COLLEGE OF SCIENCE AND TECHNOLOGY

SCHOOL OF SCIENCES

DEPARTMENT OF BIOLOGY

ACADEMIC YEAR: 2023-2024

MASTER'S PROGRAM IN BIODIVERSITY CONSERVATION AND NATURAL RESOURCES MANAGEMENT

Species Distribution Modelling of Medicinal and Culturally plants of Rwanda

Graphical abstract

A thesis submitted in partial fulfillment of the requirements for the degree of Master in Biodiversity Conservation and Natural Resources Management

By

Delphine Mpayimana

Reg number: 217095887

Supervisors: Prof Beth Kaplin PhD
Dr. Aloysie Manishimwe PhD

Kigali, August 2025

DECLARATION

I, **Delphine MPAYIMANA**, declare that this master's dissertation **"Species Distribution Modelling of Medicinal/ culturally significant plants in Rwanda"** is the result of my own work as a part of accomplishment of the necessities for the award of a master's degree in Biodiversity Conservation and Natural Resource Management at the University of Rwanda, College of Science and Technology and has not been submitted or repoted for any other degree at the University of Rwanda or any other institutions/Universities. All foundations that I have used or cited have been shown and recognized in the references.

Signed: 

Delphine MPAYIMANA/ Reg. Number: 217095887

Date 15 August 2025

APPROVAL

I certify that this research project entitled "**Species Distribution Modelling of medicinal and culturally significant plants in Rwanda**" was done under my supervision and has been submitted for examination/ revision with my approval.

Research Supervisor: **Prof Beth Ann Kaplin** **14 August 2026**

Dr Aloysie MANISHIMWE **12/08/2025**

Assoc. Prof. Dieudonné MUTANGANA

Head of Biology Department

School of science

College of Science and Technology

Nyarugenge on....../.... /2025

Prof. Denis NDANGUZA Dean, School of science

College of Science and Technology

Nyarugenge on....../.... /2025

ACKNOWLEDGEMENT

I would like to express my deepest gratitude to my co-advisor, **Dr Israel Borokini** Assistant Professor at Montana State University, whose generous support made it possible for me to travel to the United States. Under his supervision, I had the opportunity to learn species distribution modeling and engage with other students in his lab. I am equally thankful to **Montana State University** for hosting me during this valuable learning experience.

My heartfelt thanks go to my direct supervisor, **Prof. Beth Kaplin**, who has been by my side from the beginning of this project. She believed in me even when I struggled to believe in myself thank you, Professor, your unwavering support has never gone unnoticed.

I am also sincerely grateful to **Dr. Aloysie Manishimwe**, whose kindness and understanding meant so much throughout this journey.

A special thank you to my sister **Diana Nibobana**, who always cheered me on, followed up on my progress, and ensured I had everything I needed to pursue my studies. I also extend my warmest appreciation to my **mother** and all my **family members** for their endless love and support.

DEDICATION

I dedicate this thesis to the Almighty God, who has been my constant source of strength, wisdom, and guidance throughout this journey. Without His grace, this work would not have been possible.

TABLE OF CONTENTS

LIST OF FIGURES

LIST TABLES

ABSTRACT

Species overexploitation poses a critical threat to biodiversity, particularly in the Global South where reliance on natural resources for livelihoods is substantial. In Africa, a significant portion of the population relies on medicinal plants and animals for primary healthcare. With Africa's escalating population growth, there is an urgent need to understand the potential consequences on medicinal plant species, as increased harvesting may heighten extinction risks. Therefore, this study aims to address this concern by modeling the potential distribution of 14 medicinal and culturally significant native plant species in Rwanda. Using spatial occurrence records obtained from the Global Biodiversity Information Facility (https://www.gbif.org/), and climatic predictors downloaded from WorldClim (https://www.worldclim.org/), I fitted species distributions models (SDMs) using bioclim envelope algorithms in the *dismo* R package. Model performance was evaluated using both area under the curve (AUC) of the receiver operating characteristic plot and True Skill Statistics (TSS). High-performing models were integrated into weighted average ensemble models to predict potential geographic distributions of each of the 14 species within Rwanda. The predicted suitable areas were refined by excluding urbanized and degraded areas, providing a comprehensive overview of habitat suitability for each species. Response curve method was used to assess the contribution of the predictor variables to the ecological niche, while the niche breadth of all species was calculated. The results of this study have significant application for conservation efforts in Rwanda by highlighting existential threats to medicinal plant species and identifying areas for conservation prioritization.

CHAPTER 1: INTRODUCTION

Background

Medicinal plants are plants that contain phytochemicals or other substances which are used for therapeutic purposes (Sofowora et al., 2013; Borokini et al., 2013). These species have been used in human societies for millennia for primary health care (Ramathal & Ngassapa, 2001; Tan et al., 2021). Archaeological studies show that early humans had and applied their knowledge of the medicinal uses of various plants (Petrovska, 2012; Hardy 2019). To date, more than 80% of the populations in the developing economies, including Africa, depend on medicinal plants for primary health care (Flinkenflögel et al., 2015; WHO, 2020; Gahamanyi et al., 2021), while 50% of the world's pharmaceutical drugs were derived or inspired from medicinal plants (Newman and Cragg, 2020). Even in advanced economies, such as the United States, one in four American adults rely on complementary and alternative medicine (U.S. National Center for Complementary Integrative Health, 2017). Medicinal plants provide a variety of ecosystem services (Feng et al., 2023); between 50,000 and 70,000 plants are used for medicinal purposes globally (UNEP, 2012). Medicinal plants are at the core of traditional medicine, an unorthodox medical system that involves herbal medicine (Borokini and Lawal 2014). In Africa, reliance on medicinal plants can be attributed to limited access to hospital care and medical facilities, insufficient number of medical doctors, and the presence of strong traditions of traditional healers using native plants. For example, it was reported that there is one doctor for every 5,000 people in Africa (World Health Organization Africa Regional Office, 2006). The richness of medicinal plants in Africa could be attributed to the bioaccumulation of secondary metabolites due to the intensity of solar radiation in areas close to the equator (Mahomoodally, 2013); these phytochemicals are also produced as part of plant defenses against herbivores, underscoring the significance of strong and selective biotic interactions in tropical ecosystems (Divekar et al., 2022).

The sub-Suharan Africa human population has an annual growth rate of approximately 2.5% (Abramova, 2022). Thus, Africa also has one of the youngest human populations in the world. It is estimated that the African population will reach 2.5 billion, or 26% of the projected global human population, and it may continue to grow to reach a projected 38% by the year 2100 (IMF 2023). With an increasing population and economic development, demand for land for construction, urbanization, and food production will Increase, enhance the global habitat destruction. Additionally, population growth will also increase dependence on natural resources for livelihoods, including medicinal/culturally plants for primary health care, which can drive species extinction due to overexploitation (Nshimiyimana et al., 2023)

Africa's fast-growing population and rising economic pressures call for innovative conservation strategies beyond the traditional development-focused approach. Despite the scale of the challenge, there is still hope. With unified and sustained action in the coming decades, biodiversity loss across the continent can be significantly reduced. (Chapman et al., 2022) Moreover, global annual trade in medicinal plants is estimated at over USD 100 billion, and it is projected to continue to increase (Chapman et al., 2022) placing harvesting pressure on wild stocks of medicinal flora. Knowledge of medicinal plants is deeply tied to the Indigenous and Local Knowledge systems and biocultural heritage and identity of many human groups; therefore, extirpation and extinction of medicinal plants will have adverse effects on traditional ecological knowledge and persistence of vulnerable Indigenous communities.

Species distribution modeling (SDM) is widely used to describe species-habitat relationships, map species ranges, evaluate species rarity, identify environmental factors that influence species persistence and limit distributions, and to predict the potential current and future distributions (Elith et al., 2006; Guisan et al., 2006; Sousa-Silva et al., 2014; Phillips et al., 2017; Borokini et al., 2023). It is based on the niche theory that predicts the persistence and distribution of species are constrained by specific biotic and abiotic factors and dispersal ability (Soberon and Peterson, 2013; Pironon et al., 2018). Since the knowledge of the geographical distributions of most species is lacking (Wallacian shortfall; Lomolino 2004), SDMs can be used to predict the distribution of potential niche and suitable habitats, which can then be used to select and prioritize areas for field surveys. SDM-guided fields have resulted in the discovery of new populations of the target species (Burns et al., 2020; Borokini et al., 2023). Due to the increasing global demand for medicinal plants and the need for their conservation, SDMs can be used to identify suitable areas for commercial cultivation of medicinal plants, while also mapping areas for translocation of imperiled species and conservation management.

Rwanda is a small landlocked country located in East Africa, within the Albertine Rift Valley, which is a biodiversity hotspot. Despite its relatively small size, it has diverse habitats and ecosystems ranging from humid montane and sub-montane forests to savannas (Plumptre et al., 2003), as well as topographic complexity, characterized by mosaics of numerous mountains and watersheds, which influence precipitation patterns across the country (NBSAP, 2016). This landscape heterogeneity supports a large number of plant and animal diversity. For example, Rwanda harbors 151 mammals, 670 birds, 87 reptiles and amphibians, and 2150 vascular plants (REMA, 2015). This includes the iconic and endangered primate species driving ecotourism: Mountain gorillas (*Gorilla beringei beringei*), golden monkeys (*Cercopithecus mitis kandti*), L'Hoest (mountain monkey) and Chimpanzees (*Pan troglodytes*), among others (Mulindahabi et al., 2011; (Durydiwka et al., 2022).

The Nyungwe forest, contiguous with Kibira National Park, Burundi, is the largest remaining mountain rainforest in East Africa, and one of the continent's oldest rainforests, which is rich in many endemic orchid species, ferns, begonia and other seed plants (Mulindahabi et al., 2011). Rwanda is one of the few countries in the world with increasing trends in forest cover due to intensified afforestation projects (World Bank 2019). The rich floristic diversity in Rwanda provides important ecosystem services for the people, including over 70% of the population who depend on traditional medicine for primary healthcare (Kamagaju et al., 2013; Uwase et al., 2017; Gahamanyi et al., 2021).

