

BINDURA UNIVERSITY OF SCIENCE EDUCATION

DEPARTMENT OF NATURAL RESOURCES MANAGEMENT

**PREDICTING THE IMPACTS OF CLIMATE CHANGE ON THE ECOLOGICAL NICHE
OF UAPACA KIRKIANA (MÜLL. ARG.) IN SOUTHERN AFRICA**

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Dedication

I dedicate this dissertation to the Nyaguse family. Your unwavering love, support and belief in me made this achievement possible.

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Abstract

Climate change poses a growing threat to the ecological niches of indigenous tree species across southern Africa, with significant implications for biodiversity, ecosystem function, and rural livelihoods. *Uapaca kirkiana* Müll. Arg. (mahobohobo/wild loquat) is a keystone indigenous fruit tree of the Miombo woodland ecosystem, providing critical food security, income, and medicinal value to millions of rural communities in Zimbabwe and across south-central Africa. Despite its ecological and socio-economic importance, quantitative, spatially explicit assessments of how climate change will affect the distribution of *U. kirkiana* in southern Africa particularly Zimbabwe remain limited. This study applied the Maximum Entropy (MaxEnt) species distribution modelling algorithm, implemented through the Wallace platform in R, to: (i) determine the key environmental variables driving the current potential distribution of *U. kirkiana* in southern Africa; (ii) project the impacts of climate change on its habitat suitability at 2070 and 2100 under SSP climate forcing scenarios; and (iii) identify conservation and management implications for Zimbabwe. Georeferenced occurrence records ($n = 362$) were sourced from the Global Biodiversity Information Facility (GBIF) and subjected to spatial thinning at 75 km. Nineteen bioclimatic variables from WorldClim v2.1 were used as environmental predictors. The optimal MaxEnt model (fc.H_rm.1) achieved excellent predictive performance, with a training Area Under the Curve (AUC) of 0.899 and a Continuous Boyce Index (CBI) of 0.969. Annual precipitation (BIO12), minimum temperature of the coldest month (BIO6), and precipitation seasonality (BIO15) were identified as the principal environmental drivers of the species' current distribution. Current suitable habitat was concentrated across the Miombo woodland belt spanning Zimbabwe, Zambia, Tanzania, Malawi, and Angola. Future projections revealed a progressive and accelerating southward shift in suitable habitat by 2070 and 2100, with substantial new suitable areas emerging in South Africa's interior highlands alongside some habitat loss in northern lowland areas of the current distribution. These findings highlight the urgency of protecting highland refugia in Zimbabwe, integrating *U. kirkiana* into national climate adaptation strategies, and investing in domestication and agroforestry programmes to safeguard the species' ecological and socio-economic contributions under a changing climate.

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LIST OF ACRONYMS AND ABBREVIATIONS

AUC	Area Under the Receiver Operating Characteristic Curve
BIO	Bioclimatic Variable
CBNRM	Community-Based Natural Resource Management
CBI	Continuous Boyce Index
CMIP6	Coupled Model Intercomparison Project Phase 6
DEM	Digital Elevation Model
GBIF	Global Biodiversity Information Facility
GCM	General Circulation Model
GPS	Global Positioning System
IPCC	Intergovernmental Panel on Climate Change
MaxEnt	Maximum Entropy Algorithm
R	Statistical Computing Software
RCP	Representative Concentration Pathway
SDM	Species Distribution Model/Modelling
SRGH	Zimbabwe National Herbarium and Botanic Garden
SSP	Shared Socioeconomic Pathway
SRTM	Shuttle Radar Topography Mission
TSS	True Skill Statistic
VIF	Variance Inflation Factor
WorldClim	Global Climate and Weather Data Repository
ZPWMA	Zimbabwe Parks and Wildlife Management Authority

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Climate change is one of the most serious and rapidly increasing threats to the world's biological diversity, affecting ecosystem functioning, shifting species' distributions, and reducing the ecological services upon which humanity relies (Bellard et al., 2012; Thomas, 2010; Pörtner et al., 2022; IPCC, 2023; Bonebrake et al., 2018; Moritz and Agudo, 2013). Global mean surface temperatures have warmed by around 1.1°C since the pre-industrial period, and are projected to reach 3-4°C above pre-industrial levels by the end of the 21st century in high-emissions scenarios (Skea et al., 2021; Masson-Delmotte et al., 2021; Bellard et al., 2014). This in turn leads to cascading biological effects such as shifts in phenology, niche shifts, range contractions, and for species with low mobility and/or narrow thermal tolerance, local and global extinctions (Lenoir and Svenning, 2015; Pacifici et al., 2015). Understanding these challenges requires effective predictive frameworks particularly Species Distribution Models (SDMs) capable of using climate change scenarios to produce detailed predictions on future species habitat suitability (Araújo et al., 2019; Elith and Graham, 2009).

Southern Africa, and specifically Zimbabwe, is one of the most vulnerable regions to climate change, with warming trends already surpassing global rates and future projections suggesting more extreme warming, drought and precipitation variability (Kruger and Sekele, 2013; Shongwe et al., 2009; Midgley and Bond, 2015). In Zimbabwe, mean annual temperatures have increased by approximately 0.02-0.03°C annually, with a more pronounced increase in the lowveld and semi-arid areas (Jury, 2014; Mazvimavi, 2010; Nangombe et al., 2018). The Miombo woodland ecosystem, which spans 3.8 million km² of south-central Africa, is the most extensive tropical woodland biome in Africa and one of its most important from an ecological and socio-economic perspective (Chidumayo, 1997; Campbell et al., 2007). Despite being ecologically significant, the Miombo Eco region is the fastest-deforested tropical Eco region due to the expansion of subsistence farming, charcoal burning, commercial timber harvesting and increasingly climate change (Campbell et al., 2007; Midgley and Bond, 2015; Muluneh, 2021). Indigenous fruit trees play a critical role in the food security and livelihoods of rural communities across the Miombo ecoregion, providing essential fallback food and supplementary income during times of seasonal food stress and/or agricultural distress (Akinnifesi et al., 2006; Maghembe et al., 1998; Mithofer et al., 2006).

Uapaca kirkiana Muell. Arg. (Euphorbiaceae), popularly known as wild loquat or 'mahobohobo' or 'mazhanje' in Zimbabwe, 'masuku' in Zambia and Malawi, is one of the most abundant and people-friendly indigenous fruit trees of the Miombo woodland ecosystem in southern Africa (Ngulube et al., 1995; Akinnifesi et al., 2006). It is found naturally in eight countries growing in woodlands between 500-2,000 metres above sea level (Ngulube et al., 1995; Chirwa and Akinnifesi, 2007). In Zimbabwe, *U. kirkiana* fruits are one of the most favoured and consumed wild fruits, providing an important food security buffer when staple food stocks are depleted (Ramadhani, 2002; Kadzere et al., 2001; Mithofer et al., 2006). Research shows that access to *U. kirkiana* and other wild fruits lowers the likelihood of household poverty during the peak of the food shortage period by 33% (Mithofer et al., 2006; Emerton, 1998). Despite its ecological and socio-economic significance, *U. kirkiana* populations are facing an uncertain future from land clearing, charcoal making, urbanisation, unsustainable harvesting, and climate change (Kokou et al., 2024b; Jinga et al., 2020; Ngulube et al., 1996).

Species Distribution Models (SDMs) are widely used in conservation biology and ecology to predict climate-induced changes in species' distribution (Guisan and Thuiller, 2005; Elith and Graham,

2009; Phillips et al., 2006). In the case of *U. kirkiana*, Jinga et al. (2020) were the first to apply SDMs to estimate the effects of climate change for southern African species, showing substantial reductions in suitable habitat under projected warming scenarios. These results highlight the need for developing new, country-specific models for Zimbabwe using the latest Shared Socio-economic Pathway (SSP) scenarios and Zonation-based spatial prioritisation, to support national conservation strategies with fine-scale environmental variables (Jinga et al., 2020; Araújo et al., 2019; Moilanen et al., 2022).

1.2 Problem Statement

Uapaca kirkiana is a keystone species in Zimbabwe's Miombo woodlands, delivering essential nutritional, economic and ecological benefits to millions of rural households that rely on it for food, livelihoods and cultural values (Ramadhani, 2002; Akinnifesi et al., 2006; Chawafambira et al., 2020). Yet, the species' population is declining rapidly due to over-harvesting, habitat destruction, deforestation, as well as climate change (Jinga et al., 2020; Campbell et al., 2007; Ngulube et al., 1996). Climate change temperatures in Zimbabwe are already rising faster than the global average, with projected rises of up to 3.5°C by 2050 under high emission scenarios, as well as increasing droughts and altered rainfall patterns (Kruger and Shongwe, 2004; Nangombe et al., 2018; Shongwe et al., 2009). These changes are likely to affect the current microclimate that supports *U. kirkiana* populations in the country's Miombo woodlands, possibly shrinking suitable habitat, driving distributional contractions to higher altitudes, and jeopardising its future in lower-elevation communal areas where human reliance on the species is most acute.

While the value of *U. kirkiana* for rural livelihoods in Zimbabwe and southern Africa is acknowledged, there is a clear gap in knowledge: no broad-scale species-specific, spatial assessment of the potential impact of climate change on the ecological niche, potential suitable habitat and distribution of *U. kirkiana* has been undertaken for Zimbabwe. Lacking such specific spatial information, Zimbabwe's conservation managers, decision-makers, agroforestry practitioners, and community resource managers cannot rely on evidence to support their decisions regarding where to focus conservation effort, where to establish community-based woodlands, or how to design *U. kirkiana* domestication and cultivation initiatives. Our study begins to fill this information gap by producing the first high-resolution, Zimbabwe-specific predictive model of *U. kirkiana*'s current and future ecological niche across multiple Shared Socio-economic Pathway (SSP) climate scenarios.

1.3 Research Objectives

1.3.1 Main Objective

To map the current and future potential distribution of *Uapaca kirkiana* in southern Africa under climate change scenarios, and to determine areas for conservation and management for sustainable use in Zimbabwe.

1.3.2 Specific Objectives

1. To assess the major environmental factors influencing the current potential range of *Uapaca kirkiana* in southern Africa, using MaxEnt species distribution modelling software.
2. To examine the effects of climate change on the potential distribution of *U. kirkiana* in Zimbabwe by 2100 under the SSP3-7.0 and SSP5-8.5 climate change scenarios by quantifying habitat gains and losses, and changes in the distribution pattern.
3. To prioritise and map key areas for the conservation and cultivation of *U. kirkiana* in Zimbabwe under current and projected climate change scenarios using Zonation software.

