UNIVERSITY OF NAIROBI

Prosopis juliflora invasion in Baringo, Kenya: Exploring its impacts on LULC dynamics, *Vachellia tortilis*, selected ecosystem services, livelihoods and potential spread under climate change

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PLAGIARISM STATEMENT

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DECLARATION

I declare that this Thesis has been solely composed by me. Further, it has not previously formed the basis for the award of any other degree, title or recognition.

DEDICATION

To a string of people with big hearts who had my back throughout this back-breaking journey:

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ABSTRACT

Savanna grasslands are invaluable, but face threats from multiple stressors such as land degradation, woody encroachment and climate change. While it is expected that climatic changes will continue to exacerbate existing stressors, rapid invasion by woody plants such as *Prosopis juliflora* is now widely considered a key factor accelerating degradation in grasslands. This raises concerns about the functioning and sustainability of these ecosystems. In the savanna grasslands of Baringo County in Kenya, *Prosopis juliflora* (hereafter referred to as *"Prosopis"*) was introduced in 1982/83 to alleviate firewood shortage and mitigate desertification. However, it has become invasive and continues to disperse to new areas at exceptional rates, impacting on the environment, economies and people. This study utilized various datasets and methodologies to analyze the 1) spatio-temporal changes in *Prosopis* coverage in Baringo County since its introduction, 2) implications of these changes on other land-uses and land-cover, native *Vachellia tortilis*, livelihoods, biodiversity and selected ecosystem services (ES), and 3) impacts of current and predicted future climate change on suitable habitat of alien *Prosopis* and the dominant native *Vachellia tortilis*, which is currently highly threatened by *Prosopis* invasion. *Prosopis* spread at a rate of 640 ha / year between 1988 and 2016, replaced over 30% of other valuable land-uses/land-cover and caused significant livelihood losses. Further, grassland restoration is as effective as *Prosopis* invasion in replenishing soil organic carbon, and does not comprise the provisioning of other ES, while *Prosopis* limits fodder productivity and species diversity. Species distribution models revealed that climate warming will have profound effects on species geographic ranges of both alien and native species. Climate models predict both habit expansion and contraction. The adverse effects (habitat encroachment) of invasive plants on biodiversity will equally persist in the face of the envisaged climatic changes. Over 30% of the predicted future suitable habitat for *Vachellia tortilis* is also suitable for *Prosopis*, indicating possible invasion into these habitats in future. These findings suggest an integrated approach to *Prosopis* management to prevent further spread. Further, effects of climate change should be mainstreamed in policies addressing invasive species, land degradation and biodiversity loss.

Keywords: *Prosopis juliflora*, *Vachellia tortilis*, grassland restoration, climate change, Kenya.

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LIST OF ABBREVIATIONS /ACRONYMS AND SYMBOLS

ASALs	Arid and Semi-arid Lands
AUC	Area Under the receiver operating Curve
BRT	Boosted Regression Trees
CABI	Centre for Agriculture and Biosciences International
CDE	Centre for Development and Environment
CDM	Clean Development Mechanism
CDR	Climate Data Record
CEP	Climate and Environmental Physics Department, University of Bern
CGLS	Copernicus Global Land Service
CMIP	Coupled Model Inter-comparison Project
CNRM-CM5	Centre National de Recherches Météorologiques Climate Model 5
COP	Conference of Parties
CV	Cross-validation
ECV	Essential Climate Variables
EDRR	Early Detection and Rapid Response
ES	Ecosystem services
ETM+	Enhanced Thematic Mapper plus
FAO	Food and Agriculture Organization
GBIF	Global Biodiversity Information Facility
GCMs	Global Circulation / Climate Models
GCOS	Global Climate Observing System
GDP	Gross Domestic Product
GIS	Geographic Information Systems
GIUB	Geographisches Institut - Universität Bern
GPS	Global Positioning System
HFP	Global Human Footprint Index
INM-CM4	Institute of Numerical Mathematics Climate Model 4
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
KALRO	Kenya Agricultural and Livestock Research Organization
KEFRI	Kenya forestry Research Institute
LULC	Land-Use and Land-Cover

MAXENT	Maximum Entropy
MODIS	Moderate Resolution Imaging Spectroradiometer
MPI-ESM-LR	Max Planck Institute Earth System Model, low resolution
NDVI	Normalized Difference Vegetation Index
OA	Overall Accuracy
OLI	Operational Land Imager
OOB	‘out-of-bag’
PA	Producer’s Accuracy
RAE	Rehabilitation of Arid Environments Trust
RCP	Representative Concentration Pathway
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RF	Random Forest
RGEB	Random generation with exclusion buffer
ROIs	Regions of Interest
R4D	Swiss Programme for Research on Global Issues for Development
SDC	Swiss Agency for Development and Cooperation
SDMs	Species Distribution Models
SNSF	Swiss National Science Foundation
SOC	Soil Organic Carbon
SRTM	Shuttle Radar Topography Mission
SSA	Sub-Saharan Africa
SVM	Support Vector Machine
SWIR	Short Wave Infrared
TM	Thematic Mapper
TSS	True Skill Statistic
UA	User’s Accuracy
UNESCO	United Nations Educational, Scientific and Cultural Organization
Uni-Bern	University of Bern
UNFCCC	United Nations Framework Convention on Climate Change
UTM	Universal Transverse Mercator
VHR	Very High Resolution
WGS	World Geodetic System 1984
WTP	Willingness-to-pay

GLOSSARY OF TERMS

Bioclimatic variables	Is a set of 19 variables (bio1 to bio19), derived from the monthly temperature and rainfall values to generate biologically meaningful indicators that describe how the climate system affects ecosystems and services.
Climate refugia	Areas where a species may migrate to or persist during large-scale, long-term climate change, or areas of climate suitability, or areas with tolerable environmental conditions for the focal species.
Cross-Validation (CV)	It is a technique for evaluating the performance of machine learning models. It is also a resampling method that uses different portions of the dataset to train and test a prediction model on different iterations.
Essential Climate Variables (ECV)	ECVs are are a set of 54 land, ocean and atmosphere variables representing the chemical, physical or biological earth processes that critically contributes to the characterization of the earth's climate.
General Circulation Model (GCM)	Also known as Global Climate Model is a complex mathematical / numerical representation of the major climate system constituents (land surface, ocean, atmosphere, and sea ice), and their interactions.
Human Footprint Index	The measure of the cumulative human pressure on the environment which is estimated using eight variables including population density, built-up environments, electric power infrastructure, roads, railway, crop and pasture lands and navigable waterways(Venter et al., 2018b)(Venter et al., 2018b).

Land-cover	The observed physical and biological cover on the earth's surface mainly the man-made features and vegetation.
Land-use	The human use of land for economic or cultural purposes such as agricultural, recreational, residential, and industrial.
Out-of-Bag (OOB)	It is an evaluation technique for measuring the prediction error of machine learning models that use bootstrap aggregation (bagging). Bagging uses subsampling with replacement to create training samples (dataset) for the model to learn from.The method generates an OOB error estimate which the mean prediction error on each training sample, using the trees that did not have the sample in their bootstrap sample.
Producer's Accuracy (PA)	Image classification accuracy output that indicates how accurately the classification results meet the expectation of the person doing the classification (producer). It is also known as Type 2 error and shows the false negatives (errors of omission). It is calculated by dividing the total number of classified points that match with the reference dataset by the total number of reference points for that class.
Soil Organic Carbon (SOC)	It is the measurable portion of soil organic matter. Organic matter comprises about 2 – 10% of soil mass and contributes to soil structure, nutrient and moisture retention and availability, carbon sequestration and degradation of pollutants.
Species richness	The number of different species per unit area.
Standard Error	The standard error of the mean is a measure of how a population mean is likely to differ from a sample mean.
User's Accuracy (UA)	Image classification accuracy output that shows false positives i.e. type 1 error (incorrect

	classification of pixels or errors of commission). It is computed by dividing the total number of classified points that match with the reference dataset by the total number of classified points for that class.
“4 per 1000” Initiative	Soils for Food Security and Climate Initiative is a global plan and agreement launched by the French Government at the Paris Climate Summit in 2015. It aims to reverse global warming, soil degradation, rural poverty, and worsening public health by promoting regenerative agriculture and land use practices. It proposes to increase the level of carbon stored in surface soils (top 30-40 cm) by 0.4% annually in the next 25 years.

CHAPTER 1: INTRODUCTION

1.0 Introduction

In this chapter, the general introduction and background information about the study are presented. It provides a brief highlight on the issue of woody encroachment, particularly exotic invasive species into grassland ecosystems and the interactions between the current global changes – climatic changes, biological invasions and land-use and land-cover changes. The subsections include background to the study, problem statement, objectives, justification and significance, scope and limitations, and thesis structure.

1.1 Background

Grassland ecosystems characterize many of the world's arid lands and make up about 40% of the total land area globally (Millennium Ecosystem Assessment, 2005; White et al., 2000). They are dominated by grasses and shrubs and are seasonally maintained by grazing, fire, drought and / or freezing temperatures (White et al., 2000). They comprise savannas, woodlands, tundra and shrublands (White et al., 2000). Although grasslands are found in every region of the world, Sub-Saharan Africa has the largest total area of grassland at 14.5 million km^2 (White et al., 2000). Grasslands are invaluable because they provide comprehensive economic and ecological benefits to society (Gobelle and Gure, 2018) such as food, forage, biodiversity, carbon storage and recreation (White et al., 2000), and thus have substantial, multi-dimensional conservation value (Archer, 2010). However, they are under severe threat from multiple stressors such as land degradation (Gibbs and Salmon, 2015), desertification (White et al., 2000), global warming and climate change (Chen et al., 2019), woody encroachment, and land-use changes (Bhattarai, 2013; Gibbs and Salmon, 2015), thereby raising concerns about the combined implications of these multiple stressors on the functioning and sustainability of these ecosystems (Archer, 1995; Côté et al., 2016; Zijp et al., 2017).

Woody encroachment (Ratajczak et al., 2012), also referred to as shrub encroachment (Eldridge et al., 2011) or bush encroachment (Ward, 2005) is the rapid invasion or sometimes gradual proliferation of trees and shrubs into semi-arid and arid grasslands (Belay et al., 2013; Hudak et al., 2003). Other terminologies used include 'woody weed invasion' (Booth et al., 1996), and 'thicketization'- a transition from a degraded grassland to woodland (Archer et al., 2001; Maestre et al., 2009). While an exacerbation of existing stressors is expected to continue due to climate change, (Bagne et al., 2012), rapid invasion of woody plants is currently one of the multiple factors accelerating degradation in arid and semi-arid areas (Archer, 2010; Belay et al., 2013; Dickie et al., 2014; Jackson et al., 2002). For instance, transitions in plant community composition from grass to woody shrub have been associated with undesirable effects such as; change in ecosystem goods and services, increased water erosion (D'Odorico et al., 2012; Jackson et al., 2002), alteration of biodiversity patterns (Archer et al., 2001; Lunt et al., 2010), alteration of land surface-atmospheric interactions and nutrient cycling (Archer et al., 2001). These effects have altered the general functioning and structure of grassland ecosystems, which eventually undermines their productivity, long-term economic viability and ecological integrity (Tefera et al., 2008). Multiple triggers have been implicated in woody encroachment processes which include overgrazing often coupled with changed fire regimes (Lunt et al., 2010; Roques et al., 2001), reduced grazing intensity, feeding on tree seed pods by livestock and later dispersing them in dung, above-average rainfall (O'Connor, 1995; Venter et al., 2018a), severe droughts (Roques et al., 2001), rising atmospheric CO_2 (D'Odorico et al., 2010; Scholes and Archer, 1997), agricultural abandonment (Cramer et al., 2008; Mbaabu et al., 2019), long-term climate change (D'Odorico et al., 2012, 2010; Knapp et al., 2008), and introduction of exotic trees (Archer, 2010; Ndhlovu et al., 2016; Shackleton et al., 2015a; Yapi et al., 2018).

While trees or shrub encroachment in grasslands may be seen as a natural ecological process where encroaching species are native and previously already present at lower densities in these landscapes (D'Odorico et al., 2012), in some cases it is not. This is particularly more so in many historically degraded savanna grasslands as well as hot, arid and semi-arid parts of Africa (Pasiecznik et al., 2001), Asia (Ratnam et al., 2016) and Australia where efforts to combat desertification led to intentional introductions of alien woody plants (Carboni et al., 2016; Pasiecznik et al., 2001; Shackleton et al., 2014; Simberloff, 2013; Vila, 2013). The most widely used tree species are of the genus *Prosopis* (mesquite – belonging to the family Fabaceae) which consists of about 44 species (Burkart, 1976; Patnaik et al., 2017).

From the native lands in South America, Mexico and the Caribbean, these species have in the past 200 years been introduced to various regions globally such as Hawaiian Islands in 1828, India in 1877, Australia in 1921, Philippines and Sri Lanka (Kathiresan, 2020; Shackleton et al., 2014; Van Klinken and Campbell, 2001). In Africa, about five *Prosopis* spp.: *P. glandulosa, P. velutina, P. juliflora, P. chilensis* and *P. pallida* were introduced in Senegal (1822), South Africa (1880), Sudan (1917), Kenya (1948), Somalia (1950) and Ethiopia

(1970) among other countries (Choge et al., 2022; Hoshino et al., 2012; Maundu et al., 2009; Pasiecznik et al., 2001; Wakie et al., 2016; Wuad and Abdulahi, 2021). *Prosopis* was preferred for rehabilitating degraded lands due to its rapid proliferation and ability to withstand harsh climate in tropical drylands (Pasiecznik et al., 2001). However, although these species provide some benefits such as firewood, timber and shade, they have become extremely weedy and invasive (Shackleton et al., 2014). Their rapid spread has been linked to biodiversity loss (Linders, 2019), land-cover and land-use changes (Mbaabu et al., 2019), and water reduction in streams and ground reservoirs (Archer, 2010; Dzikiti et al., 2017). Moreover, allelopathic effect of *Prosopis* leads to loss of herbaceous vegetation which increases erosion, flood risk, and reduces fodder availability. Together, these changes threaten the livelihoods of pastoral dependent communities particularly in grassland ecosystems in Sub-Saharan Africa. The contrasting environmental, social and economies impacts have raised contentious issues about this plant species (Van Wilgen and Richardson, 2014) particularly when there are no efficient and effective management strategies in place (Shackleton et al., 2014), partly owing to the paucity of reliable information on the key attributes of this species in the invaded range.

Faced with the four great global changes occurring today – climate change, biological invasions, enhanced geochemical cycles (particularly carbon and nitrogen), and land-use changes (Dukes and Mooney, 1999; Simberloff, 2013) – grasslands have only become more vulnerable to degradation in recent decades. These factors are interlinked, influence each other and generate synergistic interaction impacts (Dukes and Mooney, 1999; Simberloff, 2013; Walther et al., 2009). For instance, current and predicted future climatic changes (IPCC, 2018), elevated CO_2 and Nitrogen levels as well as habitat modifications are expected to influence species' range expansion and contraction (Pearson and Dawson, 2003), not only for native flora, but also for aliens, and allow expansions in areas they would not have previously occurred (Bellard et al., 2013; Dukes and Mooney, 1999; Thuiller, 2004; Thuiller et al., 2007). On the other hand, invasion by alien plant species such as *Prosopis*, has resulted in notable changes in land-use and land-cover (Mbaabu et al., 2019) and affected the geochemical cycles in many regions where the species have invaded (Ansley et al., 2006; Geesing et al., 2000; Mohanraj et al., 2022; Soper et al., 2016). Moreover, anthropogenic responses to these global changes have the potential to enhance or compromise the sustainability of grasslands. For example, tree planting in degraded grasslands, sometimes even planting invasive alien varieties, has legitimately been embraced as a strategy for addressing land degradation (Archer, 2010) and also for climate change mitigation under the Kyoto Protocol's Clean Development Mechanism (CDM) and the program for Reducing Emissions from Deforestation and Forest Degradation (REDD+) (Law et al., 2015; Parr et al., 2014).

From a global context, previous studies have investigated multiple themes on grassland biomes and their implications on these ecosystems, economies, biodiversity and livelihoods (Archer et al., 1988; Baasch et al., 2016; Bardgett et al., 2021; Briggs et al., 2005; Buisson et al., 2019; Conant, 2010; Hector et al., 2010; Leys et al., 2018; Veldman et al., 2015; Waldén and Lindborg, 2016). These themes include land degradation, climate change, woody encroachment, carbon sequestration, grassland restoration, fire, plant diversity and grassland conversion or land-use and land-cover changes. The implications of these on grassland ecosystems have been widely documented. For example, degradation of grassland threatens the livelihoods of millions of people who depend on grasslands for multiple uses such as food, fibre, fuel and cultural values (Bardgett et al., 2021). Global grassland degradation cost livestock production about US$ 6.8 billion between 2001 and 2011 (Kwon, 2015), with severe consequences for rural populations dependent on livestock (Bardgett et al., 2021). Moreover, degradation of grasslands is the real culprit for major environmental issues since these ecosystems are important for biodiversity conservation, water and climate regulation, forage production and global biogeochemical cycles. Changes from grasslands to croplands or disturbances through overgrazing, fire and invasive species threaten biodiversity in grassland ecosystems, with potential remarkable losses in soil carbon (Murphy et al., 2016; Smith et al., 2008).

The problem of woody encroachment into grasslands has been widely studied globally (D'Odorico et al., 2012; Huang et al., 2018), with examples from North America (Knapp et al., 2008; Ratajczak et al., 2012; Van Auken, 2009), Mediterranean region (Maestre et al., 2009), South America (Adamoli et al., 1990; Silva et al., 2002), Asia (Kathiresan, 2020; Ratnam et al., 2016), Australia (Burrows et al., 1990; Fensham et al., 2005; Fensham and Fairfax, 2003; Lunt et al., 2010; Price and Morgan, 2008), Iberian Peninsula (Europe) (Montané et al., 2007) and Africa (Venter et al., 2018a). Despite all these studies, the linkages of their effects on land-use and land-cover, biodiversity, livelihoods, ecosystems services, and their interactive effects with climate change have rarely been investigated.

In the last two decades, woody encroachment in African grasslands has received increased research attention (Coetsee et al., 2013; Roques et al., 2001; Ruwanza and Shackleton, 2016; Venter et al., 2018a; Ward, 2005). The implications of these invasions have also been widely studied. For example, in Ethiopia, Dalle et al. (2006) found that woody encroachment in Borana lowlands had reached critical cover threshold (≥ 50%), which decreased fodder availability for livestock. Gobelle and Gure (2018) studied the impacts of tree invasion on plant diversity and carbon stocks. They found that tree invasion reduced species diversity and richness of herbaceous plants, while carbon stocks varied with tree density or cover. In southern Africa veldt, minimal gains in ecostystem carbon were observed after woody plant encroachment (Coetsee et al., 2013). Soil organic carbon decreases were also reported in semi-arid grasslands of South Africa following woody plant encroachment (Hudak et al., 2003; Mureva et al., 2018). Mitchard and Flintrop (2013) analysed tree invasion and deforestation in woodlands in Sub-Saharan Africa through a review of studies between 1982 and 2006. They found that woody encroachment increased north of the Congo basin while deforestation was prevalent in the Miombo woodlands. Trends in woody cover in Namibia’s savanna have been mapped using MODIS data (Wingate et al., 2019); it was found that woody cover decreased in dry forests but increased in shrublands. Belay et al. (2013) studied ecosystem responses to tree invasion in the semi-arid Omo region of Ethiopia. Contrary to findings in many other studies, they found that plant diversity and richness correlated positively with tree invasion.

In Kenya, few studies have investigated the effects of woody encroachment (Herlocker et al., 1981), until recently when *Prosopis* invasion became an issue of economic, environmental and social concern. Most of these studies on *Prosopis* in Kenya have been done from the year 2000 onwards (Adoyo et al., 2022; Andersson, 2005; Choge et al., 2022, 2022; Choge and Pasiecznik, 2005; Eschen et al., 2021; Kyuma et al., 2016; Linders et al., 2020; Maundu et al., 2009; Mulinge et al., 2016; Muturi et al., 2013; Mwangi and Swallow, 2005; Ng et al., 2017). However, these studies have largely focused on management and the impacts of *Prosopis* on livelihoods due to public outcry by the affected communities inhabiting the invaded areas. As such, local studies were significantly biased in their thematic scope to only social and economic aspects while leaving out the environmental component. This undermines the principle of sustainability in development which should consider three pillars (economic, social, and environmental). Consequently, this created a gap in knowledge and understanding of the spatial distribution of the species, spread rates and impacts of the spread on other land-uses and land-cover, native plant diversity and rural livelihoods, and how these would interact under the changing climatic conditions. This thesis therefore identified this gap in knowledge and attempted to fill it.

The rapid spread of invasive alien trees like *Prosopis juliflora* has posed complex management challenges, particularly in developing countries. This is partly because of contrasting views regarding their beneficial and harmful aspects and a lack of or unclear policies regarding their management (Laxén, 2007; Patnaik et al., 2017; Tiwari, 1999; Van Wilgen and Richardson, 2014). This is exacerbated by paucity of knowledge on their distribution, extent and nature of spread, benefits, costs and effective management interventions (Shackleton et al., 2014). Consequently, this scenario has led to a lack of consensus on management of *Prosopis* invasions in different contexts, giving chance to a mix of trial management approaches such as chemical, biological and mechanical control, management by 'utilization', eradication, toleration as well as acceptance of the 'newcomer' species as important for local biodiversity enrichment (Walther et al., 2009), regardless of their efficacy, socio-economic and ecological implications.

In Kenya, initial *Prosopis* introductions occurred in Taita Taveta County, Bamburi in Mombasa County, Bura in Garissa County, Hola in Tana River and Turkana County. In the semi-arid grasslands of Baringo County, *Prosopis spp* were first planted in 1982 to combat land degradation, mitigate desertification and alleviate shortage of firewood and livestock fodder (Little, 2019; Schwartzstein, 2019). Although about 3 *Prosopis* varieties (*P. pallida, P. juliflora and P. chilensis*) were introduced in Baringo County, only *Prosopis juliflora* is invasive (Castillo et al., 2021), and has continued to colonize new areas at exceptional rates, with remarkable impacts on the ecosystem such as biodiversity loss (Linders, 2019; Linders et al., 2019), and human welfare such as loss of livelihoods due to cropland and pasture invasion (Mbaabu et al., 2019; Mooney, 2005; Mwangi and Swallow, 2005; Pimentel et al., 2005). Over time, *Prosopis* has become extremely unmanageable owing to fast proliferation rates and and high survival rate trough coppicing after cutting (Mwangi and Swallow, 2005). This invasion has continued to paralyze the livelihoods of the agro-pastoral Baringo communities, who have blamed it for loss of ecosystem services and biodiversity on their landscape. As a result, they have continued to pile pressure on the government (one that sactioned *Prosopis* introduction) and scientific community for more sustainable solutions (Mwangi and Swallow, 2005; Truth, Justice, and Reconciliation Commission, 2011). However, faced with this predicament, following a legal suit by Ilchamus community against the Government of Kenya in 2006, the government in its defense argued that the semi-arid area in Kenya would be utilized better through planting and managing *Prosopis* for carbon sequestration and climate change mitigation. The Government of Kenya considered this move valid, legitimate and consistent with global environmental and sustainable development goals because Kenya is a Party to the United Nations Framework Convention on Climate Change (UNFCCC) as well as the Kyoto Protocol (Kenya Law, 2007; Little, 2019).