However, biodiversity in Rwanda is threatened by habitat loss, agriculture-based land use changes, poaching, protected area encroachment, illegal tree felling, alien invasive species, human-wildlife conflict, illegal grazing, illegal mining, and overexploitation outside protected areas (Rwanda NBSAP, 2016). These anthropogenic pressures are driven primarily by human population growth and poverty which result in reliance on natural resources for livelihoods (Rwanda NBSAP, 2016; NISR, 2016; Li et al., 2021). The use of medicinal plants in Rwandan culture is deeply rooted;

therefore, overexploitation of medicinal plants will have profound effects on Rwandan traditional knowledge system, biocultural heritage, and healthcare of the people.

1.2. Research Problem/ Statement of the Problem

In Rwanda, many medicinal and culturally significant plant species are under increasing threat due to habitat loss, climate variability, and land-use changes. Despite their importance to local primary healthcare and cultural practices, the ecological requirements and distribution patterns of these species remain poorly understood. This lack of spatial and ecological knowledge hinders effective conservation and sustainable use. To address this gap, I used species distribution models (SDMs) to map the potential distribution of 14 medicinal and culturally important plant species, identify the main environmental variables shaping their niches, and analyze their habitat preferability to document their drivers of change.

1.3. General Objective/ Aim/ Purpose

The goal of this study is to model the current potential selected native medicinal and culturally significant plants in Rwanda and identify the bioclimatic variables that contribute to their ecological niches.

1.3.1. Specific Objectives

1. To model the current potential distribution of selected medicinal and culturally significant plant species in Rwanda using species distribution models (SDMs) across African region.
2. To identify and analyze the environmental variables that most influence the ecological niches of these plant species.
3. To evaluate how environmental factors shape the spatial distribution patterns of these species.

1.3.2. Research Questions

a. What are the environmental factors that significantly influence the ecological niches of selected medicinal and culturally significant plants in Rwanda?
b. How do these environmental conditions contribute to the geographic distribution pattern of the medicinal and culturally significant plants across Rwanda?

1.4. Significance of the study

This thesis will produce a number of deliverables which will have implications for research and conservation medicinal/culturally important plants in Rwanda. This includes the following:

a) A map of the potential geographical range for each of the 14 medicinal plants in Rwanda.

b) An ensemble map showing the potential distribution of the 14 species and the portion of their ranges in and outside of protected areas and it will support their special conservation.

c) Contribution to the empirical understanding of the relationship between the species' distributions and the environmental predictors (or: identification of environmental factors that drive the distribution of these 14 MCP in Rwanda).

The preliminary findings from this thesis was first presented to the International Association for Landscape Ecology-North America 2024 (IALE-NA) held in Oklahoma City and secondly at the Association for Tropical Biology and Conservation Conference (ATBC 2024) in Kigali. I also presented virtually at Student Conference for Conservation Science - New York 2024 (SCC-NY)_ held at New York City. Also, the thesis will be submitted to the University of Rwanda as part of the completion of my master's degree programme, while a paper will be written and published in a relevant peer-reviewed journal “Biotropica.”

CHAPTER 2: LITERATURE REVIEW

From the beginning, human societies have interacted with and depended on nature for livelihoods, including for food and medicine (Pimentel et al., 1997, Pretty, *2002*). However, as human populations continue to increase, especially in the Global South, reliance and exploitation of natural resources have increased, resulting in extinction threats to biodiversity (Kareiva et al., 2007*;* Laurance et al., 2014). Threats to biodiversity are particularly high for species with relatively small geographical ranges and limited climatic tolerances (Trew, 2020). However, the conservation of biodiversity, especially prioritization for threatened plants and animals, is hindered by our limited understanding of their spatial distribution, that is, Wallacean shortfall (Lomolino, 2004).

Numerous studies highlight the significance of traditional medicine in many African societies, including Rwanda, where it holds cultural and medicinal importance. According to Gessler et al. (2001), traditional healers in Rwanda play a pivotal role in healthcare, often utilizing a variety of indigenous plant species with perceived therapeutic properties (Ramathal & Ngassapa, 2001). Moreover, the work of Murekatete et al. (2017) highlights the rich biodiversity of medicinal plants in Rwanda, showcasing the potential for in-depth exploration of their distribution and cultura significance.

The exploration of traditional medicine and the utilization of medicinal plants in Rwanda is a field set for survey, offering a unique intersection of ecological and cultural dimensions. As highlighted by Twagirayezu et al. (2018), the dependence on traditional healing practices remains substantial in the Rwandan population, underscoring the need for a comprehensive understanding of the distribution and availability of medicinal flora. This knowledge, often passed down through generations, reflects the complex relationship between communities and their natural environment.

Species distribution models (SDMs), also called ecological niche models (ENMs), have been used to predict the geographical distributions of threatened medicinal plants to identify areas for conservation (Guisan et al., 2006). There are numerous examples of studies where SDMs were used to model the ecological niches and geographical distributions of medicinal plants (e.g., Qazi et al., 2022 ; Feng et al. 2022 ; Ali et al., 2023). Further, SDMs are useful in conservation management such as mapping the ranges of endangered and threatened species (Barbosa et al., 2012) and predicting the potential distribution of alien invasive species (Papes, 2007). Furthermore, SDMs are used to map areas of increased threats due to overexploitation and to designate areas for conservation prioritization (Faleiro et al., 2015).

Several algorithms and statistical methods have been developed to fit species distribution models. These methods include regression methods such as generalized linear models (GLMs), generalized additive models (GAMs), machine learning approaches including maximum entropy (maxent), boosted regression trees (BRT), and random forest (RF), among others; envelope methods such as bioclim, and ordination methods (Sofaer et al., 2019; Li and Wang 2013 ; Elith and Leathwick, 2009). These methods have been shown to have varying statistical and predictive performances and they are affected by data availability and sample size. For example, maxent and envelop methods are often used for presence-only species data, while other methods require presence and true absence geospatial data for accurate modeling.

CHAPTER 3: METHODOLOGY

2.1. Study species and occurrence records

I used systematic literature review to identify culturally important and medicinal plants in Rwanda. The literature review was conducted using search strings containing “medicinal plant”, “traditional medicine”, “herbal medicine”, “cultural belief”, and “Rwanda” in Google scholar between September 2023 and February 2024. This resulted in the selection of 14 medicinal and culturally significant plants (Table 1). For each of these 14 plant species, I used the Plants of the World Online database (www.powo.kew.org) to verify their taxonomic names and to determine if they naturally occur in Rwanda. Occurrence records for each of these species were obtained from the Global Biodiversity Information Facility (GBIF; www.gbif.org/). Using the CoordinateCleaner R package (Zizka et al. 2019), I removed duplicate records, data with no geographic coordinate information, greater than 1 km uncertainty, and records outside of their natural ranges, including those associated with botanical gardens and museums, taxonomic errors and other systematic errors. The final occurrence records for each of the 14 species were used for the SDM fitting (Table 1)

Table 1 Profile of the 14 medicinal and culturally significant plants in Rwanda, the occurrence records, and bioclimatic variables used for the species distribution modeling

ID	Scientific names	Plant family	Local names	Medicinal and cultural uses	References	Occurrences	Bioclimatic variables*
1	*Guizotia scabra* (Vis.) Chiov.	Asteraceae	*Igishikashike*	By the use of its boiled leaves, it is used to intestinal worms and diarrhea. The ash from burned leaves is used for abortion.	Kokwaro 1993	176	Bio2, Bio4, Bio9, Bio14, Bio15, Bio16, Bio18, Bio19
2	*Rotheca myricoides* (Hochst.) Steane & Mabb.	Lamiaceae	*Umukuzanyana*	Boiled or crushed roots are used to alleviate chest pain, treat colds, reduce gum bleeding, and aid in digestion.	Mukungu et al. 2016	348	Bio2, Bio3, Bio5, Bio8, Bio13, Bio14, Bio15, Bio18, Bio19
3	*Leucas martinicensis* (Jacq.) R.Br.	Lamiaceae	*Akanyamapfundo*	Fresh leaves are crushed with some water and the resulting liquid is used for the treatment of gonorrhea.	Kokwaro 1993	637	Bio2, Bio3, Bio8, Bio9, Bio13, Bio14, Bio15, Bio18, Bio19
4	*Cyperus papyrus L.*	Cyperaceae	*Urufunzo*	Dried straws and stems are used for domestic energy for cooking.	Udari 2018	740	Bio2, Bio3, Bio8, Bio9, Bio13, Bio14, Bio15, Bio18, Bio19
5	*Jasminum fluminense* Vell.	Oleaceae	*Umuhotora*	Leaves and roots are used in treating gastrointestinal disorders and hypertension.	Joshi et al. 2022	202	Bio2, Bio3, Bio8, Bio9, Bio13, Bio14, Bio15, Bio18, Bio19

6	*Momordica foetida* Schumach.	Cucurbitaceae	*Umushishiro*	Fresh leaf juice is used to treat constipation, and as an abortifacient and purgative	Watt & Breyer-Brandwijk 1962	417	Bio2, Bio3, Bio8, Bio9, Bio13, Bio14, Bio15, Bio18, Bio19,
7	*Brillantaisia cicatricosa* Lindau	Acanthaceae	*Ikirogora*	Leaves are new source of antibacterial agent	(Faparusi et al. 2012)	71	Bio2, Bio3, Bio8, Bio9, Bio14, Bio15, Bio16, Bio18, Bio19
8	*Lagenaria sphaerica* (Sond.) Naudin	Cucurbitaceae	*Umutanga*	Seed oil is applied topically to treat migraine. Fruits help to reduce liver inflammation and to clean stomach	Mehboob et al. 2022	162	Bio2, Bio3, Bio8, Bio9, Bio13, Bio14, Bio15, Bio18, Bio19
9	*Acalypha petiolaris* Hochst.	Euphorbiaceae	*Umugonampiri*	Fresh or dried leaves are crushed, boiled and the decoction is used to treat liver diseases. A root decoction is used for painful urinary in children.	Kokwaro 1993	735	Bio2, Bio3, Bio8, Bio9, Bio13, Bio14, Bio15, Bio18, Bio19
10	*Olea europaea* L.	Oleaceae	*Umunzenze*	The leaves used to treat urinary infection and diarrhea.	Rev et al. 2007	2919	Bio2, Bio3, Bio8, Bio9, Bio13, Bio14, Bio15, Bio18, Bio19
11	*Cenchrus trachyphyllus* (Pilg.) Morrone	Poaceae	*Umukaranka*	The roots used to treat body pain, menstrual disorders, and urinary infections.	Sosef 2019	35	Bio2, Bio3, Bio4, Bio8, Bio12, Bio14, Bio15, Bio16, Bio18, Bio19,