1.4 Justification of the Study

The study is justified scientifically, socio-economically and politically. Scientifically, it fills an important gap in the species distribution modelling research for *U. kirkiana* in Zimbabwe and southern Africa, as no study to date has produced a detailed, high-resolution, Zimbabwe-focused analysis using MaxEnt modelling, multiple SSP climate change scenarios and Zonation-based spatial prioritisation. The socio-economic rationale is strong: rural populations in Zimbabwe, especially in the highveld and transitional Miombo regions, are heavily dependent on food security and livelihood strategies that rely on *U. kirkiana*, and the presence of wild fruit trees can reduce the probability of household poverty during seasonal food shortages by 33% (Mithofer et al., 2006). In terms of policy, the study helps Zimbabwe meet its obligations under the Convention on Biological Diversity (CBD), the United Nations Framework Convention on Climate Change (UNFCCC) and the Zimbabwe National Biodiversity Strategy and Action Plan (NBSAP), providing evidence-based, spatially explicit data in a GIS format to directly inform national biodiversity planning and community-based natural resource management.

1.5 Aim of the Study

The primary objective of this study is to forecast climate change impacts on the ecological niche of *Uapaca kirkiana* in southern Africa, and particularly in Zimbabwe, and to develop spatially explicit, evidence-based, priority maps for sustainable cultivation and conservation of the species to guide national biodiversity strategies and community-based natural resource management initiatives.

1.6 Research Questions

This research is aimed at addressing the following four research questions, in line with the aforementioned objectives:

- Which environmental factors drive the current potential distribution of *Uapaca kirkiana* in southern Africa, and what is the distribution of habitat suitability for *Uapaca kirkiana* in Zimbabwe under current climate conditions?
- How will climate change impact on the spatial extent, distribution and suitability for *Uapaca kirkiana* in Zimbabwe by 2100 under the SSP3-7.0 and SSP5-8.5 climate change scenarios, and what are the likely magnitudes of habitat gain and loss?
- Where in Zimbabwe is it most important to conserve and plant *Uapaca kirkiana* under current conditions and in the future, based on Zonation-based prioritization?
- Which climate-informed and evidence-based conservation and management options can be recommended to secure the future survival and sustainable use of *Uapaca kirkiana* populations in Zimbabwe under the effects of climate change?

CHAPTER 2: LITERATURE REVIEW

2.1 Ecology and Natural Distribution of *Uapaca kirkiana*

2.1.1 Geographical Range

Uapaca kirkiana is endemic to the Miombo ecological zone of south-central Africa, where it has been reported from Angola, Burundi, Malawi, Mozambique, Tanzania, the Democratic Republic of Congo (DRC), Zambia and Zimbabwe, all within the Zambezian center of phytoendemism (White, 1983; Malaisse, 1997). Jinga et al. (2020) applied the MaxEnt algorithm to 84 georeferenced occurrence records and nine environmental variables to produce the first statistically rigorous and continuous model of the species' current distribution in south-central Africa, confirming its association with the distribution of miombo woodlands. A weakness of Jinga et al. (2020) is the small sample size (84 occurrence records) for the entire Southern African distribution, which could lead to sampling bias, particularly in poorly sampled regions such as Angola and the DRC. The present study overcomes this by including more occurrence records from the Global Biodiversity Information Facility (GBIF) and applying spatial thinning to reduce sampling bias before fitting the MaxEnt model.

2.1.2 Climatic and Edaphic Requirements

In its natural habitat, *U. kirkiana* is associated with a unimodal rainfall regime of 500-1,400 mm annually, mostly during a 4-5 month wet period, followed by a 5-7 month dry period. Average daytime temperatures vary from 18-29°C during the hot season to 12-24°C during the dry season (Malaisse, 1997; Chirwa and Akinnifesi, 2007). It prefers well-drained, infertile sandy or gravelly soils with an acidic pH (4.5-6.5) and is found at altitudes of 500-2,000 m (Chirwa and Akinnifesi, 2007). Jinga et al. (2020) report that bioclimatic variables were more important than edaphic variables at the regional scale a common pattern in plant SDM studies, where climate sets the broad limits of a species' range, while soil conditions determine local presence (Pearson and Dawson, 2003). For this study, bioclimatic variables from WorldClim are therefore the best primary predictors for the first objective.

2.1.3 Population Structure and Carbon Storage

Population structure analyses show that *U. kirkiana* natural stands mainly consist of small-diameter trees of 10–20 cm DBH, with relatively few large, mature individuals over 45 cm, indicating ongoing disturbances from harvesting and land-use pressures (Nsenga et al., 2025). A comprehensive inventory study in Malawi recorded maximum carbon storage of 57.80 tCO₂/ha found in northern Malawi, where annual rainfall exceeds 1,600 mm, with an estimated economic value of around USD 578 per hectare (Nsenga et al., 2025). While this study offers valuable insights, it is limited to Malawi and does not include climate change projections gaps addressed by the present study's regional SDM modelling and Zonation analysis for Zimbabwe.

Table 2.1: Summary of ecological requirements of *Uapaca kirkiana* in Southern Africa

Ecological Parameter	Range / Condition	Source
Annual Precipitation	500–1,400 mm	Malaisse (1997); Chirwa & Akinnifesi (2007)
Wet Season Duration	4–5 months	Malaisse (1997)
Dry Season Duration	5–7 months	Malaisse (1997)
Mean Temperature (hot season)	18–29°C	Malaisse (1997)
Mean Temperature (dry season)	12–24°C	Malaisse (1997)

Altitude	500–2,000 m asl	Chirwa & Akinnifesi (2007)
Soil Ph	4.5–6.5 (acidic)	Ramachela (2006)
Soil Type	Sandy/gravelly, infertile, well-drained	Chirwa & Akinnifesi (2007)
Ectomycorrhizal Association	Amanita, Cantharellus, Lactarius, Russula	Hogberg & Pearce (1986)
Maximum Carbon Storage	57.80 tCO ₂ /ha (northern Malawi)	Nsenga et al. (2025)
Economic Value	~USD 578/ha	Nsenga et al. (2025)

2.2 The Miombo Woodland Ecosystem

The Miombo woodland is the largest dry tropical forest biome in Africa, spanning 1.9 to 2.7 million km² across Angola, DRC, Malawi, Mozambique, Tanzania, Zambia, and Zimbabwe (White, 1983; FAO, 2020). Zimbabwe is a transition zone, with wet Miombo in the Eastern Highlands and drier Miombo on the central plateau, making it especially sensitive to vegetation changes caused by climate change. The ecoregion hosts near-threatened and endangered species such as *Pterocarpus angolensis*, *Afzelia quanzensis*, and *Uapaca kirkiana* (Ribeiro et al., 2020), but only 5.4% of the total miombo area is protected under the highest IUCN protected area categories, revealing a conservation gap that justifies the spatial gap analysis in the third objective of this study. Human activities including farming, charcoal making, wood harvesting, population growth and urbanisation continue to threaten miombo woodlands, with cropland expanding from approximately 100,000 to 272,000 km² between 1961 and 2014 across the seven Miombo countries (FAOSTAT, 2023). Climate change is considered to be on a different scale to these local human impacts, as it changes the fundamental environmental conditions that allow species to live rather than simply reducing population size within a stable range (Ribeiro et al., 2020).

Table 2.2: Projected distribution changes for Miombo woodlands and *Uapaca kirkiana* under climate change scenarios

Study	Species / Group	Scenario	Projected Change	Time Period
Jinga et al. (2020)	Wet miombo woodlands	RCP4.5 / RCP8.5	Contraction: –28.6% to –41.6%	2050–2070
Jinga et al. (2020)	Dry miombo woodlands	RCP4.5 / RCP8.5	Expansion: +17.3% to +22.7%	2050–2070
Jinga et al. (2020)	<i>U. kirkiana</i>	RCP8.5	Contraction: –14.9% (2050); –20.6% (2070)	2050–2070
Jinga et al. (2020)	<i>U. kirkiana</i>	RCP6.0	Slight expansion: +1.3%	2050
Mwase et al. (2023)	<i>U. kirkiana</i> (Malawi)	SSP2-4.5 / SSP5-8.5	Upward altitude shift; range reduction	2070–2100
Nsenga et al. (2025)	<i>U. kirkiana</i> (Malawi)	Observed rainfall gradient	Higher rainfall = greater C storage and resilience	Present

2.3 Climate Change in Southern Africa and Zimbabwe

Southern Africa is one of the most climate-vulnerable regions, with temperatures rising at twice the global average (IPCC, 2021). In Zimbabwe, annual average temperatures have risen by approximately 0.3°C per decade since 1900, with more frequent and intense droughts, such as the major droughts of 1991/92, 2015/16 and 2018/19, which caused crop losses and food insecurity in the country (Mazvimavi, 2010). The Shared Socioeconomic Pathways (SSPs) are the most recent climate scenarios developed as part of CMIP6 and used in the IPCC Sixth Assessment Report (AR6, 2021). SSP3-7.0, which assumes a world with uneven development and weak climate policies, projects a global mean temperature increase of 2.8 to 3.6°C by 2100. Under SSP5-8.5, which assumes fossil-fuel development with no emissions mitigation, warming is expected to be greater than 4.4°C by 2100 (IPCC, 2021). For Zimbabwe, these scenarios project average annual temperature rises of 2 to 3.5°C (SSP3-7.0) and 3.5 to 5°C (SSP5-8.5) by 2100, with decreased rainfall and increased droughts. The use of both SSP3-7.0 and SSP5-8.5 in this study presents planners with a range of potential climate futures and highlights the need for climate mitigation and adaptation, meeting the second objective.

2.4 Bioclimatic Variables in Species Distribution Modelling

Bioclimatic variables are created from monthly temperature and precipitation data to produce ecological predictors that reflect annual trends, seasonal changes, and climatic extremes important for organisms (Fick and Hijmans, 2017). The WorldClim v2.1 database offers a standard set of 19 bioclimatic variables (BIO1–BIO19) at 2.5 arc-minute resolution, based on climate data from 1970 to 2000, with CMIP6-downscaled future outputs available under four SSP scenarios (WorldClim, 2023). Several of the 19 standard bioclimatic variables have been shown to be important for the distribution of *U. kirkiana*. Jinga et al. (2020) identified annual precipitation (BIO12), precipitation seasonality (BIO15), mean temperature of the warmest quarter (BIO10) and precipitation of the driest quarter (BIO17) as the key variables in south-central Africa. Mwase et al. (2023) in Malawi found temperature variables, particularly minimum temperature of the coldest month (BIO6) and mean temperature of the coldest quarter (BIO11), to be more important. This variability justifies using a combination of precipitation and temperature predictors for the MaxEnt models developed for the first objective, with pairwise correlation testing to retain only non-collinear predictors. This study uses WorldClim v2.1 for the current baseline and WorldClim CMIP6 products for the 2070 (mean from 2061 to 2080) and 2100 (mean from 2081 to 2100) projection periods under both SSP scenarios.

