.3%). In East Asia, research on *Cyclobalanopsis gilva* also demonstrated the importance of bio_17, which accounted for 16.9% of the model’s explanatory power (Liu *et al.*, 2024).

The influence of the two precipitation variables on habitat suitability for African elephants’ preferred forage plants is largely due to their impact on soil moisture dynamics. In arid and semi-arid ecosystems, precipitation directly affects soil water availability, which in turn influences plant physiology, survival, and distribution. Rodríguez-Iturbe *et al.* (2001) showed that irregular rainfall drives fluctuations in soil moisture, shaping plant water uptake strategies. Porporato *et al.* (2003), studying the Kalahari, found that soil moisture closely follows rainfall patterns, with drier areas showing rapid depletion and heightened plant stress. Patrick *et al*. (2009) observed that desert plant performance is closely tied to precipitation variability through its effects on soil moisture and nitrogen cycling. Zeppel *et al.* (2014) reported that seasonal and extreme rainfall changes alter soil moisture profiles, affecting plant water relations and productivity. Similarly, Falkenmark and Rockström (2008) emphasized that in Sub-Saharan savannas, rainfall patterns critically influence soil water storage and root-zone moisture availability.

In the study, elevation played a limiting role in the ecological niche of African elephants' preferred forage plants. Habitat suitability was highest between 600 and 1000 m a.s.l., declined up to 1400 m, and plateaued beyond this level. This suggests that the studied forage species are adapted to moderately elevated zones, likely due to optimal temperature, moisture, and soil conditions that support germination, growth, and survival (Downing *et al.,* 2024; Rita *et al.*, 2021). The importance of elevation in this study may be attributed to its role in moderating microclimatic conditions such as temperature, humidity, and moisture, which influence the habitat suitability of African elephants' preferred forage plants. Elevation significantly shapes these microclimates, affecting species persistence and distribution. For instance, Downing *et al.* (2024) found that in the alpine zone of Mount Kenya, elevation was the main driver of near-surface temperature variation, with a lapse rate of 0.5 °C per 100 m. Lower elevations experienced wider diurnal temperature ranges up to 14 °C at 3,400 m compared to 6 °C at 4,200 m with occasional extremes exceeding 25 °C. Thermal buffering was most pronounced above 4,200 m, where ground cover and microtopography mitigated temperature extremes.

Similarly, Rita *et al.* (2021) reported that in Mediterranean beech treelines, topography and aspect shaped microclimates, providing thermal refugia beneath forest canopies. Below-canopy temperatures were up to 2.4 °C cooler on south-facing slopes and 1.0 °C cooler on northwest-facing slopes compared to open areas. Canopy buffering reduced temperatures by an average of 2.5 °C, with stronger cooling effects on hotter days, sometimes exceeding 8.6 °C. These findings support the role of elevation in creating favorable microhabitats that enhance forage plant survival and distribution.

The elevation range reported in this study (0–2000 m a.s.l.) aligns with the natural niches of the studied species (Beentje,1994; Bhardwaj *et al*., 2024; Coppock, 1994; Hall & Walker, 1991; Jaouadi *et al*., 2013; Oluoch *et al*., 2024; Orwa *et al*., 2009; Skerman, 1982).

Also, these findings align with field studies highlighting the role of elevation in shaping plant species richness and diversity in savannas, where both generally decline with increasing elevation (He *et al*., 2024; Wang *et al*., 2024). Environmental factors such as temperature, soil properties, and land-use intensity further interact with elevation to influence vegetation patterns (He *et al*., 2024; Wang *et al*., 2024). In valley-type savannas, herbaceous species tend to dominate at lower elevations, while shrubs are more prevalent at higher elevations (He *et al*., 2024).

Habitat suitability for African elephants' preferred forage plants varied notably across LULC categories. Shrubland, built-up areas, and bareland showed the highest suitability, while waterbodies, agricultural land, and woodland had moderate suitability. These results suggest that open or disturbed landscapes may provide more favorable conditions for forage plant presence than more vegetated or cultivated areas.

The high suitability of shrubland and bareland, along with the moderate suitability of woodland, likely reflects the adaptability of African elephants' preferred forage plants to diverse habitats. These species thrive in open or disturbed areas where factors such as ample sunlight, low canopy cover, and frequent disturbances like grazing or trampling create favorable conditions for growth and regeneration (D'Odorico *et al.*, 2013; Schultka & Cornelius, 1997; Vetaas, 1992).

This result aligns with previous studies showing that many forage plant species have broad ecological tolerances, allowing them to thrive in diverse habitats. *Vachellia tortilis*, for example, is known to establish in dry bushlands, bushed grasslands, riverine areas, woody grasslands, and arid scrublands (Maundu & Tengnäs, 2005). Likewise, *B. aegyptiaca* occurs across a wide range of environments, including savanna woodlands, bushlands, thickets, riverine zones, and desert vegetation along wadis and seasonal watercourses (Beentje, 1994; Hall & Walker, 1991; Orwa *et al*., 2009; Sagna *et al*., 2014). *Ziziphus mucronata* also displays strong ecological flexibility, commonly found on lower slopes, streambanks, and riparian areas, as well as in open woodlands, bushlands, and disturbed savanna grasslands where reduced competition facilitates its establishment (Orwa *et al*., 2009).

The findings for shrubland are supported by research in the Datuk Gedang Wildlife Corridor in Indonesia, where shrubland, along with secondary forests and certain plantation areas, was identified as a key land cover type that significantly enhanced overall forage availability for Sumatran elephants (Kuswanda *et al*., 2023). Similarly, in northern Kenya, Schultka and Cornelius (1997) reported that shrublands dominate heavily grazed rangelands, primarily consisting of drought- and grazing-tolerant species such as *Acacia reficiens*, *A. brevispica*, and *Commiphora* spp.

Built-up areas showed unexpectedly high suitability for African elephant preferred forage plants, challenging the typical assumption that such areas lack ecological value due to human infrastructure. This may be attributed to remnant vegetation patches, protected green spaces like urban parks, or edge habitats where native forage species persist. It could also reflect transitional zones misclassified as fully urban but still supporting natural vegetation.

The findings on built-up areas are consistent with previous studies showing that urban and peri-urban zones can support considerable biodiversity, even within fragmented savanna landscapes. McKinney (2002) noted that urban areas may still harbor native species within remnant habitats, parks, and green spaces. Boon *et al.* (2016) found that peri-urban zones often maintain higher tree and shrub diversity than urban cores, emphasizing their conservation value. Cao *et al.* (2024) recorded 530 vascular plant species in the urban fringe of Jiangdong New District, China, with diversity strongly clustered spatially, indicating that urban edges can retain structured plant communities. In Durban, South Africa, Boon *et al.* (2016) reported that urban savanna fragments supported diverse woody vegetation despite urban encroachment.

In Malawi, Chimaimba *et al.* (2020) documented 168 tree species across six land-use types in Zomba City, with institutional areas showing the highest richness. The study highlighted that diversity patterns were shaped by land-use intensity and human management. In Kenya, Galvin and Ellis (2008) reported that remnant patches in the Athi-Kaputiei plains, despite fragmentation, still support native flora and wildlife. Similarly, Kuria *et al.* (2017) observed that species like *V. tortilis* are commonly integrated into homesteads and croplands, often as part of soil conservation strategies.

Agricultural areas, though mainly used for crop production, often support limited native plant diversity due to intensive cultivation, overgrazing, pesticide use, and habitat fragmentation (Dorrough *et al.*, 2008; Murray *et al.*, 2021; Schmidt *et al.*, 2016; Veldman *et al.*, 2014; Vieira *et al.*, 2021). However, this study found that agricultural lands still offered moderate habitat suitability for African elephant forage plants, likely due to remnant native vegetation and forage species persisting along field margins and uncultivated edges (Nye *et al.*, 2020).

This observation is supported by studies indicating that extensively managed or low-intensity agriculture can sustain native plant diversity. For example, Pellegrini *et al.* (2021) found that low-intensity farming in northeastern Italy limited exotic invasions while maintaining native species richness. Buhk *et al.* (2017) reported that moderate agricultural intensity in Central Europe supported higher beta diversity in structurally complex landscapes, while intensive practices led to community homogenization. Similarly, Liira *et al.* (2025) showed that field margins and grasslands in diverse agricultural systems supported greater forb and legume richness than intensively managed areas, with plant functional composition influenced by land-use history and regional species pools.

These findings are echoed in the study by Kuswanda *et al.* (2023) in the Datuk Gedang Wildlife Corridor, Jambi Province, Indonesia, where various land use types, including secondary forests, plantations, shrublands, and cultivated/open lands, collectively supported high forage plant diversity for elephants. Shrublands, open lands, and plantations contributed significantly through pioneer grasses and shrubs in undergrowth and edge habitats. Notably, 94.5% of the corridor was deemed suitable for elephant forage, underscoring the conservation value of both natural and modified habitats in fragmented landscapes.