1.2 Problem Statement

Historically, many tropical drylands including Baringo lowlands in Kenya, have undergone continuous degradation partly due to extreme climatic events such as drought, and poor land-use practices such as overgrazing (Little, 2019, 1992). Land degradation in Baringo over the past 300 years culminated into acute shortage of ecosystem goods and services which have persisted todate. This prompted rehabilitation efforts through tree planting including use of invasive species such as *Prosopis juliflora*, to avert possible desertification and to fortify the crumbling drylands (Schwartzstein, 2019). However, some of the introduced trees such as *Prosopis juliflora* have become very invasive over time causing damages to people and the environment. Baringo county in Kenya is a classic example of an ecosystem experiencing devastating effects of *Prosopis juliflora* tree invasion since its introduction in the early 1980s (Mbaabu et al., 2019b). At the start of this study in 2016, reliable estimates of *Prosopis juliflora* invasion needed to guide decision makers on policy were lacking. Specifically, there were information gaps regarding the invasion and spread of *Prosopis juliflora*, at what rates and the extent of invasion in Baringo County, its impacts on other land-use and land-cover, livelihoods and native biodiversity. This gap needed to be filled to support evidence-based policy making on *Prosopis* management in Kenya. Additionally, these estimates would be useful in enhancing the understanding of the implications of invasion on other land-uses and land-cover to land owners, conservationists and other stakeholders. Changes in land-uses and land-cover (LULC) need to be addressed because they are the primary mechanisms of losses of biodiversity, ecosystem services and livelihoods, which would derail economic development and eventually curtail the achievement of many Sustainable Development Goals including SDG 1-3, 6, 8, 10, 15 and 16 (United Nations, 2023).

Besides land degradation and invasive plant species, Baringo drylands are also threatened by climate variability, effects of which would amplify the negative effects of land degradation and *Prosopis* invasion such as soil erosion, loss of herbaceous biomass, biodiversity and water. In relation to this, there were gaps in understanding and knowledge of how the current and predicted future climatic changes would influence *Prosopis* invasion as well the habitat of key native flora –*Vachellia tortilis* (formerly *Acacia tortilis)*. *V. tortilis* is a characteristic species in savanna grasslands, whose distribution is currently highly threatened by *Prosopis* invasion (Mbaabu et al., 2019). Moreover, studying the past *Prosopis* invasion dynamics and modeling the effects of future climatic changes could provide invaluable cues needed to understand the evolutionary history and future ecological dynamics on how the co-existing native and alien species may react to an altered climate. Moreover, projecting potential future changes in species geographic ranges in the context of biological invasions is important for developing adaptive invasive plants management. This enables identification of refugia as well as areas of vulnerability (threatened habitat) for native flora (Baumgartner et al., 2018), particularly to *Prosopis* invasion, for prioritization of biodiversity conservation efforts and resources. Further, this will inform policy decisions on current and future management of degraded and invaded savanna grasslands (Keppel et al., 2015). Additionally, this would also help to mitigate potential problems of climate change on ecosystems, people and economies early enough.

1.3 Objective of the study

1.3.1 Main Objective

The main objective was to provide reliable estimates of alien *Prosopis* spread in Baringo County, Kenya and an understanding of the implications of the invasion dynamics on people and the ecosystem in the face of climate change.

1.3.2 Specific objectives

i. To estimate the spatial extent and dynamics of alien *Prosopis* invasion, its impacts on land-use and land-cover, selected native biodiversity (*Vachellia tortilis*) and rural livelihoods.
ii. To evaluate and compare the impact of *Prosopis* invasion vs. grassland restoration on soil organic carbon stock, plant species richness and herbaceous biomass over the past 30-35 years.
iii. To assess the impact of climate change on *Prosopis juliflora* and *Vachellia tortilis* geographic ranges under current (1970-2000) and future (2041-2060 and 2071-2100) climate change scenarios, identify areas potentially at risk of *Prosopis* invasion and climate refugia for *Vachellia tortilis.*

1.3.3 Research Questions

1. What is the current (as at 2016) spatial distribution of *Prosopis juliflora* and how has it evolved over the past 25-30 years?
2. What are the spatial dynamics (invasion rate and density) over time in the study area, and how has it impacted the native *Vachellia tortilis*?
3. How much grassland and agricultural land has been lost to *Prosopis juliflora* invasion and what are the implications on livelihood?
4. What are the impacts of *Prosopis juliflora* cover and grassland restoration on the soil organic carbon, plant species richness and herbaceous biomass?
5. Where are the suitable habitats for *Prosopis juliflora* and *Vachellia tortilis* under current (1970-2000) and future (2041-2060 and 2071-2100) climate change scenarios?
6. Which areas are suitable for *Vachellia tortilis* but are at risk of *Prosopis juliflora* invasion in future?
7. Which factors influence habitat suitability for both species and under current and future climate conditions?

1.4 Justification and Significance

1.4.1 Justification

Nearly half of the African continent is covered with savanna grasslands which hosts most of the world’s mammals, rich in biodiversity and supports numerous livelihoods. Despite their vital significance, these grasslands have numerous threats with land degradation, woody tree encroachment and climate change as most pressing. Baringo region is mainly arid and semi-arid and part of the larger savanna biome. Besides climate change and land degradation, this region is suffering devastating effects of alien *Prosopis* invasion. Invasion by alien species such as *Prosopis* are a key driver of landscape changes and biodiversity loss, with negative implications on livelihoods. Although *Prosopis* introduction and its subsequent invasion has been a highly contested topic which elicited a legal battle and attracted global attention, it still remains persistent with no solutions at hand partly due to lack of effective management strategies and policy framework. Policy frameworks need to be backed up by scientific evidence. For Baringo and other invaded areas in Kenya, crucial data such as *Prosopis* invasion dynamics (past and current extents), and its impacts was initially lacking. Moreover, predicted future climate change is expected to amplify alien species invasions as well as modify habitats for native species. As such, it is not known which areas are at risk of future

Prosopis invasion as well as how *Prosopis* and a selected key native species (*Vachellia tortilis*) will respond to climate change. *Vachellia tortilis* was selected for modeling because it is a key species characteristic of savanna grasslands that is currently being replaced by *Prosopis* colonization (Mbaabu et al., 2019). Furthermore, with the current global debates advocating for forest expansion into grasslands for carbon sequestration (as opposed to the expected grassland restoration), the extent to which afforestation can remarkably increase carbon stocks without compromising the provisioning of other ecosystem services is not known. Soil organic carbon assessment in *Prosopis* invaded areas and restored grassland was given consideration in this study because carbon sequestration is recognized as an important ecosystem service (Nelson et al., 2008). Besides, soil organic carbon is one of the three indicators used by UNCCD to assess land degradation neutrality because it represents the capacity of the land to provide ecosystem services (Feng et al., 2022). Baringo County and its environs was selected as case study because it presents a nexus of climate change, biological invasions, and land-use and land-cover changes, which are part of the current global challenges.

1.4.2 Significance

The findings will inform adaptive policies for management of *Prosopis* in Baringo and other invaded areas in Kenya amid climate change. They enhance the understanding of both native and alien tree species response to climate change and contribute to knowledge on global discourses regarding afforestation of grasslands for climate mitigation or addressing land degradation. Moreover, they will reveal potential target areas for prioritization of *Vachellia tortilis* conservation attention, action and resources, amid adverse *Prosopis* invasion threat. It is hoped that the findings will inform future actions on the management of savannas and grasslands and key tenets mainstreamed in national and county policies aimed at reversing and mitigating the current global problems of land degradation, climate change, invasive species and biodiversity loss.

1.5 Scope and Limitations of the Research

1.5.1 Scope

This study focuses on three themes, namely biological invasions, land-use and land-cover changes and climate change within the context of savanna grassland biome. The impacts of *Prosopis juliflora* invasion on LULC are further extended to analyze the invasion implications on native biodiversity (*Vachellia tortilis*) and livelihoods. The geographic scope is the larger rift valley area, comprising Baringo County and part of the surrounding counties with similar climate, topography and species dispersion i.e. where the target species are found. The time scope for invasion impact and soil organic carbon analysis was 40 years. The period under consideration was 1970-2000 (for current climate); 2041-2060 (for near future climate) and 2071-2100 (for distant future climate). A variety of data (qualitative and quantitative) representing climate, topography, landscape structures, species occurrence, socio-economic and other important satellite derived variables were used. A combination of different research approaches were used including time-series analysis for LULC change detection, field sampling and laboratory analysis, and climate modeling.

1.5.2 Limitations

Analysis of *Prosopis* spread since its introduction was limited by the fact that in the premier years 1982-1987 when *Prosopis* was just introduced, the planted individual trees were still very young, small and barely detectable on the 30 m Landsat imagery. This limitation was overcome by excluding these early years from the analysis. Moreover, some areas such as Arabal and Mukutani of Marigat sub-region were also excluded, even though they are invaded by *Prosopis*. This is because groundtruthing was not possible due to heigthened insecurity associated with banditry and inter-ethinic conflicts. At the time of data collection, these zones were quarantined for security reasons.

1.6 Structure of the Thesis

Chapter one introduces the research, while chapter two provides a review of literature. The study area and research methods are described in chapter three. Chapter four deals with the *Prosopis* spread since its introduction and the effects of the spread on land-use and land-cover changes, key biodiversity and human well-being. Chapter five sheds light on the recent and current discourses regarding climate mitigation in grasslands and dryland ecosystems. It analyses the climate mitigation potential of two contrasting strategies to land degradation on soil organic carbon stocks, biodiversity and herbaceous biomass. Chapter six is about the effect of climate change on *Prosopis* invasion and the habitat of native *Vachellia tortilis* in the current and future climate. It further investigates the effect of projected *Prosopis* spread on the habitat of *Vachellia tortilis*, with the aim of identify safe refuges for prioritizing of native Vachellia conservation amid the threats of climate change and *Prosopis* encroachment. Chapter seven provides a synthesis, draws conclusions across all the chapters and provides recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

A review of pertinent literature on the thematic scope of each objective is provided in this chapter. The chapter starts with what has been studied regarding mapping historical changes of the invasive *Prosopis juliflora* and the implications of these changes on land and people. Then, a review of literature on the impacts of *Prosopis* invasion and grassland restoration on selected ecosystem services, and finally how past and future climatic changes affect species geographic range (suitable habitats of both alien *Prosopis juliflora* and the native *Vachellia tortilis*). The chapter concludes with a summary of what is known and not known about the topic and reveals information gaps, some of which, this study attempted to fill.

2.2 Mapping historical spread of *Prosopis juliflora* and analyzing invasion effects on land and livelihoods

African drylands experienced severe degradation attributed to drought in the 1970s and before (Brahic, 2009; Gaulter, 2012), which precipitated tree planting including alien species. Deliberate introductions of alien trees have occurred in many arid lands in Africa because they provide some benefits to rural communities through provisioning of goods and services (Choge et al., 2022; Mbaabu et al., 2019). *Prosopis* species, which are native to Central and South America are listed among the International Union for Conservation of Nature's (IUCN's) list of 100 World's worst invasive alien species (Lowe et al., 2000). They were first introduced in Taita Taveta town for ornamental reasons in 1948, Bamburi, Mombasa in 1973 to rehabilitate quarries (Herlocker et al., 1981), and later in Baringo lowlands in Kenya in 1982 under the Fuelwood Afforestation Extension Project (Kaur et al., 2012; Kimani et al., 1990). The introductions in Baringo were aimed at mitigating land degradation and alleviating shortage of firewood (Kariuki, 1993; Schwartzstein, 2019). *Prosopis* spp., also locally known as 'mesquite' in native lands, and 'Mathenge' or 'Promi' in Baringo, are nitrogen-fixing perennial (multi-stemmed or single-canopy) trees, with a high tolerance to arid conditions (Andersson, 2005; Pasiecznik et al., 2001). In Baringo, they proliferated and flourished fast even on degraded and barren land where regeneration of natural vegetation seemed slow, difficult or impossible owing to constant ecosystem disturbances such as fire and overgrazing (Doran et al., 1979). Thus, they were at first appreciated for scaling down dust storms and soil erosion, as well as providing shade, and pods for livestock fodder (Choge and Pasiecznik, 2005; Kinyua, 1989). However, a few decades after introduction, these trees became extremely problematic which caused havoc particularly in farmlands and grazing areas (Mwangi and Swallow, 2005) by causing substantial landscape changes and losses of livelihood (Mbaabu et al., 2019). These trees have been widely recognized as super invaders and are a threat to environmental and economic sustainability in the invaded range (Shackleton et al., 2014). This presents considerable management challenges to the affected countries. Therefore, studying their spatio-temporal extent and spread rate is important for developing sustainable control and management strategies.

Owing to their multi-faceted and damaging impacts (Table 2.1), analysis of the distribution of invasive plants at landscape level in space and time has become popular in the recent years because the invasion patterns and the associated proximate causes can be correlated (Brown and Carter, 1998; Shiferaw et al., 2019c).

Table 2.1 Positive and negative attributes of *Prosopis* trees

Positive and negative attributes of *Prosopis* trees		
Positive	**Negative**	**References**
Firewood and charcoal production	Loss of water resources	Walter and Armstrong (2014)
Wood		Walter and Armstrong (2014)
Pods for fodder	Loss of natural pastures for livestock	Wise et al.(2012)
Medicinal products	Loss of biodiversity	Choge et al. (2007), Haregeweyn et al.(2013)
Shade	Invasion of agricultural land – impacts household economies and human welfare	Walter and Armstrong (2014)
Soil stabilization	Blockage of paths and roads – impending movement	Abdulahi et al.,(2017)
	Direct harm or injury to livestock and people	Ayanu et al.,(2015)
Carbon sequestration and storage		Abdulahi et al.(2017)
Microclimate regulation		Abdulahi et al.(2017), Ilukor et al. (2016)
Human food		Choge et al.(2007)
Support honey production by providing forage for bees		Wise et al.(2012)
Effective fencing tree		Walter and Armstrong (2014)

Mapping of invasive species is necessary for designing effective control and management strategies to prevent spread into new locations (Grice et al., 2011) as well as to support monitoring of the outcomes of management interventions (Mbaabu et al., 2021). Remote sensing technology is a cost-efficient means for analysing the distribution of aliens plants and monitoring their geographical expanse even in difficult terrain or inaccessible areas (Huang and Asner, 2009). Remote sensing data from Very High Resolution (VHR) sensors can be used for analyzing changes on the landscape and enable discrimination of *Prosopis* species from other co-existent vegetation such as *Vachellia tortilis* (Adam et al., 2017; Mirik and Ansley, 2012; Ng et al., 2017). However, these datasets are tasked, and the data source archives have limited reliability and temporal resolutions such as the early years of *Prosopis* introduction in a site (e.g. 1980s). Therefore they cannot be used to study past changes in *Prosopis* distribution. Thus, satellite data / imagery that has been consistently acquired, and over a considerable period such as from the Landsat sensor or the moderate-resolution imaging spectroradiometer (MODIS) are used for such assessments. Such data have been utilised to map the distribution of *Prosopis* invasions worldwide (Kaurivi et al., 2003; Meroni et al., 2017; Ndungu et al., 2019; Ng et al., 2016b; Wakie et al., 2014). Distribution maps from previous studies show that *Prosopis* has colonized millions of hectares of arid lands in the Americas, Australia, Asia and Africa (Robinson et al., 2008; Singh and Joshi, 1979; Vidhya et al., 2017) and the species is currently found in over 129 countries (Shackleton et al., 2014). In Africa, it was estimated that *Prosopis* had invaded over 4 million hectares of rangelands by the year 2010 (Luizza et al., 2014; Witt, 2010; Witt et al., 2018). Shiferaw et al. (2019c) used Landsat 8 Surface Reflectances, topographic, climate and landscape features data to map *Prosopis* spread in Afar Region, Ethiopia. *Prosopis* invasion has been mapped in South Africa by Van den Berg et al. (2010) by combining MODIS, soil and terrain datasets. Mureriwa et al. (2019) mapped *Prosopis* distribution in South Africa using SPOT-6 satellite data and machine learning classification algorithms. Mureriwa et al. (2016) examined *Prosopis* spectral separability from other co-existent vegetation in South Africa by analyzing field spectral measurements using the guided regularized Random Forest technique. Adam et al. (2017) mapped the spread of *Prosopis glandulosa* using WorldView-2 satellite imagery and machine learning classifiers on a South African landscape.

In Kenya, Alvarez et al. (2019) classified the infestation risk of Lake Baringo Basin to *Prosopis juliflora* using environmental variables. They found that two variables: distance of invaded areas from original *Prosopis* plantations, and water availability had the highest predictive potential of future invasion risks. Kyuma et al. (2016) mapped the spatio-temporal dynamics in *Prosopis* spread in Southern Kenya between 2000–2013 using net primary productivity products and MODIS NDVI. They found that *Prosopis* correlated positively with increases in temperature (from 33°C in 2000 to 37°C in 2014); and negatively with precipitation decline (from 600 mm in 2000 to 250 mm in 2014). They also found that *Prosopis* invasion increased and took over 70% of land that was previous occupied by other land-uses and land-cover such as bushlands and woodlands. These studies show that assessing and monitoring *Prosopis* distribution in Africa and Kenya has gained attention in recent years. However, at the beginning of this study in 2015, reliable estimates of the spatial evolution and dynamics of *Prosopis* invasion and its effects on land-use and land-cover (LULC) and consequently on rural livelihoods were lacking for Kenya. Although Amboka and Ngigi (2015) mapped and monitored the spatio-temporal cover changes of *Prosopis* colonization in Baringo from 1985 to 2010, their findings are likely flawed because their spatial scope (geographical extent) does not correspond to the known *Prosopis* invaded areas in Baringo. Their study shows *Prosopis* cover in the area starting at longitude 35.3° E to 35.8° E East of Prime Meridian, which represents highlands (Kabartonjo, Kabarnet and Tugen Hills) which are covered with plantation forest and other indigenous vegetation. *Prosopis* currently is found in the lowlands zones around Lake Baringo (starting from about longitude 35.8° E to 36.1° E). This flaw can be attributed to failure to carry out rigourous groundthruthing or validation of findings. Kiage et al. (2007) also studied land-use and land-cover changes around Lake Baringo for the period between 1986 and 2000. They found up to 40% forest cover loss over the 14-year period, as well as 10% loss of Lake Baringo surface area due to lake sedimentation.

Most Sub-Saharan Africa rural communities are dependent on their natural environment for livelihood. Although *Prosopis* invasion offers some benefits to rural communities such as firewood, timber and charcoal (Maundu et al., 2009; Mbaabu et al., 2021; Mwangi and Swallow, 2008; Shackleton et al., 2015b), previous studies show that *Prosopis* invasions on previously productive landscapes have damaging effects on livelihoods in the invaded areas (Bekele et al., 2018a). For example, a global review of alien species invasion impacts on local livelihoods and human well-being has been provided by Shackleton et al. (2019). They established that many of these alien plant species provide livelihoods benefits to communities in the form of natural capital and job creation. On the other hand, these species negatively impact livelihood assets as households incur high labour and financial costs to manage them thus impoverishing human, physical, and financial capital (Bekele et al., 2018a; Linders et al., 2020). In India, Walter and Armstrong (2014) investigated the benefits, threats and potential of *Prosopis*. They identified *Prosopis* benefits such as bio-power production, fuelwood and charcoal, and negative effects such as invasion of farmlands leading to high labour imputs, and eventually farm abandonment. Further, *Prosopis* invaded irrigation canals limiting water supply to the irrigation fields and high canal maintenance costs. Invasion of river banks also led to blockage of water flows which led to flooding and siltation of crop fields. In Africa, *Prosopis* invasion impacts on livelihoods have been previously studied (Bekele et al., 2018b; GIZ, 2014; Haile, n.d.; Ilukor et al., 2016; Mehari, 2015; Rogers et al., 2017; Seid et al., 2020; Shiferaw et al., 2021; Wakie et al., 2012; Zeray et al., 2017). In Kenya, Mwangi and Swallow (2008) studied the effects of *Prosopis* invasion on rural livelihoods in Lake Baringo area. They concluded that, unlike other juridisdictions globally, few benefits of *Prosopis* have been realized in Baringo especially in areas where the invasion is advanced, which led to strong local support for eradication of the species. Maundu et al. (2009) investigated the effects of *Prosopis* invasion on Kenya's arid and semi-arid landscapes and on local livelihoods. They found that *Prosopis* was important for charcoal and livestock fodder, while the prominent harmful effects were invasion of pastureland, cropland and homesteads. These reviews demonstrate that impact of *Prosopis* invasion on livelihoods has received significant research attention in recent years. Overall, these studies have provided evidence with conclusions that the overall costs of these invasions outweigh the benefits. For example, 86% of case studies in the review study by Shackleton et al. (2019), listed livelihood costs due to *Prosopis* while 79% listed benefits to local livelihoods. Similary, in Ethiopia, 84% of surveyed households rated *Prosopis* as undesirable and blamed it for invading dwellings and grazing areas (Mehari, 2015). Further, 70% of survey respondents from invaded areas in Kenya indicated that overall, *Prosopis* had negative impact on their livelihoods and that life would be better without *Prosopis* (Maundu et al., 2009; Seid et al., 2020).

Although these previous studies have contributed significantly in improving the understanding of the impacts of *Prosopis* invasion on livelihoods, most of them were descriptive or qualitatative in nature, and lacked hard numbers on which policy decisions can be anchored. Most importantly, they have not empirically linked the spatial changes in *Prosopis* cover to the livelihoods. Therefore, this study sought to link the spatial fractional cover (area covered by *Prosopis*) and land-use and land-cover dynamics to the monetary costs of managing this cover in important land-uses / land-cover that are crucial for livelihoods.

2.3 Comparison of the effects of *Prosopis* spread vs. grassland restoration on climate mitigation, plant species richness and herbaceous biomass

Carbon is a basic element of life and is constantly exchanged between the various planetary repositories – atmosphere, lithosphere, biosphere (terrestrial plants and animals), water and the oceans. Of these repositories, oceans store more carbon than the rest (containing about 38,000 gigatons (Gt) which is 16 and 60 times the carbon in the biosphere and atmosphere, respectively (Schröder, 2010). In the terrestrial space, soils are the largest pool, comprising more carbon than the atmosphere and vegetation combined (FAO, 2017). Comparably, soils also hold more stable carbon stocks than woody biomass which consist mainly transitory carbon (Doney et al., 2006). Nevertheless, soil organic carbon (SOC), which comprises about 66% of soil carbon globally (Batjes, 1996), responds to land deterioration (Dlamini et al., 2014), with substantial negative effects on soil quality, productivity and greenhouse gas emissions (IUCN, 2015). Hence, stopping and addressing land degradation through restoration of degraded landscapes is important for building sustainable agro-ecological systems (UNCCD, 2017; UNDP, 2015) and improved human well-being.

Grassland biomes make up about 25% of global land area (Ontl and Janowiak, 2017), comprise about 40% of the Earth's natural vegetation (Ramankutty et al., 2008) and contain significant amount of the world's SOC (Conant et al., 2017). As such, they substantially contribute to environment, economies, and provide numerous cultural benefits (Parr et al., 2014). For example, about 20% of the global population's livelihoods are dependent on grasslands for fuel wood, food, medicinal plants and grazing. They also provide habitat for a sizeable diversity of flora and fauna (White et al., 2000). Additionally, they constitute about 30% of total net primary productivity (terrestrial) globally, and provide other ecosystem goods and services such livestock forage, tourism, regulation and storage of water flows (White et al., 2000). In doing so, they sustain the lives of more than one billion people worldwide (Bai et al., 2008; Conant, 2010). Yet, despite their significance, they continue to face multifaceted risks ranging from climate change, anthropogenic disturbances and alien plant species invasion (Mbaabu et al., 2021). Thus, they are under severe threat from conversion to other land-uses and degradation (Gibbs and Salmon, 2015), thereby limiting their capacity to provide and support essential ecosystem services and functions.

The Clean Development Mechanism (CDM) and the program for Reducing Emissions from Deforestation and Forest Degradation (REDD+) of the United Nations have received substantial adoption awareness in various countries in recent years (UNFCCC, 2023). Through the CDM, countries with an emission-limitation or emission-reduction under the Kyoto Protocol are allowed to implement emission-reduction projects in developing countries (UNFCCC, 2022a). The REDD+ (also known as Warsaw Framework for REDD+) is a guiding framework on activities by national governments to scale down emissions from forest loss and forest quality deterioration, and for sustainable forest management and conservation in developing countries (UNFCCC, 2022b). In response to these mechanisms, afforestation activities in degraded grasslands have been legitimately proffered as valid climate change mitigation strategies (Law et al., 2015; Parr et al., 2014). Consequently, degraded grasslands have become target areas for afforestation including use of invasive alien plant species, with some countries commercializing carbon credits under the Kyoto Protocol (Chisholm, 2010; Dickie et al., 2014).