12	*Pericopsis angolensis* (Baker) Meeuwen	Fabaceae	*Umubanga*	Tree stands are used for local apiculture, the wood yields good timber for construction, and its bark is used to relieve stomach disorders, blood in urine, and diarrhea.	Orwa, Mutua, Kindt, and Jamnadass 2009	136	Bio2, Bio4, Bio8, Bio14, Bio15, Bio16, Bio18, Bio19,
13	*Scepocarpus hypselodendron* (Hochst. ex A.Rich.) T.Wells & A.K.Monro	Urticaceae	*Umuse*	Its leaves and roots back are used to treat a number of parasitic and infectious illnesses, including ringworms, athlete's foot rot, tetanus, typhoid, intestinal parasites, abscesses, malaria, and amoebiasis.	Maiyo et al. 2024	47	Bio2, Bio4, Bio8, Bio13, Bio14, Bio15, Bio18, Bio19
14	*Stephania abyssinica* (Quart. -Dill. & A.Rich.)	Menisperma ceae	*Umuhanda*	Leaves are used for treatment of stomach aches, headaches, inflammation, and gastrointestinal disorders.	Firehun, and Nedi 2023; Chakraborty et al. 2000	136	Bio2, Bio3, Bio8, Bio9, Bio13, Bio14, Bio15, Bio18, Bio19

2.2. Species distribution modeling

I fitted SDMs for each of the 14 species in 1 km resolution using random forest (RF), boosted regression trees (BRT), and generalized linear regression models (GLMs) in sdm R package (Naimi and Araujo 2016; R Core Team 2023). A random forest (RF) is a machine learning algorithm used for tasks such as classification and prediction (Salman et al. 2024). Boosted regression trees (BRT) are described as a machine learning method that combines multiple simple trees in sequence to improve prediction accuracy by correcting previous errors (McCluskey et al. 2014). Generalized linear models (GLMs) extend linear regression by allowing for response variables from the exponential family and linking their expected values to predictors using a flexible link function (Gentle et al. 2012). I used 19 bioclimatic predictor variables (1970 - 2022) from the WorldClim database version 2; (Fick & Hijmans, 2017) to model the current distribution of the 14 selected medicinal/culturally plants. These 19 variables represent temperature and precipitation variability, total, or mean values at global scales, but I reduced their extents to Africa. I conducted a variance inflation factor (VIF) analysis to reduce multicollinearity; on the basis of VIF > 10, we reduced the 19 variables to eight predictors for each of the species (Table2) using the usdm R package (Naimi et al. 2014). For each species, I fitted 30 model replicates, 10 each for the three algorithms, using 70% of occurrence data as training and the remaining 30% as independent test data. Since I do not have true absence points, I generated 10,000 random points within the geographical extent for each species. Model performance was evaluated using the area under the curve (AUC) of the receiver operating characteristic (ROC; Hanley and McNeil 1982) plot and True Skill Statistics (TSS; Allouche et al. 2006). We then generated an ensemble prediction map of continuous probabilities of suitability for each of the species using the weighted average method based on the AUC metric (AUC > 0.7). The relative importance of the predictor variables to the SDMs for each of the 14 modeled species was assessed using the response curves method (Phillips et al. 2006), while partial response plots, illustrating the probability of occurrence of each species along the predictor gradient, were calculated using the evaluation strip method (Elith et al. 2005). Since Rwanda was the focus of the study, I trimmed the ensemble prediction maps for all species showing their continuous probabilities of occurrence in the country and then summed them all to produce a richness map. The richness ma shows the aggregated continuous probabilities of occurrence of all 14 modeled medicinal and culturally significant plants in Rwanda. I also used model-determined thresholds to discriminate the continuous probabilities of occurrence of all 14 ensemble prediction maps into presence and absence maps.

Table 2 A list of the 19 bioclimatic variables used for fitting the species distribution models of the 14 medicinal and culturally significant plants in Rwanda

Bioclimatic variable	**Calculation and ecological significance**	**Scientific Unit**
BIO1	Annual Mean Temperature	°C (or 0.1°C)
BIO2	Mean Diurnal Range	°C
BIO3	Isothermality	%
BIO4	Temperature Seasonality	°C ×100
BIO5	Max Temperature of Warmest Month	°C
BIO6	Min Temperature of Coldest Month	°C
BIO7	Temperature Annual Range	°C
BIO8	Mean Temperature of Wettest Quarter	°C
BIO9	Mean Temperature of Driest Quarter	°C
BIO10	Mean Temperature of Warmest Quarter	°C
BIO11	Mean Temperature of Coldest Quarter	°C
BIO12	Annual Precipitation	mm
BIO13	Precipitation of Wettest Month	mm
BIO14	Precipitation of Driest Month	mm
BIO15	Precipitation Seasonality	%
BIO16	Precipitation of Wettest Quarter	mm
BIO17	Precipitation of Driest Quarter	mm
BIO18	Precipitation of Warmest Quarter	mm
BIO19	Precipitation of Coldest Quarter	mm

CHAPTER 4: RESULTS

4.1. Contribution of predictor variables to species' niches

The response curves generated for the 14 plant species illustrate how their predicted habitat suitability varies with key bioclimatic variables. Overall, all species showed strong preferences for certain temperature and precipitation related variables, with sharp drops in suitability outside specific thresholds. Notably, BIO14 (precipitation of driest month) and BIO15 (precipitation seasonality) were consistently dominant.

Guizotia scabra, Jasminum fluminense, Brillantaisia cicatricosa, and *Momordica foetida* showed steep response curves to BIO14 and BIO15, indicating high sensitivity to changes in dry-month precipitation and precipitation variability. For these species, suitability peaks in moderate precipitation ranges, with sharp declines at extremes implying potential vulnerability to drought or irregular rainfall patterns. *Lagenaria sphaerica*, *Leucas martinicensis*, and *Scepocarpus hypselodendron* responded strongly to BIO2 (mean diurnal range) and BIO3 (isothermality). Their curves show narrow peaks, suggesting that daily and seasonal temperature consistency plays a crucial role in their distribution. BIO8 (mean temperature of wettest quarter) was particularly influential for *Cenchrus trachyphyllus* and *Rotheca myricoides*, indicating their preference for stable wet-season temperatures.

Pericopsis angolensis shows consistently narrow tolerance across almost all variables, especially BIO14, BIO15, and BIO2. This could imply a narrower ecological niche or a higher sensitivity to climate change. *Olea europea* shows less variability in response and appears to be more of a generalist, with broad peaks across most variables. *Cyperus papyrus* responded moderately but consistently to nearly all variables, reflecting its known adaptability to wetland conditions but still showing clear thresholds in BIO13 (precipitation of wettest month) and BIO19 (precipitation of coldest quarter). *Acalypha petiolaris* showed strong declines beyond specific thresholds of BIO13, BIO15, and BIO9 (mean temperature of driest quarter) indicating sensitivity to both dry-season temperature and wet-season precipitation. *Stephania abyssinica* displayed moderate to strong responses across a range of variables, particularly BIO13, BIO15, BIO2, and BIO19. The species showed relatively broader tolerance compared to highly specialized species but still exhibited noticeable declines beyond certain precipitation thresholds, indicating a reliance on stable rainfall patterns despite some thermal flexibility (Figure 2).

Table 3 Performance metrics for species distribution modeling of the 14 culturally significant and medicinal plants in Rwanda

Species	**AUC_{RF}**	**AUC_{BRT}**	**AUC_{GLM}**	**TSS_{RF}**	**TSS_{BRT}**	**TSS_{GLM}**
Guizotia scabra	0.94	0.84	0.87	0.25	0.15	0.07
Brillantaisa cicatricosa	0.88	0.72	0.66	0.53	0.37	0.18
Cenchrus trachyphyllus	0.93	0.5	0.79	0.55	0.3	0.65
Stephania absynnica	0.91	0.91	0.75	0.34	0.37	0.25
Pericopsis angolensis	0.72	0.73	0.6	0.47	0.36	0.29
Momordica faetida	0.85	0.89	0.78	0.17	0.17	0.02
Jasminum fluminense	0.84	0.84	0.64	0.34	0.31	0.19
Acalypha petiolaris	0.81	0.81	0.64	0.19	0.16	0.29
Lagenaria sphaerica	0.93	0.85	0.72	0.29	0.30	0.06
Leucas martinicensis	0.83	0.85	0.8	0.14	0.14	0.17
Rotheca m	0.91	0.91	0.85	0.18	0.12	0.28
Scepocarpus hypselodendron	1	0.3	0.98	0.28	0.15	0.13
Cyperus papyrus	O.94	0.82	0.91	0.35	0.35	0.23
Olea europaea	0.92	0.71	0.6	0.34	0.23	0.01

AUC_{RF} = Area Under the curves for Random Forest
TTS $_{RF}$= True Skill Statistics for Random Forest
AUC_{BRT} = Area Under the curves for Boosted Regression Trees
TSS_{BRT}= True Skill Statistics for Boosted Regression Trees
AUC_{GLM} = Area Under the curves for Genelarized Linear Model
TSS GLM= True Skill Statistics Genelarise Linear Model

The performance of species distribution models (SDMs) varied across the 14 plant species and three modeling algorithms: Random Forest (RF), Boosted Regression Trees (BRT), and

Generalized Linear Models (GLM). Overall, the models performed well in terms of discrimination ability, with AUC values generally high across all species, particularly for RF, which consistently yielded AUC values above 0.90 for most species (e.g., *Guizotia scabra*, *Cenchrus trachyphyllus*, *Scepocarpus hypselodendron*). However, TSS values were notably lower across models, indicating challenges in accurate threshold-based classification. Random Forest outperformed both BRT and GLM in most cases, not only achieving the highest AUCs but also relatively better TSS scores (e.g., *Cenchrus trachyphyllus*, TSS RF = 0.55) see (Figure S2).