Waterbodies generally offer low suitability for terrestrial forage plants due to constant inundation that restricts herbaceous and woody plant growth (Striker, 2012). However, in this study, waterbodies showed moderate suitability for African elephant forage plants, likely reflecting adaptive strategies to fluctuating inundation (Colmer & Voesenek, 2009). Species such as *V. tortilis*, *B. aegyptiaca*, *A. mellifera*, and *Z. mucronata* have been reported near ponds, along wadis, in waterlogged areas, and in depressions with available groundwater and clayey soils (Adebayo & Mosoko, 2019; Britz, 2004; Chothani & Vaghasiya, 2011; Coughenour & Elias, 1993; Maier *et al*., 2006; Maundu & Tengnäs, 2005; Orwa *et al.*, 2009). Their presence along riparian zones in the current study likely accounts for the observed habitat suitability.

The present findings support the broader ecological consensus that riparian zones are critical for conserving native plant diversity in both natural and modified landscapes. These ecotones often serve as biodiversity reservoirs, even under environmental stress and human disturbance. For example, Meave and Kellman (1994) found that riparian forest fragments in Costa Rica’s tropical savannas supported high rainforest plant diversity, with 292 species taller than 0.5 m recorded in just 1.6 hectares.

Similarly, Fousseni *et al.* (2014), in the Sudanian savanna of northern Togo, recorded 61 woody species across 25 families in riparian forests, primarily native to the Sudanian and Sudano-Zambezian regions. Despite pressures from agriculture, fire, grazing, and wood extraction, these riparian systems retained structural complexity and supported high native biodiversity, highlighting their ecological resilience.

In a localized context, Koskey *et al.* (2021) found that riparian zones along Kenya's Njoro and Kamweti Rivers maintained high native species diversity, even adjacent to agricultural and urban areas. Herbaceous species dominated disturbed sites, while forested sections remained rich in indigenous trees and shrubs, with consistently high Shannon diversity indices.

## 5.4 Potential Impacts of Climate Change on Habitat Suitability for African Elephants and their Preferred Forage Plants under Future Climate Scenarios (SSP245 and SSP585) across Future Time Horizons (2041–2060 and 2081–2100).

The results on potential impacts of climate change on habitat suitability for African elephants under SSP245 and SSP585 for the period 2041–2060 and 2081–2100 indicate a substantial decline in the extent of suitable habitats for African elephants, accompanied by a marked expansion of unsuitable habitats.

This result suggests that climate change, under both moderate (SSP245) and high-emission (SSP585) scenarios poses a significant threat to the future habitat availability for African elephants. The substantial decline in suitable habitats implies that key environmental conditions necessary for elephant survival, such as access to water, forage, and favorable temperature and precipitation patterns, are likely to deteriorate or shift beyond the ecological tolerance of the species.

The marked expansion of unsuitable areas indicates that large portions of the current or potential range may become inhospitable, potentially leading to increased habitat fragmentation, restricted movement, and intensified human–elephant conflicts as elephants are forced to move into areas with human activity in search of resources. Overall, this trend signals heightened vulnerability for elephant populations and underscores the urgency for adaptive conservation strategies that incorporate climate projections.

These findings are consistent with projections from previous studies that have reported widespread habitat loss for elephants under future climate scenarios. Dejene *et al.* (2021) projected substantial declines in highly suitable habitats for African elephants across the continent under both RCP4.5 and RCP8.5, accompanied by an increase in unsuitable areas. Similarly, Mpakairi *et al.* (2019) anticipated a considerable reduction in elephant habitat suitability in Zimbabwe’s Hwange National Park as a result of future climate change. Comparable trends have also been observed for Asian elephants. In India and Nepal, Kanagaraj *et al.* (2019) projected substantial losses in suitable habitats under RCP8.5, particularly when land use change was considered alongside climate projections. Budhathoki *et al.* (2023) further reported that in Nepal’s Madhesh Province, suitable habitats for Asian elephants are expected to decline significantly under SSP245 and SSP585 scenarios, with a corresponding increase in marginally suitable and unsuitable areas. Collectively, these studies reinforce the current study's findings, highlighting the widespread impact of climate change on elephant habitat suitability across both African and Asian ranges.

Similarly, future climate scenarios (SSP245 and SSP585) for the periods 2041–2060 and 2081–2100 project substantial shifts in habitat suitability for African elephants' preferred forage plants, with the most significant changes occurring in low suitability areas. Depending on the scenario and time frame, low suitability habitats are projected to either decline by up to 115.25 km² (37.65%) or increase by as much as 100.50 km² (32.83%).

The projected fluctuations in low suitable habitats, underscore their high sensitivity to future climate variability and sensitivity to climate change conditions. This degree of change suggests that such areas may function as transitional zones, with the potential to either deteriorate into unsuitable habitats or improve in quality under certain climate scenarios. Their responsiveness, particularly to changes in key climatic variables such as precipitation and temperature, highlights their potential role in either buffering against broader habitat loss or accelerating fragmentation. As such, low suitability zones may serve as early indicators of habitat transformation and should be prioritized for monitoring and adaptive management under climate change scenarios.

The results of this study align with prior research indicating that future habitat suitability for key savanna species may increase, decrease, or remain stable depending on regional landscape conditions and climate scenarios. *Vachellia tortilis*, for example, is projected to expand its suitable range under climate change. Bio *et al.* (2024) and Mechergui *et al.* (2021) both reported future range expansion for the species in Niger and Tunisia, respectively, with notable spatial shifts toward drier zones. These findings suggest that *V.*

*tortilis* is likely to benefit from warmer, drier future climates. Similarly, *S. mellifera* is expected to experience increasing habitat suitability across climate models. Bravo-García *et al.* (2024) and Chérif *et al.* (2022) indicated expansion of its suitable range under both high- and moderate-emission scenarios, pointing to its resilience in changing environmental conditions.

In contrast, projections for *B. aegyptiaca* show regional variation. Seid *et al.* (2024) reported stable or modest range expansion in Ethiopia under moderate warming. However, Gufi *et al.* (2023) projected habitat loss under more extreme scenarios, and Oluoch *et al.* (2024) found that the species may lose all suitable habitat in parts of northern Kenya, highlighting its sensitivity to increasing climatic extremes.

Projected shifts in forage plant suitability under SSP245 and SSP585 for the periods 2041–2060 and 2081–2100 may influence African elephant abundance, movement patterns, and foraging behavior (Ferry *et al.*, 2021; Wenborn *et al.*, 2025). In northwest Namibia, elephants moved from Etosha National Park into highlands to access preferred forage species like *Sterculia africana* and *Commiphora glaucescens* growing on mountain slopes (Wenborn *et al.*, 2025). In Hwange National Park, Zimbabwe, long-term elephant presence altered woody vegetation structure, reducing taller plants and increasing shorter ones, which in turn affected elephant distribution as they searched for suitable forage (Ferry *et al.*, 2021).

# CHAPTER SIX

# CONCLUSIONS AND RECOMMENDATIONS

## 6.1 Conclusions

In conclusion, African elephants and their preferred forage plants are highly vulnerable to climate change impacts, with current and future habitat suitability exhibiting marked spatial variability. Under current conditions, low-suitability habitats dominate much of the landscape for elephants, particularly in transitional central regions, while highly suitable areas are limited and localized mainly in the south. Similarly, the forage species face widespread unsuitability, especially in central and northern areas. Future projections under SSP245 and SSP585 scenarios indicate a progressive decline in suitable habitats and a shift toward unsuitability, particularly in northern zones, including key protected areas such as Nasalot and South Turkana.

Precipitation of the Coldest Quarter (bio_19) and LULC were the most influential predictors of elephant habitat suitability, jointly accounting for 77.1% of the variation, while Precipitation Seasonality (bio_15). Precipitation of the Driest Quarter (bio_17), elevation, and LULC were the primary drivers of the distribution of African elephant preferred forage plants, collectively accounting for approximately 91% of the model's percentage contribution.

Climate change is projected to significantly alter the habitat landscape for African elephants and their preferred forage plants. Under both SSP245 and SSP585 scenarios for the mid- and late-century periods, suitable habitats for elephants are expected to decline markedly, with a concurrent expansion of unsuitable areas, posing a serious threat to their spatial distribution and long-term survival. Likewise, forage plant suitability is projected to undergo substantial shifts, particularly within low-suitability zones, which may either contract or expand depending on the scenario and time frame.

## 6.2 Recommendation for Conservation and Management of African Elephants and Their Preferred Forage Plants

1. Focus conservation efforts on areas projected to remain or become highly suitable, particularly Rimoi and Kamnarok National Reserves. These core zones are critical for sustaining viable elephant populations and should receive long-term protection and effective management.
2. Establish and maintain ecological corridors and buffer zones around protected areas to facilitate elephant movement and gene flow, especially between fragmented patches. Moderately suitable areas surrounding core habitats offer strategic opportunities for such interventions.
3. Implement climate-resilient restoration initiatives in low-suitability and degraded regions, particularly around Nasalot and South Turkana Reserves, to expand usable habitat and reduce fragmentation.
4. Incorporate key climatic variables such as cold-season precipitation and dry-season rainfall into conservation planning. Prioritize areas with stable seasonal moisture, and adopt adaptive strategies like watershed protection, vegetation restoration, and enhancement of dry-season water sources.