However, the extent to which woody plant expansion or alien tree invasions can increase SOC is largely dependent on the land-cover or land-use type, tree species planted and climatic conditions. Therefore, the attempts that rely on above-ground carbon stocks from tree plant invasions to reduce atmospheric concentration of greenhouse gases may be inappropriate and inaccurate as demonstrated in other studies globally. For example, Jackson et al. (2002), investigated the effect of tree invasion along varying precipitation amounts and compared carbon between a non-invaded grassland site and one that was invaded for about 30 to 100 years in Texas, USA. They found a clear negative relationship between soil organic carbon and precipitation when grasslands were invaded by woody vegetation. Other studies have reported similar findings that actually, tree or shrub expansion into grasslands can cause declines in valuable soil carbon stocks (Conant et al., 2017; Conant and Paustian, 2002; Jackson et al., 2017; Smith, 2005). Additionally, over-emphasis on above-ground carbon stocks is probably because most of the studies on soil carbon have limited their analyses to upper soil (usually top 15-30 cm), potentially missing out on the substantial SOC stored at greater depths in grassland soils (Ward et al., 2016). Most importantly, the co-benefits and trade-offs with other ecosystem services should be identified and factored in decision making on soil carbon management actions, so as to promote ecosystem service multifunctionality (Manning et al., 2018). Notably, even in situations where tree expansion in tropical savannas increases carbon stocks, it may concurrently limit biodiversity and other ecosystem services

(ES). Because healthy grasslands have the potential to substantially accumulate huge amounts of carbon, degraded grassland restoration and implementation of sustainable grazing management would be an alternative climate change mitigation strategy in the target regions (Byrnes et al., 2018). In some previous studies, grasslands recorded a greater carbon accumulation to the roots than forests, hence remarkable replenishment of diminished SOC stocks in degraded grassland may be achieved through restoration as quickly as encroachment by woody species (Jobbágy and Jackson, 2000). In Kenya, a few studies related to this topic were found in literature. Sainepo et al. (2018) compared soil organic carbon and total nitrogen stocks in four land-use types (shrubland, agricultural land, grassland and bareland) in Narok County. They found that SOC was variable across the land-use types where shrubland had highest levels (31.26 Mg C ha^{-1}) and lowest in bareland (12.85 Mg C ha^{-1}). Total Nitrogen was highest in shrubland (4.22 Mg N ha^{-1}) and lowest in bareland (1.6 Mg N ha^{-1}). Also, surface (0-15 cm) soils contained higher SOC and TN stocks than sub-surface (15-30 cm) soil. Oduor et al. (2018) tested the use of pasture enclosures to enhance soil carbon (organic and particulate) and microbial biomass. They found that use of enclosures were valuable in enhancing vegetated cover and soil properties in tropical rangelands. Eschen et al. (2021) assessed the potential contribution of *Prosopis juliflora* management and grassland restoration on soil carbon sequestration and local livelihood support in Baringo County. Their predictions indicate that clearing *Prosopis* and restoring the formerly degraded grasslands would financially benefit households through income from increased livestock numbers, charcoal and carbon credits. By the start of this study in 2016, no previous studies had compared soil organic carbon stored in the different land-uses / land-cover types in the study area.

2.4 Modeling the impact of climatic changes on suitable habitat for *Prosopis* and *Vachellia tortilis*

2.4.1 Climate change–biological invasions–biodiversity nexus

Alterations in vital aspects of the environment like temperature and precipitation are occurring due to climatic changes (Thuiller et al., 2007), with potential implications on the functioning of global ecosystems (Ehrlén and Morris, 2015). Variations in the intensity and frequency of these aspects coupled with their associated extreme climatic occurrences *i.e.,* flood, drought and fires (Bellard et al., 2013) modify ecosystems, rearrange climatic zones with a likely emergence of novel conditions and a complete disappearance of some climate profiles (Baumgartner et al., 2018). These alterations may increase the vulnerability of ecosystems to biological invasions and thereby create exceptional opportunities for growth and dispersal of invasive species (Bellard et al., 2013; Thuiller et al., 2007). Simultaneously, this decreases the resistance of natural plant community assemblages to invasion through disturbances in the dynamic equilibrium that maintains them (Thuiller et al., 2007).

Projected future climate change and biological invasions will certainly interact, creating a complex imbalanced relationship between invasive species and the host ecosystem elements (Thuiller et al., 2007). Notably also, both micro- and regional climate can potentially be influenced by regional dynamics in community and ecosystem structure, thus providing complex feedback effects which may impact the rate of ecosystem change (Thuiller et al., 2007). These complex interactions will undoubtedly lead to severe ecological disturbances, a crucial mechanism in mediating the dispersal, establishment and dramatic explosion of invasive alien species. Both climate change and alien plant species invasion may have profound influence on species geographic ranges (Araújo and Guisan, 2006), with substantial ramifications for biodiversity (Baumgartner et al., 2018). For instance, elevated CO_2 levels coupled with a warmer and drier climate is predicted to cause over 40% species turnover in local communities in Europe (Thuiller et al., 2007). Invasion by alien plant species is putatively the second most important cause of biodiversity loss after land-use changes (Bellard et al., 2013; Kathiresan, 2020). These species are of concern because managing them and maintaining indigenous flora and fauna in the natural host ecosystems is substantially problematic (Halmy et al., 2019; Thuiller et al., 2007). This is because they can alter ecosystems through naturalization and establishment of viable populations with high growth rates that can potentially displace indigenous biodiversity (Fernandes et al., 2019; Thuiller et al., 2007). Inevitably, this modifies disturbance regimes culminating into potential transformation of the structure and functioning of the ecosystem (Fernandes et al., 2019; Thuiller et al., 2007), which is a threat to conservation and existence of native species (Halmy et al., 2019). Additionally, these invasive alien plant species inflict severe damage to society through a raft of socio-economic, ecological, and health impacts in the affected areas (Halmy et al., 2019; Simberloff, 2013; Simberloff et al., 2013). For instance, invasive plants may reduce agricultural yields, water availability and negatively affect the provisioning of natural ecosystems services (Witt et al., 2018), thus impoverishing livelihoods and restraining sustainable development (McNeely et al., 2001).

Given the projected complexity and stress on natural systems introduced by changed climatic conditions, the forecasted dynamics of alien plant invasions may make survival of native plant species in those ecosystems a tall order. Therefore, in order to protect natural ecosystems from invasive alien plants species encroachment and to safeguard native species in these ecosystems from the adverse effects of the aliens amid climatic changes, comprehensive studies and measures on these three interacting issues are required. There has been increased attention to identify vulnerable geographical spaces in anticipation of future invasions (Fernandes et al., 2019). This is particularly relevant because efforts to control or eradicate naturalized invasive species are costly and logistically difficult (Fernandes et al., 2019), hence preventing new invasions and expansion of established invasive species are considered the most feasible and cost effective ways of managing invasive species.

Remote sensing data and techniques are invaluable for mapping distribution of alien species and predicting areas potentially at risk of invasion (Rocchini et al., 2015), more so during global environmental change. Species Distribution Models (SDMs), also referred to as habitat suitability models, ecological niche models, resource selection functions, and climate envelope models (Araújo and Peterson, 2012; Elith and Leathwick, 2009) have been extensively used (Elith and Leathwick, 2009) to investigate effects of climate variability (Beaumont et al., 2008; Dullinger et al., 2012; Eckert et al., 2020; Engler et al., 2013, 2009) on plant species habitats (i.e. ecological niches) (Bellard et al., 2013; Eckert et al., 2020; Fernandes et al., 2019; Guisan et al., 2017; Ng et al., 2018; Thuiller et al., 2005). These models relate species occurrences at known locations with environmental data in order to provide an understanding or predict species dispersal in space and time (Elith and Leathwick, 2009). On the basis of the assumption that the environmental preferences and tolerances of species are explained by the currently known locations of the species populations, these models predict habitat suitability of species in other locations unoccupied by the species (Elith and Leathwick, 2009). Although these models seem to generally poorly simulate the complex and intertwined interactions observed in the real world such as the nexus between climate change, biological invasions, and biodiversity, they may provide invaluable cues for the identification of ecosystems threatened by the development of such interactive effects (Elith and Leathwick, 2009). This is critical for the identification of climate refugia for prioritization of attention, action and resources for managing alien invasions and conservation of native biodiversity. Climate refugia are areas where species may migrate to or survive during extensive, prolonged climatic change (Keppel et al., 2015), or areas of climate suitability or those with tolerable ecological conditions for the keystone species (Baumgartner et al., 2018). Thus, SDMs are a suitable approach to investigate the implications of anthropogenically-induced environmental change on biodiversity and the contributing role of climate change (Thuiller et al., 2007).

Understanding how climate change will influence invasive species range distribution and consequently the interactive effect on native species in the host ecosystem requires simultaneous predictions of effects of climate change on the habitat of both invasive and native species as well as the concomitant effect of invasive species on indigenous species' habitat. Despite the wide recognition of the dramatic and multifaceted impacts of non-native plant species, mapping and predicting their distribution range and impacts in the face of climate change has hardly been done in Kenya. Moreover, there are currently no published studies on the impacts of their projected range shifts on native species in the invaded range. Previous work has tended to disproportionately focus on modelling the effect of climate variability on invasive species (Eckert et al., 2020; Kyuma et al., 2016; Mbaabu et al., 2019; Muturi et al., 2013; Ng et al., 2018, 2016a; Witt et al., 2018) or native species (Becker et al., 2016; Shackleton et al., 2017b; Witt et al., 2018) separately, without considering the interactive impacts of projected invasions to native species under climate change. This begs the question on how the projected climatic changes will influence future *Prosopis* invasion and consequently, the impact that would have on native *Vachellia tortilis*, a keystone species in the savanna biome.

Although it is difficult to conceptualize and analyze the complex interrelationships between the changing climate and invasion dynamics (Thuiller et al., 2007), this study attempted to fill the current gap on the interactive effect of changing climate on biological invasions and the subsequent effect of these invasions on indigenous biodiversity in the invaded range using alien *Prosopis* and native *Vachellia tortilis* as a case study. This study is considered important for providing insights on the adaptive management of alien plant invasions and systematic planning for conservation of native biodiversity. Moreover, anticipating invasive alien plants in future distributions is important for promoting precautionary management decisions and actions including mitigating new introductions, early detection of invasion and controlling their spread (Bellard et al., 2013; Fernandes et al., 2019). Most importantly, identifying and protecting climate refugia is one of the three explicit strategies considered for mainstreaming adaptation to climate change into national conservation of biodiversity (Game et al., 2011; Groves et al., 2012), needed to drive conservation effort under the Convention on Biological Diversity (Game et al., 2011).

2.5 Summary

Previous studies provide evidence that *Prosopis* is an aggressive invader with significant implications on nature and people. The inclusion of this species in the IUCN's list of most damaging invasive species is a confirmation. However, review of pertinent literature revealed a number of gaps in knowledge in relation to the thematic scopes under investigation in relation to *Prosopis* invasion. These gaps included lack of reliable estimates of the spatial extent and dynamics of *Prosopis* invasion and its associated impacts on LULC, native dominant *Vachellia tortilis* species and consequently on rural livelihoods. With regards to impacts on rural livelihoods, previous studies show that *Prosopis* invasion is both benefial and costly to livelihoods, but overall, the costs outweigh the benefits. However, previous analyses have largely been qualitative in nature except for the work by Maundu et al. (2009), who estimated the cost of managing *Prosopis* in invaded croplands. However, their study did not establish a link between *Prosopis* invasion or cover with the monetary cost, as the cost of removing *Prosopis* per unit area is dependent on the density of invasion. The current study uses a different approach of first estimating the fractional cover of *Prosopis* and the average willingness to pay for *Prosopis* removal by households in the affected areas, and then uses these to estimate the total costs of clearing the presently invaded croplands and grazing land, which is the current knowledge gap.

The role of trees or forests in climate mitigation and rehabilitation of degraded landscapes cannot be underestimated. However, different ecosystems and / or biomes require context-specific strategies for addressing land degradation and climate mitigation options. Previous literature has revealed that some previous management interventions on savannas such as afforestation especially using alien invasive plants for climate mitigation are controversial. In particular, these interventions have been criticised because alien plant invasions especially by *Prosopis* has been linked to alteration of biodiversity patterns, rural livelihood impoverishment, and land-use and land-cover changes thereby, undermining ecological integrity and economic viability of invaded landscapes. At the start of this study, there was a long standing contentious issue between decision makers and other relevant stakeholders on how to deal with *Prosopis* menace in the study area. There was a conflict of interest where communities demanded compensation and eradication of the species while the government advocated for its management and promotion for carbon credits under REDD+ mechanism. However, promotion of woody alien species has received increased criticisms in recent years due to its associated impacts, and restoration of degraded land to original grasslands has been cited as a better alternative. In view of these, the knowledge gap was whether it is *Prosopis* proliferation or restoration back to native grassland that would effectively mitigate climate change without compromising biodiversity and other ES provisioning.

There is agreement from previous studies that indeed global environmental change, in particular, climate change is altering our ecosystems, posing serious threats to habitats and survival of biodiversity. Moreover, it is expected that climate change will likely exacerbate biological invasions. Previous work has disproportionately focused on modeling the effect of climate change on environmental range of invasive species or native species separately, without considering the interactive impacts of projected invasions to native species under climate change. The next chapter focuses on the methods used to answer the research questions associated with the highlighted gaps in literature.

CHAPTER 3: STUDY AREA AND METHODS

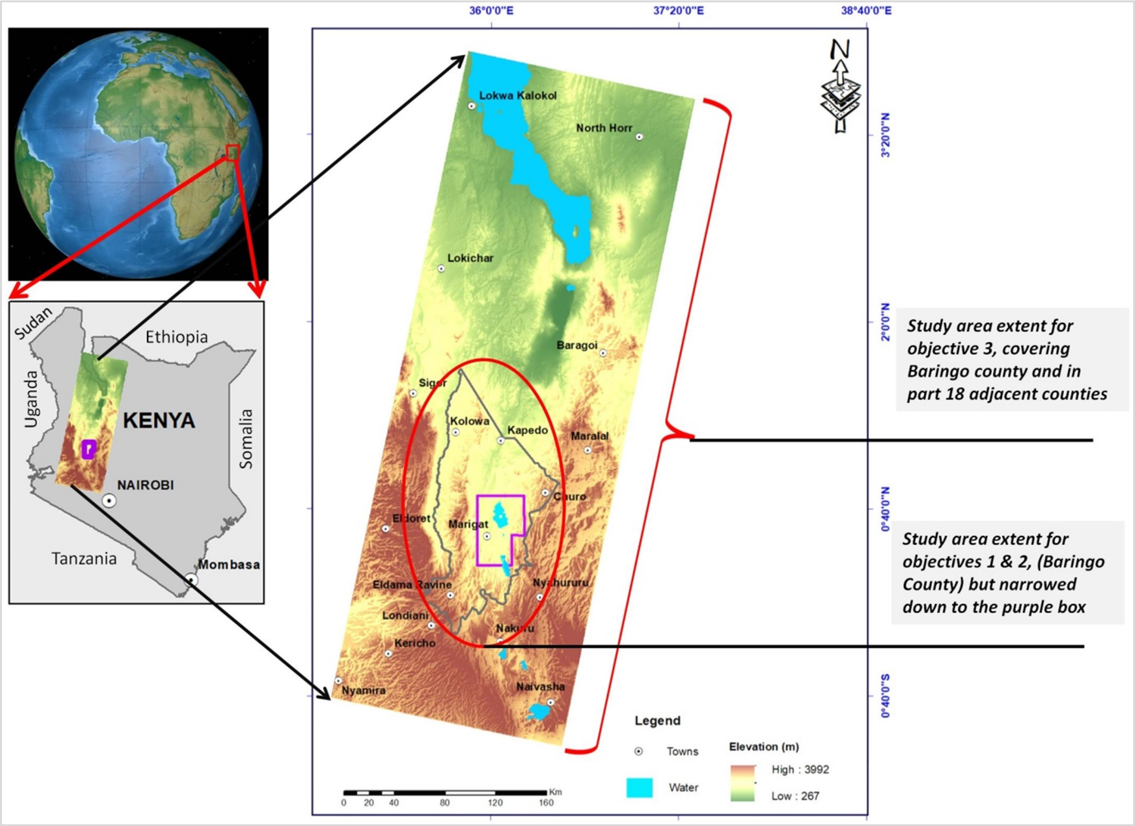
3.0 Introduction

This section provides relevant biophysical and socio–cultural background information about the study area(s) with the intention of enhancing the understanding of the system in which this study is based. Further, the methods adopted for each objective are described in detail.

3.1 Study area(s)

3.1.1 Study area(s) description

The eastern rift valley system, which the Great Rift Valley in Kenya is part of stretches from Afar region in Ethiopia to Lake Natron in Tanzania. It is characterised by rifts and faults, a series of lakes and volcanoes, hills and escarpments. It has a unique combination of altitude, precipitation, soil and vegetation. The overall study is based in the semi-arid zone of the Great Rift Valley in Kenya (Figure 3.1). It covers the County of Baringo and in part eighteen (18) surrounding counties, spanning an area of 95,866 Km^2. The study extent considered for each objective varied depending on the research questions. Marigat sub-region of Baringo County which extends from longitude 35° 20′ E to 36° 20′ E and latitude 0° 10′ N to 0° 50′ N was considered for objective one and two. The larger rift valley region stretching between latitudes 3° 55' N to 1° 1' S and longitudes 35° 50' E to 37° 26' E, and partly covering the 18 counties was additionally considered for objective three. Objective three involves species distribution modeling under climate change hence the consideration for a larger study area as recommended by Pearson and Dawson (2003). This study was aimed at mapping and understanding the two species ecological niches (both current and future) in order to inform conservation decisions, planning, resource management and mitigating further spread of invasive alien *Prosopis* species. For this reason, the spatial extent tended toward the local scale.


Study area extent for objective 3, covering Baringo county and in part 18 adjacent counties

Study area extent for objectives 1 & 2, (Baringo County) but narrowed down to the purple box

Figure 3.1 The extent of the study area considered for the three research objectives.

3.1.2 Biophysical setting

3.1.2.1 Climate

Climatic conditions are very varied, just like the huge variations in altitude. Over 35% of the study area is very steep. The lowest point in the study area has an elevation of 267 m a.s.l, while the highest point stands at 3992 m a.s.l (Figure 3.1). Due to these variations, the counties therein receive varying amounts of rainfall. The highlands (located in the southern part of the study area) are mild, usually with temperatures below 28°C and yearly precipitation of between 1000-1500 mm (Keitany et al., 2013). The lowland zones are relatively warmer and dry with temperatures usually reaching over 35 °C, with an average altitude of 700 m a.s.l, and total annual precipitation is between 300-700 mm (Olang, 1988). The wind speed ranges between (minimum) 0.60 m/s to 1.5 m/s and (maximum) 2.73 m/s to 4.81 m/s (www.worldclim.org). The month of July is the least windy while August is the windiest.

3.1.2.2 Vegetation

Genrally, the study area has a mosaic of loamy, clay, sand and rocky soils, with loamy soils dominating the highlands. Lowlands have a mostly a patchy distribution of loam, clay, sandy and rocky soils. The highlands have relatively well drained soils and dense vegetation cover of evergreen forests (both indigenous and exotic). Currently, the lowland vegetation comprises predominantly a mixture of woody native and exotic species, although historically, the landscape was characterised by *Vachellia*-dominated shrubland and different grasses (Kiage and Liu, 2009; Maitima, 1991). Over the last three centuries, land degradation of unprecedented magnitude has been witnessed in the area, driven primarily by anthropogenic pressure (livestock keeping) and climate variability (Little, 2019, 1992).

3.1.2.3 Land Uses and Resources

The steep variations in environmental gradients strongly influence the physical conditions of the land, which consequently bears on the distribution of flora and fauna. The area comprises different agro-ecological zones which favour different land-use patterns, economic and cultural activities. The highlands are suitable for cultivation of crops such as maize, beans, fruits and vegetables. The lowlands are semi-arid and predominated by livestock and bee keeping ventures, and minimal crop farming under irrigation (Omwega and Norgbey, 2004). The area hosts diverse and spectacular tourist attractions in terms of physical resources such as mountains, rivers, lakes, wildlife and the rift valley scenery itself, making the zone a tourism hotspot in the country.

3.1.2.4 Physiography and Drainage

The process leading to the formation of the Rift Valley (RV) is continuous, but much of its present shape is attributed to tectonic activity during the mid-Pleistocene period (Morgan, 1969). The present ranges and escarpments such as the Mau, Losiolo, Elgeyo, Nguruman and Aberdare range resulted from magmatic hot spots that separated the ground when the valley opened up. This give rise to a mosaic landscape comprising a unique combination of topographic features with different elevations such as hills, river valleys, plains, lakes and volcanic rocks. This region hosts a series of volcanic mountains such as Longonot, Paka, Silali, Menengai, Olkaria, Namarunu, Emuruangogolak, Eburu and Korosi. The rivers drain into the lakes or swamps. The major lakes include Baringo, Bogoria, Turkana, Nakuru, Naivasha and Elmenteita (Lelenguyah, 2013). Water supply is mainly from lakes and rivers.

3.1.2.5 Water Resources

The main rivers within the study area are Turkwel, Kerio, Perkerra, Molo, Loboi, Suguta of Arabal and Waseges. There are also several fresh and salt water lakes which include Baringo, Bogoria, Nakuru, Elmenteita, Naivasha, Turkana and Magadi. These lakes have important functions such as fishing, mining, tourism, species habitat, provision of water and agricultural support.

3.1.2.6 Biophysical vulnerabilities

The semi-arid region is characterised by sparse population mainly pastoralists and subsistence farmers. Over 80% of the population live in rural areas with high poverty incidence levels at ~58.7%. Economically, agriculture is the economic base of most residents, with crops such as tea, maize and a good blend of horticultural crops and livestock keeping. Productive agriculture and livestock keeping, which are the primary livelihood sources, are greatly limited by environmental deterioration and constant water shortages. The region is also prone to human conflicts arising from natural resources scarcity i.e. water, pasture and boundary disputes. Due to its unique and varied geography, it is one of the tourism hotspots in Kenya (Keitany et al., 2013).

3.1.3 Socio-economic setting

3.1.3.1 Political and Administrative Context

Kenya runs on a federal system of governance with operations at both counties and national government. There are 47 counties, each headed by an elected governor. The counties host constituencies, which are divided into administrative wards. These regions exist as devolved functional units since 2013 as enshrined in the Constitution of Kenya 2010. Following this, some government functions such as health services, agriculture, trade development and implementation of some national government policies on environmental conservation of forests, soil, and water and utilization of natural resources were devolved to the county governments (KLRC, 2022).

3.1.3.2 Economic context

The country's estimated population was 54.98 million in 2021 (World Bank, 2022a). In the same year, Gross Domestic Product (GDP) was US$ 110.35 billion, with an annual GDP growth rate of 7.5% and a GDP per capita growth of 5.1% (World Bank, 2022b). The proportion of unemployed youth has nearly doubled, from 7.3% in 2016 to 13.8% in 2021. The proportion of the country's population living below US$1.9 per day reduced from 19.2 million (35.7%) in 2020 to 18.8 million (34.3%) in 2021 (Guguyu, 2022), but currently stands at 40% due to Covid-19 (Nyawira, 2021). The GDP for all the counties included relative to the national value is less than 10%. For example, of the 18 counties considered, Nakuru County had the highest GDP in 2017 at US$ 10.3 million against a national GDP of US$ 163.76 million. However, in terms of GDP per capita, some counties in the central rift valley such as Nyandarua and Nakuru has significantly higher values (up to 215%) than the national average (Kenya National Bureau of Statistics, 2019). The study area has a mix of highland and lowland zones. The poverty incidence levels on the highland areas such as Eldoret, Iten, Nyahururu, Kericho and Londiani are lower compared to the lowlands such as Marigat, Mararal, Turkana, Marsabit, Laikipia and Samburu (Data Science Ltd, 2019). This is because the highlands are more economically productive due to favourable climatic conditions while the lowlands are generally semi-arid with low resource base, conflicts, poor soils and unfavourable climate. Statistically, all the counties included in the study have poverty incidence levels of over 30%, with Turkana as the poorest county at 87.5% (Data Science Ltd, 2019). The main economic activities include tourism, agriculture, lumbering, bee and livestock keeping.