2.5 Species Distribution Modelling: Theory and Methods

2.5.1 Ecological Niche Theory and SDM Foundations

Species distribution models (SDMs) link species occurrence data to environmental variables in space, generating maps of potential habitat and allowing predictions under alternative scenarios (Peterson et al., 2011). SDMs are grounded in the theory of the ecological niche, defined by Hutchinson (1957) as the environmental conditions that enable a species to sustain a population. One of the limitations of SDMs is the assumption of niche conservatism that a species' climatic niche is conserved through time and can be used to predict future distributions under climate change (Thuiller et al., 2008). For a long-lived tree species such as *U. kirkiana*, which has limited dispersal and a long generation time, this assumption is more defensible than for short-lived species, but SDM projections for *U. kirkiana* should nonetheless be interpreted as climatic suitability rather than exact predictions.

2.5.2 MaxEnt Algorithm: Strengths and Weaknesses

Maximum Entropy (MaxEnt) modeling, created by Phillips et al. (2006), is the most popular SDM algorithm globally and has been used in all previous SDM studies of *U. kirkiana* (Jinga et al., 2020; Mwase et al., 2023). MaxEnt uses presence-only occurrence data and background pseudo-absences, estimating the probability distribution of maximum entropy given the environmental characteristics of the occurrence sites. A key issue is the potential for overfitting the model with default regularization settings. Jinga et al. (2020) applied default settings without tuning regularization, which may have reduced the transferability of their future projections. This study optimises the regularization multiplier using the ENMeval package in R (Merow et al., 2013), representing a major advancement in SDM studies of *U. kirkiana*. Published SDMs for *U. kirkiana* have performed well: Jinga et al. (2020) reported AUC greater than 0.9, and Mwase et al. (2023) reported AUC greater than 0.9, TSS of 0.86, and SEDI of 0.95.

2.5.3 Variable Selection and Multicollinearity

Variable selection is a critical step in SDM. Best practice involves testing pairwise Pearson correlations among possible bioclimatic variables and excluding those with an absolute correlation coefficient of 0.7 or higher, keeping only relevant, non-collinear predictors (Radosavljevic and Anderson, 2014). Both Jinga et al. (2020) and Mwase et al. (2023) used Pearson correlation screening to narrow down from 19 variables to a subset of 7–9, then used MaxEnt's Jackknife test to rank variable importance. This study follows the same method but also applies VIF analysis to thoroughly address multicollinearity among the chosen predictors.

Table 2.3: Comparison of key SDM studies on *Uapaca kirkiana* and related miombo species

Study	Species	Algorithm	Scenario	Key Finding	Limitation Identified
Jinga et al. (2020)	<i>U. kirkiana</i>	MaxEnt	RCP2.6–8.5 (CMIP5)	Range contracts –20.6% by 2070 under RCP8.5	Small dataset; default regularization; no 2100; no Zimbabwe prioritization
Jinga et al. (2020)	Wet/dry miombo spp.	MaxEnt	RCP2.6–8.5 (CMIP5)	Wet miombo –41.6%; dry miombo +22.7% by 2070	17 species; no 2100 projections; no Zonation
Mwase et al. (2023)	<i>U. kirkiana</i> (Malawi)	MaxEnt	SSP2-4.5 / SSP5-8.5 (CMIP6)	Upward altitude shift; range reduction in Malawi	Malawi only; no 2100 end-of-century; no conservation prioritization
Nsenga et al. (2025)	<i>U. kirkiana</i> (Malawi)	Field inventory	Observed rainfall gradient	57.80 tCO ₂ /ha C storage; USD 578/ha value	No climate projections; Malawi only; no SDM
This Study	<i>U. kirkiana</i> (Zimbabwe)	MaxEnt + Zonation	SSP3-7.0 & SSP5-8.5 (CMIP6)	Current + 2070 + 2100 + Zimbabwe conservation priority map	—

2.6 Climate Change as the Primary Threat to *Uapaca kirkiana*

U. kirkiana is threatened by climate change through multiple physiological pathways. Increasing temperatures increase the demand for evapotranspiration, exacerbating soil moisture deficits during the growing season. The species' optimal temperature for net photosynthesis is 25-30°C; prolonged temperatures above this threshold reduce carbon gain (Chidumayo, 2007). Seedling establishment is especially vulnerable, as high temperatures and low soil moisture interfere with germination and root development in the species' preferred sandy soils. Climate change also shifts the timing and predictability of seasonal cues for leaf flush, flowering and fruiting, potentially leading to mismatches between phenological events and favourable conditions (Mwase et al., 2023). Jinga et al. (2020) demonstrated that the species' distribution is likely to contract under most scenarios by 2050 and 2070, with a 20.6% loss of suitable habitat under RCP8.5 by 2070, primarily in low-elevation areas of Zimbabwe, Zambia and Mozambique. Mwase et al. (2023) verified an upward shift in the core of suitable *U. kirkiana* habitat in Malawi under CMIP6 SSP scenarios, consistent with the global pattern of species shifting to cooler climates at higher altitudes (Parmesan and Yohe, 2003). Human stressors logging, over-harvesting, fire frequency, and insecure land tenure compound the threat of climate change, creating a threat multiplier effect that makes the vulnerability of *U. kirkiana* much higher than climate change alone would suggest (Ribeiro et al., 2020). In Zimbabwe, where 72% of the population is rural and heavily reliant on natural resources (ZimStat, 2022), the long-term consequences of climate-induced habitat loss for *U. kirkiana* represent a potential food security crisis.

2.7 Conservation Planning and Spatial Prioritization

Systematic conservation planning (SCP) is a scientific approach to designing and implementing biodiversity conservation measures that optimise the use of scarce resources (Margules and Pressey, 2000). In the case of *U. kirkiana* and the broader Miombo biome, SCP involves integrating current and future SDM results with information on areas that are currently protected, community land ownership, and areas that are threatened. Zonation is a free, fast spatial conservation planning program that generates a priority map where each pixel is assigned a value between 0 (least priority) and 1 (most priority), based on an iterative algorithm which removes the most dispensable pixel in each iteration (Moilanen et al., 2005, 2022). It provides a continuous prioritisation over the entire study area rather than a binary map allowing conservation planners in Zimbabwe to identify high priority areas which must be protected and mid-priority areas suitable for community-based management and agroforestry.

In Zimbabwe, the formal network of protected areas (PAs) covers approximately 27% of the country but is disproportionately located in the drier and wildlife-rich areas in the south and west, with the Miombo woodlands of the central and eastern highlands where *U. kirkiana* is found being poorly protected (ZIMPARKS, 2020). By intersecting Zonation priority maps of *U. kirkiana* with the boundaries of Zimbabwe's PAs, this study will identify: high priority sites already included in the PA network; high priority sites not yet protected; and climate refugia areas which remain suitable to *U. kirkiana* in both 2070 and 2100 scenarios as the most critical areas for investment. To the best of the author's knowledge, such analysis is new for *U. kirkiana* in Zimbabwe.

2.8 Identified Research Gaps

The literature review highlights four gaps in relation to the research objectives. Firstly, there are no studies that use the CMIP6 SSP3-7.0 and SSP5-8.5 scenarios to model the distribution of *U. kirkiana* to the year 2100 in Zimbabwe the earlier models have been based on CMIP5 RCP scenarios

(Jinga et al., 2020) or are focused on Malawi (Mwase et al., 2023), without projections to 2100. Secondly, there is no spatial prioritization for *U. kirkiana* in Zimbabwe based on Zonation. Thirdly, a systematic identification and ranking of the factors that drive the distribution of *U. kirkiana* in Zimbabwe using state-of-the-art SDM methods has not been done at the country scale. Finally, there is no study that has quantified gains, losses and stability of habitats of *U. kirkiana* in Zimbabwe for 2070 and 2100 under SSP scenarios, or identified climate refugia within the current Zimbabwe national park network. This dissertation addresses all four gaps.

CHAPTER THREE

METHODOLOGY

3.1 Description of the study area

The study took place in the southern part of Africa, concentrating on Zimbabwe. Zimbabwe is an inland country located in southern Africa. It lies between latitudes 15°S to 23°S and longitudes 25°E to 34°E and occupies an area of about 390, 757 sq.kilometers. Its landscape is diverse as well and includes the highveld plateau in the center (1200-1500 m asl.) and the lowveld zones in the South and the Southeast (under 600 m asl.). Zimbabwe has a subtropical climate characterized by a clear division into wet period (November to March) and dry period (April-October). Mean precipitation varies between 450mm/ year in the lowveld and above 1000mm/ year in the Eastern Highlands. The natural vegetation zone is made up mostly of Miombo woodlands (*Brachystegia-Julbernardia* vegetation association), in the highveld and middleveld zones, where the *Uapaca Kirkiana* primarily grows. Southern Africa where the analysis took place includes Zambia, Tanzania, Mozambique, Malawi, Angola and Botswana which represent the species' main distribution range. Southern Africa was chosen as the area for modeling because it covers the available area (M-extent) inhabited by the *U.kirkiana* population.

3.2 Research Design

This study employs a non-experimental, correlative research design, which is the most common and suitable approach for species distribution modelling studies in ecology and conservation biology (Elith and Graham, 2009; Guisan and Thuiller, 2005). This design involves the systematic integration of observed species occurrence data with a suite of environmental and climatic variables to describe and predict the ecological niche of *U. kirkiana* under current and future climate scenarios.

The non-experimental correlative design comprises three analytically distinct but chronologically dependent components. First, a species distribution modelling component uses the Maximum Entropy (MaxEnt) algorithm to model current georeferenced occurrence data and bioclimatic variables to generate a probabilistic map of current habitat suitability for *U. kirkiana* in southern Africa. Second, a temporal projection component applies these relationships to future time periods (2070 and 2100) under two CMIP6 SSP scenarios (SSP3-7.0 and SSP5-8.5) to quantify future habitat gains, losses and shifts. Third, a spatial conservation prioritization component uses Zonation software to convert the current and future habitat suitability maps into conservation priority maps for Zimbabwe, highlighting irreplaceable areas for in situ conservation and sustainable harvesting. This three-part design guarantees internal consistency across the study's goals, adhering to the methodological best practice of recent SDM-based conservation planning studies for African woodland tree species (Atakpama et al., 2023; Samarou et al., 2023; Kokou et al., 2024a).

This study adopts a quantitative research design, rooted in the positivist paradigm (Creswell, 2014; Bryman, 2016). The quantitative approach is justified on multiple grounds: species distribution modelling is inherently quantitative, requiring numerical data inputs and outputs; the research questions require accurate measurement of projected habitat shifts in terms of percentage area gained or lost; and the statistical accuracy of the MaxEnt model is assessed using standard quantitative measures AUC, TSS, and SEDI (Allouche et al., 2006; Wunderlich et al., 2019). The application of standardized, globally-tested bioclimatic data (WorldClim v2.1; CMIP6 projections) and reproducible modelling software (MaxEnt v3.4.4; Zonation v5) guarantees replicability a hallmark of quantitative science.