5. Recognize and manage the role of agricultural and built-up areas in supporting elephant movement. Promote elephant-compatible land-use practices, reduce human-elephant conflict, and ensure safe passage through mixed-use landscapes.
6. Protect remaining natural vegetation and regulate development to limit habitat degradation. Sustainable agriculture and controlled land-use practices should be integrated into broader landscape-level conservation strategies.
7. Conservation planning should consider both broad-scale (e.g., land use, precipitation) and fine-scale factors (e.g., proximity to water, vegetation productivity, terrain). Microhabitat features are especially important for designing site-specific interventions such as corridors and watering points.
8. Engage local communities, landowners, and stakeholders in adaptive management practices. Incorporating traditional knowledge and participatory approaches can enhance the effectiveness and sustainability of conservation actions.

## 6.3 Recommendation for Further Research Work

Future research should focus on the following related areas;

1. Long-term monitoring of habitat changes in relation to shifting climate variables, land use, and elephant movement patterns. This would validate model projections and help assess real-time changes in habitat suitability.
2. Incorporating GPS collar tracking data into habitat models could enhance understanding of how elephants actually respond to predicted suitability patterns, including seasonal and long-distance movements across gradients of habitat quality.

3. Since built-up and agricultural areas show moderate suitability, future studies should investigate how these areas contribute to or mitigate human-elephant conflicts, and how land-use change influences elephant behavior.
4. Research at finer spatial resolutions could explore how elephants select microhabitats within broader suitability zones, especially in relation to vegetation structure, forage quality, and water availability.
5. Future studies could model the impact of extreme climate events such as prolonged droughts or heatwaves on habitat suitability and elephant survival, which may not be fully captured by long-term average climate projections.
6. Evaluating the success of habitat restoration efforts and ecological corridors in maintaining connectivity between suitable habitats would be valuable for informing management decisions.
7. Including socioeconomic data such as population growth, agricultural expansion, or infrastructure development in future models could offer a more comprehensive view of future habitat dynamics and conservation risks.
8. Examining how elephant habitat shifts affect and are affected by interactions with other species (e.g., predators, other herbivores) and ecosystem processes (e.g., fire regimes, vegetation dynamics) would deepen ecological insights.
9. Conduct detailed field studies to assess the nutritional quality and seasonal variation of preferred forage plants across different habitat types and elevations to better understand forage availability and elephant dietary needs.

10. Investigate the effects of climate variability and extreme weather events on the growth, regeneration, and phenology of key forage species to predict how changing conditions may influence elephant foraging behavior and habitat use.
11. Utilize GPS tracking and landscape connectivity modeling to study elephant movement patterns in relation to forage distribution under current and future climate scenarios, identifying critical corridors and barriers.
12. Examine how agricultural expansion, settlement growth, and infrastructure development impact forage plant distribution and elephant foraging patterns, with an emphasis on mitigating human-elephant conflicts.
13. Evaluate the effectiveness of habitat restoration interventions, such as reforestation or controlled burns, in enhancing forage availability and quality in degraded or marginal habitats.
14. Develop models combining high-resolution remote sensing data with ground-based vegetation assessments to improve the accuracy of forage plant habitat suitability predictions across spatial and temporal scales.
15. Identify and prioritize core forage habitats critical for elephant survival, considering both ecological factors and socio-economic contexts, to inform targeted conservation actions and protected area management.

By addressing these areas, future research can provide deeper insights and practical tools to support adaptive conservation and sustainable management of African elephants and their forage resources under changing environmental conditions.

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# APPENDICES

## Appendix I: Data sheet for the collection of species occurrence points

| | | |
|---|---|---|
| **Species:** | | |
| **Study area:** | | |
| **Source of data:** | | |
| **Habitat type:** | | |
| **Collectors' name:** | | |
| **Date of collection:** | **Time:** | |
| | | |
| **Species ID** | **Latitude** | **Longitude** |
| | | |
| | | |
| | | |
| | | |

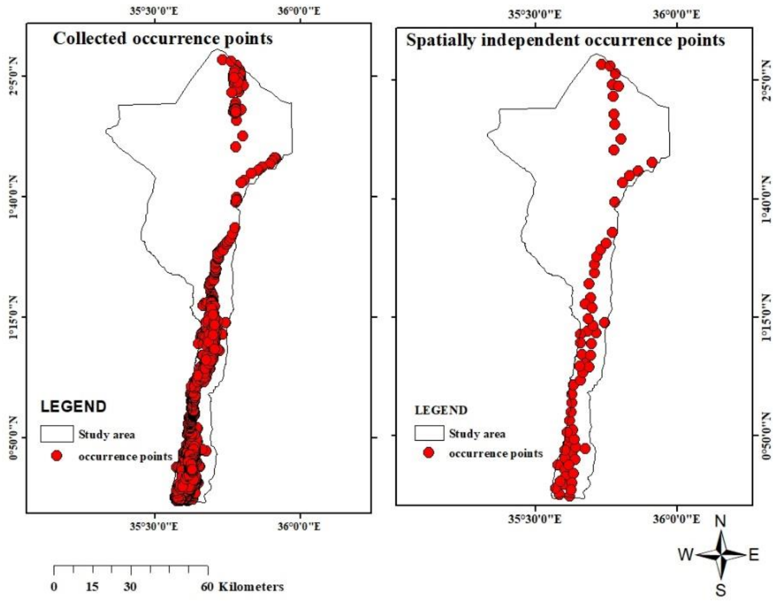
## Appendix II: Records of collected occurrence points for African elephants' preferred forage plants

| **Species** | **Family** | **Number of points** |
|---|---|---|
| *Balanites aegyptiaca (L.) Delile* | Zygophyllaceae | 83 |
| *Vachellia tortilis* (Forssk.) Galasso & Banfi | Fabaceae | 68 |
| *Vachellia mellifera (Vahl) P.J.H. Hurter* | Fabaceae | 51 |
| *Ziziphus mucronata* Willd. | Rhamnaceae | 21 |
| *Vachellia brevispica* (Harms) Kyal. & Boatwr. | Fabaceae | 5 |
| **Total** | - | **228** |

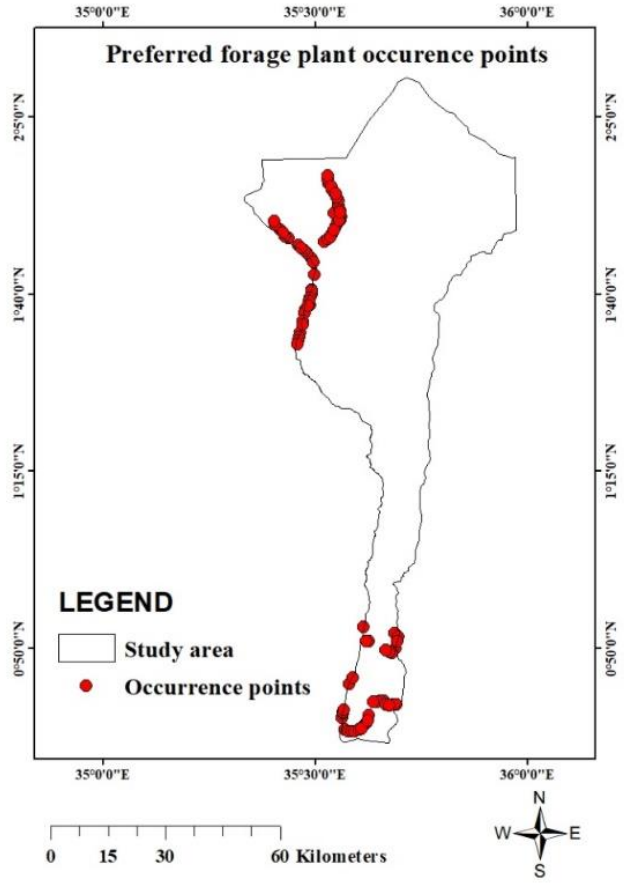
## Appendix III: Spatial filtration and spatial autocorrelation of African elephant occurrence points

| Species | (x, y) tolerance (km) | Number occurrence points (n) | Global Moran's Index | Expected Index | Variance | z-score | p-value |
|---|---|---|---|---|---|---|---|
| African elephant | 0 | 4092 | 0.044 | 0.000 | 0.000 | 17.98 | 0.000 |
| ,, | 0.5 | 2860 | 0.044 | -0.00 | 0.000 | 17.980 | 0.000 |
| ,, | 1.0 | 200 | 0.547 | -0.005 | 0.000 | 18.848 | 0.000 |
| **,,** | **1.5** | **133** | **-0.005** | **-0.015** | **0.004** | **0.14** | **0.889** |
| ,, | 2.0 | 69 | 0.112 | -0.015 | 0.005 | 1.778 | 0.075 |
| ,, | 2.5 | 67 | 0 | 0 | 0 | 0 | 0 |
| ,, | 3.0 | 57 | 0.765 | 0.018 | 0.013 | 6.864 | 0.000 |

## Appendix IV: Spatial distribution pattern of the collected occurrence points and the spatially independent (filtered) occurrence points for African elephants



## Appendix V: Spatial distribution patterns of collected occurrence points for African elephants' preferred forage plants