3.1.3.3 Social Setting

Kenya is diverse in ethnicities (45 ethnic groups) and rich in culture. The study area hosts diverse communities including Kalenjins, Maasai, Ilchamus, Tugens, Pokot and Turkana. The population densities are varied, with high densities (e.g Kericho County 390/km^2) in the highlands and low densities (e.g Turkana County 14/km^2) in the lowlands (World Bank, 2023). Nearly three-quarters of the study area is within the rift valley zone. It is the most populated region in Kenya, with about 12.7 million people (Nyawira, 2019) and population density of 90/km^2 in 2019 (World Bank, 2023). Although the population has been rising steadily over the years since 1979, the rates of decadal increase have been on the decline (annual growth rates 1979: 5.4%; 1989: 4.0%; 2009: 4.3% and 2019: 2.7%) (City Population, 2019). The male to female ratio is 49.5% to 50.5%. Both nationally and regionally, the proportion of youth and children (0 – 29 years) represents two-thirds of the total population; while people aged 65 and above represent only 3.9% (City Population, 2019). Kenya had a national literacy rate (% population aged 15 years and above who are able to read and write) of 82% in 2018, up from 72% in 2007 (World Bank, 2022c). According to the 2019 census report, primary education is the highest education level for about 50% of the population, while about 25% have received education up to secondary level. About 9.3% have no education (Kamer, 2022). The study area has differential literacy levels with southern parts having high literacy e.g. Uasin Gishu 80%, while the northern part has very low literacy levels e.g. Turkana 20% (Kapchanga, 2022; KNBS, 2015).

3.1.3.4 Health and Social Services Setting

Health is one of the devolved (partly) national functions under the new Constitution. Although the overall running of health matters rest under the national Ministry of Health, county governments oversee the running of county healthcare facilities, cemeteries, and promotion of veterinary services and primary healthcare among other functions (KLRC, 2022). Social services such as land administration, public housing, public transportation, fire services, early childhood and development education (ECDE) and social work are managed by the county governments.

3.1.3.5 Regulatory Framework

Legislation on all issues affecting society is a mandate of the national government. County governments are mostly tasked with implementation of the national government policies, but are also mandated to develop regulatory frameworks on the devolved functions as contained in the Fourth Schedule of the Kenyan constitution (Makena, 2019). Climate change and environmental facets are enshrined in the Kenyan Constitution in Articles 2, 10, 42, 69, 70 and 162. These are further supported by various statutes and policies such as the Environment and Management Co-ordination Act (EMCA) 1999, Treaty Making and Ratification Act 2012, and the Climate Change Act 2016. The EMCA Act is the operative law on all environmental matters. The regulators of these legal provisions and frameworks include institutions such as the National Climate Change Council, the National Environment Management Authority (NEMA), the National Environment Tribunal, the Environment and Land Court, the Climate Change Directorate and national and county governments (Mallowah and Oyier, 2022). Climate change has received recognition as both a national and global threat to sustainable development. Since the country's economy is largely dependent on sectors that are highly susceptible to climate variability and extreme weather events such as tourism, rainfed agriculture and natural resources (USAID, 2023), successive climate change impacts cause about 3% – 5% annual losses of Gross Domestic Product, thereby impeding development efforts (Ministry of Environment and Forestry, 2020). In this regard, the country has developed policies and strategies on climate change which include the Climate Change Act of 2016, the National Climate Change Action Plan III (NCCAP III under review) (Ministry of Environment, Climate Change and Forestry, 2023), the updated Nationally Determined Contribution (2020), the National Adaptation Plan (NAP) 2015-2030, the National Climate Change and Response Strategy, and the National Climate Change Framework Policy (Ministry of Environment and Forestry, 2020).

3.1.3.6 Socio-Economic Vulnerabilities

Socio-economic factors such as high poverty, illiteracy and unemployment rates, and high natural resource dependency for jobs, food and income are prevalent both nationally and regionally (East Africa/Africa). In this era of global environmental changes such as those induced by climate variability, both urban and rural communities remain increasingly exposed to socio-economic vulnerabilities. The rich highlands zones in the study area are dependent on agriculture and forestry which are threatened by extreme climatic changes such as floods, drought and forest fires. For example, Kenya has persistently experienced severe droughts in the last 10 years: 2010 - 2011, 2016 - 2017 and 2020 – 2022 (Relief Web, 2022). The 2017 drought negatively affected over 2.7 million people countrywide by causing humanitarian disruptions through displacement, hunger, and loss of livelihood (Mlaba, 2021). The recent drought (2020 - 2022), has affected more than 4.2 million Kenyans (about 24%) of the ASAL population, caused loss of more than 2.4 million livestock and exacerbated inter-ethnic conflicts over limited access to resources among pastoralist communities (Relief Web, 2022). The affected ASAL areas include a large part of the 18 counties considered in this research such as Turkana, Marsabit, Baringo, Samburu, West Pokot, and Laikipia. Wildlife populations have seriously been affected with the recent severe loss of over 10,000 crocodiles recorded in the Lake Kamnarok Game Reserve (The New Times, 2023).

Deforestation and forest degradation is prevalent which severely affects livelihoods, habitat and important ecosystem services. With an ever upward trending population both locally and nationally, the semi-arid lowlands are inevitably the only available zones for agricultural expansion due to pressure for more food and raw materials. The rising population coupled with arable land scarcity in the productive highlands have induced human migration to marginal areas with little regard to their ecological limitations. This has exerted pressure resulting in substantial deterioration of the land which threatens the livelihoods of thousands of residents in these areas. In particular, drylands such as in Baringo, Turkana and Marsabit generally exemplify most of the challenges of marginal and fragile semi-arid areas (Johansson and Svensson, 2002). These drylands are also prone to human conflicts arising from natural resources scarcity i.e. water, pasture and boundary disputes (Lelenguyah, 2013). Currently, the lowlands are very fragile, threatening livelihood security and environmental sustainability. The situation is presently aggravated by climate change and rapid spread of invasive alien plant species such as *Prosopis juliflora and Opuntia stricta* (Strum et al., 2015).

3.1.4 The Study Region and Target Species

Kenya is one of the richest countries in Africa in terms of flora and fauna due to its diverse climate and habitat. Its ecosystem comprises of different vegetation zones such as grasslands, open (shrub) savanna and wooded savanna, forest, woodland, bushland and desert. The low-lying regions (low elevation) within the Great Rift Valley zone are largely arid and semi-arid. They were historically dominated by a mix of grass species and a scanty distribution of woody tree mixture (Maitima, 1991). The dominant trees are the *Vachellia* (Acacia) species such as *Vachellia tortilis, Vachellia nilotica, Vachellia mellifera, Vachellia kirkii* and *Vachellia reficiens* among others. In this study, two tree species native *Vachellia tortilis* and exotic *Prosopis* species were considered. *Vachellia tortilis* is a vital tree species in savannas because it is provides animal fodder, wood, charcoal, and aesthetic values (Ng et al., 2017). The study considered areas under *Prosopis* species because it is highly invasive and presently catalyzing LULC changes in the study area (Mbaabu et al., 2019). Since its introduction in the study area, it has contributed to about 30% loss of *Vachellia tortilis*- dominated vegetation between 1983 and 2016 (Mbaabu et al., 2019). It is therefore considered a threat to the native plant biodiversity particularly to *Vachellia* species due to its fast rate of habitat colonization and displacement of native plants.

3.1.4.1 Species Description

Vachellia tortilis

The genus *Vachellia* is a large group of leguminous woody trees in the family Fabaceae. There are over 1342 recognized different Acacia species globally. Acacia's are the most widespread trees is Sub-Saharan Africa, but also occur in southern USA, the Caribbean and South America, Southern Europe, Middle East, India and Australia (Dharani, 2006). *Vachellia tortilis* (Table 3.1), also widely and previously known as *Acacia tortilis* (Forssk.) Hayne, is one of the 132 different *Vachellia* species in Africa and one of the six endemic *Vachellia* in the rift valley zone (Groot and Hall, 1989).

Prosopis juliflora

Prosopis is a genus of leguminous flowering plants in the family Fabaceae. It has about 44 recognized species (Burkart, 1976). They are native to the Americas (40 species from western North America to Patagonia), and (4 species in southwest Asia and Africa) (Van Klinken and Campbell, 2001). From the native lands, these species have been introduced to various regions globally (Kathiresan, 2020; Shackleton et al., 2014; Van Klinken and Campbell, 2001). In their introduced range, some of these species have become naturalized and hybridized. A detailed discription of these two species is available in Table 3.1.

Table 3.1 A summary of the two species distribution, characteristics, habitat, adaptation and uses.

Species	Distribution	Characteristics	Habitat and Adaptation	Uses
 ***Vachellia tortilis***	Native to African Savanna and Sahel. Also found in parts of southern Europe and the Middle East	It is a perennial slow-growing leguminous thorny tree, with an umbrella-shaped canopy. It is 4-20 m tall, usually multi-trunked, rough bark (medium grey to almost black), leaves are up to 2.5 cm long, white or cream aromatic flowers, pods (up to 14 seeds), multiple lateral roots and a deep tap root system.	Grows mostly in arid and semi-arid lowland zones at elevations of below 1000 m but may also be found at slightly higher elevations, tolerates annual precipitation and temperature of approximately 100 to 1000 mm and 18 to 28 °C, respectively but withstands higher temperatures of up to 50 °C and rainfall as low as 40 mm (Netshisaulu, 2012). It grows on sandy, rocky alkaline soils with pH of 6.5 to 8.5. It is drought resistant; compound leaves with 6 to 22 tiny leaflets to minimize water loss in dry seasons and deep roots to tap water from the deep water table (Dharani, 2006).	Timber, fence posts, firewood, charcoal, fodder and foliage, honey production, medicinal, dunes reclamation (Roy et al., 1973), tannin, tourist attraction, species habitat, etc.
 ***Prosopis juliflora***	Native to Latin America. Have been introduced worldwide but mainly to Africa, Asia and Australasia (Van Klinken and Campbell, 2001).	*Prosopis juliflora* is an evergreen, perennial fast-growing nitrogen-fixing thorny, single canopy trees (up to 15 m height) or multi-stemmed shrubs (3-5 m tall). It has bipinnate leaves, golden-yellow flowers and produces pods with numerous seeds. Has a main deep taproot extending even up to 80 m down, and a dense knit of lateral roots.	Grows in a variety of soils; rocky, sandy, loam, waterlogged and saline soils within an elevation range of 300 – 1900 m a.s.l. They are salt and drought tolerant due to their ability to tap underground water due to the deep roots, fast proliferation and massive seed production. It's a fast invader and highly allellopathic which suppresses understory vegetation, thereby helping to reduce competition for nutrients and water wherever it grows.	Firewood, charcoal, food for humans and livestock, bee forage for honey production, live fencing and timber.

3.1.5 Conceptual Framework

The impacts of *Prosopis* invasion on the landscape and its implications on ecosystem goods and services provisioning, and rural livelihoods were framed around the United Nation's three pillars of sustainability viz social, environment and economic (Figure 3.2) (Purvis et al., 2019). This is premised on the fact that the environment or climate system influences *Prosopis* invasion, which in turn affects ecosystem multifunctionality. While antropogenic activities are the main culrprit behind climatic changes through greenhouse gas emissions, the resultant climatic changes also influence the ecosystems and species present in those ecosystems. Disturbances on the ecosystem or environment affects the provisioning of the ecosystem services which have a bearing on livelihoods and human well-being. These operate within political or governance ecosystems whose decisions influence the state of all the three pillars. Moreover, this framework is embedded or emphasizes the need for adopting transdisciplinary and One Health appproaches when addressing societal issues such as land degradation, biological invasions and climate change.

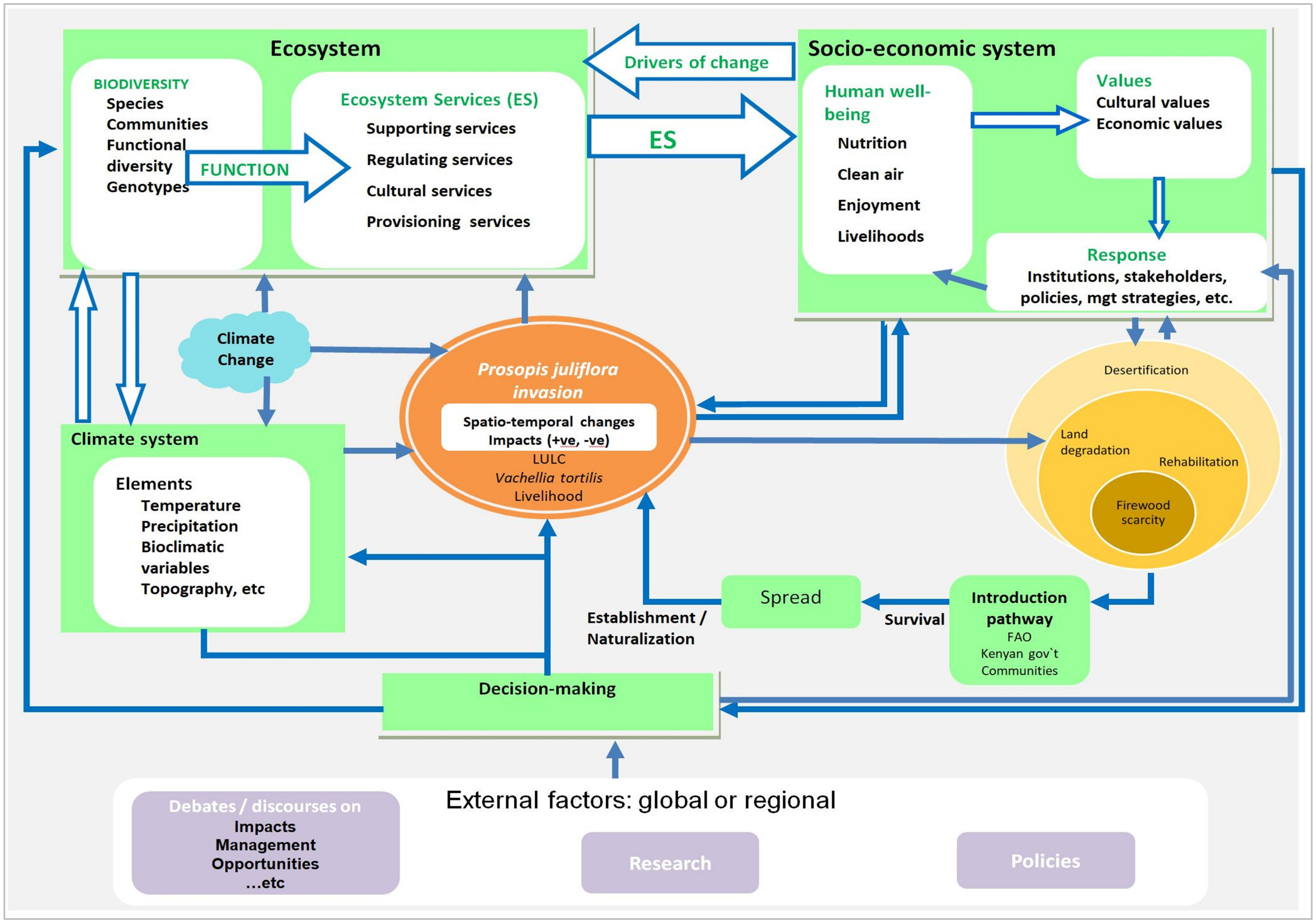


Figure 3.2 Conceptual framework on the interrelationships between *Prosopis* invasion, LULC, ecosystem services and rural livelihood under climate change.

3.1.6 Research Design

This study was part of the CABI's woody weeds project in East Africa www.woodyweeds.org. The study area was purposively selected to represent areas invaded by *Prosopis* and / or *Lantana camara* in Kenya, Ethiopia and Tanzania. In each country case (within the invaded areas), samplings plots were randomly selected. Mixed methods (qualitative and quantitative) approaches were used. The land-use and land-cover types present in the study area such as *Prosopis*, cropland, mixed vegetation and water were mapped and qualitatively described, while spatio-temporal changes in these LULC were quantitatitvely analysed. Further, the impacts of *Prosopis* invasion on livelihoods and other ecosystem services were also partly qualitatively described. When projecting climate change impacts on future habitat of *Prosopis* and *Vachellia* and the likely impact of future *Prosopis* invasion on indigenous *Vachellia tortilis*, habitat comparisons and identification of climate refugia was partly done qualitatively. Quantitative spatial analysis methods were used to quantify dynamics in land-use and land-cover as well as to estimate the current and future suitable areas for *Prosopis* and *Vachellia tortilis*. Comparisons of soil organic carbon stocks, species richness and herbaceous biomass across selected land-use / land-cover categories were done quantitatively.

3.2 Methods per objective

3.2.1 Estimation of the spatial expansion, dynamics and impacts of alien *Prosopis* trees

The focus of this objective was on the small area (Marigat subregion) shown by a purple polygon in Figure 3.1. This was informed by a) *Prosopis* plantations were first established in Marigat and invasion progression has been observed over time, b) although Baringo County has three unique ecological units, *Prosopis* has survived and naturalized in the lowlands around lakes Baringo and Bogoria, and c) there is a high concentration of invaluable LULCs for supporting diverse livelihoods activities in this zone. Therefore, mapping of *Prosopis* invasion and relevant LULCs were carried out in this zone as it is currently the invasion hotspot.

3.2.1.1 Analysis of Spatial Changes in Land-Use and Land-Cover

Ground truthing Data

To assess *Prosopis* spread and LULC changes in space and time (the period 1988 to 2016), ground reference data were needed. Therefore, groundthruth data points for training and validating satellite image classification were collected in Marigat subregion between October

2015 and June 2016, a period that spans a dry and wet season, using a handheld GPS receiver. For analysis of historical imagery i.e. for images acquired before 2016, groundtruth data was collected through visual interpretation of Very High Resolution (VHR) satellite imagery available via the Google Earth Pro (Google Earth Pro, 1987). Information acquired on the Google Earth Pro was supplemented with visual interpretation of the Landsat satellite data and verified from seven local elderly residents with long-term indigenous knowledge about the study area's LULC change history, including chiefs, farmers, livestock officers and other community leaders. Furthermore, the selection of groundtruth data points was informed by the distinct pattern of species occurrence attributes such as along linear features like roads, rivers and in settlements, as well as vegetation differentiation due to variation in elevation, soil types, homogeneity and contiguity. Separation of *Prosopis* from other LULC types was enhanced by seasonality and vegetation scantiness due to aridity conditions.

Initially, 13 LULC types were identified for which regions of interest (ROIs) or small polygons were digitized for each class. LULC classification was then performed on the 13 classes which were then aggregated to eight most prominent and predominant classes. The aggregation criterion was informed by study goals and the LULC types present in the study area. The considered classes are described and presented in **Table 3.2**.

Table 3.2 Land-use and land-cover (LULC) classes present in the study area

Class ID	**LULC**	**Classification Description**
1	*Prosopis*	Woody alien shrub predominating the lowland areas around Lake Baringo
2	*Vachellia tortilis*	An umbrella-shaped native tree speciespredominantly found within the tropical ASALs
3	Mixed Vegetation	A combination of native trees and shrubs that exist as a mix of single stands or as small patches and water weeds.
4	Grassland	Areas predominantly covered by grass
5	Bareland	Areas with little or no vegetation cover (uncovered soils)
6	Rainfed cropland	Farmlands that entirely depend on rainfall for crop production
7	Irrigated cropland	Farmlands that are equipped to provide water
8	Water	Visible surface water such as in rivers, lakes and dams

For the analysis of objective two, classes 1, 4 and 5 were considered. They were further subdivided to form five LULC classes as follows: pristine grassland, degraded grassland, *Prosopis*-low density, *Prosopis*-high density, and restored grassland (*see section 3.2.2*).

3.2.1.2 Remote Sensing Data Selection and Pre-processing

This objective focused on the period 1988-2016. Spatial temporal analysis relies on availability of good quality satellite data or imagery. For this reason, 30 m spatial resolution Landsat data which are freely available were considered. Cloud-free satellite images were chosen from 1988 (base year) because prior to this date, *Prosopis* was hardly visible on Landsat data. More so, invaded areas in the study area were mostly small patches and within the original *Prosopis* plantations' perimeter. Images were selected at 7 year intervals as follows: 1988, 1995, 2002, 2009 and 2016 (Table 3.3). Seven years interval is considered ideal to observe any spatial changes in vegetation cover between the intervals. The end date 2016 was considered as the latest because that was the last available data date in the Climate Data Record (CDR) archive during data collection for this study.

From the Landsat Surface Reflectance CDR, Landsat images which have already been atmospherically corrected were downloaded (Masek et al., 2006; Roy et al., 2016). Atmospheric correction (AC) involves the removal of atmospheric effects (scattering and absorption effects) on the image reflectance values acquired by satellite or airborne sensors. AC is one of the most important image pre-processing steps and failure to do so produces erroneous results about the area under study (Hadjimitsis and Themistocleous, 2008). For all the five time steps, Landsat data bands blue, green, red, near infrared (NIR), and two shortwave infrared bands (SWIR1 and SWIR2) (i.e. bands 1-5, 7) were selected. Although Landsat data is sufficient for vegetation mapping, it has limitations for species mapping because of its medium spatial resolution. Therefore, in order to reliably detect species in this study, three data-enhancement strategies were employed. First, dry and wet season's normalized difference vegetation indices (NDVI) were calculated. NDVI represents a ratio-based index comprising information about biological and physical properties of the earth's surface, thereby increasing the separability of different landscape components (Vidhya et al., 2017). Secondly, both dry and wet season data were considered because the study context is semi-arid with two distinct climate seasons. These two two seasons enabled maximization of the spectral differences between *Prosopis* and other native vegetation such as *Vachellia* spp. and seasonal herbaceous vegetation, for optimization of component separability during the analysis. *Prosopis* spp. present in the study area are evergreen and tend to maintain a higher growth vigor and canopy than the present natural vegetation during the dry season (Rembold et al., 2015). For each time step, dry season images were selected for the period between January and March, and April and August for the wet season. Lastly, in each time step data, elevation data from the Shuttle Radar Topography Mission (SRTM) was also included because, *Prosopis* spp. growth is limited to areas with elevations below 1500 m a.s.l in the study area (Orwa et al., 2012).

In total, five time-step datasets comprising 15 bands each were created. Further, the datasets were pre-processed (mosaicking, cloud masking and band/layer stacking). Mosaicking is the process of combining or merging two or more images to a single raster dataset (mosaic). The satellite data may have been obtained at different dates, at different viewing angles or from different satellite sensors (Zhang et al., 2018). Cloud masking involves detection and removal of clouds and their shadows from the images. Optical satellite sensors like Landsat cannot provide clear images on cloudy days. Usually, nearly 60% of the earth's surface is under cloud cover in a year (Wang et al., 1999), with tropical environments accounting for the largest share of cloud cover (Candra et al., 2016), where on average, images obtained by Landsat-7 ETM+ sensor contain about 35% cloud cover (Ju and Roy, 2008). As such, product quality must be enhanced by removing both clouds and shadows. Finally, for each time-step, all the 15 bands / layers were stack together into one single image with same spatial extent and resolution.

Table 3.3 Characteristics of satellite data used for the classification.