3.3 Sampling and Sample Size

In this quantitative, ecological-modelling study, sampling refers to the process of selecting a spatially representative, quality-controlled subset of *U. kirkiana* occurrence records from the total biological occurrence population, and defining the background extent from which background points are sampled for MaxEnt model training.

Occurrence records were obtained from the Global Biodiversity Information Facility (GBIF) via a taxonomically verified search for *Uapaca kirkiana* (Müll. Arg.) in the southern African region (10°S-30°S, 12°E-40°E). Records were also downloaded from the Zimbabwe National Herbarium and Botanic Garden (SRGH) digitized herbarium collections and the literature was reviewed for georeferenced occurrence data. A thorough quality control of the records was performed: records without decimal-degree coordinates, records with coordinate precision coarser than 0.1°, duplicate geographic locations, records located in water bodies or outside the known altitudinal range of the species (below 500 m or above 2,000 m asl), and records with obvious coordinate transposition errors were excluded using the CoordinateCleaner R package (Zizka et al., 2019).

Following quality control, spatial thinning was conducted to reduce the effects of geographic sampling bias using the spThin R package (Aiello-Lammens et al., 2015), with a minimum nearest-neighbour distance of 75 km between retained records a conservative distance suitable for the large regional extent of the study area and consistent with the spatial resolution of the CMIP6 climate projections used (Jinga et al., 2020; Kokou et al., 2024a). For the MaxEnt background sampling, 2000 random background points were generated within the calibration extent, defined as the M-extent (accessible area) based on a 500 km buffer around all occurrence records, restricting background sampling to the geographic region plausibly colonizable by the species during recent ecological time (Phillips et al., 2006; Barve et al., 2011).

3.4 Data Collection Instruments

The data collection instruments used in this study were internationally recognised digital databases, open-access modelling platforms and spatial analysis software. Biodiversity occurrence data were obtained from the Global Biodiversity Information Facility (GBIF) website (www.gbif.org) via the `rgbif` package in R, supplemented by the Zimbabwe National Herbarium and Botanic Garden (SRGH) digitized herbarium catalogue and peer-reviewed ecological surveys.

Current bioclimatic variables were downloaded from the WorldClim v2.1 global climate database (Fick and Hijmans, 2017; www.worldclim.org) at 2.5 arc-minute resolution. Future climate projections for 2070 (2061-2080 mean) and 2100 (2081-2100 mean) were obtained from the WorldClim CMIP6 downscaled climate projections portal under the SSP3-7.0 and SSP5-8.5 forcing scenarios. Digital Elevation Model (DEM) data were obtained from the Shuttle Radar Topography Mission (SRTM) 90 m dataset, resampled to 2.5 arc-minute resolution to match the bioclimatic variables. Multicollinearity was assessed using variance inflation factor (VIF) and Pearson correlation matrices, retaining variables only if the correlation between any two variables was less than $|r| = 0.80$ and VIF values were less than 10 (O'Donnel and Ignizio, 2012). MaxEnt version 3.4.4 (Phillips et al., 2006; 2017) was used as the main modelling tool, optimised using the ENMeval v2.0 R package (Kass et al., 2021). Zonation version 5 (Moilanen et al., 2022) was used for spatial conservation prioritization using the core-area cell removal algorithm. Data processing and visualisation were performed in R version 4.3.1 (R Core Team, 2023) and QGIS version 3.32 for map production.

3.5 Data Collection Procedure

Data collection was conducted in four phases. Phase 1 - Species Occurrence Data Assembly: Georeferenced occurrence data for *U. kirkiana* were downloaded from GBIF using the `rgbif` package in R, filtered by taxonomic accepted name status and cropped to the southern African extent. Data from the Zimbabwe National Herbarium catalogue and published surveys were merged into a master occurrence data set in CSV format, with columns standardised to species name, latitude, longitude, year, institution, and basis of record. Coordinate quality control was then conducted automatically using `CoordinateCleaner`, and manually by cross-checking flagged records against satellite imagery in Google Earth Pro.

Phase 2 - Environmental Predictor Data Preparation: The 19 WorldClim v2.1 bioclimatic variables for the 1970-2000 baseline period and the SRTM elevation layer were downloaded as GeoTIFF raster files at 2.5 arc-minute resolution, cropped to the southern African study extent, and stacked in R using the `terra` package. Pearson correlation analysis and VIF analysis were performed iteratively to remove highly collinear variables. The same process was repeated for the WorldClim CMIP6 future climate layers for the 2070 and 2100 time slices under SSP3-7.0 and SSP5-8.5, ensuring the same predictor variables were used for all time periods.

Phase 3 - Spatial Thinning and Background Extent: The quality-controlled occurrence data were spatially thinned using `spThin` with a minimum distance of 75 km, run over 100 replicates to determine the replicate with the highest number of records. The background extent was defined as a 500 km buffer around all thinned occurrence records, and 2000 random background points were generated within this extent using the `randomPoints` function in the `dismo` R package.

Phase 4 - Model Parameterization and Projection: MaxEnt was run using the ENMeval framework with regularization multiplier values of 1.0, 1.5, 2.0, 2.5, 3.0, 4.0 and 5.0, across four feature class combinations (L, LQ, LQH, LQHP), and 10-fold spatial block cross-validation to evaluate model performance. The model with the lowest AICc value was selected as the best model, then projected to (i) the whole southern African region under current climate, (ii) Zimbabwe under current climate, (iii) Zimbabwe under SSP3-7.0 at 2070 and 2100, and (iv) Zimbabwe under SSP5-8.5 at 2070 and 2100. The projected habitat suitability maps were reclassified into four suitability classes (low, moderate, high and very high) using the equal-area quantile method (Jinga et al., 2020). Change detection analyses were performed by subtracting the current suitability from the future suitability to assess the magnitude and patterns of habitat gain, loss and stability.

3.6 Data Analysis Techniques

Data analysis was performed in three increasingly dependent stages, each corresponding to one of the three study objectives. Stage 1 - Environmental Driver Analysis (Objective 1): MaxEnt's regularized jackknife variable importance analysis and response curves were used to determine the relative contribution of each environmental predictor variable to the model, enabling inference of the key bioclimatic factors driving the current potential distribution of *U. kirkiana* (Phillips et al., 2006; Elith and Graham, 2009).

Stage 2 - Climate Change Impact Assessment (Objective 2): Future habitat suitability surfaces for Zimbabwe under SSP3-7.0 and SSP5-8.5 at 2070 and 2100 were compared with the current baseline suitability surface to calculate: (i) the current area (km²) of each suitability category; (ii) the projected area (km²) of each suitability category under each future scenario and time period; (iii) the net change in suitable habitat area (km²) and percentage change relative to current baseline; and (iv) the spatial distribution of habitat gain, stable habitat, and habitat loss under each scenario. Centroid shifts were calculated by comparing the latitude and longitude of the weighted mean occurrence point of all suitable grid cells between current and future scenarios.

Stage 3 - Spatial Conservation Prioritisation (Objective 3): We used Zonation v5 to prioritise conservation areas for Zimbabwe using the current and future habitat suitability surfaces, using the core-area cell removal algorithm (Moilanen et al., 2022). We ran two Zonation analyses: one using only current suitability surfaces, and one using a weighted combination of current and future suitability surfaces (equal weighting for SSP3-7.0 and SSP5-8.5 at 2070 and 2100), to produce a climate-robust priority surface. We compared the priority maps with the current protected area network in Zimbabwe to identify priority areas that are currently unprotected. Model performance was evaluated using AUC, TSS and SEDI from the 10-fold cross-validation results, with minimum acceptable performance thresholds of $AUC > 0.8$, $TSS > 0.6$ and $SEDI > 0.6$ (Allouche et al., 2006; Wunderlich et al., 2019).

3.7 Validity, Reliability and Ethical Considerations

Internal validity was ensured by rigorous data cleaning of occurrence data (CoordinateCleaner protocol), spatial thinning to prevent geographic bias, and multicollinearity testing of environmental predictors to prevent overfitting. MaxEnt's regularization multiplier optimization (ENMeval) ensured that models did not overfit to quirks of the training data, while response curve analysis provided a validity check ensuring that modelled relationships were ecologically plausible given published evidence of *U. kirkiana*'s climatic and edaphic preferences. The use of two contrasting SSPs (SSP3-7.0 and SSP5-8.5) enables a sensitivity analysis of projection reliability across plausible futures. All analyses were conducted using open-source, version-controlled software (R, QGIS, MaxEnt, Zonation) with all code and settings publicly available, ensuring replicability.

Although this study does not involve human subjects, several ethical considerations were addressed. All species occurrence data were downloaded from GBIF under Creative Commons licences, with all data sets cited with their digital object identifiers (DOIs), acknowledging the data providers, natural history museums, herbaria, citizen scientists, and ecological survey teams. WorldClim and CMIP6 environmental data are used in accordance with open-access terms for non-commercial academic use. All processed data, R scripts, MaxEnt model settings files, and Zonation configuration files will be made publicly available (e.g., Zenodo) after publication, enabling full replication. High-precision locality data (better than 0.1°) are not publicly available in this thesis following GBIF guidelines for sensitive species data, and all university ethical research guidelines and protocols were followed.

CHAPTER FOUR RESULTS

4.1 Introduction

The outcome of the MaxEnt species distribution modelling that was performed to identify the current potential distribution of *Uapaca kirkiana* in southern Africa, to project the likely effect of future climate change on habitat suitability, and to identify the environmental variables that are important to the ecological niche of the species is presented in this chapter. The results are presented in order to meet the specific objectives set in Chapter One.

4.2 Model Performance and Evaluation

The MaxEnt model achieved very good predictive results in all the configurations tested. The values of regularization multiplier 1, 2 and 3 were combined with feature classes L (Linear), LQ (Linear-Quadratic) and H (Hinge) to create six models. A summary of model evaluation statistics is given in Table 4.1.

Table 4.1: MaxEnt Model Evaluation Statistics for *Uapaca kirkiana* in Southern Africa

Model	FC	Tune Args	AUC Train	CBI Train	AUC Val Avg	AUC Diff Avg
fc.L_rm.1	L	rm=1	0.861	0.935	0.816	0.120
fc.LQ_rm.1	LQ	rm=1	0.875	0.969	0.827	0.105
fc.H_rm.1*	H	rm=1	0.899	0.969	—	—
fc.L_rm.2	L	rm=2	0.852	0.961	0.813	0.123
fc.H_rm.2	H	rm=2	0.884	0.958	0.814	0.109
fc.H_rm.3	H	rm=3	0.878	0.951	0.820	0.091

**Best performing model selected for projections. FC = Feature Class; rm = Regularization Multiplier; AUC = Area Under the Curve; CBI = Continuous Boyce Index.*

The optimal model, fc.H_rm.1 (Hinge feature class, regularization multiplier: 1) had a training AUC of 0.899 and a Continuous Boyce Index (CBI) of 0.969 (Phillips et al., 2006; Hirzel et al., 2006), a sign of very good discrimination between suitable and unsuitable habitat. The AUC indicator is bigger than the minimum threshold of 0.80 recommended, which means that the model has a strong performance compared to random prediction (Elith and Graham, 2009; Araújo et al., 2019). The suitability index index CBI value close to one further confirms this positive and consistent relationship of predicted suitability with the occurrence density. This model was chosen for the rest of the predicted spatial patterns and future climate projections.