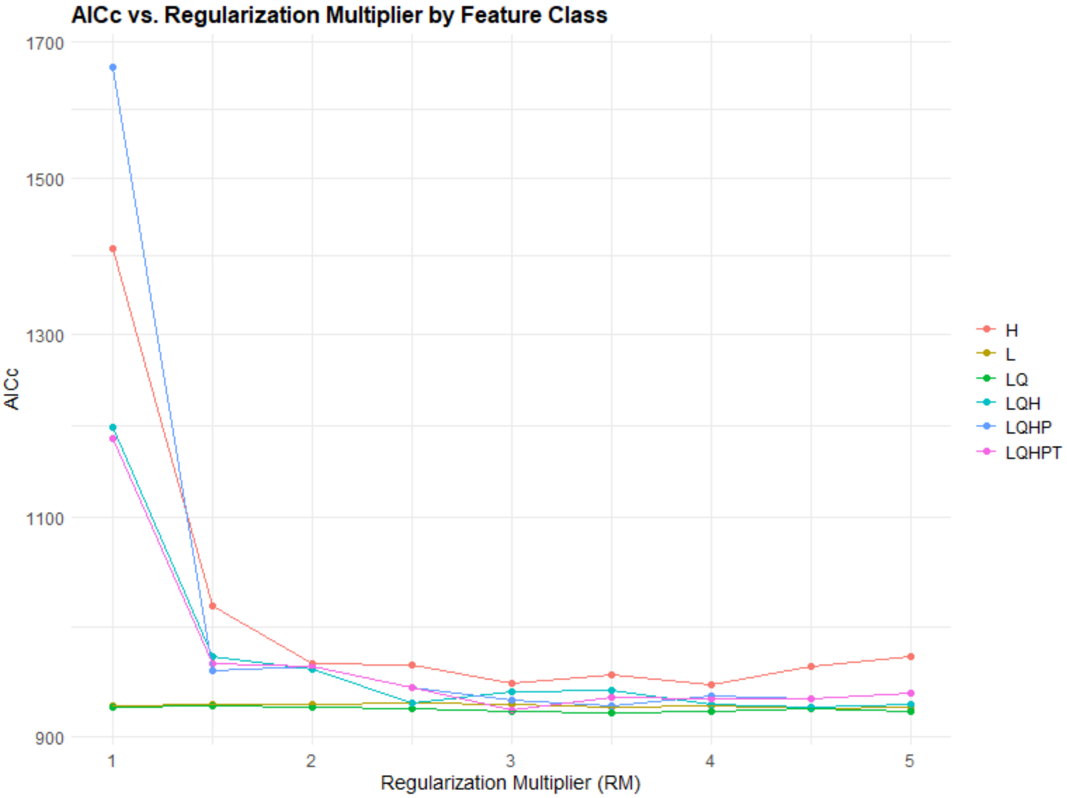
## Appendix VI: Preselected environmental variables for modeling habitat suitability for African elephants

| Predictor variable | Code | Unit |
|---|---|---|
| **Bioclimatic** | | |
| Mean Monthly Diurnal Range | bio_2 | °C |
| Isothermality | bio_3 | index |
| Temperature Seasonality | bio_4 | °C |
| Precipitation Seasonality | bio_15 | mm |
| Precipitation of the Coldest Quarter | bio_19 | mm |
| **Biophysical** | | |
| Elevation | - | meters |
| Slope | - | degrees |
| Aspect | - | degrees |
| Euclidean distance to waterbodies | - | meters |
| **Vegetation** | | |
| Normalized Difference Vegetation Index (NDVI) | - | index |
| **Anthropogenic** | | |
| Land use/land cover | - | categories |
| Euclidean distance to roads | - | meters |

## Appendix VII: Preselected environmental variables for modeling habitat suitability for African elephants' preferred forage plants

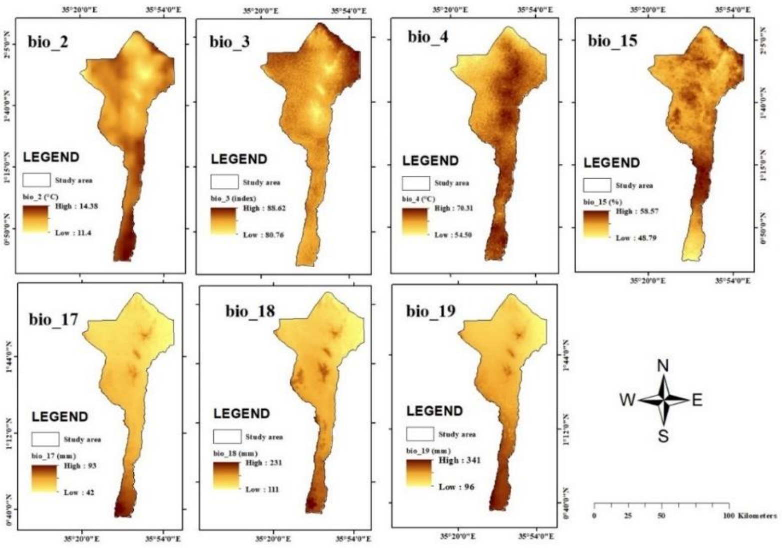
| Environmental variable | Code | Unit |
|---|---|---|
| **Bioclimatic** | | |
| Precipitation Seasonality | bio_15 | % |
| Precipitation of the Driest Quarter | bio_17 | mm |
| Precipitation of the Warmest Quarter | bio_18 | mm |
| **Biophysical** | | |
| Elevation (elevation from sea level) | - | Meters |
| Aspect | | Degrees |
| Euclidean distance to waterbodies | - | Meters |
| **Vegetation** | | |
| Normalized Difference Vegetation Index (NDVI) | - | Index |
| **Anthropogenic** | | |
| Land use/land cover | - | Categories |

## Appendix VIII: Feature combinations and regularization multiplier used to predict potential current and future suitable habitats for African elephants

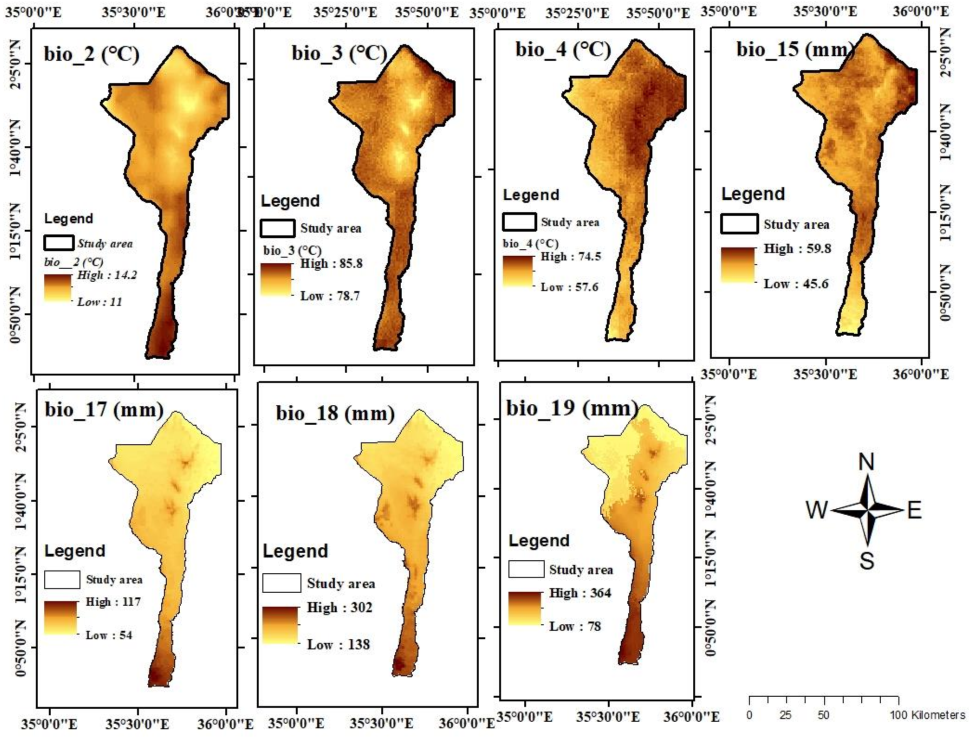


## Appendix IX: Feature combinations and regularization multiplier for predicting the potential current and future suitable habitats of African elephants' preferred forage plants