Interestingly, while GLM generally showed the weakest performance, it yielded the highest TSS for *Brillantaisia cicatricosa* (0.88) and *Cenchrus trachyphyllus* (0.65), suggesting good classification for those species. In contrast, species such as *Momordica foetida* and *Olea europaea* exhibited very low TSS values across all models, despite high AUCs, highlighting the models' limited ability to distinguish presence from absence at specific thresholds. These discrepancies between AUC and TSS suggest that while the models are effective at ranking habitat suitability, their reliability in presence/absence classification varies and depends on both species' traits and modeling technique. Overall, Random Forest emerged as the most robust algorithm, offering balanced performance in both suitability mapping and binary classification for the majority of species (Table3).

4.2. Comparative algorithm performances

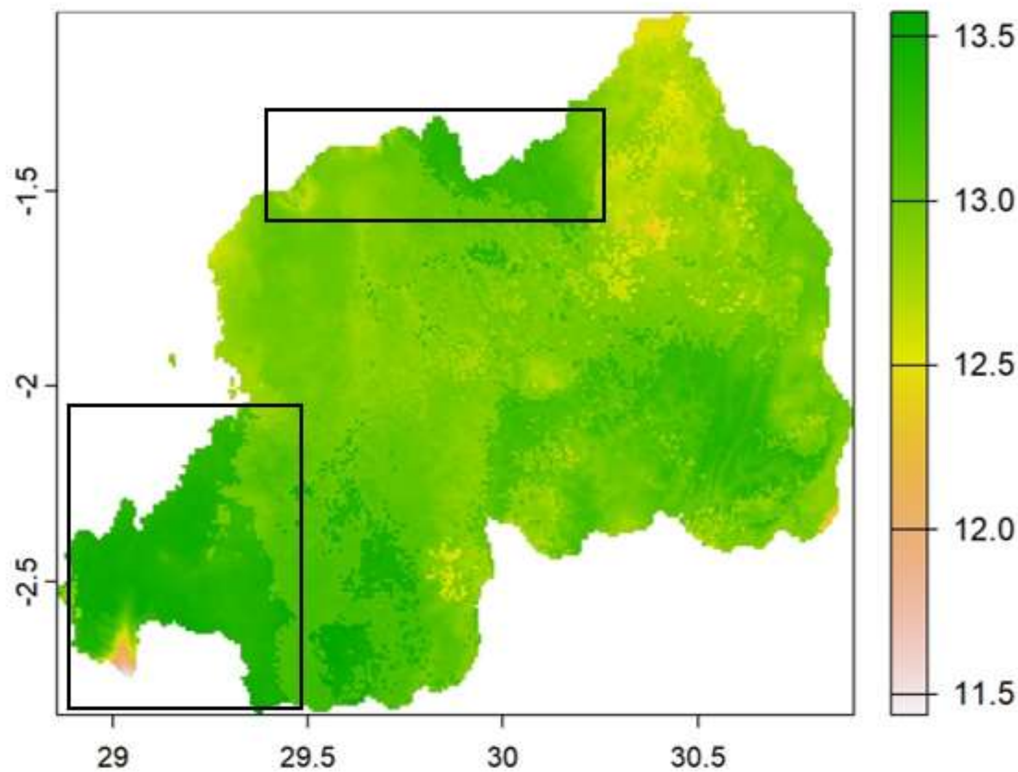


Figure 1 Richness map of predicted distribution of all 14 species in Rwanda

The ensemble species richness map (Figure 1) illustrates the potential distribution of the 14 medicinal/culturally significant plant species across Rwanda. The color gradient, ranging from pale pink (lower richness, ~11.5 species) to dark green (higher richness, up to 13.5 species), highlights notable geographic variation in species co-occurrence. The highest richness values indicated by darker green patches are concentrated in the southwestern and northeastern regions of the country**.** These areas include districts such as Rusizi, Nyamasheke, and Musanze, which are known for their ecological complexity and protected montane forest systems. Nyungwe National Park (southwest) and Volcanoes National Park (northwest), which are biodiversity hotspots. Model reliability from Table 3: Species with high AUC scores (e.g., *Guizotia scabra*, *Stephania abyssinica*, *Rotheca myrcoides, and Brillantaisa cicatricosa*) likely contributed to the strong predictive power in these areas. Conversely, the eastern and central regions appear with relatively lower richness values, suggesting either fewer suitable niches or lower overlap in species' ecological preferences. These patterns may also reflect lower occurrence data density or habitat fragmentation, land use change in those areas not only there but across Africa region (Figure S1). Overlaying this richness map with Rwanda's protected area network confirms that a substantial portion of the suitable habitat for these species falls within conservation (protected) areas, reinforcing the importance of protected parks in maintaining plant diversity and traditional medicine resources, even though these protected areas extended beyond their current boundaries and forest cover and habitat has been lost. Furthermore, prediction of all species across Africa where >0.7 poor performed and <0.7 well performed see (Figure 5).

CHAPTER 5 DISCUSSION

In my study I assessed the potential geographic distributions of 14 plant species using ensemble modeling approaches combining Random Forest (RF), Boosted Regression Trees (BRT), and Generalized Linear Models (GLM). Model evaluation using AUC and TSS scores revealed varying performance across species and algorithms, reflecting differences in the predictability and environmental niche breadth of each species.

5.1. Model Performance and Predictive Accuracy

In general, Random Forest models yielded higher AUC scores for most species (ranging from 0.81 to 1.00), suggesting strong discriminatory power between suitable and unsuitable habitats. For instance, *Scepocarpus hypselodendron* had an AUC of 1.00 under RF, indicating nearly perfect classification. Similarly, *Cenchrus trachyphyllus* and *Guizotia scabra* also exhibited high AUCs (0.93–0.94), suggesting that their distributions are strongly associated with accurately represented environmental gradients.

However, TSS values which account for both omission and commission errors were generally lower across all models, with GLM often performing poorly. For example, *Momordica foetida* and *Olea europaea* had TSS values close to zero under GLM, indicating poor model fit and limited ability to correctly classify presence versus absence. In contrast, *Brillantaisia cicatricosa* showed a strong TSS score of 0.88 under GLM, indicating that its distribution is well explained by the predictor variables used in the model. These variations suggest that while AUC provides a threshold-independent assessment of model discrimination, TSS provides a more conservative estimate of actual predictive performance, especially for species with limited or clustered occurrences.

5.2. Spatial Distribution and Habitat Associations

The projected maps show that species richness of all 14 species is higher in the southwestern and northwestern regions of Rwanda, corresponding to Nyungwe National Park and Volcanoes National Park, respectively. These areas are characterized by high precipitation, cool temperatures, and steep elevational gradients, which contribute to habitat heterogeneity and microclimatic diversity, this can be similar to why we have Bioclim variables which outperform other variables because some studies have shown that at broad and regional scales, species distributions are influenced by temperature, precipitation and seasonal moisture (Woodward 1988).

Species such as *Guizotia scabra*, *Rotheca myricoides*, and *Stephania abyssinica* showed wide potential distributions extending into these montane zones, aligning with the high environmental suitability in Nyungwe and Volcanoes. The performance of models for these species was consistent across algorithms, indicating reliable predictions in climatically stable environments. On the other hand, species like *Leucas martinicensis* and *Lagenaria sphaerica* had relatively lower TSS scores despite good AUC values, suggesting possible model overfitting or underrepresentation of their niche variability. This might reflect the presence of these species in disturbed or transitional zones where environmental predictors alone may not fully capture habitat suitability. Meanwhile the environmental drivers in Nyungwe and Volcanoes National Parks involved Bioclimatic variables likely influencing these distributions including Annual Mean Temperature (BIO1), Annual Precipitation (BIO12), Precipitation Seasonality (BIO15), Minimum Temperature of Coldest Month (BIO6).

These variables are especially relevant in Nyungwe and Volcanoes, where cold-adapted species thrive and precipitation is both high and seasonally variable (Plumptre et al., 2007; REMA, 2015; FAO, 2020). Species with narrow temperature tolerances or dependence on moist montane forests were more confined to these regions, while more generalist or drought-tolerant species showed broader potential ranges across the country. Similar to the findings of Rwanda Environment Management Authority (REMA, 2018), Rusizi district is acknowledged for its rich biodiversity and commitment to corporate responsibility in environmental protection, health, and safety of its surrounding communities, which give us the reason that they are not totally complementary rely on the natural plants in their primary daily life.

My study showed that Rusizi and Nyamasheke Districts had the highest predicted richness of the 14 species. Coincidentally, this region has been recognized for its abundance in natural resources, notably as the location of Nyungwe National Park a biodiversity hotspot. Additionally, it is noted for relatively low dependence on natural resources for primary healthcare, partly due to the presence of many health facilities in the area (REMA, 2015; Masozera et al., 2006). Land use change over time has led to significant anthropogenic impacts in various districts across Rwanda, particularly affecting biodiversity and natural resources. These changes have resulted in habitat fragmentation, degradation, and the loss of medicinal and culturally important plant species, which are often highly sensitive to environmental disturbances and land conversion (Ndayisaba et al., 2021; Bizuru et al., 2015).

Few of the plants are in open accessible areas as shown in the (Figure 3) where pale pink (lower richness, ~11.5 species) to dark green (higher richness, up to 13.5 species) the highest richness values indicated by darker green patches are concentrated in the southwestern and northeastern regions of the country known for their ecological complexity and protected areas like Nyungwe National Park (southwest) and Volcanoes National Park (northwest)those in open accessible that are intact with human activities (traditional healers) and other anthropogenic activities like land use change and urban expansion which is why the finding show difference in richness of medicinal/culturally plants species.