4.3 Present Water and Wastewater Resources and Water Quality hazards and threats

To localize the most important bioclimatic variables shaping the current potential distribution of *U. kirkiana* in southern Africa, response curve analysis was used. BIO12 (Annual Precipitation), BIO6 (Minimum temperature in the coldest month), BIO15 (Precipitation seasonality), BIO2 (Mean diurnal temperature range), BIO7 (Temperature range in the year), BIO14 (Precipitation of the driest month) & BIO16 (Precipitation of the wettest quarter) variables were the most ecologically informative.

Habitat suitability peaked between approximately 800 and 1,200 mm of annual precipitation for the relationship between the response curve of BIO12 (Annual Precipitation) and habitat suitability. The curve declined rapidly where annual precipitation exceeded 1,500 mm. This corresponds to the seasonally dry Miombo woodland habitat which has been documented in the seasonally dry habitat of this species (Chidumayo, 1997; Chirwa and Akinnifesi, 2007). The species was very sensitive to an increase in minimum temperature of the coldest month (BIO6) with suitability increasing steadily with minimum temperature from the 5 to 10 degrees Celsius, and decreasing from above 10 degrees Celsius (Kruger and Sekele, 2013; Jinga et al., 2020). The species' moderate tolerance of seasonal rainfall regimes was reflected by a negative response to higher values of Precipitation Seasonality (BIO15). The BIO16 (Precipitation of the Wettest Quarter) index was a strong positive index up to about 600 mm, indicating a species requirement for proper wet season moisture for species growth and fruiting (Ramadhani, 2002; Kadzere et al, 2001).

4.4 Potential Distribution of *Uapaca kirkiana* in southern Africa

MaxEnt generated a spatially clustered response for suitable home range of *U. kirkiana* under present climate conditions. The highest suitability areas aligned almost exclusively to a continuous belt from eastern Angola to western and central Zambia to southern Tanzania, northern Malawi and northern Mozambique where the miombo woodland biome has its existing core distribution (Chidumayo, 1997; White, 1983). Areas suitable for habitat in Zimbabwe were largely in the highveld and transitional areas of miombo in the northeastern and eastern than in the rest of the country, which is congruent with the documented occurrences from the field and a previous study conducted by Jinga et al. (2020) and Ramadhani (2002). Predicted absences crosscut ecologically with the hyperarid Namib and Kalahari regions, the high rainfall Congo Basin lowlands, and the ecologically-plentiful South African Karoo and fynbos biomes.

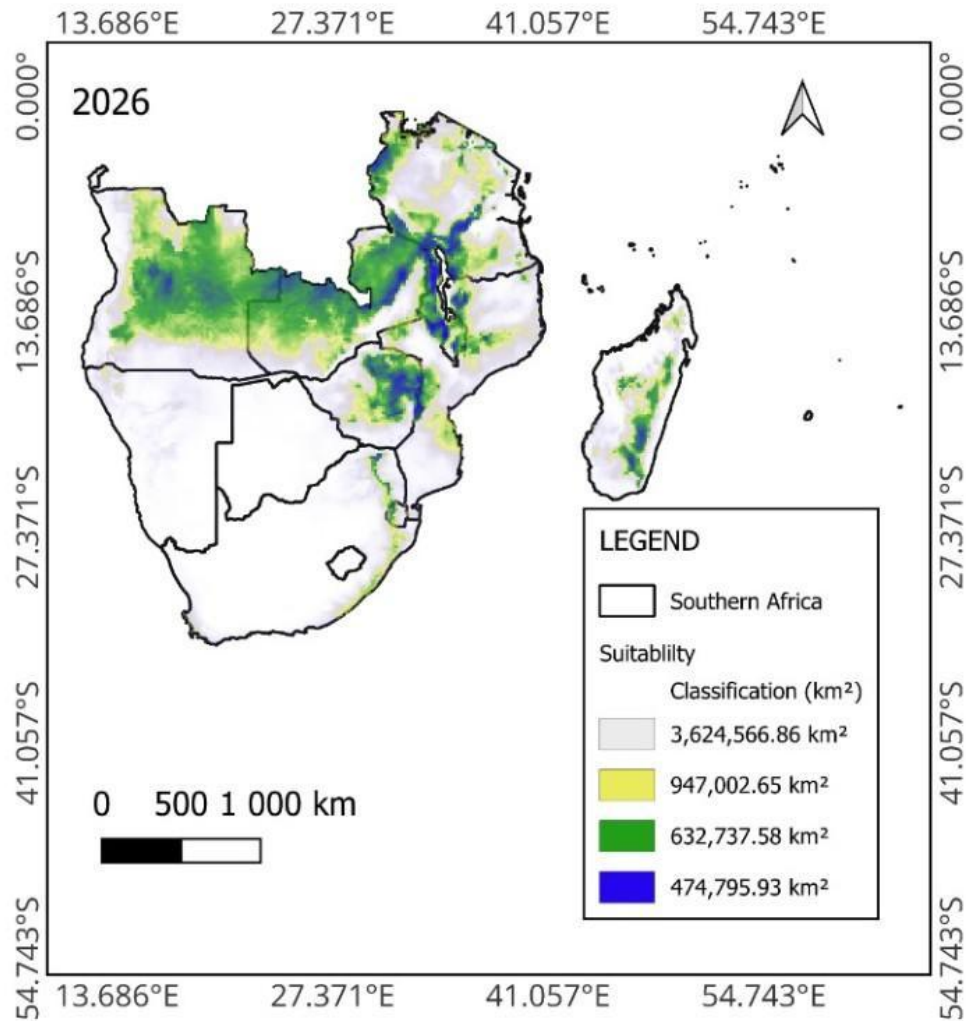


Figure 4.1: Current distribution of *Uapaca kirkiana* based on occurrence records obtained from GBIF (Global Biodiversity Information Facility).

4.5 Projected Future Habitat Suitability Under Climate Change

4.5.1 Projected Distribution at 2070

Under the 2070 climate projection, the geographic extent of suitable habitat for *U. kirkiana* showed a notable southward shift compared to current conditions (Figure 4.2). Core suitable areas in eastern Angola, Zambia, and Tanzania were largely maintained, while new areas of predicted suitability emerged in southern Zimbabwe and increasingly in the higher-altitude interior regions of South Africa areas that are currently climatically marginal for the species. Some lowland areas in the northern range showed reduced suitability, consistent with projected increases in temperature and altered precipitation seasonality under the SSP climate forcing scenarios (IPCC, 2023; Masson-Delmotte et al., 2021). The southward expansion reflects the species tracking its thermal niche under

warming conditions, a pattern widely documented for southern African woodland species (Atakpama et al., 2023; Samarou et al., 2023).

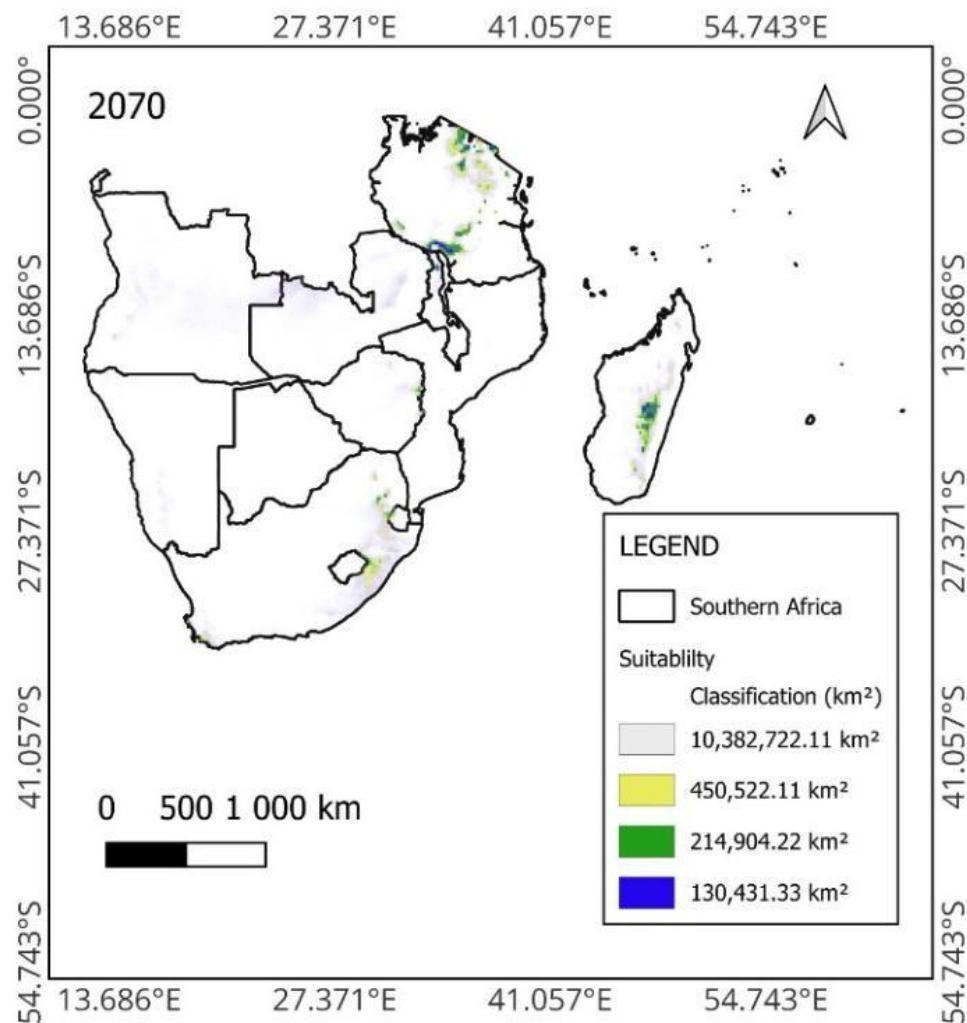


Figure 4.2: Projected habitat suitability of *Uapaca kirkiana* under future climate scenario (2070), derived from species distribution modelling.