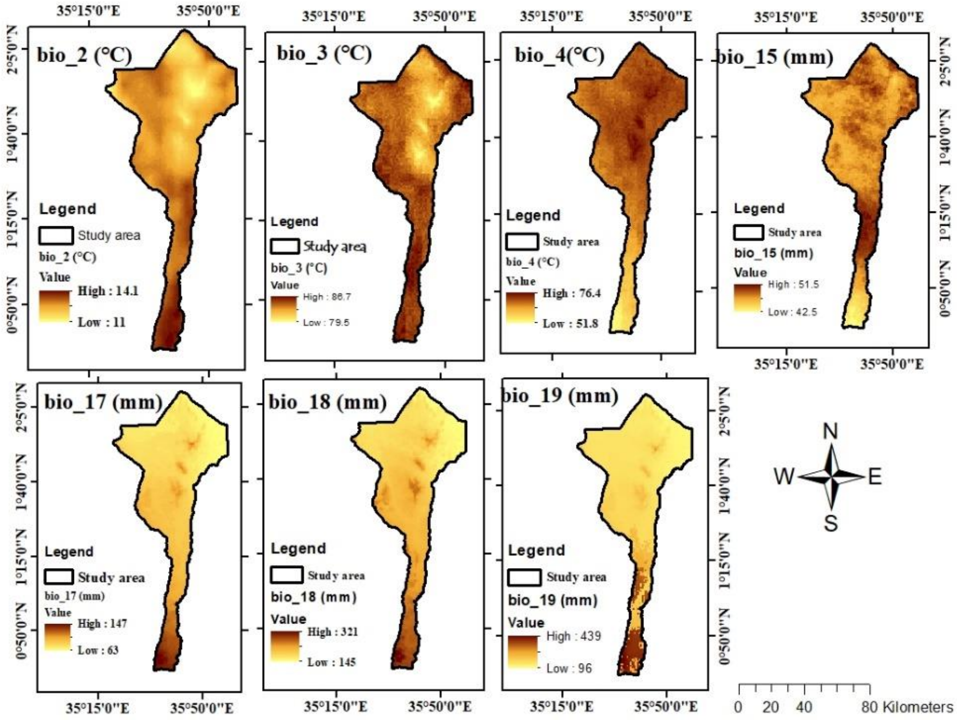
## Appendix X: Maps of the Current Climate Scenario (1970–2000)



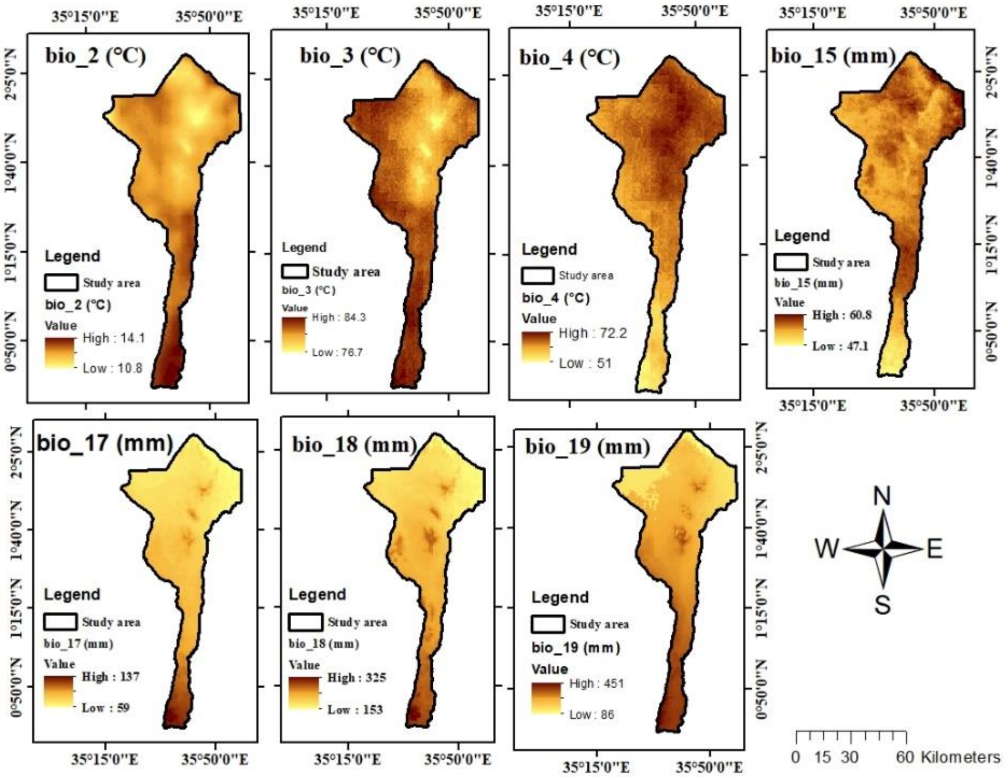
**Appendix XI: Maps showing the SSP245 future scenario for the period 2041–2060**



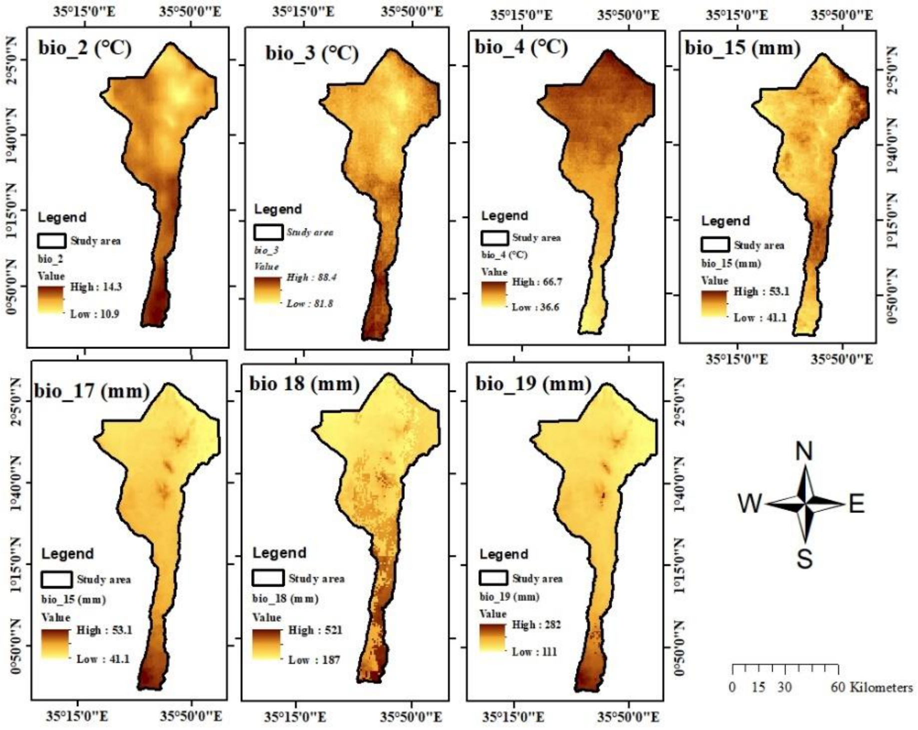
**Appendix XII: Maps showing the SSP245 future scenario for the period 2041–2060**



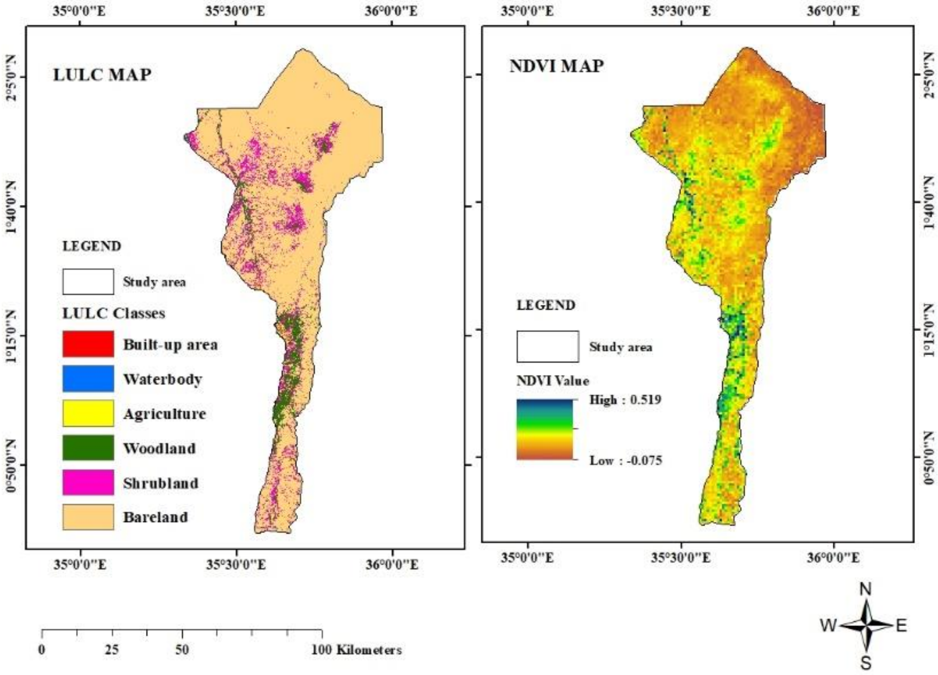
## Appendix XIII: Maps showing the SSP585 future scenario for the period 2041–2060.



## Appendix XIV: Maps showing SSP585 future scenario for the period 2081–2100



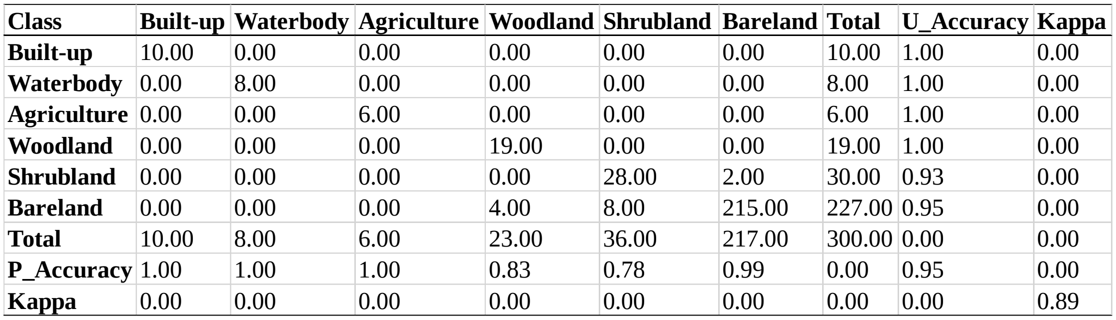
## Appendix XV: Maps showing LULC classes and NDVI indices for the year 2024 (Source: USGS website, http://ned.usgs.gov).