Species Distribution Models (SDMs) have an important role in understanding species ecology and guiding land management. They can be used to inform conservation plans for native biodiversity in Rwanda and to mitigate the effects of climate change on plant species. For example, researchers have utilized SDMs to assess the potential habitats of *Euphorbia* (Euphorbiaceae) under current and projected climate conditions (Beale et al., 2013). The findings highlight critical regions within Rwanda that harbor suitable conditions for species' survival and areas that may become suitable in the future. These insights can be useful for the Rwandan government in formulating conservation strategies, leading to the establishment of protected areas and the development of habitat restoration projects aimed at preserving this endangered species (Platts et al., 2011). The findings can guide the development of conservation policy and management practices for effective biodiversity conservation and protection of biocultural heritage.

The findings highlight the potential distribution patterns of 14 medicinal and cultural plant species across Rwanda's natural landscapes. The bioclimatic variables precipitation and temperature, including Precipitation of Coldest Quarter, Precipitation of Driest Month, Mean Temperature of Driest Quarter and Mean Temperature of Wettest Quarter, significantly influenced species distributions, aligning with previous studies (Woodward, 1988). Our approach of reducing the initial 19 bioclimatic variables to eight variables through variance inflation factor analysis (VIF) ensured that only the most relevant variables were used in modelling. The ensemble modelling approach provided strong predictions by integrating results from Random Forest, Boosted Regression Trees, and Generalized Linear Models, thereby reducing modelling uncertainties. The use of Area Under the Curves and True Skill Statistics as performance metrics ensured that only the best-performing models were considered for further analysis, enhancing the reliability of our predictions (Hanley & McNeil, 1982).

CHAPTER 5: CONCLUSION

The high habitat suitability of protected areas such as Nyungwe and Volcanoes National Parks for multiple species highlights their critical role in maintaining Rwanda's plant biodiversity. However, *Guizotia scabra, Jasminum fluminense, Brillantaisia cicatricosa*, and *Momordica foetida*, these species show suitability peaks in moderate precipitation ranges, with sharp declines at extremes implying potential vulnerability to drought or irregular rainfall patterns. Species like *Cyperus papyrus* responded moderately but consistently to nearly all variables, reflecting its known adaptability to wetland conditions this can be use in restoration activities. Species which show high habitat suitability in protected areas are *Guizotia scabra*, *Stephania abyssinica*, *Rotheca myrcoides, and Brillantaisa cicatricosa*). The relatively poor model performance for certain species under GLM and BRT highlights the importance of using ensemble approaches and field validation to refine predictions. Additionally, species showing restricted distributions or low TSS scores like *Pericopsis angolensis, Olea europea, Acalypha petiolaris* may require targeted surveys to validate model outputs and assess potential threats from habitat fragmentation or climate change they do not really show that they are preference to the protected areas as other specie

REFERENCES

Barbosa, F. G., Schneck, F., & Melo, A. S. (2012). Uso de modelos de nicho ecológico para Use Use of ecological niche models to predict the distribution of invasive species: a scientometric analysis. Brazilian Journal of Biology, 72(4), 821–829. https://doi.org/10.1590/S1519-69842012000500007

Bizuru, E., Ndikubwimana, I., & Nsengimana, C. (2015). Ethnobotanical study of medicinal plants used by communities in the Musanze and Nyabihu Districts, Northern Rwanda. Journal of Medicinal Plants Studies, 3(6), 17–24.

Borokini TI, and Lawal IO (2014). Traditional medicine practices among the Yoruba people of Nigeria: A historical perspective. Journal of Medicinal Plants Studies 2 (6): 20-33

Borokini TI, Ighere DA, Clement M, Ajiboye TO and Alowonle AA (2013). Ethnobiological survey of traditional medicine practices in Oyo State. Journal of Medicinal Plants Studies 1 (5): 1 – 16

Durydiwka, M., Zajadacz, A., & Duda-Gromada, K. (2022). Tourist Use of Rwanda National Parks in the Context of Sustainable Development. Selected Aspects. Prace i Studia Geograficzne, 67(3), 105–126. https://doi.org/10.48128/pisg/2022-67.3-06

Elith, J., Graham, C. H., Anderson, R. P., Dudík, M., Ferrier, S., Guisan, A., ... & Zimmermann, N. E. (2006). Novel methods improve prediction of species' distributions from occurrence data. Ecography, 29(2), 129–151. https://doi.org/10.1111/j.2006.0906-7590.04596.x

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. Diversity and Distributions, 17(1), 43–57. https://doi.org/10.1111/j.1472-4642.2010.00725.x

Faleiro, F. V., Silva, D. P., de Carvalho, R. A., Särkinen, T., & De Marco, P. (2015). Ring out the bells, we are being invaded! Niche conservatism in exotic populations of the Yellow Bells, Tecoma stans (Bignoniaceae). Natureza e Conservacao, 13(1), 24–29. https://doi.org/10.1016/j.ncon.2015.04.004

FAO. (2020). Forest Resources Assessment Report: Rwanda Country Report. Food and Agriculture Organization of the United Nations.

Feng G, Xiong YJ, Wei HY, Li Y, Mao LF. Endemic medicinal plant distribution correlated with stable climate, precipitation, and cultural diversity. Plant Divers. 2022 Oct 8;45(4):479-484. doi: 10.1016/j.pld.2022.09.007.

Barbosa, F. G., Schneck, F., & Melo, A. S. (2012). Uso de modelos de nicho ecológico para Use Use of ecological niche models to predict the distribution of invasive species: a scientometric analysis. *Brazilian Journal of Biology*, *72*(4), 821–829. https://doi.org/10.1590/S1519-69842012000500007

Durydiwka, M., Zajadacz, A., & Duda-Gromada, K. (2022). Tourist Use of Rwanda National Parks in the Context of Sustainable Development. Selected Aspects. *Prace i Studia Geograficzne*, *67*(3), 105–126. https://doi.org/10.48128/pisg/2022-67.3-06

Faleiro, F. V., Silva, D. P., de Carvalho, R. A., Särkinen, T., & De Marco, P. (2015). Ring out the bells, we are being invaded! Niche conservatism in exotic populations of the Yellow Bells, Tecoma stans (Bignoniaceae). *Natureza e Conservacao*, *13*(1), 24–29. https://doi.org/10.1016/j.ncon.2015.04.004

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, *37*(12), 4302–4315. https://doi.org/10.1002/joc.5086

Guisan, A., Broennimann, O., Engler, R., Vust, M., Yoccoz, N. G., Lehmann, A., & Zimmermann, N. E. (2006). Using niche-based models to improve the sampling of rare species. *Conservation Biology*, *20*(2), 501–511. https://doi.org/10.1111/j.1523-1739.2006.00354.x

Kareiva, P., Watts, S., McDonald, R., & Boucher, T. (2007). Domesticated nature: Shaping landscapes and ecosystems for human welfare. *Science*, *316*(5833), 1866–1869. https://doi.org/10.1126/science.1140170

Laurance, W. F., Sayer, J., & Cassman, K. G. (2014). Agricultural expansion and its impacts on tropical nature. *Trends in Ecology and Evolution*, *29*(2), 107–116. https://doi.org/10.1016/j.tree.2013.12.001

Nshimiyimana, A. R., Niyigena, E., & Ngwijabagabo, H. (2023). *Spatial Assessment of Urban Growth on Green Spaces in Rwanda : An insight Spatial Assessment of Urban Growth on Green Spaces in Rwanda : An insight from Rebero Mountain Landscape in Kicukiro District , City of Kigali*. *June*. https://doi.org/10.4314/rjeste.v5i1.5

Papes, M. (2007). Ecological Niche Modeling Approaches to Conservation of Endangered and Threatened Birds in Central and Eastern Europe. *Biodiversity Informatics*, *4*(0). https://doi.org/10.17161/bi.v4i0.37

Pimentel, D., Wilson, C., McCullum, C., Huang, R., Dwen, P., Flack, J., Tran, Q., Saltman, T., & Cliff, B. (1997). Economic and Environmental Benefits of Biodiversity. *BioScience*, *47*(11), 747–757. https://doi.org/10.2307/1313097

Qazi, A. W., Saqib, Z., & Zaman-ul-Haq, M. (2022). Trends in species distribution modelling in context of rare and endemic plants: a systematic review. *Ecological Processes*, *11*(1). https://doi.org/10.1186/s13717-022-00384-y

Ramathal, D. C., & Ngassapa, O. D. (2001). Medicinal plants used by Rwandese traditional healers in refugee camps in Tanzania. *Pharmaceutical Biology*, *39*(2), 132–137. https://doi.org/10.1076/phbi.39.2.132.6251

Sofaer, H. R., Jarnevich, C. S., Pearse, I. A. N. S., Smyth, R. L., Auer, S., Cook, G. L., Jr, T. C. E., Guala, G. F., Howard, T. G., & Morisette, J. T. (2019). *Development and Delivery of Species Distribution Models to Inform Decision-Making*. *69*(7), 544–557. https://doi.org/10.1093/biosci/biz045

Guisan, A., Broennimann, O., Engler, R., Vust, M., Yoccoz, N. G., Lehmann, A., & Zimmermann, N. E. (2006). Using niche-based models to improve the sampling of rare species. Conservation Biology, 20(2), 501–511. https://doi.org/10.1111/j.1523-1739.2006.00354.x

Habiyaremye, G., Nyirambangutse, B., & Nsabimana, D. (2020). Diversity and distribution of medicinal plants used by local communities in Rwanda. Journal of Medicinal Plants Research, 14(8), 417–426. https://doi.org/10.5897/JMPR2020.7045Shrestha, B. B., & Shrestha, U. B. (2019). Climate change amplifies plant invasion hotspots in Nepal. Diversity and Distributions, 25(10), 1599–1612. https://doi.org/10.1111/ddi.12969

Hardy, K (2019). Paleomedicine and the use of plant secondary compounds in the Paleolithic and early Neolithic. Evol Anthropol. 2019; 28:60-71. https://doi.org/10.1002/evan.21763

Hijmans RJ, Barbosa M, Ghosh A, Mandel A (2025). geodata: Download Geographic Data. R package version 0.6-3, https://github.com/rspatial/geodata.