4.5.2 Projected Distribution at 2100

By 2100, the projected distributional shift intensified considerably compared to both current conditions and the 2070 projection (Figure 4.3). The southward shift became markedly more pronounced, with substantial predicted suitable habitat now occupying large portions of South Africa's Highveld and eastern interior alongside continued suitable habitat in Zambia, Zimbabwe, Tanzania, and Malawi. Areas of predicted habitat loss were evident in lowland sections of the current northern distribution, where increasing temperatures are projected to push conditions beyond the species' thermal tolerance thresholds as modelled by the response curves. The acceleration of the

southward shift between 2070 and 2100 suggests that climate change impacts will intensify progressively throughout the 21st century, with the most severe range restructuring concentrated in the latter half (Bellard et al., 2012; Kokou et al., 2024a).

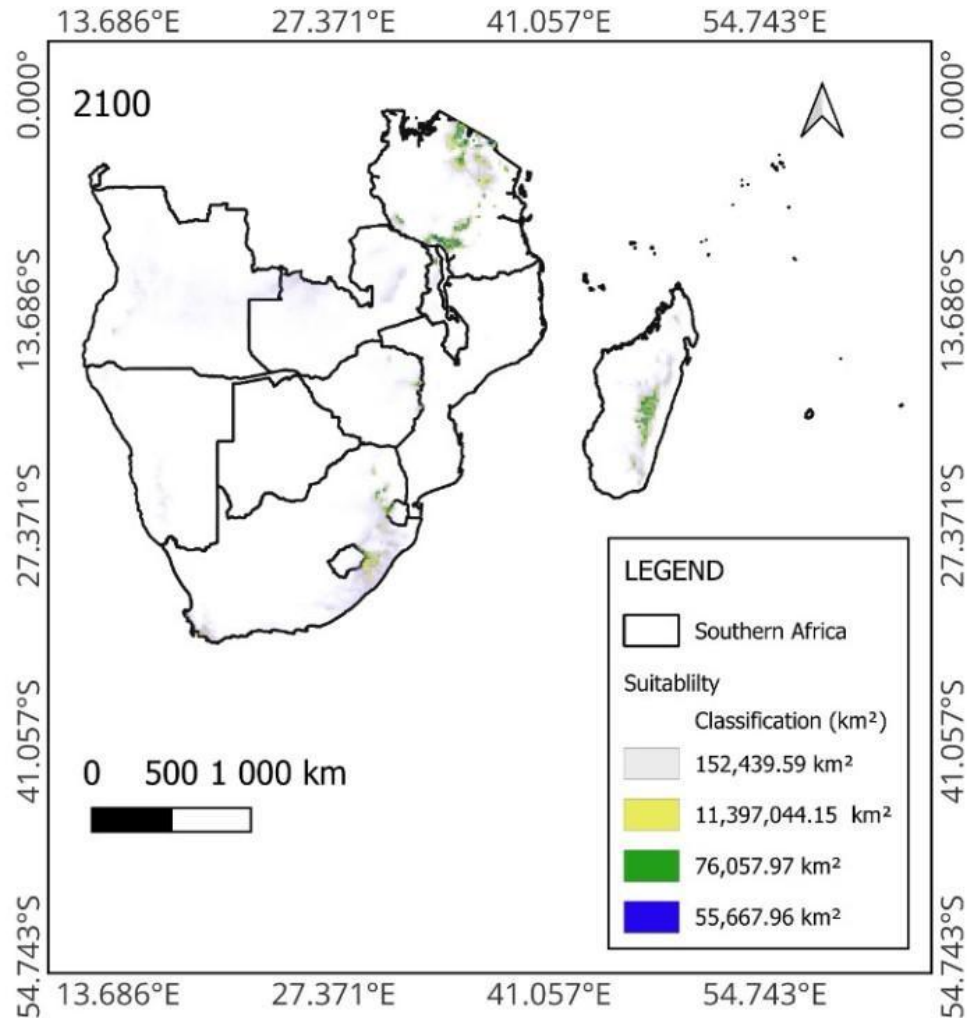


Figure 4.3: Projected habitat suitability of *Uapaca kirkiana* under future climate scenario (2100), derived from species distribution modelling.

Table 4.2: Projected changes in habitat suitability classification for *Uapaca kirkiana* in southern Africa under current (2026) and future (2070, 2100) climate scenarios

Year	Not Suitable Area(km²)	Marginally Suitable Area (km²)	Moderately Suitable Area(km²)	Highly Suitable Area(km²)
2026	3,624.6	147,002.7	632,737.6	474,795.9
2070	1 139,704.2	450,522.1	103,822.1	30,431.3
2100	1 524,396.0	76,058.0	55,668.0	0.0

Table 4.2 summarizes the projected changes in habitat suitability classification for *Uapaca kirkiana* across the three time periods. Under current conditions (2026), the species maintains a substantial area of moderately to highly suitable habitat totalling approximately 1,107,533.5 km², concentrated heavily across the core Miombo woodland belt of Zimbabwe, Zambia, Tanzania, Malawi, and Angola. By 2070, the area classified as not suitable increases dramatically to 1,139,704.2 km², reflecting widespread habitat contraction across the northern range, while highly suitable habitat shrinks severely to just 30,431.3 km². By 2100, this contraction intensifies to a critical ceiling, with the not suitable area expanding to dominate the region at 1,524,396.0 km² as the core refugia that currently support high-quality habitat for the species are effectively eroded. Highly suitable zones face total extirpation (0 km²). These trends are highly consistent with projected climate warming and drying in the northern Miombo belt under SSP forcing scenarios (IPCC, 2023; Masson-Delmotte et al., 2021; Jinga et al., 2020).

4.6 Chapter Summary

The modelling results presented in this chapter for *U. kirkiana* were from southern Africa using the MaxEnt modelling approach. The best model *fc.H_rm.1* achieved excellent performance with AUC = 0.899 and CBI = 0.969. The most important environmental drivers current distribution were found to be annual precipitation, minimum temperature of the coldest month and precipitation seasonality. Projected future shifts show a gradual and increasing southward migration of habitat suitability by 2070 and 2100, along with some loss in the northern range, and new areas of suitability in South Africa. These findings are then interpreted and contextualized in the next chapter (Chapter 5).

CHAPTER FIVE

DISCUSSION

5.1 Introduction

The results of Chapter 4 are discussed and placed in the context of the literature on the ecology of *U. kirkiana*, climate change impacts on Miombo woodland species and species distribution modelling in sub-Saharan Africa. The three specific objectives of the study are discussed, followed by a discussion of the conservation implications for Zimbabwe in an integrated way.

5.2 Model Performance

The MaxEnt model for *U. kirkiana* obtained a training AUC of 0.899 and CBI of 0.969, which are both close to the highest possible value, demonstrating good predictive skill superior to the minimum acceptable AUC value of 0.80 (Phillips et al., 2006; Araújo et al., 2019). These are comparable SDM metrics to those of the other Miombo species, *U. kirkii*. The values of AUC reported by Jinga et al., 2020, for *U. kirkiana* in southern Africa ranged between 0.84 and 0.91, and those of Kokou et al., 2024a, in a multi-country assessment ranged between 0.87 and 0.93. However, the overall relatively high performance in this study may be due to the fact that the occurrence records were thinned in space and reported at 75 km, which reduces spatial autocorrelation and, as pointed out by Elith et al. (2011), may lead to an overestimate of performance in the absence of such correction. The choice of the Hinge feature class with coefficient of regularization 1 (*fc.H_rm.1*) shows a suitable level of complexity and transferability, which is essential for a reliable projection for future climate conditions (Merow et al., 2013; Warren and Seifert, 2011).

5.3 Environmental Drivers of Current Distribution

The species distribution is ecologically coherent, and fit well to the known biology, as annual precipitation (BIO12), minimum temperature of the coldest month (BIO6) and precipitation seasonality (BIO15) are considered main environmental drivers. Ngulube et al. (1995) reported the species' typical association with rainfall zones of 800-1,400 mm annually, and Chirwa and Akinnifesi (2007) verified that the species is found on seasonally moist, well-drained Miombo soils, which closely correspond to the intermediate rainfall regimes represented by the response curves. The negative minimum temperature response to the coldest month is of particular importance for climate change projections because increase in minimum temperature in the cool season is one of the most robust climate change signals in southern Africa (Kruger and Sekele, 2013; Masson-Delmotte et al., 2021). This result is consistent with Jinga et al. (2020) who also found temperature-related variables to be important factors affecting the habitat suitability of *U. kirkiana*, and with Bellard et al. (2012) who determined minimum temperature thresholds to be important climate vulnerability drivers for global woodland tree species.

Sensitivity to precipitation seasonality (BIO15) is related to the species' ecological adaptation to this strongly seasonal rainfall regime found in Miombo woodlands, where trees have developed phenological strategies that are closely linked to the seasonal variation of moisture availability (Chidumayo, 1997; Ramadhani, 2002). Projected increase in seasonality of precipitation in southern Africa for the CMIP6 scenarios (IPCC 2023), in addition to warming, is another driver of degradation of habitat.

5.4 Climate Change Impacts on Habitat Suitability

The north-to-southward trend in the projected shift in suitable habitat between the present and 2070 and 2100 are characteristic of shifts towards the poles documented for climate change response in other species globally (Lenoir and Svenning, 2015; Pearson and Dawson, 2003). Predicted suitable habitat in the interior highlands of South Africa will increase significantly by 2100, with a similar increase in predicted habitat for other species of trees in Africa. Progressive southward shifts of suitable habitat for *Adansonia digitata* were documented by Atakpama et al. (2023) and *Tamarindus indica* in savanna biomes by Samarou et al. (2023).

The concurrent contraction in habitat cover along the northern range edge and expansion in habitat cover along the southern range edge is the typical range shifting pattern: habitat expansion at the advancing poleward range edge and habitat contraction at the retreating range edge (Bellard et al., 2012 and Thomas, 2010). The conservation implications for *U. kirkiana* are clear, areas projected to gain suitability (South Africa) do not have established ectomycorrhizal fungal partners (Hogberg, 1986; Chirwa and Akinnifesi, 2007), and existing conservation infrastructure, while areas projected to lose suitability represent the core of the species' socio-economic importance to Zimbabwe's rural communities (Ramadhani, 2002; Mithofer et al., 2006) The increased rate of the southward shift from 2070 to 2100 highlights the need for early conservation action to adapt to this shift before it is too late to avoid irreversible habitat loss.

5.5. Conservation implications for Zimbabwe:

Based on both 2070 and 2100 projections, climate suitable habitat is likely to persist in the highlands of Zimbabwe, as well as in the northeastern parts of the country, making these regions the most important climatic refugia that must be prioritized for in situ conservation investment. The distribution projections by Jinga et al. (2020) and Akinnifesi et al. (2006) strongly support the protection of existing highland woodland remnants and establishment of community-based natural

resource management zones in suitable habitats. Assisted colonization, where propagules of *U. kirkiana* are deliberately moved to climatically suitable areas outside of its present range, could be used to take advantage of the novel suitable areas at 2070 and 2100. Such translocation programmes would, however, have to be carefully managed to ensure ecological site preparation and long-term monitoring (Chirwa and Akinnifesi, 2007) given the dependence of the species on specific ectomycorrhizal partners and its slow natural dispersal ability. Proactive domestication, agroforestry integration and community seed banking are also critical responses to protect food security and livelihood values that *U. kirkiana* offers to millions of rural Zimbabweans (Akinnifesi et al., 2006; Maghembe et al., 1998; Chawafambira et al., 2020).