## Appendix XVI: Area (km²) and proportion (%) of land occupied by the LULC classes

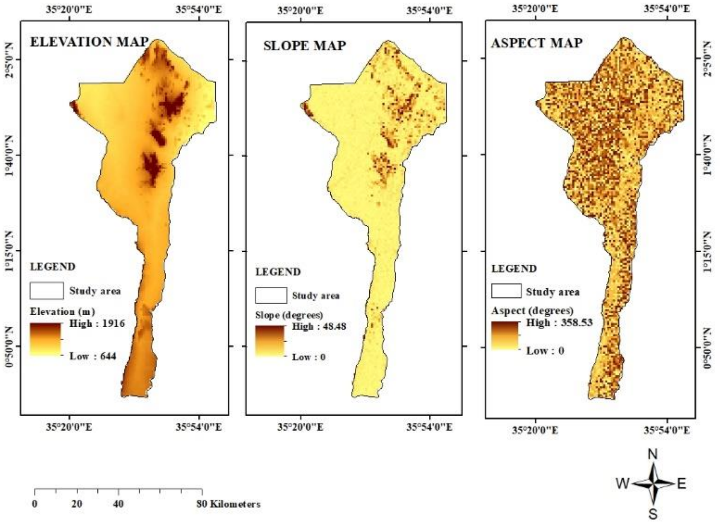
| LULC class | Area (km2) | Proportion (%) |
|---|---|---|
| Buit-up area | 5.13 | 0.11 |
| Waterbody | 15.43 | 0.33 |
| Agriculture | 31.78 | 0.68 |
| Woodland | 309.21 | 6.58 |
| Shrubland | 419.59 | 11.05 |
| Bareland | 3819.22 | 81.26 |
| **Total** | **4700.36** | **100** |

## Appendix XVII: Accuracy assessment matrix of the classified land use/land cover

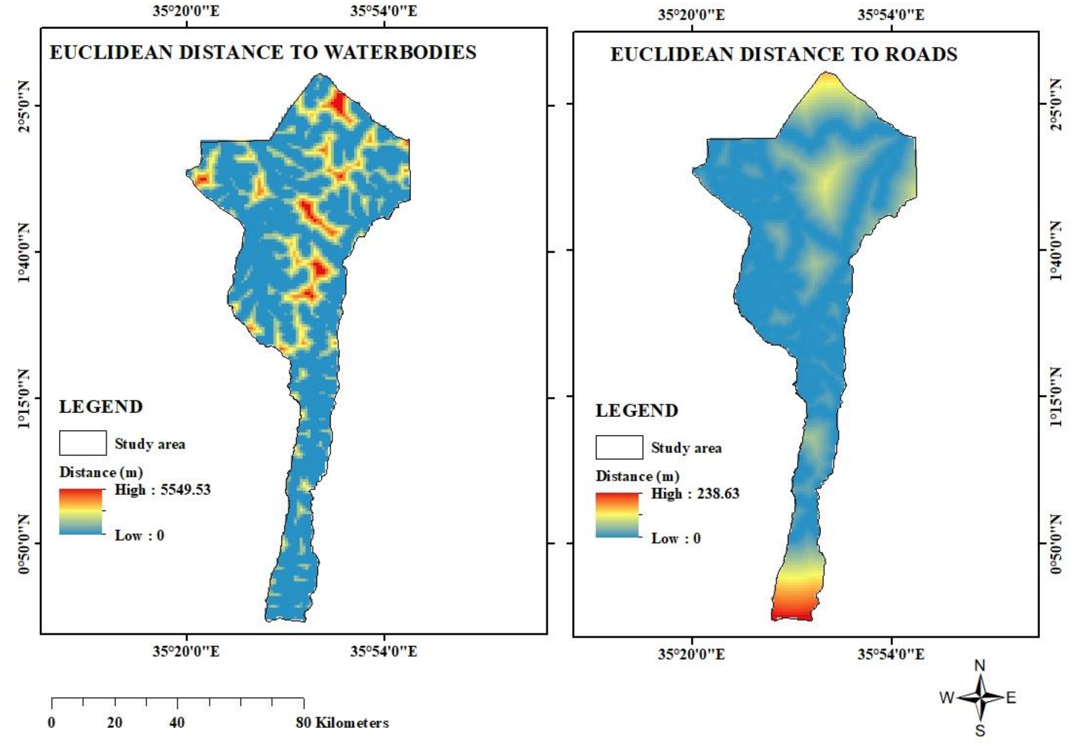


| Class | Built-up | Waterbody | Agriculture | Woodland | Shrubland | Bareland | Total | U_Accuracy | Kappa |
|---|---|---|---|---|---|---|---|---|---|
| **Built-up** | 10.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 10.00 | 1.00 | 0.00 |
| **Waterbody** | 0.00 | 8.00 | 0.00 | 0.00 | 0.00 | 0.00 | 8.00 | 1.00 | 0.00 |
| **Agriculture** | 0.00 | 0.00 | 6.00 | 0.00 | 0.00 | 0.00 | 6.00 | 1.00 | 0.00 |
| **Woodland** | 0.00 | 0.00 | 0.00 | 19.00 | 0.00 | 0.00 | 19.00 | 1.00 | 0.00 |
| **Shrubland** | 0.00 | 0.00 | 0.00 | 0.00 | 28.00 | 2.00 | 30.00 | 0.93 | 0.00 |
| **Bareland** | 0.00 | 0.00 | 0.00 | 4.00 | 8.00 | 215.00 | 227.00 | 0.95 | 0.00 |
| **Total** | 10.00 | 8.00 | 6.00 | 23.00 | 36.00 | 217.00 | 300.00 | 0.00 | 0.00 |
| **P_Accuracy** | 1.00 | 1.00 | 1.00 | 0.83 | 0.78 | 0.99 | 0.00 | 0.95 | 0.00 |
| **Kappa** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.89 |

## Appendix XVIII: Maps showing various topographic features (Source: USGS, http://ned.usgs.gov).



**Appendix XIX: Maps showing Euclidean distance to roads (Source: OpenStreetMap, https://www.openstreetmap.org) and Euclidean distance to waterbodies (Source: HydroSHEDS, https://www.hydrosheds.org).**



### Appendix XX: Training, test, and average AUC values of the MaxEnt model for African elephants

| Replicate | Training AUC | Test AUC |
|---|---|---|
| 0 | 0.857 | 0.842 |
| 1 | **0.860*** | 0.852 |
| 2 | 0.874 | 0.852 |
| 3 | 0.865 | 0.882 |
| 4 | 0.868 | 0.852 |
| 5 | 0.870 | **0.834*** |
| 6 | 0.871 | 0.871 |
| 7 | 0.864 | 0.882 |
| 8 | **0.877*** | 0.847 |
| 9 | 0.875 | **0.880*** |
| **Average** | **0.868 ± 0.006** | - |

### Appendix XXI: Training, test, and average AUC values of the MaxEnt model for African elephants’ preferred forage plants

| Replicate | Training AUC | Test AUC |
|---|---|---|
| 0 | **0.893*** | 0.890* |

| | | |
|---|---|---|
| 1 | 0.886 | **0.828*** |
| 2 | 0.881 | 0.889 |
| 3 | **0.864*** | 0.842 |
| 4 | 0.889 | 0.902 |
| 5 | 0.886 | 0.865 |
| 6 | 0.889 | 0.885 |
| 7 | 0.881 | 0.879 |
| 8 | 0.881 | **0.914*** |
| 9 | 0.883 | 0.844 |
| **Average** | **0.883 ± 0.007** | - |

## Appendix XXII: Average 10th percentile training presence cloglog thresholds for habitat suitability of African elephants under current and future scenarios.

| **Scenario** | **Current** | **SSP245** | **SSP245** | **SSP 585** | **SSP585** |
|---|---|---|---|---|---|
| **Period** | **1970–2000** | **2041–2060** | **2081–2100** | **2041–2060** | **2081-2100** |
| **Replicate** | **Threshold** | **Threshold** | **Threshold** | **Threshold** | **Threshold** |
| 0 | 0.1722 | 0.1781 | 0.1471 | 0.1687 | 0.1239 |
| 1 | 0.1773 | 0.1453 | 0.1441 | 0.2002 | 0.1632 |
| 2 | 0.1169 | 0.1509 | 0.2043 | 0.1519 | 0.1370 |
| 3 | 0.1354 | 0.2006 | 0.2055 | 0.1664 | 0.1604 |
| 4 | 0.1452 | 0.2098 | 0.1865 | 0.1713 | 0.1475 |
| 5 | 0.1816 | 0.1776 | 0.1554 | 0.1479 | 0.1686 |
| 6 | 0.1416 | 0.1716 | 0.1721 | 0.1859 | 0.1686 |
| 7 | 0.1426 | 0.1211 | 0.1894 | 0.1608 | 0.2022 |
| 8 | 0.1487 | 0.1550 | 0.1797 | 0.1893 | 0.1599 |
| 9 | 0.1700 | 0.1415 | 0.144 | 0.1766 | 0.1731 |
| **Average** | **0.1532** | **0.1651** | **0.1728** | **0.1719** | **0.159** |