Hijmans RJ, Phillips S, Leathwick J, Elith J (2024). dismo: Species Distribution Modeling. R package version 1.3-15, https://github.com/rspatial/dismo.

https://rema.gov.rw

https://www.fao.org/forest-resources-assessment

https://www.rema.gov.rw/soe/

Kamagaju, L., Bizuru, E., Minani, V., Morandini, R., Stevigny, C., Ghanem, G., and Duez, P. (2013). An ethnobotanical survey of medicinal plants used in Rwanda for voluntary depigmentation. Journal of Ethnopharmacology 150 (2): 708-717

Kareiva, P., et al. (2007). Conservation in the Anthropocene. Breakthrough Journal, 3, 26-36.

Kareiva, P., Watts, S., McDonald, R., & Boucher, T. (2007). Domesticated nature: Shaping landscapes and ecosystems for human welfare. Science, 316(5833), 1866–1869. https://doi.org/10.1126/science.1140170

Laurance, W. F., et al. (2014). Averting biodiversity collapse in tropical forest protected areas. Nature, 489(7415), 290-294.

Laurance, W. F., Sayer, J., & Cassman, K. G. (2014). Agricultural expansion and its impacts on tropical nature. Trends in Ecology and Evolution, 29(2), 107–116. https://doi.org/10.1016/j.tree.2013.12.001

Lomolino, M.V. (2004) Conservation biogeography. Frontiers of Biogeography: new directions in the geography of nature (ed. by M.V. Lomolino and L.R. Heaney), pp. 293–296. Sinauer Associates, Sunderland, Massachusetts

Mahomoodally F.M. Traditional medicines in Africa: An appraisal of ten potent African medicinal plants. Evid. Based Complement. Altern. Med. 2013;2013:617459. https://doi.org/10.1155/2013/617459

Masozera, M. K., Alavalapati, J. R. R., Jacobson, S. K., & Shrestha, R. K. (2006). Assessing the suitability of community-based management for the Nyungwe Forest Reserve in Rwanda. Forest Policy and Economics, 8(2), 206–216. https://doi.org/10.1016/j.forpol.2004.08.001

MINITERE (2015). Rwanda's Second National Communication under the United Nations Framework Convention on Climate Change (UNFCCC). Ministry of Natural Resources, Kigali, Rwanda.

Mugabo, J. (2022). Spatial and temporal patterns of rainfall distribution in Rwanda. Rwanda Meteorology Agency Reports.

Murekatete, N., Bizuru, E., & Nyirambangutse, B. (2017). Documentation and inventory of medicinal plants used in the treatment of livestock diseases in Rwanda. Journal of Medicinal Plants Research, 11(16), 331–339.

Ndayisaba, F., Karamage, F., Mupenzi, C., Nahayo, L., & Zhang, C. (2021). Assessing land use and land cover changes and their impact on ecosystem services in Rwanda from 1990 to 2020. Environ mental Challenges, 5, 100243. https://doi.org/10.1016/j.envc.2021.100243

Newman, DJ · Cragg, GM (2020). Natural products as sources of new drugs over the nearly four decades from 01/1981 to 09/2019. J Nat Prod. 2020; 83:770-803, https://doi.org/10.1021/acs.jnatprod.9b01285

Nshimiyimana, A. R., Niyigena, E., Nyandwi, E., Ngwijabagabo, H., & Rugengamanzi, G. (2023).Spatial Assessment of Urban Growth on Green Spaces in Rwanda: An insight from Rebero Mountain Landscape in Kicukiro District, City of Kigali. *Rwanda Journal of Engineering, Science, Technology and Environment, 5*(1). https://doi.org/10.4314/rjeste.v5i1.5

Papes, M. (2007). Ecological Niche Modeling Approaches to Conservation of Endangered and Threatened Birds in Central and Eastern Europe. Biodiversity Informatics, 4(0). https://doi.org/10.17161/bi.v4i0.37

Petrovska, BB. (2012). Historical review of medicinal plants' usage. Pharmacognosy reviews, 2012 Jan; 6 (11):1-5. 10.4103/0973-7847.95849

Pimentel, D., et al. (1997). Environmental and Economic Costs of Soil Erosion and Conservation Benefits. Science, 267(5201), 1117-1123.

Pimentel, D., Wilson, C., McCullum, C., Huang, R., Dwen, P., Flack, J., Tran, Q., Saltman, T., & Cliff, B. (1997). Economic and Environmental Benefits of Biodiversity. BioScience, 47(11), 747–757. https://doi.org/10.2307/1313097

Plumptre, A. J., Behangana, M., Davenport, T. R. B., Kahindo, C., Kityo, R., Ndomba, E., … Eilu, G. (2007). The biodiversity of the Albertine Rift. Biological Conservation, 134(2), 178–194. https://doi.org/10.1016/j.biocon.2006.08.021

Pretty, J. (2002). Agri-Culture: Reconnecting People, Land and Nature. Earthscan.

Qazi, A. W., Saqib, Z., & Zaman-ul-Haq, M. (2022). Trends in species distribution modelling in context of rare and endemic plants: a systematic review. Ecological Processes, 11(1). https://doi.org/10.1186/s13717-022-00384-y

R Core Team (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Ramathal, D. C., & Ngassapa, O. D. (2001). Medicinal plants used by Rwandese traditional healers in refugee camps in Tanzania. Pharmaceutical Biology, 39(2), 132–137. https://doi.org/10.1076/phbi.39.2.132.6251

REMA. (2015). Rwanda State of Environment and Outlook Report 2015. Rwanda Environment Management Authority.

REMA. (2015). Rwanda State of Environment and Outlook Report 2015. Rwanda Environment Management Authority.

Silva, L.D., Elias, R.B., and Silva, L. (2021). Modelling invasive alien plant distribution: A literature review of concepts and bibliometric analysis. Environmental Modelling and Software 145: 105203

Sofaer, H. R., Jarnevich, C. S., Pearse, I. A. N. S., Smyth, R. L., Auer, S., Cook, G. L., Jr, T. C. E., Guala, G. F., Howard, T. G., & Morisette, J. T. (2019). Development and Delivery of Species Distribution Models to Inform Decision-Making. 69(7), 544–557. https://doi.org/10.1093/biosci/biz045

Sofowora A, Ogunbodede E, Onayade A. (2013). The role and place of medicinal plants in the strategies for disease prevention. Afr J Tradit Complement Altern Med. 10(5):210-29. doi: 10.4314/ajtcam.v10i5.2.

Thuiller, W., Lafourcade, B., Engler, R., & Araújo, M. B. (2009). BIOMOD – a platform for ensemble forecasting of species distributions. Ecography, 32(3), 369–373. https://doi.org/10.1111/j.1600-0587.2008.05742.x

Trew, B. T. (2020). Vulnerability of global biodiversity hotspots to climate change. Global ecology and Biogeography, 7.

Twagirayezu, G., Smith, E., & Paciorek, C. J. (2018). Medicinal plants used in traditional medicine by Oromo people, Ghimbi District, Southwest Ethiopia. Journal of Ethnobiology and Ethnomedicine, 14(1),

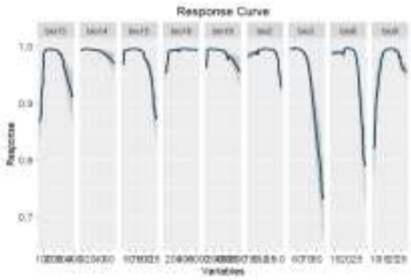
Woodward, F.I. (1988) Temperature and the distribution of plant species. Plants and Temperature (eds S. P. Long & F. I. Woodward), pp. 59-75. Cambridge University Press, Cambridge.

World Health Organization Traditional Medicines. [(accessed on 8 October 2020)];2008 Available online: http://www.who.int/mediacentre/factsheets/fs134/en/

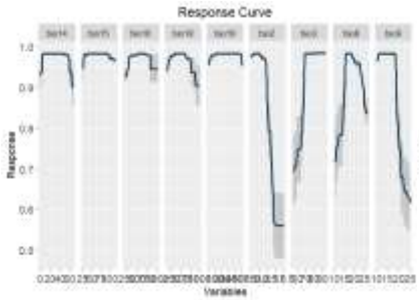
Zizka A, Silvestro D, Andermann T, Azevedo J, Duarte Ritter C, Edler D, Farooq H, Herdean A, Ariza M, Scharn R, Svanteson S, Wengstrom N, Zizka V, Antonelli A: (2019). “CoordinateCleaner: standardized cleaning of occurrence records from biological collection databases.” Methods in Ecology and Evolution, -7. doi:10.1111/2041-210X.13152

SUPPLEMENT INFORMATION (APPENDIX)

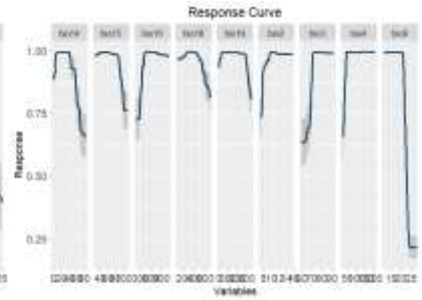
Figure 2 Response Curves of all 14 selected plants species