	Acquisition date		**Year assigned**
Sensor	**dry season**	**wet season**	**to classification**
Landsat 5 TM	Mar, 1989	July, 1987	1988
Landsat 5 TM	Jan, 1995	Mar,1995	1995
Landsat 5 TM	Feb, 2002	July, 2002	2002
Landsat 5 TM	Jan, 2010	June, 2008	2009
Landsat 8 OLI	Feb, 2016	July, 2015	2016

3.2.1.3 Classification of Landsat Satellite Data

Classification of satellite images involves categorizing / classifying and labeling groups of pixels (picture elements) on an image based on specific rules. The two general image classification methods are supervised and unsupervised (Abburu and Babu Golla, 2015). Supervised classification involves visually selecting reference data (training samples) on the image and assigning them to pre-selected categories or classes such as grass, water, crop and roads, in order to create statistical measures to be applied to the entire image. Common supervised classification methods include Maximum Likelihood, Minimum Distance to Mean, Fisher classifier, Artificial Neural Network (ANN), Mahalanobis Distance, K-Nearest Neighbour, Decision Tree, Image segmentation (object based analysis), Support Vector Machine, Random Forest, Semantic Based and Parallelepiped or Box classifier (Abburu and Babu Golla, 2015; Akgun et al., 2004). Unsupervised classification is a computerized process and does not use training/reference/sample data, but instead, uses an algorithm to systematically detect specified characteristics of an image during image processing. The two frequently used algorithms are ISODATA and K-means.

In this study, Random Forest (RF) classifier – a supervised classification (Machine Learning) technique (Breiman, 2001) was used for classifying the images into the LULC types listed in (Table 3.2). The classification was done using the RF package in R software version 3.4.4 (Breiman, 2001b; R Core Team, 2018). RF is a type of decision tree algorithm that builds an ensemble or many self-learning decision trees i.e. "forest" to categorize the image pixels. The trees are grown randomly and predictions are made by individual trees, which are finally averaged (Cutler et al., 2007). Many decision trees (i.e. ensemble) are preferred as they provide one strong and robust decision compared to a single decision tree. RF uses self-learning trees and each tree automatically defines rules at each node on the basis of the training dataset. Growing each tree requires a different randomly selected bootstrap sample (reference /ground truth) data. Two-thirds of this sample data is used for fitting the RF model, while 30% is used for prediction and estimation of the associated error ('out-of-bag' (OOB) error). Once the fit RF model is satisfactory, it is then applied to the entire dataset or image to be classified (Liaw and Wiener, 2014).

Therefore, in this study, we generated five RF models (i.e. one model for each time-step) (Figure 3.6A). Then, 70% of the reference data (manually delineated ROIs) were used to train each RF model, which was then applied to each data stack (each time-step), while 30% of the samples were used for validation (accuracy assessment of the classification output). For each model, 1000 trees were grown and all other RF function arguments were kept at default settings.

3.2.1.4 Accuracy Assessment

Maps created through image classification should procedurally report an estimate of classification accuracy. This is important because decision making or scientific analysis with data of low or unknown accuracy results in information with low reliability and propagated error effects, hence limited value. In principle, accuracy assessment compares classification estimates with reality and quantifies the difference between the two which is reported as an error and the smaller the error, the better the result. In LULC classification, the estimates are the classes mapped for each pixel and reality represents the actual LULC in the areas corresponding to each pixel in the dataset.

In addition to the OOB error estimate provided by the RF model, an independent 10-fold cross-validation accuracy assessment was performed. Cross-validation (CV) method evaluates the accuracy or skill of machine learning models on sample data by dividing the reference data into two sets (training and validation). In this process, the training and validation samples are assumed to be independent. CV has a single parameter called k, hence the name k-fold cross-validation, where k represents the number of groups that a given data sample is split into. Therefore, when a specific k value is chosen, it is replaces k in the model. In this study, k was replaced with 10, hence the data sample was split into 10 groups making it a 10-fold cross-validation procedure. In k-fold cross-validation, first, the dataset is randomly divided into k equally (or almost equal) sized folds. Then, k number of iterations of training and validation are performed, for which each iteration uses a different fold of the dataset for model validation, while the remaining k-1 folds are used for learning (Refaeilzadeh et al., 2009). Validation is performed on a pixel by pixel basis; subsequently each pixel inside a validation polygon is compared with the same location on reference LULC type. In this study, 10-fold cross-validation runs were performed, where the training dataset were randomly partitioned 10 times with 90% and 10% for training and validation, respectively. Then, the 10 results for each classification (i.e. each time-step) were generated and confusion matrices produced for calculation of user's, producer's, and overall accuracies. K-fold cross-validation is a state-of-the art method and popular because it generates less biased model predictions than other accuracy assessment methods.

3.2.1.5 Land-Use and Land-Cover Change Analysis

Analysis of the changes in land-use and land-cover is recognized as an important research topic in the context of global environmental change and sustainable development (Lambin et al., 2003). Land-cover denotes the biological and physical attributes of the earth's surface such as forest, water, grass, while land-use is the human purpose applied for the biophysical attributes (Batunacum et al., 2018), such as agriculture, settlement etc.

Cross-tabulation matrices were used to calculate the land-use and land-cover changes for the intervals from 1988 to 1995, 1995 to 2002, 2002 to 2009, 2009 to 2016, and 1988 to 2016. Then, computations of gains, losses, net changes and rates of change were done, and visualized using charts and tables. Additionally, *Prosopis* extents and spread rates for each time interval were determined. In order to determine the impact of *Prosopis* invasion on other each LULC type and at which time interval, the net changes per LULC class per time interval were obtained by subtracting the contributions of each LULC class to *Prosopis* class (Losses to P) from their respective gains from *Prosopis* class (Gains from P). In order to understand how *Prosopis* invaded from original plantations, analysis of change statistics and a visual assessment of LULC maps were performed. This relied heavily on information about seasonal socio-economic and climatic activities including charcoal production, irrigation farming, livestock grazing, and flood events which immensely aided the interpretation of the LULC type change outputs and *Prosopis* dispersal patterns over time. This information was acquired through interactions with the host community, focus group discussions and field observations during data collection.

3.2.1.6 Estimation of the impacts of *Prosopis* invasion on livelihoods

Majority of Baringo residents are dependent on farming and livestock keeping for livelihood. Therefore, any purtubations on their natural ecosystem is bound to impact on their livelihood sustainence. In order to analyse the impact of *Prosopis* invasion on their livelihood, monetary cost of removing and managing *Prosopis* from croplands and loss of pasture (obtained from Bekele et al. (2018a)) were used as proxies. *Prosopis* spread into farmlands restricts crop production while pasture losses reduces household income and wealth, since livestock keeping is the primary livelihood source for millions of agro-pastoralists and pastoralistsin Sub-Saharan Africa (Doran et al., 1979; Kassahun et al., 2008). *Prosopis* impacts on livelihoods was analysed by combining spatial and non-spatial datasets (outputs) generated for the study area using transdisciplinary approaches. These datasets were *Prosopis* fractional cover, land-use and land-cover changes and the average willingness to pay (WTP) for removing *Prosopis* trees from affected areas in Baringo.

Prosopis fractional cover mapping

Vegetation fractional cover map is the percentage of vertical vegetation projection of the total study area (leaves, roots and stems) (Li et al., 2015; Zhang et al., 2019). In this case, it is a map showing the area covered by *Prosopis* and the respective density classes or categories such low, medium and high invasion). It is an important parameter for monitoring vegetation and development of terrestrial ecosystems. Fractional vegetation cover maps have in recent years been widely used in research on land quality deterioration and desertification assessment, climate change, soil, hydrology and invasive alien plant species (Li et al., 2015; Mishra et al., 2014; Shiferaw et al., 2019c; Zhang et al., 2019).

Prosopis fractional cover was estimated by combining field reference data on *Prosopis* occurrence (presence and absence georeferenced field data points) and a set of spatial datasets (variables) that explain *Prosopis* distribution. These spatial datasets included variables describing topography (elevation, slope, relief, landform, aspect), climate (temperature, precipitation), hydrology (distance to water bodies, rivers), vegetation indices (NDVI), soils and soil pH, anthropogenic landscape features (roads, villages, human footprint index), livestock market, grazing areas and migration routes. Some of these datasets such as livestock grazing and security routes, and markets were unavailable but vital in explaining *Prosopis* distribution as livestock are a major mechanism for *Prosopis* seed dispersal through dung. Therefore co-production of these datasets was employed. This involved participatory GIS mapping with key stakeholders and scientists such as pastoralists, village leaders, farmers, students and officers working in the forestry and livestock department in Baringo county (video and Figure 3.3). The fractional cover was then generated by regressing the occurrence points with the spatial variables using the Random Forest modeling. More details about the methodology are provided by Shiferaw et al (2019c). The output fractional cover map represented coverage from 0 – 98% (Figure 3.4).

Figure 3.3 A-C Participatory GIS mapping of livestock grazing, security and market routes and markets. A: one of the participants marking the route on the map after consultation with the others. B: Participatory mapping partipants and C, the marked routes, markets and grazing areas.

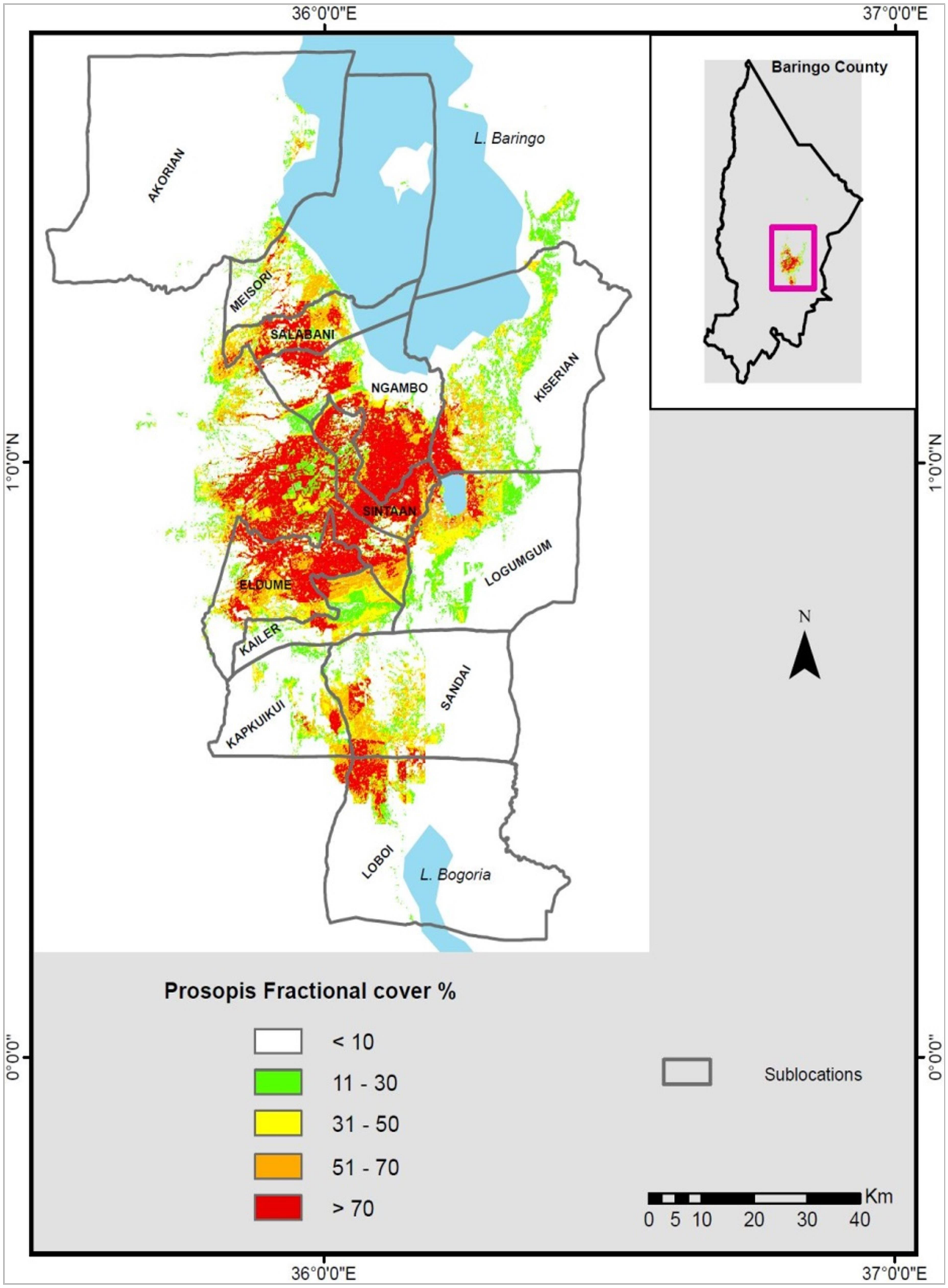


Figure 3.4 *Prosopis* fractional cover, showing the areas covered by *Prosopis* and the density of cover ranging from 0 – 98%.

Willingness to pay

Willingness-to-pay (WTP) is an economic evaluation approach anchored in the theory of collective action where members of a community collectively make efforts to solve communal problems (Freeman III et al., 2014; Kenter et al., 2011). It enables a valuation of the complex linkage between ecosystems and human well-being (Pejchar and Mooney, 2009). Therefore, WTP is useful for estimating how invasive plant species impact on human welfare using the ecosystem service approach (Bekele et al., 2018a). This study utilized the average WTP (in US$ per hectare per annum) values estimated for Baringo (Bekele et al., 2018a). The costs of physically removing *Prosopis* trees from invaded areas, which is expressed as average willingness to pay was estimated using a choice experiment conducted in a household survey of 250 participants in the invaded areas of Baringo County (Bekele et al., 2018a).

3.2.2 Impact of *Prosopis* spread and grassland restoration on soil organic carbon, plant species richness and herbaceous biomass

3.2.2.1 Selection criteria and experimental design for sampling plots

The study area comprises a mosaic of LULC types of known-age and history, which presented an opportunity to study this objective. Therefore, five LULC types representing the prevalent ground cover and distinct land-use activities in the study area were identified. These LULC types were: pristine grasslands, degraded grasslands, restored grasslands, *Prosopis*-low cover, and *Prosopis*-high/dense cover (*reference photos in Figure 3.5*). These classes were chosen, categorized and described on the basis of time, historical events and biophysical characteristics as informed by field observations, literature review and expert judgement. This was achieved through consultations with farmers, livestock keepers, village leaders and conservationists with respect to events and change dynamics in the area since 1950s or before. This reference time in the area's history was used because around mid 20th century (1950s), the area experienced a mega drought, which occurred after a prolonged dry period following the habitual seasonal bush burning in savannas and rangelands (Leys et al., 2018).

3.2.2.2 Classification and description of the land-use and land-cover types

The selected LULC types were categorized as follows: i) pristine grasslands: grasslands with more than 80% grass cover, that have been predominated by grass for more than 70 years; ii) degraded grasslands: mostly bare ground for more than 70 years; iii) restored grasslands: grasslands that were previously degradaded but restored some 25 – 35 years ago; iv)

Prosopis-low cover: invaded areas with less than 30% *Prosopis* cover and invaded some 10 – 15 years ago; and v) *Prosopis*-high cover: invaded areas with more than 80% *Prosopis* cover and invaded about 25 – 35 years ago. Pristine grasslands were historically predominantly covered with grass, moderately grazed and comprised a mixture of native grass species and shrubs. They experienced moderate grazing because as a traditional cultural practice, the pastoralists reserved them to provide pasture during the dry seasons and therefore carefully regulated grazing during the critically dry seasons (Mureithi et al., 2010). Degraded grasslands were characterized by barren soil and were unsustainably grazed over time. Sample plots on degraded grasslands were selected from communal grazing lands which markedly suffered from severe, intermittent droughts before and during the 1950s, 1965 and later (Anderson, 2016; Kiage and Liu, 2009; Little, 1992). Restored grasslands comprised degraded grasslands which got reseeded with different native grass species, including *Enteropogon machrostachyus* (Hochst.ex A. Rich.) Munro ex Benth((Hochst.ex A. Rich) Munro ex Benth, 1881), *Cenchrus ciliaris* (L)(Cenchrus ciliaris L. in GBIF Secretariat, 1753), *Eragrostis superba* (Peyr)(Eragrostis superba Peyr. in GBIF Secretariat, 1860), *Sehima nervosum* (Rottler) Stapf (Sehima nervosum Stapf, 1917), and *Cymbopogon pospischilii* (K. Schum) C.E. Hubb (Cymbopogon pospischilii (K.Schum.), 1949). They experienced moderate grazing, coupled with seasonal harvesting of biomass and grass seeds. Some of the grass species used had been recommended for reseeding severely degraded lands in Kenya (Bogdan and Pratt, 1967). All restored grasslands sites had solar-powered electric protective enclosures (Mureithi et al., 2010). *Prosopis*-invaded sites were formerly degraded grassland that later got invaded due to the expansion of the introduced alien *Prosopis* species. Sampling plots for *Prosopis*-high cover category were chosen in sites with the longest known history of *Prosopis* invasion in the study area, i.e from the early 1980s to 1990s (Mbaabu et al., 2019). Sampling was carried out in sites with *Prosopis* tree cover of < 30% and > 80% for plots with a low and high level of *Prosopis* invasion, respectively. These explicit *Prosopis* tree cover thresholds were determined using a fractional cover map of *Prosopis* for the study area (Mbaabu, 2017).

Initially, the classification and categorization of sites in the study area to the five LULC types was made on the basis of a LULC map for the study region (Mbaabu et al., 2019), as well as literature review. The final decision on whether to include the pre-selected site in the final sampling sites was made after specific field site visits for inspection and consultation with key informants from the community. All the chosen sites were situated within the same geographic region with almost homogenous elevation, topography, soil characteristics and geological history. The patchy and mosaic distribution of the LULC types enabled the selection of interspersed replicates of the categories at different spatial locations.

Plots of 15 x 15 m were randomly selected and geo-located at each selected site. For restored and pristine grassland sites, sample plots were established randomly in areas with contiguous and undisturbed grass cover. This means that tree thickets or bushes were avoided as well as driveways, gullies and slopes. In total, 63 plots (pristine grassland: 10, degraded grassland: restored grassland: 15, 16, *Prosopis*-low: 12, *Prosopis*-high: 10) were sampled for soil, herbaceous biomass and plant species richness. Soil samples were picked during the dry season (period from September – November 2017 and 2018). This was important because soil sampling during the growing season increases the effect of plant type and growth stage on SOC, especially in soil carbon fractions that have a rapid turnover rate (Hoyle, 2013). Herbaceous biomass and plant species richness were sampled in the middle of the wet seasons (April-July 2017 and 2018) when vegetative growth is at its peak.

In the field, each 15 x 15 m sample plot was sub-divided into nine subplots of 5 x 5 m (Figure 3.6B). Samples were taken from five out of the nine subplots (the centre plot and the four corner subplots). For SOC measurement, a pit was dug incrementally at the centre of each of the four corner subplots (Figure 3.5a). From this pit, 4 independent soil cores were sampled at the following four soil depth increments: 0-15 cm, 15–30 cm, 30–60 cm and 60–100 cm similar to soil sampling depth considered by (Don et al., 2011; Kutsch et al., 2009). For soil bulk density (which is the dry weight of soil per unit volume of soil), a soil pit was dug incrementally at the centre subplot and three soil cores taken at the same depth increment for all the four soil sampling depths (i.e. 3 cores at 0-15 cm, 3 cores at 15-30 cm …).

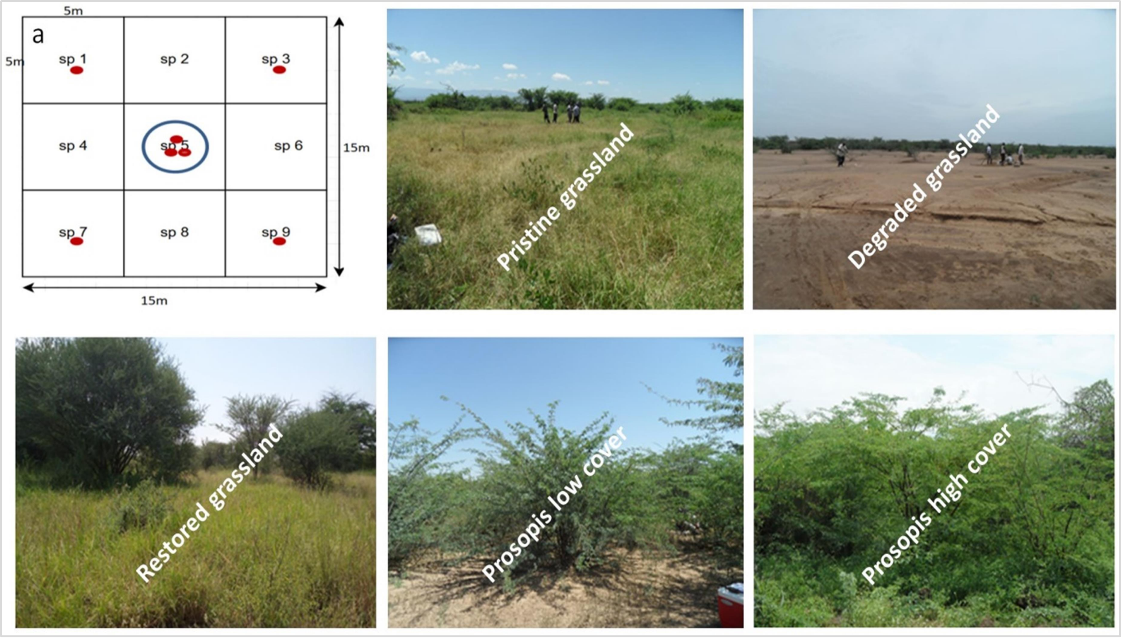


Figure 3.5 Plot design and reference photos for each land-use and land-cover type. The abbreviation "sp" means "subplot".

For measurement of herbaceous biomass and plant species richness, four of the five subplots were randomly selected and a point frame (1x1 m quadrat subdivided into a mesh of 100 squares of 10x10 cm each), placed at the centre each of the four subplots (5x5 m) within which abundances of all plant species were assessed (Floyd and Anderson, 1987). Each subplot was surveyed for vascular plants (within the quadrat) by a botanist capable of identifying more than 90% of the species encountered and samples of unknown plants collected for future identification. Plant species richness was measured by physically counting the number of squares occupied by each species and the total number recorded out of 100. Any other species existing within the large plot (15x15 m) but had not been encountered within any of the four quadrats were also recorded. Herbaceous vegetation (any vegetative growth 2 cm above the ground) samples were harvested from a 25x50 cm patch within the 1x1 m^2 quadrat, amalgamated together per plot, oven-dried and weighed to determine the dry weight. Herbaceous biomass samples analysis was done at the Kenya Forestry Research Institute (KEFRI-Nairobi) laboratories. Soil samples analysis was done at the Kenya Agricultural and Livestock Research Organization (KALRO-Kenya) soil laboratories. The Colorimetric method was used to determine the soil organic carbon (SOC) concentration (Baillie et al., 1990). Bulk density samples were first oven-dried, weighed and measured using the procedure by Klute (1986). Bulk density sample values were then used to convert the SOC concentration to ecosystem estimates of SOC stocks per unit area or volume.