## Appendix XXIII: Average 10th percentile training presence cloglog threshold for habitat suitability of African elephants' preferred forage plants under current and future climate change scenarios

| **Scenario** | **Current** | **SSP245** | **SSP245** | **SSP 585** | **SSP585** |
|---|---|---|---|---|---|
| **Period** | **1970–2000** | **2041–2060** | **2081–2100** | **2041–2060** | **2081–2100** |
| **Replicate** | **Threshold** | **Threshold** | **Threshold** | **Threshold** | **Threshold** |
| 0 | 0.3672 | 0.3310 | 0.3758 | 0.4268 | 0.4127 |
| 1 | 0.3167 | 0.3384 | 0.2483 | 0.3726 | 0.3556 |
| 2 | 0.2683 | 0.2789 | 0.3477 | 0.2817 | 0.3852 |
| 3 | 0.2720 | 0.2649 | 0.3463 | 0.2408 | 0.3676 |
| 4 | 0.3331 | 0.3443 | 0.2227 | 0.3991 | 0.3988 |
| 5 | 0.2993 | 0.2382 | 0.2700 | 0.3798 | 0.3767 |
| 6 | 0.3199 | 0.4750 | 0.3755 | 0.4482 | 0.2259 |
| 7 | 0.4279 | 0.3699 | 0.3739 | 0.3230 | 0.3469 |
| 8 | 0.3529 | 0.2954 | 0.4004 | 0.3527 | 0.3181 |
| 9 | 0.2931 | 0.3042 | 0.206 | 0.3848 | 0.3270 |
| **Average** | **0.3349** | **0.3240** | **0.3167** | **0.3609** | **0.3514** |

# Appendix XXIV: Pearson's correlation matrix of predictor environmental variable values extracted at African elephant occurrence points

| | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **bio_1** | 1 | | | | | | | | | | | | | | | | | | | | | | | | |
| **bio_2** | -0.091 | 1 | | | | | | | | | | | | | | | | | | | | | | | |
| **bio_3** | .624** | -0.085 | 1 | | | | | | | | | | | | | | | | | | | | | | |
| **bio_4** | -.591** | .280** | -.716** | 1 | | | | | | | | | | | | | | | | | | | | | |
| **bio_5** | .883** | .368** | .444** | -.374** | 1 | | | | | | | | | | | | | | | | | | | | |
| **bio_6** | .933** | -.438** | .622** | -.654** | .662** | 1 | | | | | | | | | | | | | | | | | | | |
| **bio_7** | -.229** | .973** | -.313** | .431** | .250** | -.560** | 1 | | | | | | | | | | | | | | | | | | |
| **bio_8** | .951** | -.275** | .613** | -.615** | .753** | .956** | -.403** | 1 | | | | | | | | | | | | | | | | | |
| **bio_9** | .998** | -0.055 | .594** | -.557** | .902** | .917** | -.188* | .939** | 1 | | | | | | | | | | | | | | | | |
| **bio_10** | .999** | -0.081 | .605** | -.560** | .889** | .928** | -.216* | .947** | .999** | 1 | | | | | | | | | | | | | | | |
| **bio_11** | .999** | -0.106 | .638** | -.621** | .874** | .939** | -.247** | .953** | .995** | .997** | 1 | | | | | | | | | | | | | | |
| **bio_12** | -.640** | .741** | -.519** | .549** | -.238** | -.842** | .826** | -.753** | -.606** | -.632** | -.653** | 1 | | | | | | | | | | | | | |
| **bio_13** | -.653** | .721** | -.502** | .574** | -.266** | -.849** | .803** | -.757** | -.620** | -.644** | -.666** | .988** | 1 | | | | | | | | | | | | |
| **bio_14** | -.441** | .795** | -.453** | .436** | -0.017 | -.682** | .863** | -.584** | -.402** | -.434** | -.457** | .959** | .925** | 1 | | | | | | | | | | | |
| **bio_15** | -0.158 | -.415** | .224** | 0.1 | -.398** | 0.007 | -.449** | -0.057 | -.185* | -0.154 | -0.148 | -.391** | -.287** | -.603** | 1 | | | | | | | | | | |
| **bio_16** | -.681** | .723** | -.499** | .575** | -.293** | -.873** | .804** | -.787** | -.649** | -.673** | -.693** | .992** | .996** | .922** | -.274** | 1 | | | | | | | | | |
| **bio_17** | -.461** | .766** | -.480** | .427** | -0.046 | -.691** | .842** | -.592** | -.424** | -.456** | -.477** | .959** | .920** | .994** | -.630** | .916** | 1 | | | | | | | | |
| **bio_18** | -.589** | .744** | -.514** | .541** | -.185* | -.798** | .828** | -.685** | -.555** | -.581** | -.604** | .989** | .983** | .959** | -.413** | .977** | .960** | 1 | | | | | | | |
| **bio_19** | -.705** | .698** | -.514** | .571** | -.326** | -.885** | .784** | -.823** | -.675** | -.699** | -.718** | .986** | .977** | .923** | -.303** | .989** | .918** | .958** | 1 | | | | | | |
| **elevation** | -.750** | .293** | -.588** | .345** | -.531** | -.776** | .416** | -.737** | -.741** | -.758** | -.752** | .739** | .689** | .703** | -.469** | .702** | .741** | .713** | .743** | | | | | | |
| **slope** | -0.035 | -.453** | -0.035 | -0.155 | -.231** | 0.13 | -.423** | 0.114 | -0.052 | -0.045 | -0.028 | -.312** | -.347** | -.289** | -0.066 | -.342** | -.264** | -.308** | -.300** | .188* | 1 | | | | |
| **aspect** | 0.088 | -.365** | 0.074 | -0.089 | -0.085 | .211* | -.366** | .188* | 0.075 | 0.087 | 0.094 | -.355** | -.344** | -.386** | .212* | -.351** | -.370** | -.336** | -.352** | -.206* | .343** | 1 | | | |
| **ndvi** | -.372** | .218* | -0.004 | 0.16 | -.282** | -.402** | .208* | -.424** | -.377** | -.375** | -.371** | .341** | .355** | .242** | 0.17 | .378** | .233** | .303** | .382** | .194* | -.263** | -0.035 | 1 | | |
| **settlements** | .337** | -.324** | -0.013 | -0.149 | .202* | .410** | -.306** | .354** | .340** | .346** | .344** | -.432** | -.407** | -.412** | 0.112 | -.436** | -.401** | -.399** | -.471** | -.422** | 0.119 | .261** | -.422** | 1 | |
| **roads** | -0.121 | .319** | -.234** | .202* | 0.056 | -.229** | .358** | -0.101 | -0.106 | -0.116 | -0.128 | .373** | .380** | .372** | -.231** | .354** | .393** | .423** | .324** | .257** | -0.105 | -0.003 | -.194* | -0.093 | 1 | |
| **waterbodies** | 0.103 | -0.047 | -.183* | 0.001 | 0.119 | 0.104 | -0.003 | 0.085 | 0.113 | 0.112 | 0.107 | -0.048 | -0.042 | -0.03 | -0.111 | -0.063 | -0.016 | -0.03 | -0.095 | -0.108 | -0.011 | 0.101 | -.224** | .552** | 0.005 | 1 |
| | **bio_1** | **bio_2** | **bio_3** | **bio_4** | **bio_5** | **bio_6** | **bio_7** | **bio_8** | **bio_9** | **bio_10** | **bio_11** | **bio_12** | **bio_13** | **bio_14** | **bio_15** | **bio_16** | **bio_17** | **bio_18** | **bio_19** | **elevation** | **Slope** | **aspect** | **ndvi** | **settlements** | **roads** | **waterbodies** |
| ****. Correlation is significant at the 0.01 level (2-tailed).** | | | | | | | | | | | | | | | | | | | | | | | | | |
| ***. Correlation is significant at the 0.05 level (2-tailed).** | | | | | | | | | | | | | | | | | | | | | | | | | |
| ***N = 133*** | | | | | | | | | | | | | | | | | | | | | | | | | |

# Appendix XXV: Pearson’s correlation matrix of predictor environmental variable values extracted at plant species occurrence points.