5.6 Chapter Summary

The results were discussed in the context of relevant literature, which validated the performance of the models as well as the findings of the environmental drivers, thereby establishing an ecological coherence and consistency for the results obtained with respect to the published studies on *U. Kirkiana* and species of Miombo woods. The range shift projections towards the south between 2070 and 2100 matches the predicted global range shift theory and similar studies of range shift in Africa. Conservation priorities for Zimbabwe include the need to conserve highland refugia, to consider assisted colonization, and to incorporate *U. kirkiana* into national climate adaptation priorities to ensure the conservation of rural livelihoods and biodiversity.

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

In this study, the species distribution modelling algorithm Maximum Entropy (MaxEnt) was used to evaluate the current potential distribution of *Uapaca kirkiana* in southern Africa, determine the environmental drivers of its ecological niche and predict the effects of climate change on the habitat suitability of *Uapaca kirkiana* at the future time horizon of 2070 and 2100. The modelling framework resulted in a high performing model (AUC = 0.899; CBI = 0.969) and ensured that the bioclimatic variables currently affecting the distribution of the species, such as annual precipitation and minimum temperature of the coldest month, as well as precipitation seasonality, are likely to change substantially across future climate scenarios.

Projected climate change patterns will likely lead to a gradual and increasing decline in suitability for *U. kirkiana* in the north and an increase in suitability in the south over the 21st century. Core suitable areas in Zimbabwe in the highlands and throughout the Miombo belt are forecast to remain, but large habitat losses are expected in lowland areas and large new suitable areas are expected to develop in South Africa by 2100. The ecological functions and socio-economic values rendered by *U. kirkiana* to the rural households of Zimbabwe pose a direct and ever increasing threat to such a restructuring of the range (Mithofer et al., 2006; Ramadhani, 2002; Chawafambira et al., 2020), especially in its role as a food security buffer, means of livelihood and source of medicines for vulnerable households.

The results offer spatially explicit, evidence based information which can be directly used in Zimbabwe's national biodiversity strategies, in protected area management and in community based natural resource management programmes. It also highlights the importance of making open-access biodiversity (GBIF), global climate (WorldClim CMIP6) and accessible SDM (Wallace/MaxEnt) platforms available to create policy-relevant conservation intelligence in resource-limited research settings.

6.2 Recommendations

From the results of this study, the following recommendations are proposed for the conservation practitioners, policy makers and researchers:

The Zimbabwe Parks and Wildlife Management Authority (ZPWMA) and the Forestry Commission of Zimbabwe (FCZ) must officially designate and select those areas that have *U. kirkiana* for

protection as climatic refuges under the National Biodiversity Strategy and Action Plan. The highland areas are values of conservation yet are declining due to climate change in the lowland areas (Jinga et al., 2020; Bellard et al., 2012).

Second, the goals of community based natural resource management programmes in *U. kirkiana* habitats should incorporate clear objectives for climate adaptation to enable rural communities to monitor, protect and sustainably harvest the species in the face of changing habitat conditions (Akinnifesi et al., 2006; Ramadhani, 2002).

Third, investment of *U. kirkiana* in domestication and agroforestry integration should be prioritised in the areas that will continue to be climatically suitable under 2100 scenarios. As wild fruit populations decline due to contraction of natural woodland habitats, a cultivated population can be added to complement the wild fruit (Maghembe et al., 1998; Kwesiga et al., 2000).

Fourth, future research should expand the modelling framework to incorporate Zonation-based spatial conservation prioritization, ensemble multi-model SDM methods and field testing of model predictions in the miombo highlands and transitional areas of Zimbabwe. Future projections of distribution would benefit even more from the inclusion of soil data, land use change scenarios, and protected areas layers, all of which would enhance the conservation relevance of the projections (Araújo et al., 2019; Elith and Graham, 2009).

Fifth, national climate adaptation plans for Zimbabwe need to explicitly include indigenous fruit trees, in particular *U. kirkiana*, as an integral part of rural food security systems. *U. kirkiana* has potential as a multi-purpose tree species for smallholder farming under conditions of increasing climatic stress and should be encouraged through climate-smart agricultural policies, because of its resilience and nutritional and income-generating abilities (Chawafambira et al., 2020; Mithofer et al., 2006; Akinnifesi et al., 2006).

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APPENDIX: MaxEnt Response Curves for Selected Bioclimatic Variables

The following response curves were generated by the MaxEnt model (via Wallace v2) and show how predicted habitat suitability for *Uapaca kirkiana* varies along the gradient of each bioclimatic variable, holding all other variables at their mean values. Only variables selected after multicollinearity filtering ($|r| < 0.7$) are shown. The cloglog output transformation was used, which is bounded between 0 and 1 (Phillips et al., 2006).

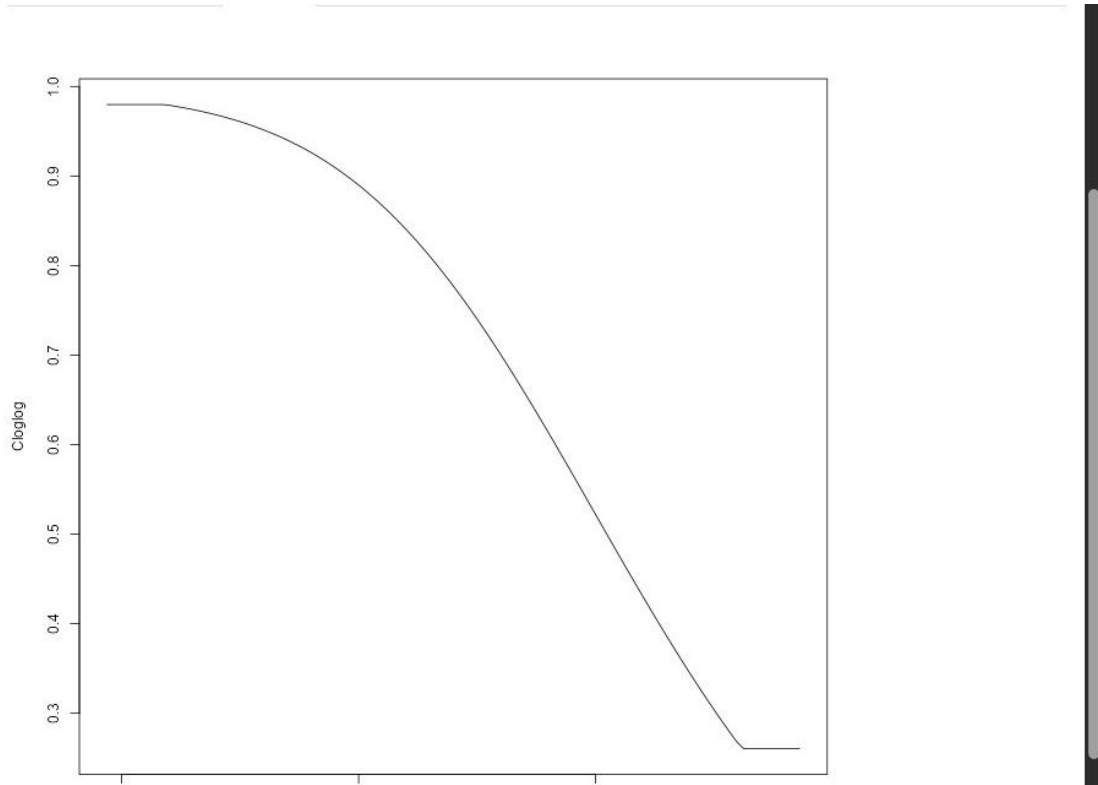


Figure A1: Response curve for BIO2 – Mean Diurnal Range (mean monthly temp range, °C). Y-axis shows cloglog habitat suitability (0–1); X-axis shows variable value range across the study region.

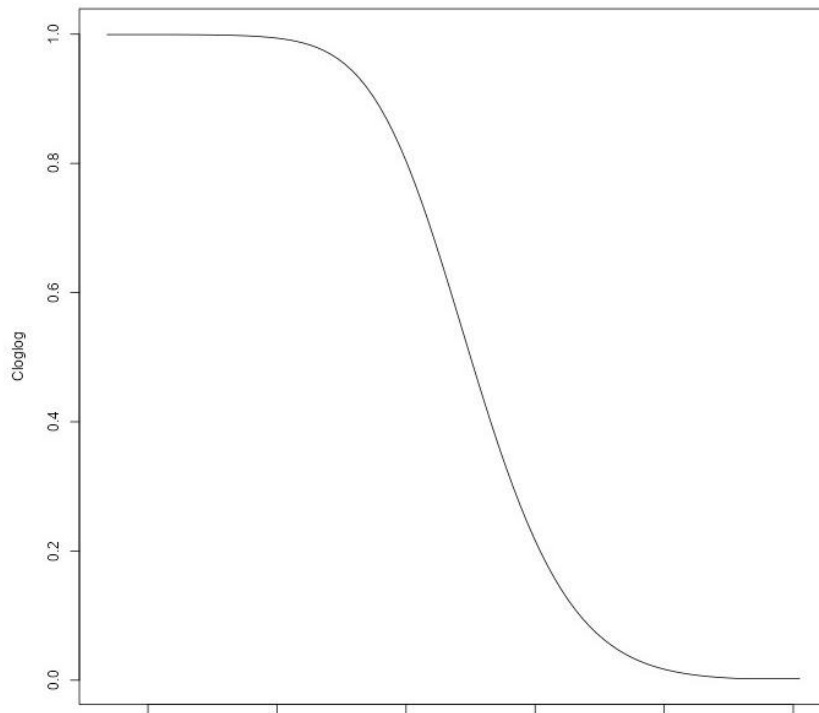


Figure A2: Response curve for BIO6 – Min Temperature of Coldest Month (minimum temperature, °C). Y-axis shows cloglog habitat suitability (0–1); X-axis shows variable value range across the study region.