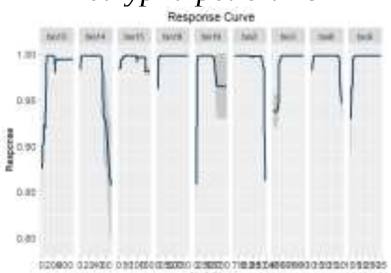
Acalypha petiolaris



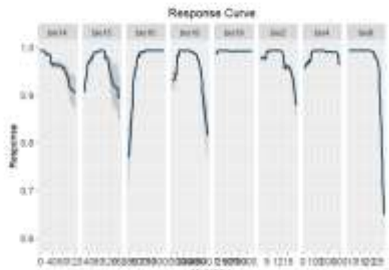
Brillantaisa cicatricosa



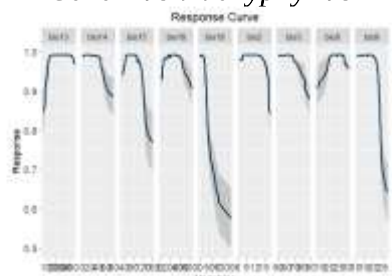
Cenchrus trachyphyllus



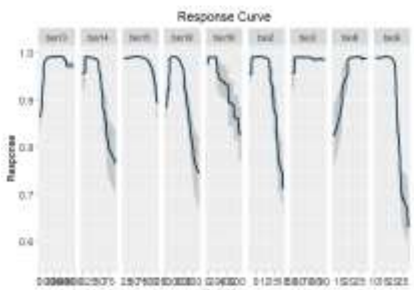
Cyperus papyrus



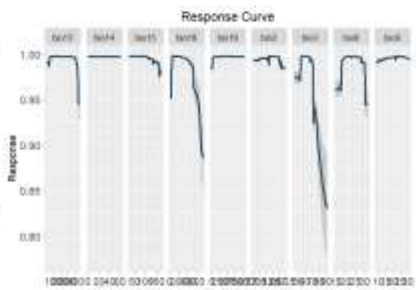
Guizotia scabra



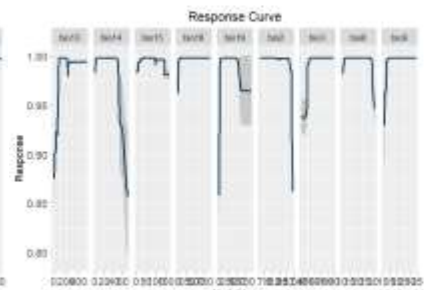
Jasminum fluminense



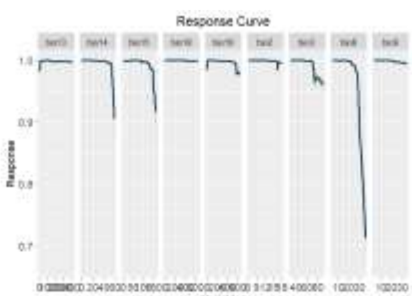
Lagenaria sphaerica



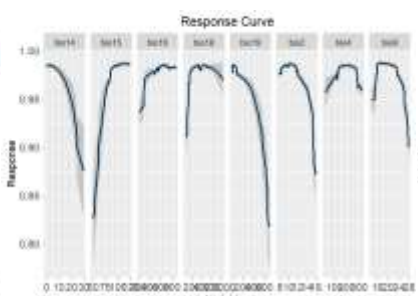
Leucas martinicensis



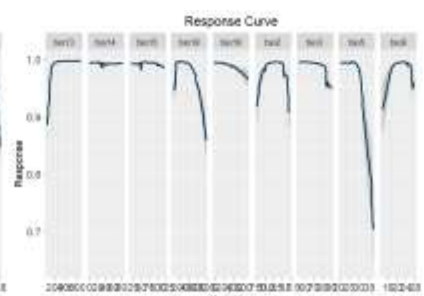
Momordica foetida



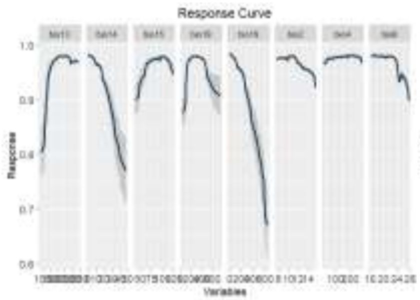
Olea europea

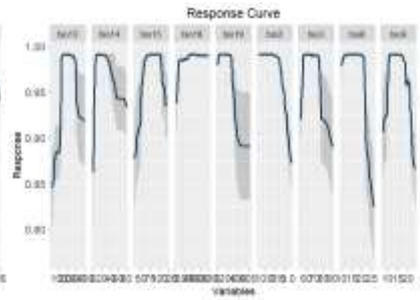


Pericopsis angolensis



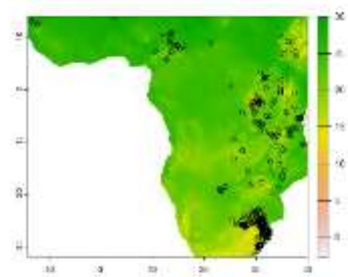
Rotheca myricoides



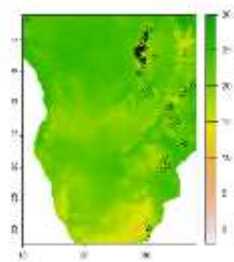


Scepocarpus hypselodendron *Stephania absynnica*

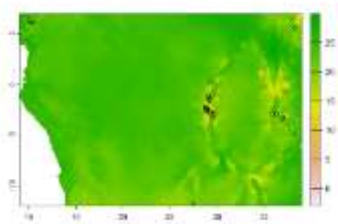
Figure 3 Occurrence points of all 14 selected MCP plants species across Africa.



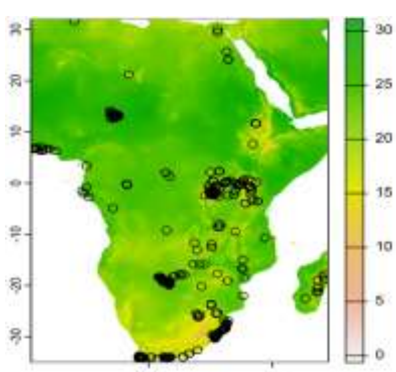
Acalypha petiolaris



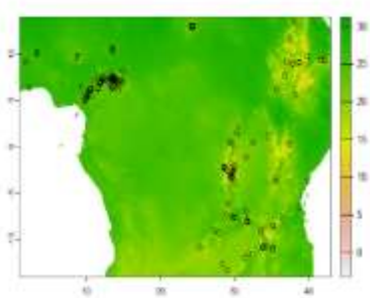
Brillantaisa cicatricose



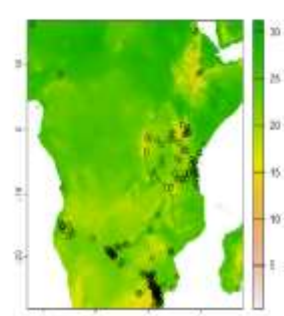
Cenchrus trachyphyllus



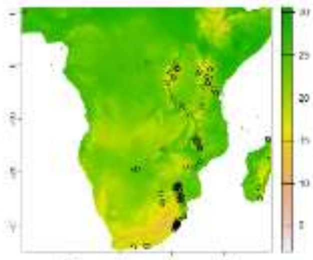
Cyperus papyrus



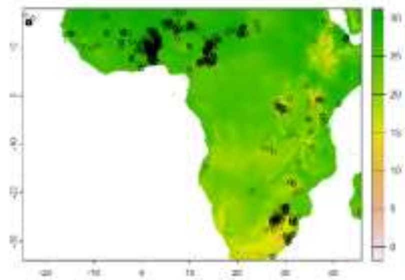
Guizotia scabra



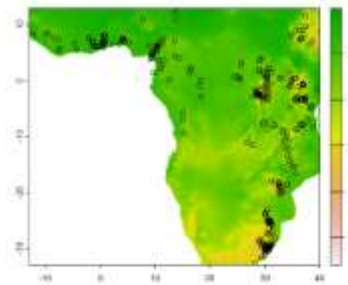
Jasminum fluminense



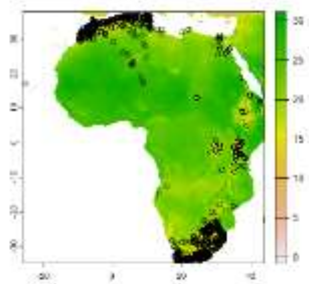
Lagenaria sphaerica



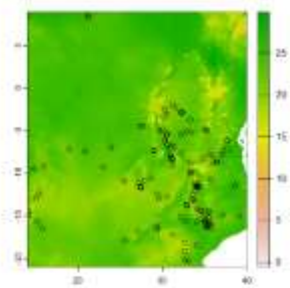
Leucas martinicensis



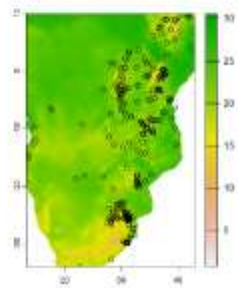
Momordica foetida



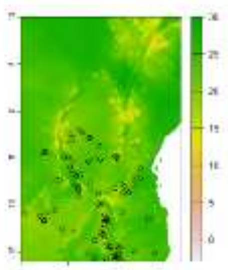
Oloe europea



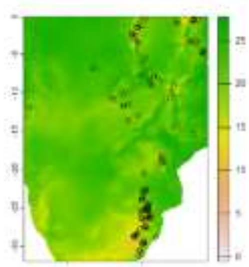
Pericopsis angolensis



Rotheca myrcoides

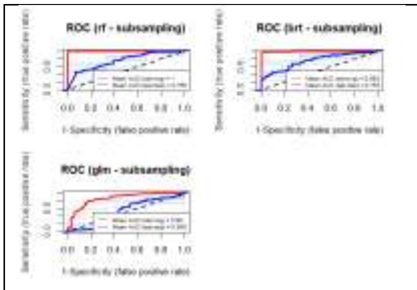


Scepocarpus hypselodendron

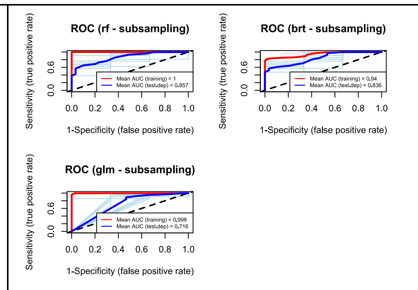


Stephania absynnica

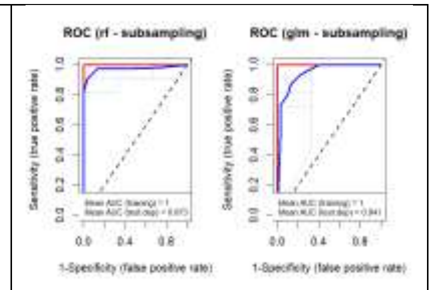
Figure 4 Receiver Operating Characteristic (ROC) plots and AUC (Area Under the Curve) shows the performance of each algorithm (RF, BRT, GLM) on each 14 MCP species.