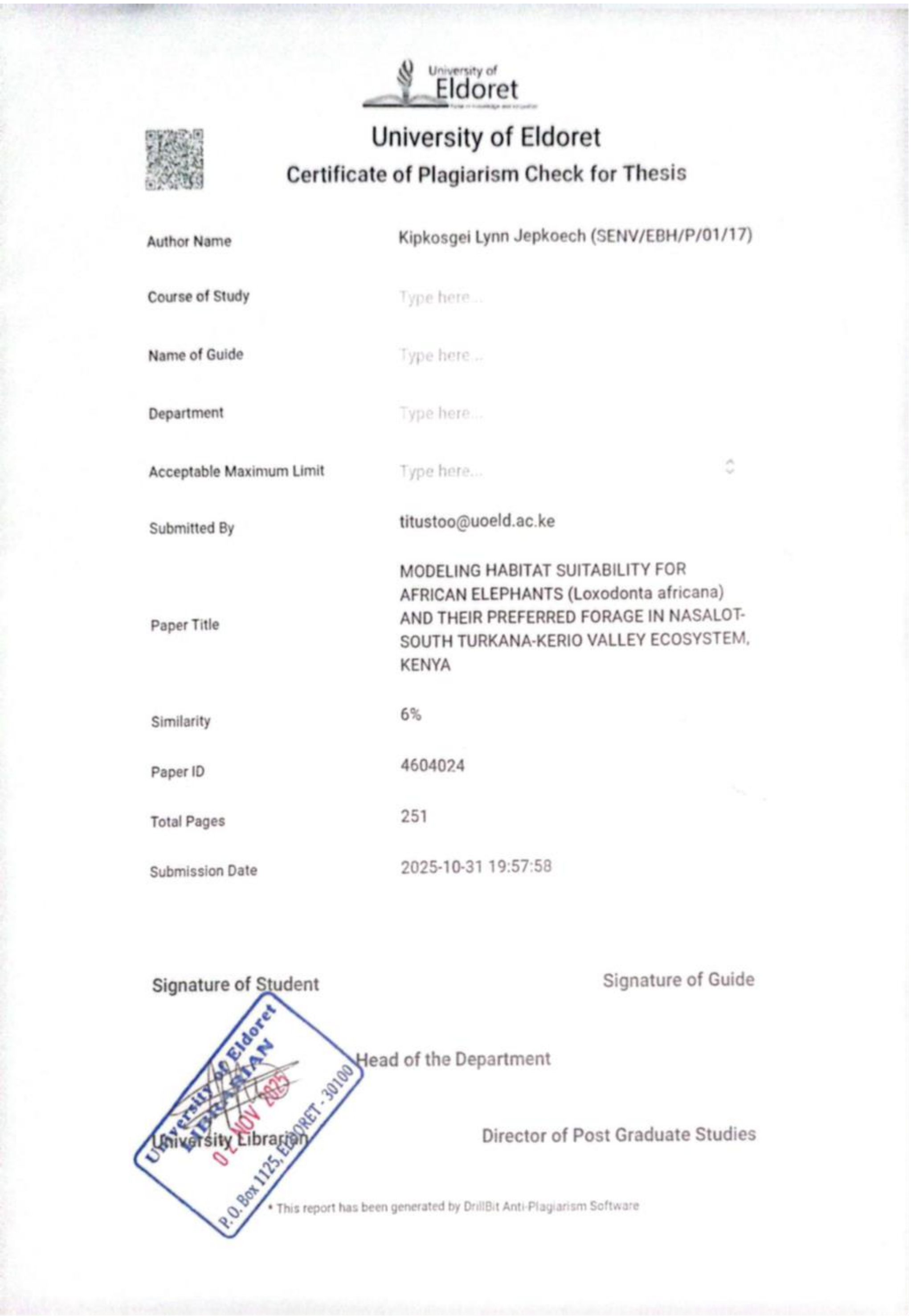
| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **bio_1** | 1 | | | | | | | | | | | | | | | | | | | | | | | | | |
| **bio_2** | .943** | 1 | | | | | | | | | | | | | | | | | | | | | | | | |
| **bio_3** | .994** | .967** | 1 | | | | | | | | | | | | | | | | | | | | | | | |
| **bio_4** | .929** | .988** | .962** | 1 | | | | | | | | | | | | | | | | | | | | | | |
| **bio_5** | .996** | .970** | .998** | .957** | 1 | | | | | | | | | | | | | | | | | | | | | |
| **bio_6** | .986** | .874** | .964** | .859** | .966** | 1 | | | | | | | | | | | | | | | | | | | | |
| **bio_7** | .936** | 1.000** | .962** | .990** | .964** | .863** | 1 | | | | | | | | | | | | | | | | | | | |
| **bio_8** | .995** | .913** | .979** | .892** | .984** | .994** | .903** | 1 | | | | | | | | | | | | | | | | | | |
| **bio_9** | 1.000** | .947** | .995** | .933** | .997** | .984** | .940** | .994** | 1 | | | | | | | | | | | | | | | | | |
| **bio_10** | 1.000** | .946** | .995** | .932** | .996** | .984** | .939** | .994** | 1.000** | 1 | | | | | | | | | | | | | | | | |
| **bio_11** | 1.000** | .938** | .992** | .922** | .994** | .988** | .930** | .997** | 1.000** | 1.000** | 1 | | | | | | | | | | | | | | | |
| **bio_12** | .501** | .733** | .588** | .768** | .573** | .363** | .748** | .426** | .511** | .509** | .486** | 1 | | | | | | | | | | | | | | |
| **bio_13** | .635** | .830** | .711** | .857** | .698** | .510** | .842** | .569** | .644** | .642** | .622** | .979** | 1 | | | | | | | | | | | | | |
| **bio_14** | .398** | .658** | .485** | .686** | .476** | .252** | .674** | .321** | .409** | .406** | .383** | .982** | .935** | 1 | | | | | | | | | | | | |
| **bio_15** | .986** | .939** | .987** | .934** | .985** | .967** | .933** | .979** | .987** | .987** | .985** | .513** | .653** | .395** | 1 | | | | | | | | | | | |
| **bio_16** | .517** | .748** | .604** | .782** | .589** | .380** | .763** | .444** | .528** | .525** | .503** | .998** | .985** | .975** | .536** | 1 | | | | | | | | | | |
| **bio_17** | .490** | .722** | .574** | .752** | .562** | .354** | .737** | .415** | .500** | .498** | .476** | .994** | .966** | .988** | .485** | .987** | 1 | | | | | | | | | |
| **bio_18** | .644** | .836** | .718** | .862** | .706** | .521** | .847** | .580** | .653** | .651** | .631** | .979** | .997** | .939** | .655** | .983** | .970** | 1 | | | | | | | | |
| **bio_19** | .421** | .670** | .515** | .712** | .497** | .278** | .687** | .341** | .432** | .430** | .406** | .993** | .954** | .981** | .442** | .990** | .984** | .951** | 1 | | | | | | | |
| **elevation** | .718** | .886** | .787** | .909** | .775** | .603** | .897** | .655** | .727** | .725** | .707** | .945** | .970** | .893** | .726** | .949** | .938** | .969** | .918** | 1 | | | | | | |
| **Slope** | .354** | 0.155 | .296** | 0.128 | .304** | .437** | 0.146 | .392** | .348** | .348** | .362** | -.266** | -.180* | -.321** | .320** | -.256** | -.266** | -.175* | -.304** | -0.103 | 1 | | | | | |
| **aspect** | .220** | .242** | .216** | .213** | .228** | .196* | .245** | .225** | .221** | .220** | .220** | 0.011 | 0.051 | -0.023 | .264** | 0.026 | -0.014 | 0.049 | 0.007 | 0.159 | 0.09 | 1 | | | | |
| **ndvi** | .388** | .330** | .380** | .351** | .376** | .402** | .322** | .391** | .386** | .388** | .389** | 0.122 | .196* | 0.074 | .374** | 0.124 | 0.125 | .210** | 0.077 | .182* | .386** | 0.056 | 1 | | | |
| **Settlement** | -0.059 | -0.093 | -0.082 | -0.156 | -0.07 | -0.041 | -0.094 | -0.037 | -0.062 | -0.062 | -0.055 | -0.115 | -0.106 | -0.111 | -0.112 | -0.113 | -0.082 | -0.121 | -0.131 | -0.057 | .170* | -.169* | -0.159 | 1 | | |
| **roads** | 0.029 | .248** | 0.088 | .254** | 0.09 | -0.078 | .258** | -0.029 | 0.036 | 0.034 | 0.017 | .671** | .561** | .759** | -0.051 | .631** | .732** | .591** | .667** | .512** | -.454** | -.220** | -0.05 | 0.002 | 1 | |
| **Waterbodies** | 0.088 | 0.018 | 0.046 | -0.048 | 0.067 | 0.119 | 0.01 | 0.129 | 0.084 | 0.084 | 0.094 | -.320** | -.236** | -.338** | 0.089 | -.297** | -.320** | -.245** | -.347** | -0.155 | .225** | .495** | -0.04 | .195* | -.412** | 1 |
| | **bio_1** | **bio_2** | **bio_3** | **bio_4** | **bio_5** | **bio_6** | **bio_7** | **bio_8** | **bio_9** | **bio_10** | **bio_11** | **bio_12** | **bio_13** | **bio_14** | **bio_15** | **bio_16** | **bio_17** | **bio_18** | **bio_19** | **elevation** | **Slope** | **aspect** | **ndvi** | **Settlement** | **roads** | **waterbodies** |

****. Correlation is significant at the 0.01 level (2-tailed).**

***. Correlation is significant at the 0.05 level (2-tailed).**

*N = 152*

## Appendix XXVI: Similarity Report



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