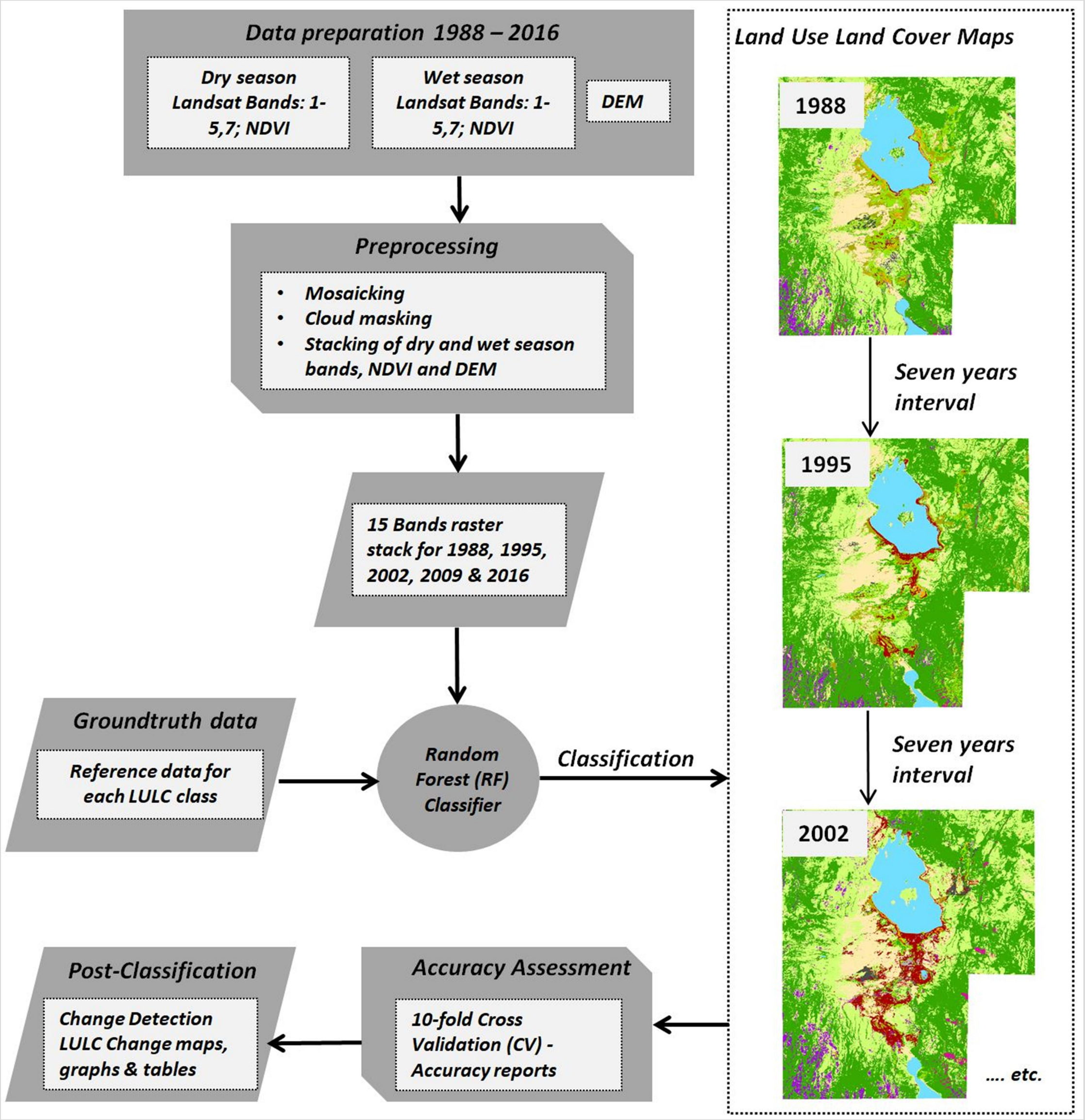


Figure 3.6A Methodological flowchart of spatio-temporal analysis of *Prosopis* spread

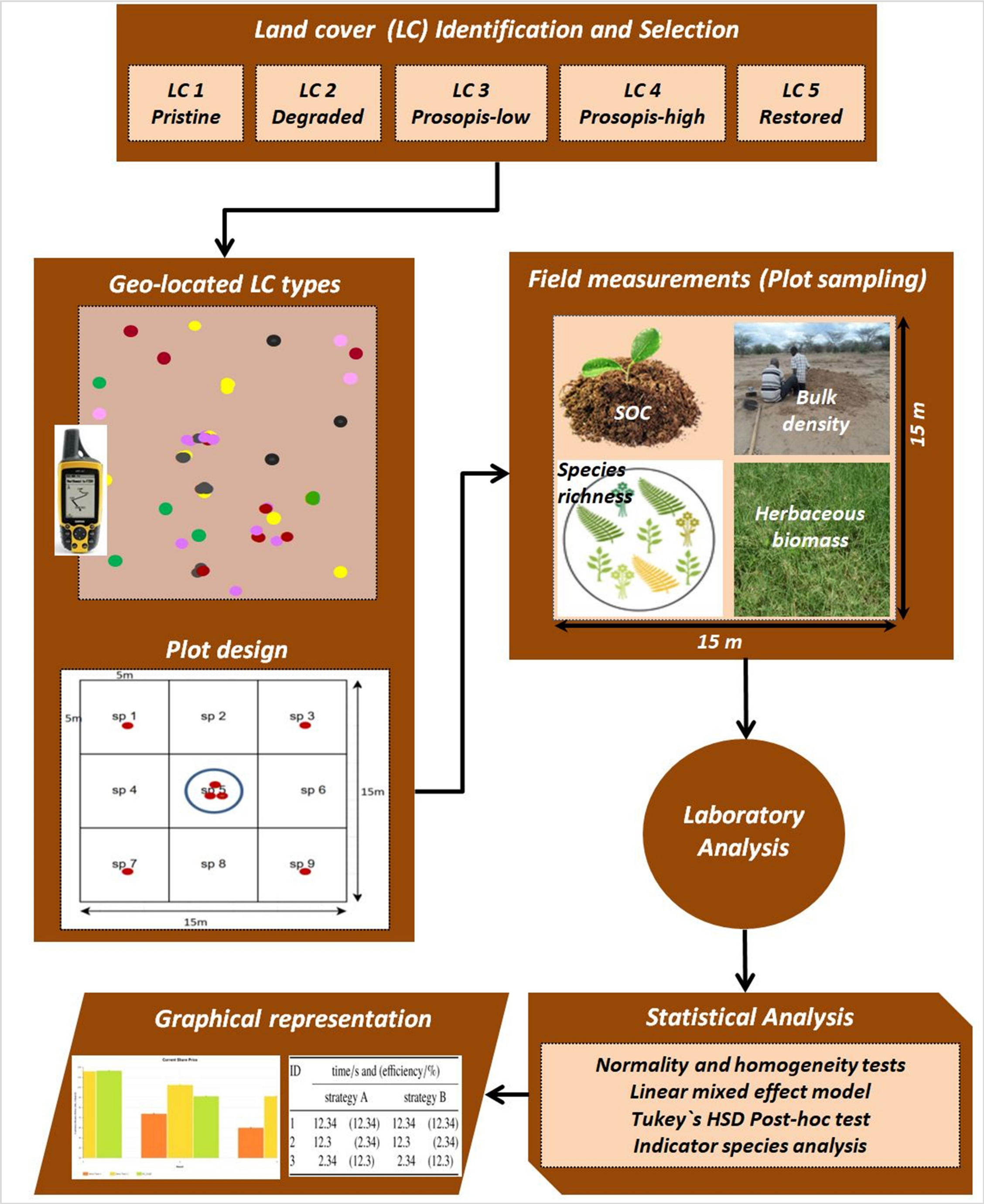


Figure 3.7B Methodological flowchart for assessment of soil organic carbon, plant species richness and herbaceous biomass.

3.2.2.4 Statistical analysis

Data analysis was done in R software (R Core Team, 2020), version 3.6.3. First, data normality and homogeneity were checked using Shapiro-Wilk's tests and by visually inspecting the residuals against the fitted values and histograms. Any dataset that did not meet the basic model assumptions were therefore log-transformed before proceeding with the statistical analysis. To determine the effect of soil depth on percent SOC and SOC per volume soil (g cm^{-3}) across land-cover types, a linear mixed effect model was fitted using the *lme* function within the *nlme* package (Pinheiro et al., 2020). The parameters land-cover type, soil depth increment and the interaction of land-cover type and soil depth increment were included as fixed effects in the model, and sample plot as random factor. Tukey's HSD Post-hoc test on the model's least square means was used to evaluate the differences between the means among land-cover types and soil depth increments. To determine how land-cover type affects SOC down to 1 m depth (full depth), herbaceous biomass, and species richness general linear models with land-cover type as fixed effect were used, followed by Tukey's HSD Post-hoc test. SOC stocks per unit area (t C ha^{-1}) were estimated using the formula: SOC t ha^{-1} = %SOC x BD (g cm^{-3}) x d (cm), where %SOC = carbon concentration of the soil sample, BD = bulk density in g cm^{-3}, and d = height of the soil depth increment (cm) (Abdallah et al., 2020; Hoyle, 2013). Then, the total SOC stocks down to 1 m depth were then derived through a summation of the SOC tons per hectare values estimated for each depth increment (Grüneberg et al., 2014; Ward et al., 2016). An indicator species analysis test using the *labdsv* package in R was used to determine the species characteristic of the different land-cover types.

3.2.3 Climate change impact on current and future *Prosopis* and *Vachellia tortilis* habitat.

3.2.3.1 Species occurrence (biodiversity) and environmental data

To model the current and future suitable habitats for the two species, species occurrence (presence) data were collected from the species distribution in the study area between 2008 and 2018. Known species locations were identified and marked with a handheld GPS Receiver. For some remote and inaccessible locations, Google Street View service was used to find species locations. *Vachellia tortilis* occurrence records were supplemented by occurrence data records obtained from Global Biodiversity Information Facility (GBIF) (https://www.gbif.org/). True absence data were lacking, therefore, background or pseudo-absence data were randomly generated in the study area using the random generation with exclusion buffer (RGEB) (Rew et al., 2021). The RGEB technique is used for adjusting distances between pseudo-absence points using a specified exclusion buffer zone, such that the pseudo-absence points are generated outside of these buffer zones. A 10 km exclusion buffer around each presence location is usually recommended in several studies in order to avoid grids that contain both pseudo-absence and presence data points (Aiello-Lammens et al., 2015; Barbet-Massin et al., 2012; Rew et al., 2021). Therefore, this recommended 10 km exclusion buffering distance was used when generating pseudo-absence data for both species. A total of 944 and 1197 (*Prosopis*) and 861 and 417 (*Vachellia tortilis*) presence and pseudo-absence (background) points were collected, respectively.

Spatial autocorrelation

Fitting species distribution models (SDMs) with spatially autocorrelated input species occurrences introduces environmental biases in the models because SDMs tend to over-fit towards the environmental bias. Having spatially clustered species occurrences introduces sampling biases which results in problems of spatial autocorrelation. Use of spatially clustered occurrence data in SDMs reduces the ability of the model to predict spatially independent data which results in inflated model values (Brown et al., 2017). Moreover, spatial autocorrelation is of concern particularly when modeling invasive species because dispersal and colonization processes strongly influences biological invasions, which in turn produces highly structured distribution patterns (Václavík et al., 2012). Therefore, eliminating or minimizing the localities with these spatial clusters of occurrences is necessary before calibrating and evaluating the model. To overcome problems of spatial autocorrelation inherent in the occurrence dataset, spatial filtering of locality data (reducing the clustered occurrence localities to a single data point) by a specified input distance and within a specified Euclidean distance was done, using the Spatially Rarefy occurrence data tool within the SDMtoolbox (Brown et al., 2017). A graduated filtering procedure at several distances e.g. (5 km^2, 10 km^2 and 30 km^2) with respect to habitat, topographic and climate heterogeneity is applied in sites with high, medium and low environmental heterogeneity, respectively. In this study, both climate and topographic heterogeneity were calculated. Climate heterogeneity computes the first three principal components (PCs) of all input climate dataset, calculates the heterogeneity of each principal component, weighs each PC heterogeneity layer depending on the amount of variation explained, and finally adds them up to create a single heterogeneity layer. To calculate topographical heterogeneity, elevation data was used. The study area was found to have medium topographical and low climate heterogeneity. Therefore, only topographical heterogeneity dataset was used to parameterize the Spatially Rarefy function at a filtering distance of 14 km^2 (resolution 14 km). This process yielded 676 and 373 (*Prosopis*) and 508 and 145 (*Vachellia tortilis*) bias corrected presence and pseudo-absence points, respectively.

Environmental data

Landscape, physical and anthropogenic variables

A suite of data representing the climate, topography and vegetation that characterize habitat diversity and environmental conditions that are vital for *Vachellia tortilis* growth and for establishment and dispersal of the alien *Prosopis* species were identified (Table 3.6). Additionally, anthropogenic data representing the cumulative human pressure on the environment was also included (Venter et al., 2018b, 2016). Some of the variables were found to be of relevance particularly those related to the hydrosphere e.g. water bodies and rivers, and biosphere e.g. albedo, evaporation and vegetation indices because they are classified as essential climate variables (ECVs) (GCOS, 2021) by the Global Climate Observing System (GCOS) (Table 3.6). They are imperative to the characterization of the Earth's climate and therefore are required for climate change analysis purposes (European Commission, 2022). Moreover, the choice of other functionally relevant variables was informed by recommendations in other related studies (Dilts et al., 2015; John et al., 2008; Synes and Osborne, 2011), for modeling species in similar ecological conditions (arid and semi-arid climates).

Finally, the following categories of variables were included: topographical variables; elevation and landforms, surface water variables; Euclidean distance to water bodies and rivers, edaphic variables; soils, vegetation indices and anthropogenic variable; Global Human Footprint Index (HFP) (Table 3.6). Raster datasets for distance to water bodies and rivers were generated by calculating Euclidean distances using the vector data for both rivers and water bodies in ArcMap 10.2.2 (ESRI, 2014). Rivers Euclidean distances were weighted by their category (streams level 1-7 were used). Then the minimum of all Euclidean distances of all layers was chosen to generate a minimum (weighted) Euclidean distance layer of the river network. The water bodies were buffered first, and then Euclidean distance was calculated. Topographical, edaphic and anthropogenic variables were provided by Eckert et al. (2020) as part of the dataset that was used for regional (Eastern Africa) modeling of invasive alien species distribution. These variables were considered for modeling as other studies have shown their prowess in influencing the target species habitat, in particular *Prosopis* spp. (Ng et al., 2018; Shiferaw et al., 2019b, 2019c).

Climate data and Climate Models

For current climate, models were fitted using two datasets: 1) from the standard bioclims and 2) from the Uni-Bern bioclims. For future climate, the climatic variables were customized to three GCMs (MPI-ESM-LR, CNRM-CM5 and INM-CM4) (Table 3.4) and one regional model dataset (Uni-Bern). The standard 19 bioclimatic variables for both current and future climatic situation were obtained from www.worldclim.org at 30-seconds (~ 1 km^2 or 0.01 degree) spatial resolution (Fick and Hijmans, 2017). Bioclimatic variables generated by the Climate and Environmental Physics (CEP) Department of the University of Bern (hereafter referred to as "Uni-Bern") were also acquired. The current climate data covered the period between 1970-2000 and near-future climate 2050 representing an average for the period 2041-2060. For the Uni-Bern climate dataset, the temporal coverage was current climate 1970-2000 and distant-future climate 2085 representing an average for the time period 2071-2100. The radiative forcing scenario RCP8.5, which is one suite of scenarios (RCPs) that describe a number of potential future pathways, was considered as the future climate change scenario. Each scenario defines the level (concentration) of carbon in the atmosphere at any point in time (climatenexus, n.d.). Although there are other plausible climate change scenarios (RCP 2.5, 4.5 and 6.0), guided by the goal of this study (to model the impact of climate change on future species habitat), it was envisaged that the real climate change impact would exist when we assumed no intervention to the climate situation – a business as usual scenario (as is the case for RCP 8.5 i.e. high emissions that would deliver about 4.3° C increase in average temperature by 2100, relative to pre-industrial temperatures). This has been vindicated by the latest climate change report by IPCC, which indicates that the world is not on track to keep global temperature rises to no more than 1.5° C (UNDP, 2022), implying that "tipping points" in the climate system are plausible (UN, 2022). It is also noted with concern that without prompt and deep emissions reductions across all sectors, meeting this temperature reduction is currently beyond reach (UN, 2022). Therefore, RCP 8.5 which is the worst case scenario seems the most likely and realistic scenario. As such, all other RCPs were excluded from the analysis.

Table 3.4 Overview of climate datasets

Climate scenario	Data / climate model	Spatial coverage	Climate period	Carbon level (RCP)
Current climate	WorldClim	Global	1970 – 2000	RCP 8.5
	Uni-Bern	Regional (East Africa)	1970 – 2000	RCP 8.5
Future climate	WorldClim			
	• *MPI*	Global	2041 – 2060	RCP 8.5
	• *CNRM*	Global	2041 – 2060	RCP 8.5
	• *INMCM4*	Global	2041 – 2060	RCP 8.5
	Uni-Bern	Regional (East Africa)	2071 – 2100	RCP 8.5

Additionally, for comparisons with our Kenya specific model generated at CEP, global Worldclim Bioclim variables were downloaded. These WorldClim datasets were acquired for three Global Climate Models / General Circulation Models (GCMs) (Table 3.5), under the Coupled Model Intercomparison Project (CMIP) Phase 5 and 6. CMIP5 was utilized for future climate data and CMIP6 for current climate data). The three models considered were CNRM-CM5, INMCM4 and MPI-ESM-LR. A detailed summary of the models is provided in (Table 3.5).

CMIP5 data was used for future climate modeling instead of CMIP6 data because in CMIP6, the needed dataset was not available at the required finer resolution of (~ 1 km^2). These models were systematically selected on the basis of regional downscaled model performance reported by Dosio et al. and McSweeney et al. (2015; 2015) for CMIP5. The models were categorized according to performance into four classes 1) *Satisfactory*, 2) *Biased,* 3) *Significantly biased*, and 4) *Implausible* (McSweeney et al., 2015). The purpose of downscaling the CMIP5 models was to identify a set of models suitable for application in regional climate change assessments for three geographical regions – Europe, Southeast Asia and Africa (McSweeney et al., 2015). The best models are those that performed well across multiple regions while the least realistic ("worst") models were those that poorly simulated the key aspects of regional climate such as temperature and precipitation (McSweeney et al., 2015). Further, during the GCM model downscaling for African climate by Dosio et al. (2015), model performance was tested on the basis of a model's ability to reproduce the principal components / characteristics of the African climate (Dosio et al., 2015) such as sea level pressure, temperature, precipitation and related indices such as consecutive dry and wet days, and the frequency of flood events, among others. Therefore, for purposes of this study, the three models were selected on the basis of their ability or inability to simulate the African climate and their temporal resolution completeness i.e. the data date (temporal) range covered our modeling time period (2050). For purposes of comparison of model performance in predicting target species' habitat distribution, the models were picked from two classes representing both extremes in terms of performance (2 Satisfactory models - with one being satisfactory but an outlier, and 1 significantly biased) (Table 3.5). This choice was premised on the understanding that usually, decisions on climate scenarios / models are based on convenience. As argued by Baumgartner et al. (2018), predictions using a few climate change scenarios or models may not capture the full range of uncertainty in future climate conditions that has been recorded by a broader set of climate models. As such, consideration of broader climate futures is highly recommended in order to yield prediction estimates that capture better the possible range of climate change impacts (Baumgartner et al., 2018). This would mean, including a suite of relevant plausible models (excluding implausible models) even though they may present qualitatively contrasting futures (Evans et al., 2014), because variability exists among simulations and no single 'best' model exists (Beaumont et al., 2008). Furthermore, variations on impacts across the predicted model outputs capture uncertainties associated with future climatic conditions hence, enabling visualization of spatial patterns of agreement about distribution and suitability of habitats in SDMs (Baumgartner et al., 2018).

Table 3.5 Summary of GCM models MPI-ESM-LR, CNRM-CM5 and INM-CM4 as well as relevant model performance attributes based on three studies (Dosio et al., 2015; Dosio and Panitz, 2016; McSweeney et al., 2015) that informed their selection for this study. Details on model teleconnections are available from Rowell (2013). The bold and italicized attributes are those that are close to or cover our study area. The performance of the models was determined by the model's ability to simulate the key aspects of regional (Africa, Asia and Europe) climates such as temperature and precipitation. The best performing models are those that performed well across multiple regions (McSweeney et al., 2015)

Modeling Centre and Country	Model name/version	Classification by performance	# Teleconnections (of 36)	Relevant model performance attributes (for African climate; either current or future climate)	References
MPI, Germany	MPI-ESM-LR	Satisfactory	29	o Performed better than all other 3 models, although a cold bias was evident o Predicts warming (though biased) over eastern Mauritania. o Overestimates precipitation in the JFM season over the western part of the sub-equatorial coast o **Shows a dry bias over Madagascar and Mozambique in the JFM season**	Dosio et al., 2015; Dosio and Panitz 2016; (McSweeney et al., 2015); Rowell , 2013
CNRM, France	CNRM-CM5	Satisfactory - Outlier	24	o ***Temperature is underestimated over South Africa and north-equatorial region, but slightly overestimated for the Congo region.*** o Temperatures over South Africa and the Sahara region are underestimated o Precipitation during the JFM season is overestimated over South Africa. o ***Predicts dryness (though biased) in the JFM season for central Africa***	Dosio et al., 2015; Dosio and Panitz 2016; (McSweeney et al., 2015); Rowell, 2013
INM, Russia	INM-CM4	Significantly biased	20	o ***Oftenly, its predictions are at one end of the ensemble range, with consistent projections of the least warming for nearly all the seasons and regions*** o Showed that its change in rainfall projections have low correlations in relation to the ensemble mean change especially for the African climate.	(McSweeney et al., 2015); Rowell , 2013

Data preparation

Finally, all data were consistently transformed to WGS84 / UTM zone 37N (EPSG: 32637), masked to the study extent (Figure 1.1), resampled using nearest neighbour interpolation technique and analyzed at 30 m spatial resolution. In order to obtain precise results and to avoid processing difficulties, all environmental variables must have the same spatial extent, resolution, origin, and projection (Hijmans and Elith, 2021). To obtain a modest variable sample, variable reduction by performing correlation analysis was done. Therefore, only variables with low correlation averages as well as the most counts of pairwise variable correlation values less than 0.6 ($r<0.6$) for each species were selected. Any variables with pairwise correlation values at or exceeding this threshold (0.6) were excluded from the analysis. Therefore, altogether, 13 functionally relevant predictor variables (*those marked with "Y"* in Table 3.6) were retained for fitting the models. The variables were assumed to best represent the physiological requirements of the two species. Moreover, a large subset of these variables has proven useful when fitting skillful SDMs in other studies in the same region (Eckert et al., 2020; Ng et al., 2018). To ensure modeling consistency and to enable model output comparisons without bias, the same standard set of variables was maintained for modeling the two species under the present and future climate change scenarios – only Bioclims were customized for each model and climate scenario. All the variables, data sources and relevant references are listed in Table 3.6.

Table 3.6 An overview of initial variables, sources and formula references for the derived variables. Variables with “Y” were included in the final model, and those with “N” excluded. Variable names with “**[2]**” means that the variable was computed for both dry and wet season. CGLS means Copernicus Global Land Service.