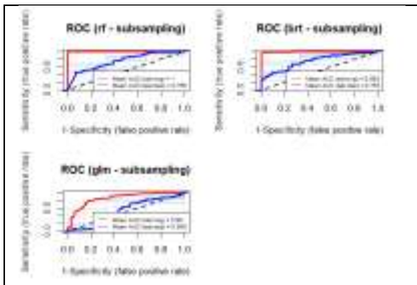
Cyperus papyrus



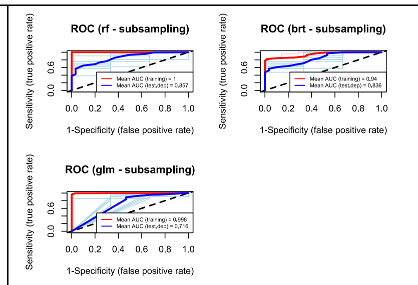
Guizotia scabra



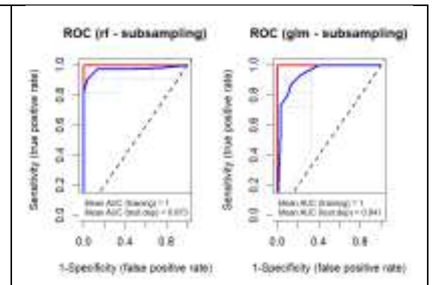
Jasminum fluminense



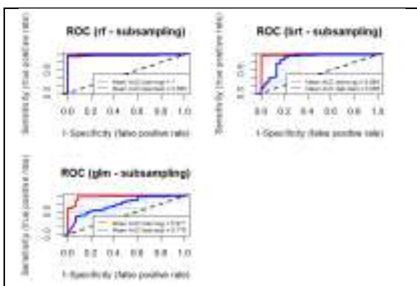
Acalypha petiolaris



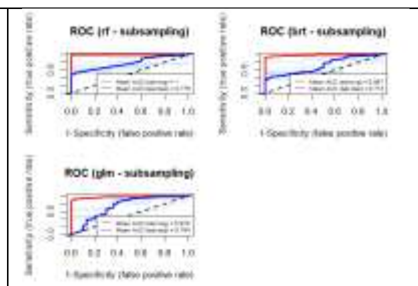
Brillantaisa cicatricosa



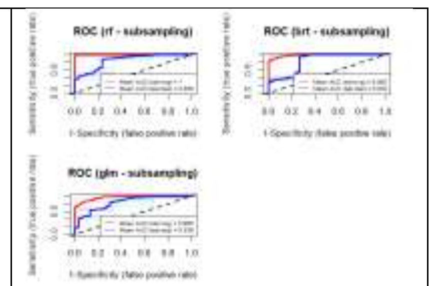
Cenchrus trachyphyllus



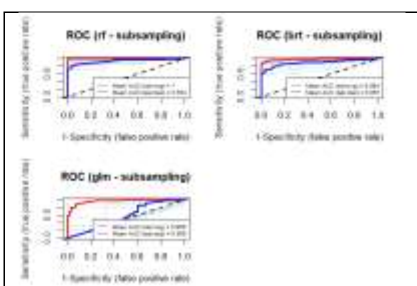
Cyperus papyrus



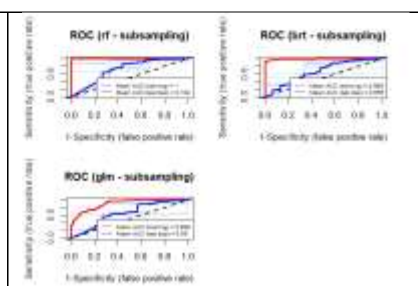
Guizotia scabra



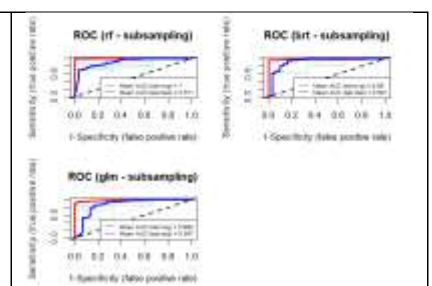
Jasminum fluminense



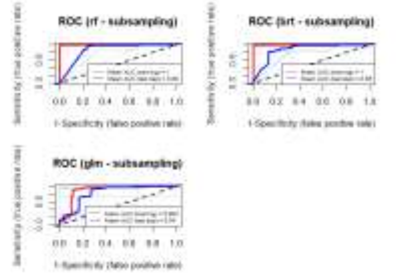
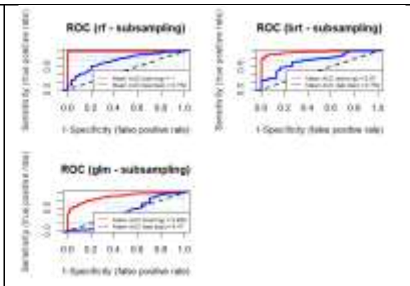
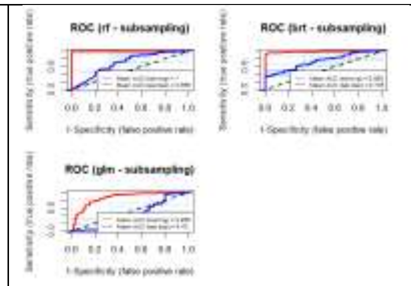
Lagenaria sphaerica



Leucas martinicensis



Momordica foetida

		
Olea europea	*Pericopsis angolensis*	*Rotheca myrcoides*

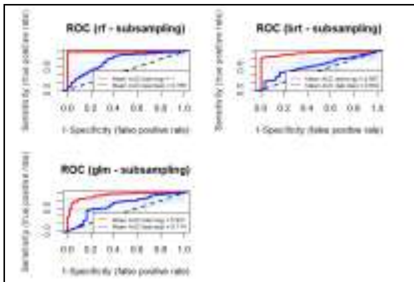
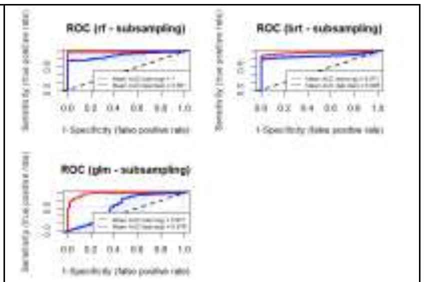
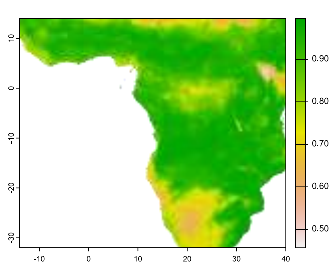
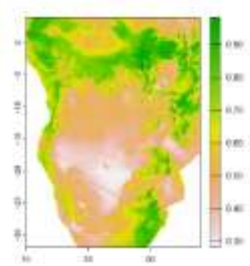
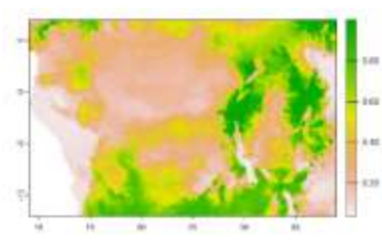
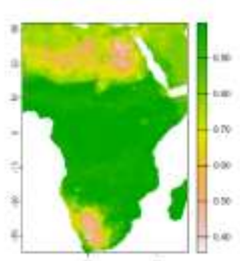
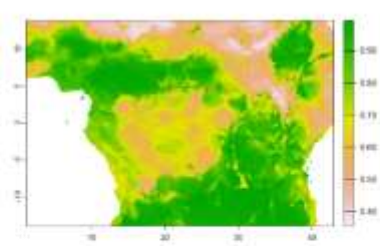
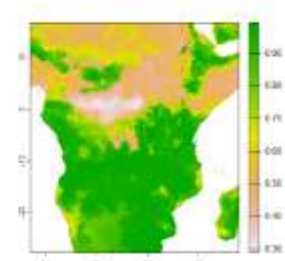
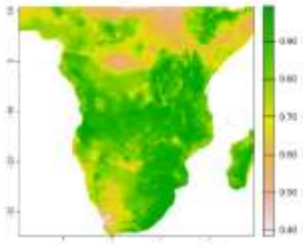
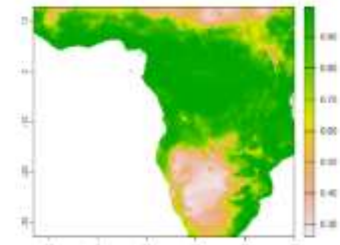
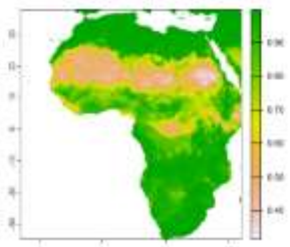
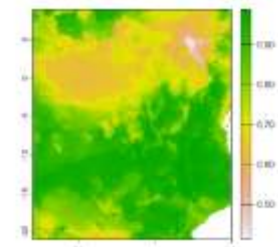
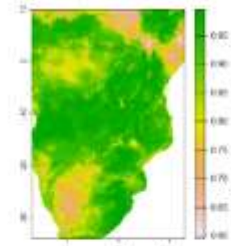
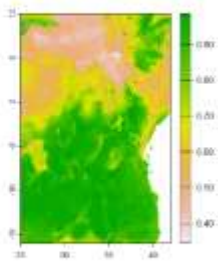
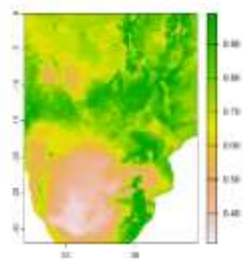
	
Scepocarpus hypselodendron	*Stephania absynnica*

Figure 5 Distribution maps of each 14 MCP species across African region

		
Acalypha petiolaris	*Brillantaisa cicatricosa*	*Cenchrus trachyphyllus*

		
Cyperus papyrus	*Guizotia scabra*	*Jasminum fluminense*

		
Lagenaria sphaerica	*Leucas martinicensis*	*Momordica foetida*
		
Olea europea	*Pericopsis angolensis*	*Rotheca myrcoides*

	
Scepocarpus hypselodendron	*Stephania absynnica*