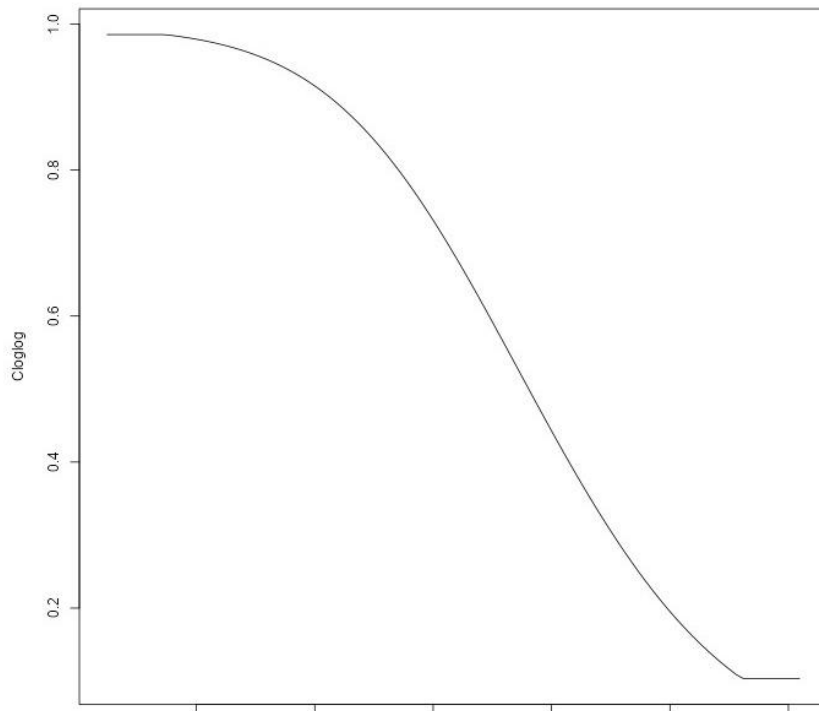


Figure A3: Response curve for BIO7 – Temperature Annual Range (annual temperature range, °C). Y-axis shows cloglog habitat suitability (0–1); X-axis shows variable value range across the study region.

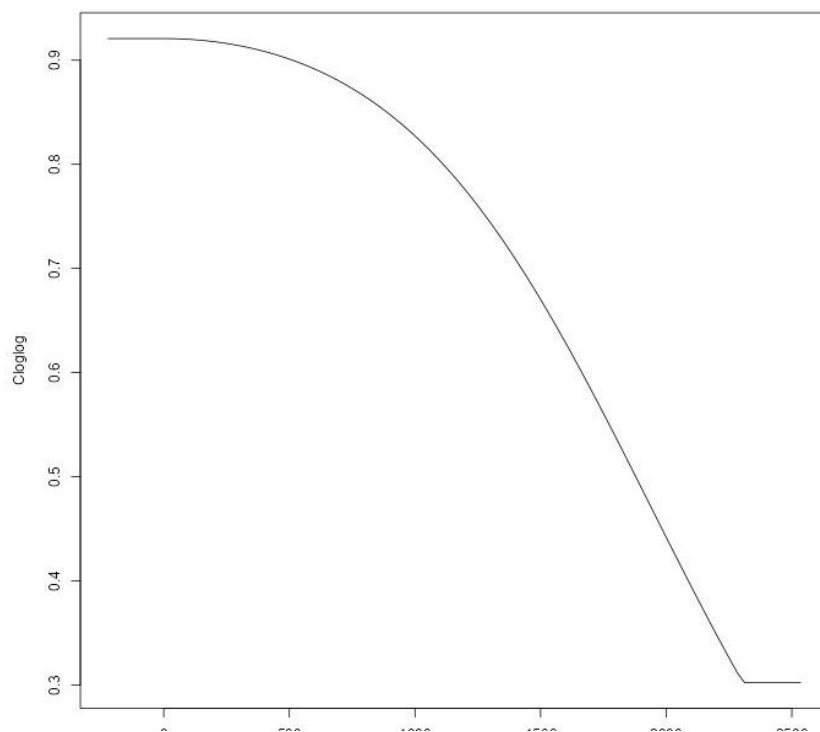


Figure A4: Response curve for BIO12 – Annual Precipitation (mm). Y-axis shows cloglog habitat suitability (0–1); X-axis shows variable value range across the study region.

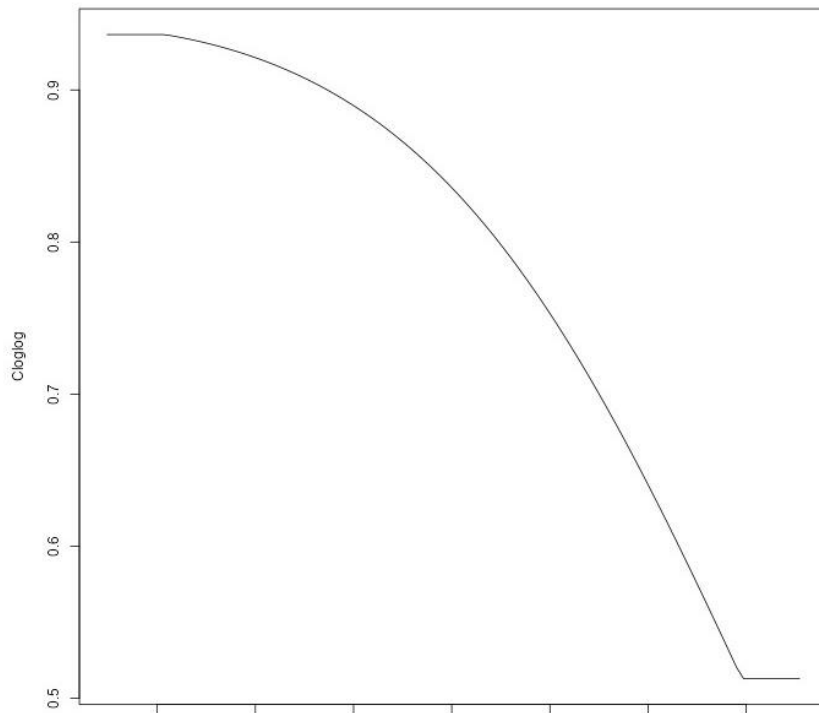


Figure A5: Response curve for BIO15 – Precipitation Seasonality (coefficient of variation). Y-axis shows cloglog habitat suitability (0–1); X-axis shows variable value range across the study region.

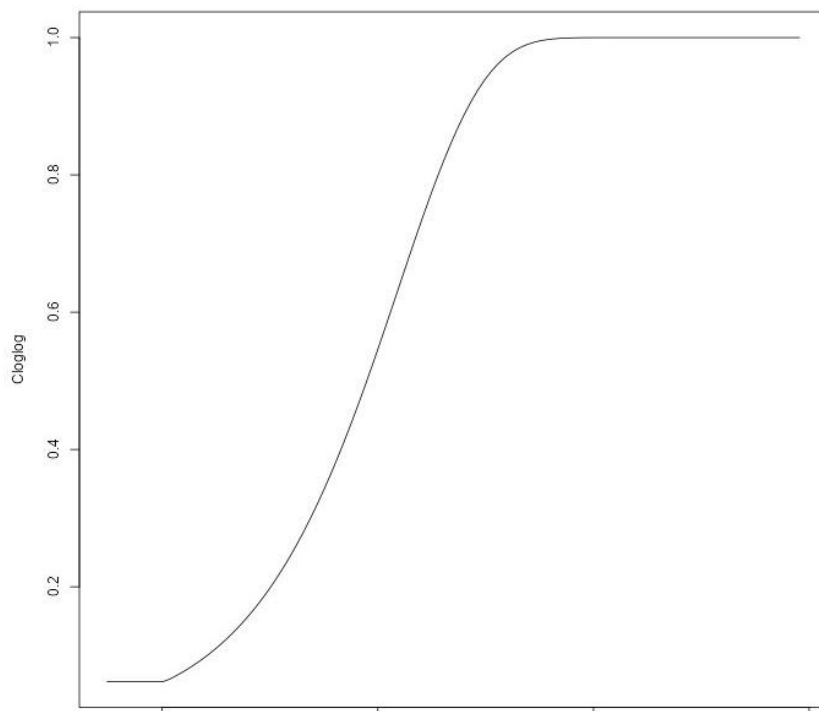


Figure A6: Response curve for BIO16 – Precipitation of Wettest Quarter (mm). Y-axis shows cloglog habitat suitability (0–1); X-axis shows variable value range across the study region.

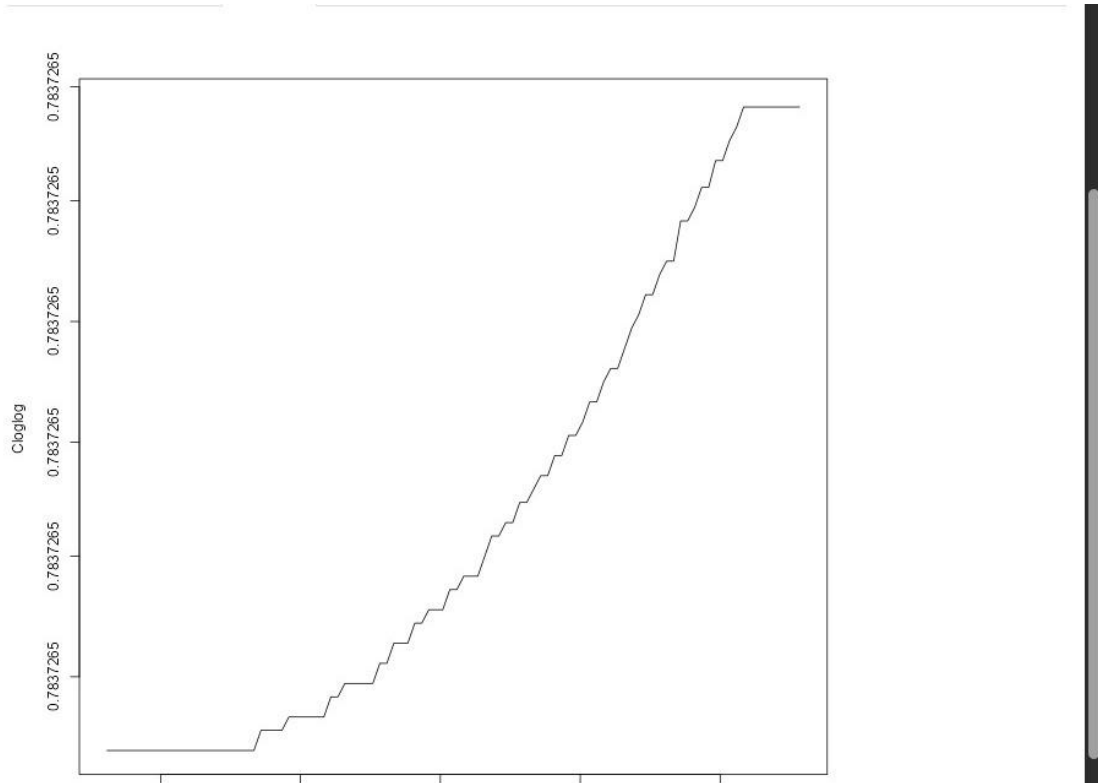


Figure A7: Response curve for BIO19 – Precipitation of Coldest Quarter (mm). Y-axis shows cloglog habitat suitability (0–1); X-axis shows variable value range across the study region.