Variable name	**Abbr.**	**Used**	**Data source**	**Formula reference**
Annual mean diurnal temperature range	Bio2	“Y”	WorldClim v2.1	
Temperature seasonality	Bio4	“Y”	WorldClim v2.1	
Maximum temperature of warmest month	Bio5	“Y”	WorldClim v2.1	
Temperature annual range	Bio7	“Y”	WorldClim v2.1	
Mean temperature of driest quarter	Bio9	“Y”	WorldClim v2.1	
Precipitation seasonality	Bio15	“Y”	WorldClim v2.1	
Bioclimatic variables (Bio1,3,6,8,10-14,16-19)	Bio….	“N”	WorldClim v2.1	
Soil map (derived from KENSOTER v. 2.0)	Soils	“Y”	KALRO	
Weighted minimum Euclidean distance to rivers	Dist_Riv	“Y”	derived	ESRI, 2014
Minimum Euclidean distance to buffered waterbodies	Dist_WB	“Y”	derived	ESRI, 2014
Elevation		“Y”	Eckert et al., 2020	
Landforms		“Y”	Eckert et al., 2020	
Global Human Footprint Index	HFP	“Y”	Eckert et al., 2020	
Absolute Minimum Temperature	AMT	“N”	derived	Prentice et al,., 1992
Actual Evapotranspiration	AcET	“N”	USGS	USGS FEWS NET, 2021
ALBEDO **[2]**		“N”	CGLS	European Union, 2018
Aridity Index	AI	“Y”		Trabucco & Zomer, 2019
Climate Water Deficit or Soil Water Deficit	CWD	“N”	derived	Lutz et al., 2010
Dry Matter Productivity **[2]**	DMP	“N”	CGLS	European Union, 2018
Fraction of Absorbed Photosynthetically Active Radiation **[2]**	FAPAR	“N”	CGLS	European Union, 2018
Fractional Vegetation Cover **[2]**	FCOVER	“N”	CGLS	European Union, 2018
Growing Degree Days	GDD	“N”	derived	Synes & Osborne, 2011
Gross Dry Matter Productivity **[2]**	GDMP	“N”	CGLS	European Union, 2018
Leaf Area Index **[2]**	LAI	“N”	CGLS	European Union, 2018
Moisture Index	Moid	“N”	derived	Box, 1981 (cited in Attore et al, 2007)
Ombrothermic Index	Oi	“N”	derived	Rivas-Martinez (1996) cited in Attorre et al. (2007)
Potential Evapotranspiration	PET0	“N”		Trabucco & Zomer, 2019
Pluviothermic Quotient	PluQ	“N”	derived	Emberger (1930) cited in Attorre et al. (2007)
Normalized Top of Canopy Reflectance **[2]**	TOCR	“N”	CGLS	European Union, 2018
Topographic Wetness Index	TWI	“N”	derived	Wolock & McCabe, 1995
Vegetation Condition Index **[2]**	VCI	“N”	CGLS	European Union, 2018
Vegetation Productivity Index **[2]**	VPI	“N”	CGLS	European Union, 2018
Normalized Difference Water Index	NDWI	“N”	derived	Vermote et al., 2016
Soil Salinity Index	SSI	“N”	derived	Ghazali et al 2020;
Normalized Difference Senescent Vegetation Index	NDSVI	“N”	derived	Qi et al., 2002

Soil Adjusted Vegetation Index	SAVI	“N”	derived	Vermote et al., 2016
Normalized Difference Vegetation Index **[2]**	NDVI	“N”	Eckert et al., 2020	
Slope	Slope	“N”	Eckert et al., 2020	
Euclidean Dist. villages	Dist_V	“N”	derived	derived

3.2.3.2 Species Habitat Suitability Modeling

SDMs are recognized and considered as useful tools for predicting habitat suitability and species distribution (Duscher and Nopp-Mayr, 2017; Rew et al., 2021; Schwager and Berg, 2021), as they are the principal means of evaluating how species respond to a multitude of environmental and climate gradients (Baumgartner et al., 2018). Generally, SDMs combine information on known species occurrence locations with co-located abiotic and biotic data such as soil, elevation, climate, vegetation indices and changes in land-use to map and predict the probability of occurrence of that species at other unsampled sites or times, e.g. considering the future climate situation (Ehrlén and Morris, 2015; Rew et al., 2021; Schwager and Berg, 2021). Usually, a fitted model is projected on spatial environmental data (raster predictor variables), which then produces continuous probabilities (scores) indicating the relative environmental suitability for a particular species (Baumgartner et al., 2018).

Two machine learning modeling approaches or algorithms - Random Forest (RF; (Breiman, 2001b) and Boosted Regression Trees (BRT; (Elith et al., 2008)), were used to model suitable habitat for species in this study. These SDM algorithms were preferred over others because they provide reliable results with higher accuracies compared to the well known entropy modeling method (MAXENT), and of high predictive accuracy and hence, are generally considered robust (Franklin, 2010; Schwager and Berg, 2021; Scornet, 2017). Moreover, these two machine learning algorithms outperformed another machine learning algorithm – Support Vector Machine (SVM), in a previous study on *Prosopis* on a national scale (Kenya) (Eckert et al., 2020). For each of the target species, both RF and BRT models were fitted using species data: presence-background (pseudo-absence) as the response (dependent) variable and the 13 raster files (*those marked with “Y” in Table 3.6*) as predictors or explanatory variables, for both current climate and future climate scenario RCP8.5. A schematic description of the methodological workflow is presented in Figure 3.7. All BRT models were calibrated using a “*Bernoulli”* family appropriate response variable of presence (1) and pseudo-absence (0) with a learning rate (shrinkage parameter) of 0.005, a tree complexity of 5, and a bag fraction of 0.5 (BCCVL, 2021; Elith et al., 2008). The learning rate (*lr*) is used to determine the contribution of each individual tree in the growing model whereby, the smaller the *lr* value, the more the trees will be built. The tree complexity (*tc*) parameter is set for controlling whether interactions are made between environmental variables. For instance, a *tc* value of 1 results in a single split and therefore the model does not take into account predictor variable interactions (BCCVL, 2021), while a *tc* value of 5 indicates five-way interactions. These two parameters determine the maximum number of trees needed for model optimization and prediction (Elith et al., 2008). As a rule of thumb, the parameters must be set to grow models with at least 1000 trees while also resulting in minimal prediction error (BCCVL, 2021). Cross-validation approach using holdout deviance reduction technique as a measure of success is used to determine the optimal number of trees to grow and *lr* (Elith et al., 2008, 2006). Use of cross-validation to progressively grow models avoids overfitting as it uses withheld portions of data to test predictive accuracy (Elith et al., 2006). The BRT modeling process is stochastic – because it includes a probabilistic or random component known as bag fraction. Introducing some stochasticity (randomness) into a boosted model improves prediction accuracy, model computing speed/time and minimizes model overfitting (Friedman, 2002). The bag fraction parameter setting in the BRT model controls the stochasticity by specifying the proportion of the dataset to be selected at each boosting step. In this study, the default setting bag fraction value of 0.5 was used, meaning that 50% of the dataset were randomly drawn without replacement from the full training set at each iteration. The default setting of 0.5 was maintained because bag fraction values in the range of 0.5 to 0.75 have been found to improve model performance and give best results for presence-absence responses (Elith et al., 2008). The BRT model was implemented in R using the 'Dismo'package, with an additional algorithm fine-tuning using the gbm.step function (Eckert et al., 2020; Elith et al., 2008).

RF, just like BRT, is a non-parametric machine learning method that performs both classification (if the response variable is a factor or categorical *–see description in section 3.2.1.3*) and regression (if response variable is a data.frame with predictor variables) (Hijmans and Elith, 2021). RF fits numerous individual trees, usually to the tune of hundreds to thousands and then combines their predictions by determining the average (Hastie et al., 2009; Valavi et al., 2021; Zurell, 2019). Each tree is fitted using a bootstrap data sample of the training dataset (a random sample) drawn with replacement, representing about 64% of the data points (Freeman et al., 2012; Valavi et al., 2021). The data samples that are not selected are referred to as out-of-bag samples, which represent about 36% of the data points, and are used for model error estimation (Freeman et al., 2012; Valavi et al., 2021). RF model was implemented in R in the function 'randomForest'(Liaw and Wiener, 2014). RF model was calibrated: model response type = regression, ntree = 1000 and nodesize = 5. Parameter '*ntree'* means number of trees. Similar to BRT, the standard recommended number of trees for fitting RF models is usually 1000 as many trees yield better results (Freeman et al., 2012; Probst et al., 2019; Scornet, 2017; Valavi et al., 2021). However, as a rule of thumb, it is recommended to start by growing (*p* x 10) trees and adjust accordingly, where *p* is the number of features or predictor variables (Boehmke and Greenwell, 2020). The '*nodesiz*e' parameter is key for controlling the complexity of individual trees. The default nodesize value for regression is 5 (Boehmke and Greenwell, 2020). The other RF model parameters were kept at default (i.e. not tuned) as RF is known to perform reasonably well at its default parameters (Valavi et al., 2021). For both models, variable importance or relevance was also automatically generated.

Soils, elevation, landforms and global footprint index were assumed to remain static and maintained for both current and future climate modeling (Table 3.6). Although soils and human footprint change over time, their descriptions for the future climate situation were lacking.

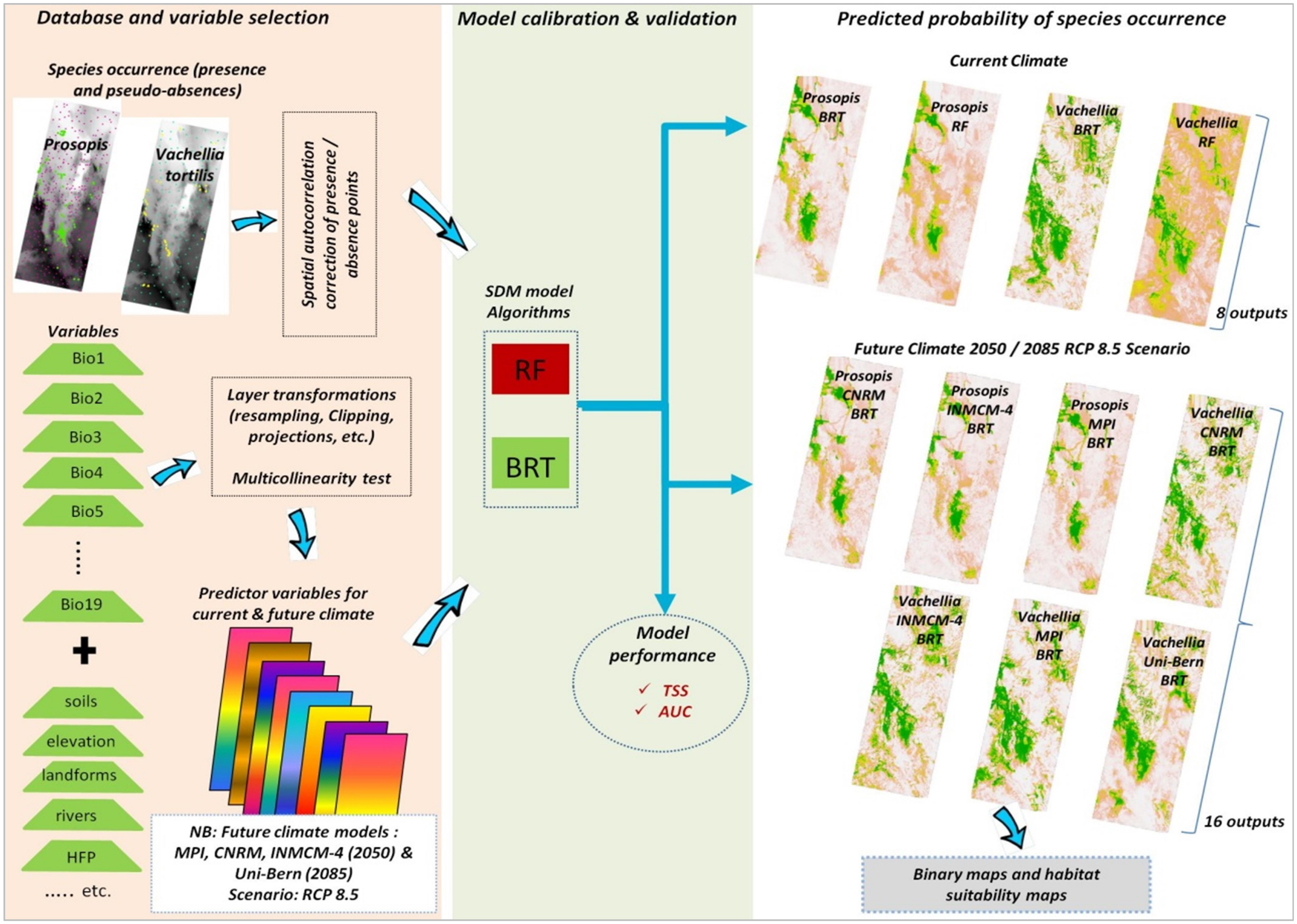


Figure 3.8 Flowchart of methods for modeling potential species distribution under current and future climate change scenarios.

3.2.3.3 Model validation

Evaluation involves testing the models predictive performance at sites by assessing the agreement between presence – pseudo-absence data records and the predictions (Elith et al., 2006). Model evaluation was done using the k-fold cross-validation technique (described in *section 3.2.1.4*), but in this case, k = 5 making it a 5-fold cross-validation (Rew et al., 2021). As a goodness-of-fit measure, both true skill statistic (TSS; Allouche et al. (2006) and Area Under the receiver operating Curve (AUC; Swets (1988)) were used. These two metrics have been widely applied in ecological studies (Barbet-Massin et al., 2012; Chefaoui and Lobo, 2008; Eckert et al., 2020; Elith et al., 2006; Iturbide et al., 2015; Liu et al., 2011; Ng et al., 2018; Rew et al., 2021; Schwager and Berg, 2021). AUC is the measure of a model's ability to discriminate between sites where the target species is present, vs. where it is absent (Elith et al., 2006; Liu et al., 2011). AUC values closer to 1 implies better discrimination performance (Rew et al., 2021). AUC was chosen as a candidate evaluation metric because it is also regarded as a relevant measure for models fitted with presence and background data (Valavi et al., 2021). TSS represents agreements (matches) and disagreements (mismatches) between observation and predictions, and is derived from sensitivity and specificity (Rew et al., 2021) or the mean of the net prediction success rate for presence sites and that for absence sites (Liu et al., 2011). It is currently touted in several studies as more realistic, practical and the best metric for evaluating the performance of SDM models (Rew et al., 2021; Shabani et al., 2018).

The AUC and TSS were calculated as the mean of five model iterations, where each iteration was built using 80% of the data and validated against the remaining 20% of the data (Rew et al., 2021). This model evaluation approach was applied for each species (n = 2), and for each model (n = 2), and for each climate - current and future - individually for each climate scenario (n = 5). Only models with TSS and AUC values of at least 0.5 and 0.9, respectively were finally accepted. These values were based on thresholds recommended in literature (Gallien et al., 2012; Rew et al., 2021), or thresholds achieved / considered in other studies in the same study region (Eckert et al., 2020). Moreover, in SDMs, models with an AUC of 0.7 are generally accepted while those with an AUC of 0.9 are considered excellent (Evans and Cushman, 2009; Rew et al., 2021; Swets, 1988). For TSS, values between 0.4 - 0.6 are considered appropriate or acceptable while values ≥ 0.8 are regarded as excellent (Rew et al., 2021).

3.2.3.4 Spatial projections

For each species, four and eight models with continuous habitat suitability predictions (probability of species presence) for current climate and future climate scenarios were produced, respectively. These continuous probability predictions were finally converted into binary maps of suitable/unsuitable species habitat, using optimum threshold values that maximize the sum of sensitivity and specificity (Baumgartner et al., 2018; Liu et al., 2013; Shabani et al., 2018) for each model. Sensitivity is the probability that an observation of a species (known presence) at a particular site is predicted correctly (i.e as presence) by the model, while specificity is the probability that an absence site is predicted correctly (i.e. as absence) (Liu et al., 2011). The optimum threshold values were generated using the *optim.thresh* function which is available in R package SDMTools following the procedure described by Eckert et al. (2020). This thresholding approach has been frequently used and recommended because of its ability to more skillfully reflect the prevalence of the modeled species (Baumgartner et al., 2018; Eckert et al., 2020; Jiménez-Valverde and Lobo, 2007; Liu et al., 2016, 2013, 2011). Using the most skilful output models or best performing models (i.e. TSS ≥ 0.5 and AUC ≥ 0.9), ensemble habitat suitability layers were generated for each species for both current and future climate (Figure 3.8). Ensembles were generated following the method described by Eckert et al. (2020). The ensemble creation approach has been widely applied in ecology (Eckert et al., 2020; Ng et al., 2018; Rew et al., 2021; Stohlgren et al., 2010), as it minimizes over-fitting and provides better predictions than predictions from single models (Rew et al., 2021).

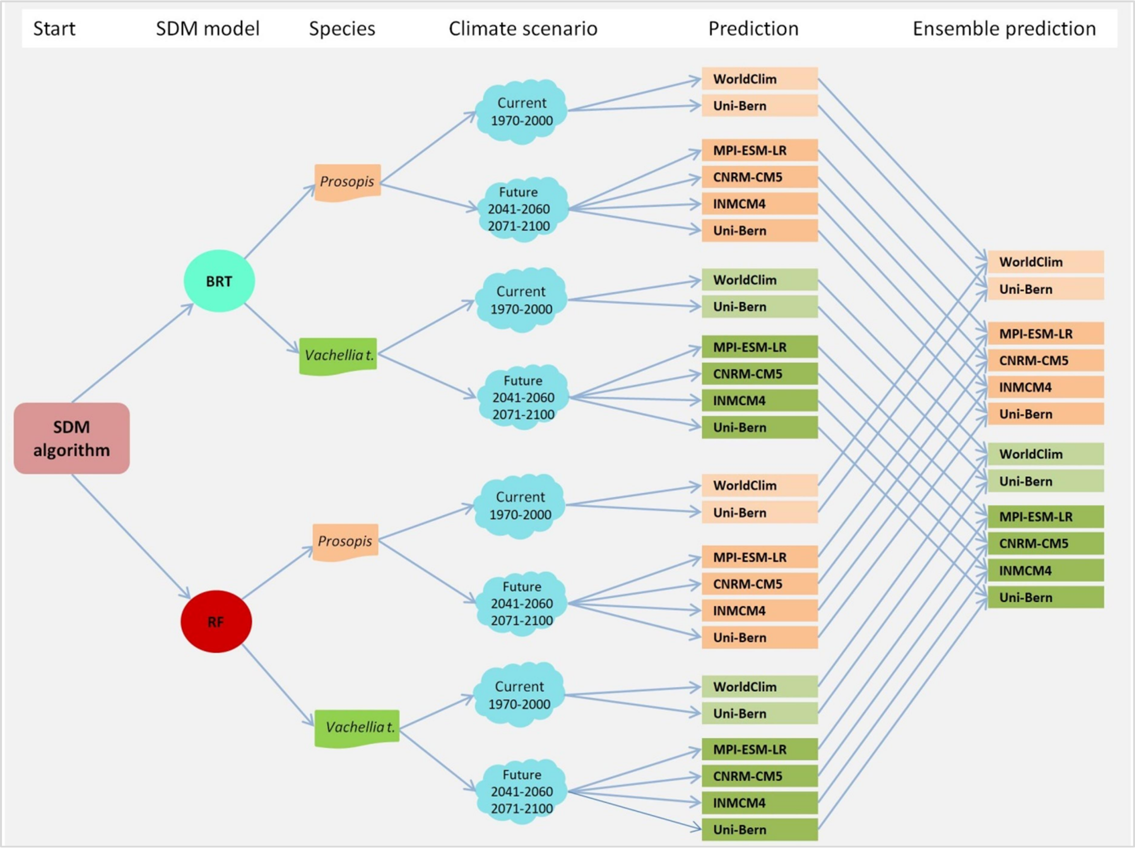


Figure 3.9 SDM modeling framework and ensembles generation scheme. Ensembles were generated by combining the BRT and RF predictions and calculating the mean probabilities predictions and optimum thresholds for each species (Eckert et al., 2020).

3.2.3.5 Comparisons of predicted spatial distributions and refugia identification

In order to reveal and understand the spatial pattern of the two species habitat, the two output raster (binary maps) for both current (present) and future climate models (each model) were combined by stacking. Then, the combined output raster was converted to a polygon and a union done. To determine the climate change effect on spatial change pattern of each species habitat, differences in habitat suitability (between SDM algorithms and between models of current and future climate scenarios) were calculated and visualized. Habitat change (contraction, expansion or no change) between the two binary SDMs (e.g. current and future SDMs) were determined by subtracting the quantified future suitable habitat area from the current suitable habitat area.

The main aim of objective 3 was to identify potential climate refugia for *Vachellia tortilis* and their vulnerability to *Prosopis* invasion in order to inform policy and management decisions for prioritization of *Vachellia tortilis* conservation actions and resources. Refugia represent areas suitable for species in the present time (i.e under current climatic conditions) and are also predicted as suitable areas during the future climate conditions (Baumgartner et al., 2018). While there are two types of refugia (ex situ and in situ) as described by Baumgartner et al. (2018), this study focused on identification of refugia (as suitable areas for the species in the current climate that are projected to retain their suitability under climate change). If, for example, an area is suitable in the current climate and unsuitable in future or vice versa, then it is not considered as refugia in this study.

3.4 Data synthesis

Diverse quantitative and qualitative data were collected for each objective. The groundtruth data (reference points and historical expert knowledge) acquired from the field was combined with Landsat time-series spatial data to analyze the changes in *Prosopis* coverage and its implications on other LULC types, using machine learning Random Forest technique in R software. Monetary cost of removing *Prosopis* from croplands and pasture loss were used as proxies for estimating *Prosopis* invasion impact on livelihoods. The monetary cost was estimated from the average willingness to pay for *Prosopis* clearing , which was determined through a choice experiment conducted in a household survey (n=250) in Baringo (Bekele et al., 2018a).

The comparison of effects of *Prosopis* spread versus restoring grassland on climate change mitigation and other ecosystem services was done on five land-use and land-cover categories. Field measurements of soil organic carbon at different soil sampling depths up to one meter below the surface, plant species richness and herbaceous biomass were carried out. Indicator species analysis was done both qualitatively and quantitatively.

Climate change models data for modeling potential future habitat of *Prosopis* and *Vachellia tortilis* were selected intentionally depending on their performance or ability to model key aspects of the East African or African climate such as temperature and precipitation. Field reference points for species presence were used to train and validate the climate models using BRT and RF species distribution models. These resulted in prediction maps for suitable / unsuitable habitats under both climate conditions. Further, the outputs for the two species were overlaid and areas of overlap identified (showing areas where native *Vachellia tortilis* would survive in future but is also at risk of invasion by *Prosopis*). Further, climate refugia were identified using this approach.

CHAPTER 4: ESTIMATION OF THE SPATIAL EVOLUTION, DYNAMICS AND IMPACTS OF *PROSOPIS* INVASION

4.1 Introduction

In this chapter, landscape changes between 1988 and 2016 were assessed and quantified for a historically severely degraded landscape in Baringo County that was later invaded by alien *Prosopis* species. The spatial and temporal changes in *Prosopis* coverage and its implications on other land-uses and land-cover, and livelihoods are analyzed and discussed.

4.2 Results

Random Forest classification algorithm generated good accuracies > 70% (producer's and user's) for all the 8 classes (*Prosopis*, *Vachellia tortilis*, mixed vegetation, grassland, bareland, rainfed cropland, irrigated cropland and water) across the 5 time steps, with the exception of *Vachellia tortilis* in 2016 (producer's accuracy =53.5%) and *Prosopis* in 2002 (producer's accuracy =53.5%). The overall accuracy ranged between 98.1 – 98.5%, while kappa coefficient ranged between 0.93 – 0.96. The degree of accuracy was better for the 2016 classification and lower for the base year (1988) (*see appendix 1.1 -1.5)*.

4.2.1 Spatial changes in *Prosopis* coverage from 1988 to 2016

The analyzed study area comprises approximately 180,000 ha. In 1988, mixed vegetation and bareland were the dominant LULC comprising about 71.5% and 8.3% of the total study area, respectively (Figure 4.1). In the same year, *Prosopis* coverage was scanty occurring mainly on the shores of Lake Baringo and as little patches in Kailer and Eldume sublocations. The prominent pathways of spread were along rivers including Lembus, Molo, Chemeron, Loboi, Sandai Perkerra, and Endao, as well as along irrigation canals and road networks (Figure 4.1C). The LULC maps reveal invasion spread corridor commencing on the southern shores of Lake Baringo southwards to Lake Bogoria through the swampy area covering Lake 94, including along the rivers draining into the lakes. From this invasion corridor (pathway), *Prosopis* expanded to the surrounding bare lands tending to the western zones of Lake Baringo, culminating into encroachment of Perkerra irrigation scheme (Figure 4.1A), a crucial agricultural facility in the area, existing since the 1950s.

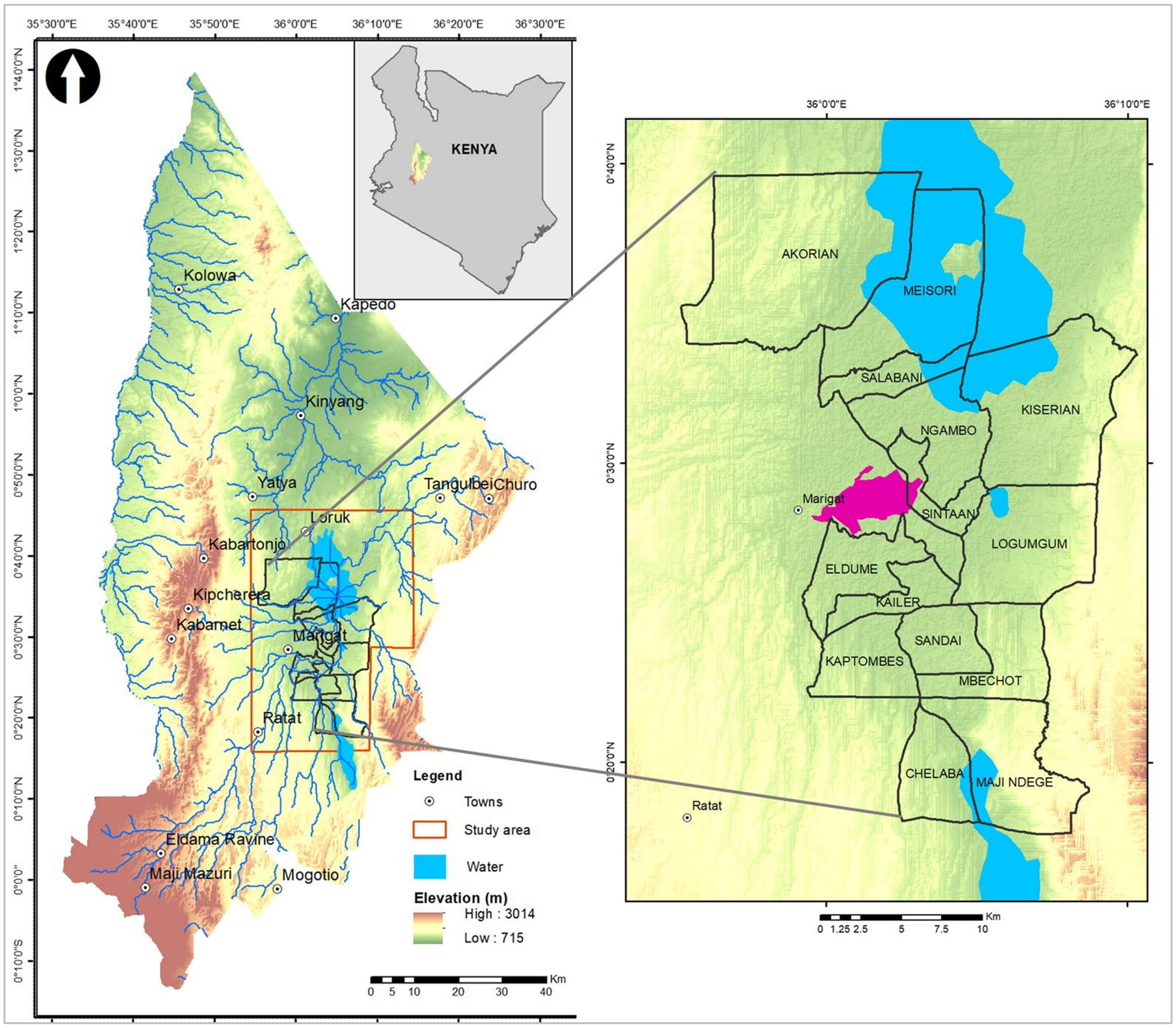


Figure 4.1A Overview map showing the extent of the study area (red boundary zone) and topography (elevation), waterways and lakes, Perkerra irrigation scheme (pink polygon), and sublocations.

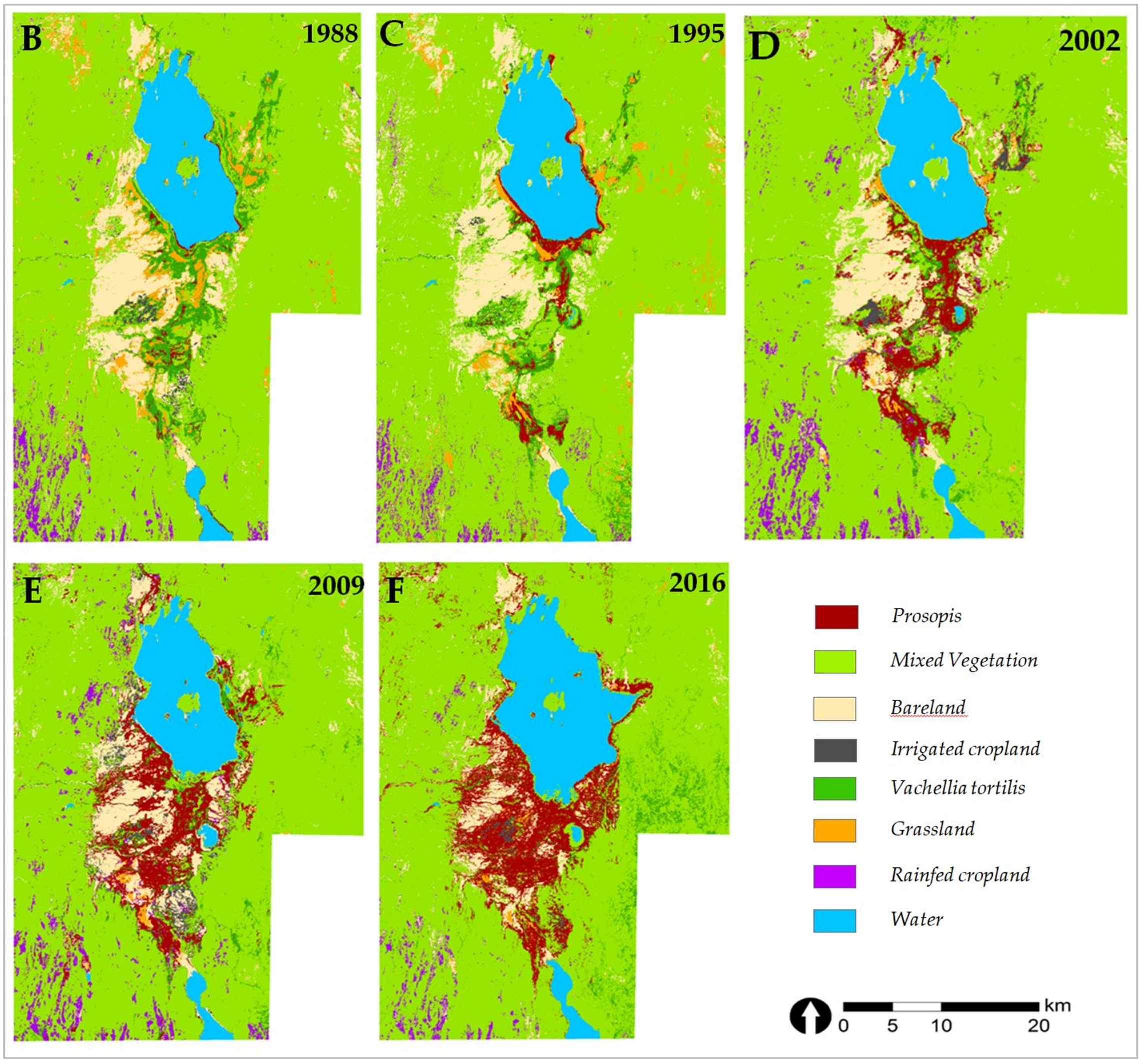


Figure 4.1B-F LULC change maps of Marigat subregion in Baringo County, Kenya, for the years 1988, 1995, 2002, 2009, and 2016.

Between 1988 and 2016, *Prosopis* coverage increased sharply and steadily, from 882 ha in 1988 up to 18,792 ha in 2016 (Table 4.1, Figure 4.2). However, the rates of increase varied among the seven-year intervals (Figure 4.2), increasing from 4.7% until 1988 to 13.1% in 1995 and stabilizing at about 27% since 2002. This translates into an annual spread rate of about 3.8 – 4.0% since 2002.

Table 4.1 LULC change proportions for each class in hectares (ha) and percent share of the total area for the years 1988, 1995, 2002, 2009 and 2016.

LULC Classes	1988		1995		2002		2009		2016	
	ha	**% share**	**ha**	**% share**	**ha**	**% share**	**ha**	**% share**	**ha**	**% share**
Prosopis	882	**0.5**	3345	**1.9**	8375	**4.7**	13568	**7.5**	18792	**10.4**
Vachellia tortilis	8517	**4.7**	6809	**3.8**	3158	**1.8**	3718	**2.1**	4915	**2.7**
Mixed vegetation	128727	**71.5**	130385	**72.4**	132969	**73.9**	124392	**69.1**	123310	**68.5**
Grassland	7229	**4.0**	5652	**3.1**	1194	**0.7**	691	**0.4**	977	**0.5**
Bareland	15001	**8.3**	16904	**9.4**	14130	**7.9**	13420	**7.5**	8503	**4.7**
Rainfed cropland	3840	**2.1**	3189	**1.8**	5531	**3.1**	5453	**3.0**	2408	**1.3**
Irrigated cropland	1501	**0.8**	473	**0.3**	1463	**0.8**	3708	**2.1**	652	**0.4**
Water	14325	**8.0**	13264	**7.4**	13204	**7.3**	15071	**8.4**	20464	**11.4**

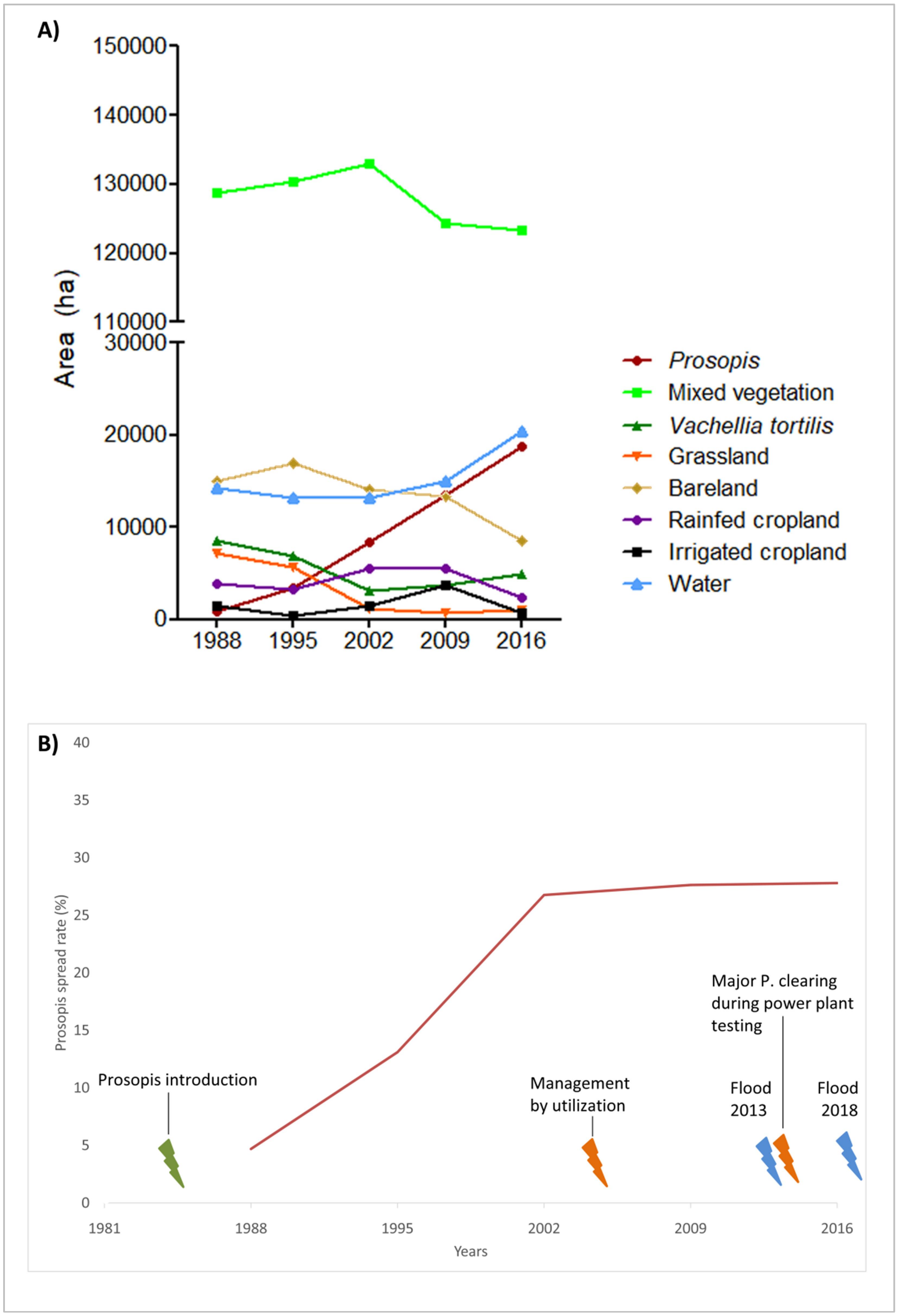


Figure 4.2 A) LULC changes in hectares (ha) for each LULC class for all the 5 time steps (from 1988 to 2016), and B) *Prosopis* spread rate for each observed 7-year time interval (not per year) since introduction (with the total invaded area in 2016 considered as 100%).

4.2.2 Changes in Land-Use and Land-Cover between 1988 and 2016

During the study period, *Prosopis* and water increased in spatial extent by 2031% and 42%, respectively, while all the other LULC classes declined (Figure 4.2A) and (Table 4.2). It was observed that water levels first declined, and then started to increase again from 2009 (Figure 4.2A). Increase in area under *Prosopis* was nearly constant since 1995 and was not affected by the 2013 floods (effect could be noticed in future) or the implementation of the 'management by utilization' (Figure 4.2 A and B).

Table 4.2 The overall net changes of LULC in hectares (ha) and percent class shares of total study area and percent class shares of case class area in 1988. Changes were calculated for 1988–1995, 1995–2002, 2002–2009, 2009–2016, and 1988–2016.

Net Changes	**1988 - 1995**			**1995 - 2002**			**2002 - 2009**			**2009 - 2016**			**1988 - 2016**		
LULC	**ha**	**% Total area**	**% of Class Area in 1988**	**ha**	**% Total area**	**% of Class Area in 1988**	**ha**	**% Total area**	**% of Class Area in 1988**	**ha**	**% Total area**	**% of Class Area in 1988**	**ha**	**% Total area**	**% of Class Area in 1988**
Prosopis	2463	**1.4**	**279.4**	5030	**2.8**	**570.4**	5193	**2.9**	**589.0**	5224	**2.9**	**592.5**	17910	**10.0**	**2031.3**
Vachellia tortilis	-1708	**-1.0**	**-20.1**	-3651	**-2.0**	**-42.9**	560	**0.3**	**6.6**	1197	**0.7**	**14.1**	-3602	**-2.0**	**-42.3**
Mixed vegetation	1658	**0.9**	**1.3**	2583	**1.4**	**2.0**	-8576	**-4.8**	**-6.7**	-1082	**-0.6**	**-0.8**	-5417	**-3.0**	**-4.2**
Grassland	-1577	**-0.9**	**-21.8**	-4458	**-2.5**	**-61.7**	-503	**-0.3**	**-7.0**	286	**0.2**	**4.0**	-6252	**-3.5**	**-86.5**
Bareland	1903	**1.1**	**12.7**	-2774	**-1.5**	**-18.5**	-709	**-0.4**	**-4.7**	-4917	**-2.7**	**-32.8**	-6498	**-3.6**	**-43.3**
Rainfed cropland	-651	**-0.4**	**-17.0**	2342	**1.3**	**61.0**	-78	**-0.0**	**-2.0**	-3045	**-1.7**	**-79.3**	-1432	**-0.8**	**-37.3**
Irrigated cropland	-1027	**-0.6**	**-68.5**	989	**0.6**	**66.0**	2246	**1.3**	**149.7**	-3056	**-1.7**	**-203.7**	-849	**-0.5**	**-56.6**
Water	-1061	**-0.6**	**-7.4**	-61	**-0.0**	**-0.4**	1868	**1.0**	**13.0**	5393	**3.0**	**37.6**	6139	**3.4**	**42.9**

Overall, the highest losses in land area for the classes considered occurred in grasslands (-86%), irrigated croplands by (-57%), bareland (-43%), *Vachellia tortilis* (-42%), rainfed cropland (-37%), and the lowest change was observed in mixed vegetation class at (-4%) (Table 4.2). It was, however, observed that the LULC classes that generally reduced in coverage also sporadically exhibited slight increases during certain intervals; for example, bareland in 1995, cropland in 2002 and 2009, and *Vachellia tortilis* in 2016 (Figure 4.3). *Prosopis* increased steadily across all the five intervals. At the initial invasion years (1988–2002), the most affected LULCs were *Vachellia tortilis* (-5359 ha) and grasslands (-6035 ha) which are crucial resources for pastoralists, while in the latter years (from 2002–2016), mixed vegetation (-9659 ha), bareland (-5626 ha), rainfed cropland (-3123 ha), and irrigated cropland (-811 ha), had marked changes (Figure 4.2A). The water levels in the lakes (Baringo and Bogoria) also declined in the former years (1988 – 2001) and increased in the latter years (2002 – 2006).

Figure 4.3 The gains and losses of each LULC class in percent shares of the total study area for intervals 1988–1995, 1995–2002, 2002–2009, and 2009–2016.

4.2.3 *Prosopis*-specific induced changes in other LULC classes

Land previously under *Vachellia tortilis* and grass (grasslands) was generally lost to *Prosopis* class between 1995 and 2002 (losses amounting to 22% and 12%, respectively), whereas the mixed vegetation area, bareland and irrigated cropland mostly got invaded by *Prosopis* between 2009 and 2016 (by 1.94%, 18% and 74%, respectively); Table 4.3, changes are visualized in Figure 4.4). Generally, *Prosopis colonization* of other LULC mostly occurred between 2009 and 2016, while the least invasion was observed between 1988 and 1995.

Cumulatively, over the 28-year period, *Prosopis* spread resulted in LULC losses of *Vachellia tortilis* by 3452 ha (-41%), grasslands by 2675 ha (-37%), bareland by 5351 ha (-36%), irrigated cropland by 373 ha (-25%), mixed vegetation by 6215 ha (-5%), and rainfed cropland by 129 ha (-3%). *Prosopis* class also gained from other LULC types, with the three largest donors being, in order of ranking, mixed vegetation which comprises mostly indigenous trees and shrubs, bareland and *Vachellia tortilis*, with a mean annual losses of 222 ha/a, 191 ha/a, and 123 ha/a, respectively. Grasslands and irrigated croplands, which are the basic livelihood sources for the agro-pastoral community were lost at a rate of 96 ha/a and 13 ha/a, respectively.

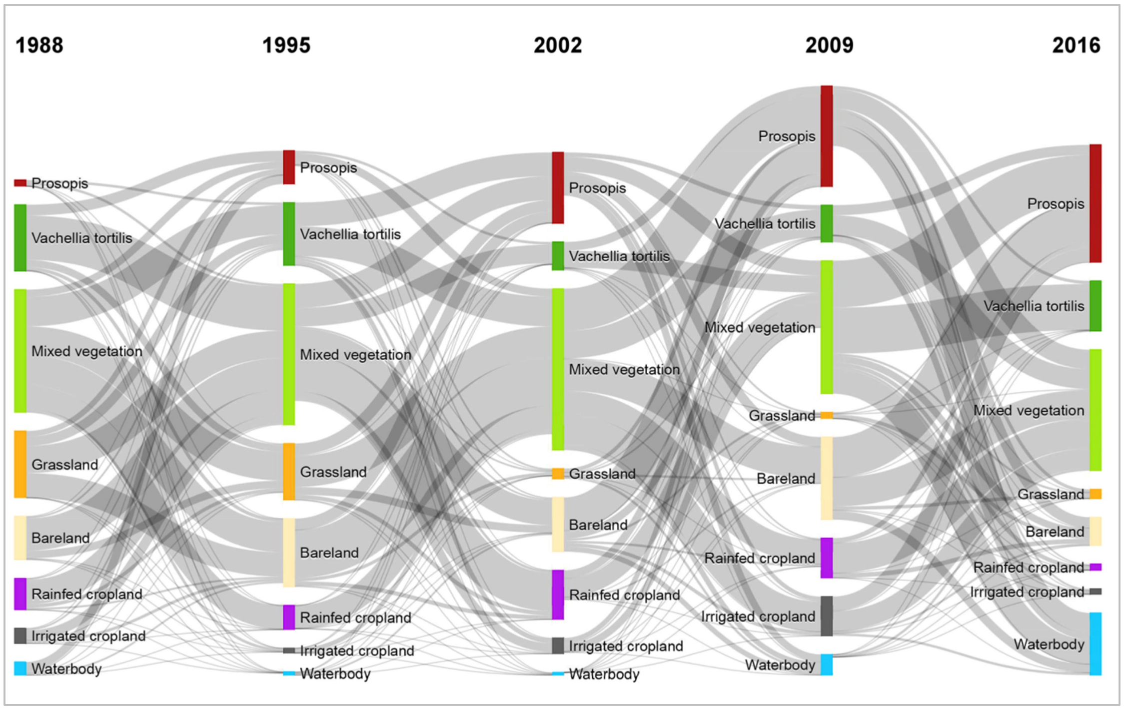


Figure 4.4 Sankey plot showing changes in area coverage from one LULC class to the other for all time steps between 1988 and 2016.

Table 4.3 The net change impact of *Prosopis* invasion on individual LULC for 1988–1995, 1995–2002, 2002–2009, 2009–2016, and 1988–2016.The numbers represent the time interval, V (*Vachellia tortilis*), P (*Prosopis*), M(Mixed vegetation), G (Grassland), B (Bareland), R (Rainfed cropland), I (Irrigated cropland), W(Water). For example, V88 – P95 =Vachellia 1988 – Prosopis 1995. The rows in bold represent the periods with the highest changes, the rows in italics the periods with lowest changes. The rows with border line represent the overall net changes associated with *Prosopis* invasion from 1988 to 2016.

Time Period	Losses to P (ha)	Gains from P (ha)	Net Change (ha)	% of Class area in 1988
V88-P95	984	235	-750	-8.8
V95-P02	**2146**	**237**	**-1909**	**-22.4**
V02-P09	*789*	*409*	*-381*	*-4.5*
V09-P16	913	281	-633	-7.4
V88-P16	3478	26	-3453	-40.5
M88-P95	*651*	*227*	*-424*	*-0.3*
M95-P02	2183	725	-1458	-1.1
M02-P09	**3837**	**1340**	**-2498**	**-1.9**
M09-P16	**4247**	**1753**	**-2494**	**-1.9**
M88-P16	6308	93	-6215	-4.8
G88-P95	510	82	-428	-5.9
G95-P02	**1042**	**163**	**-879**	**-12.2**
G02-P09	341	170	-171	-2.4
G09-P16	*126*	*285*	*159*	*2.2*
G88-P16	**2688**	**13**	**-2675**	**-37**
B88-P95	*50*	*5*	*-44*	*-0.3*
B95-P02	1009	124	-885	-5.9
B02-P09	2977	856	-2121	-14.1
B09-P16	**3644**	**974**	**-2670**	**-17.8**
B88-P16	5361	10	-5351	-35.7
R88-P95	*17*	*0.7*	*-17*	*-0.4*
R95-P02	5	16	11	0.3
R02-P09	**709**	**139**	**-571**	**-14.9**
R09-P16	423	136	-287	-7.5
R88-P16	131	3	-129	-3.4
I88-P95	*44*	*0*	*-44*	*-2.9*
I95-P02	7	58	51	3.4
I02-P09	456	368	-89	-5.9
I09-P16	**1287**	**173**	**-1115**	**-74.3**
I88-P16	378	5	-373	-24.9
W88-P95	*758*	*1*	*-757*	*-5.3*
W95-P02	44	84	40	0.3
W02-P09	0.1	637	636	4.4
W09-P16	**7**	**1822**	**1814**	**12.7**
W88-P16	10	295	285	2

4.2.4 *Prosopis* invasion impact on livelihoods

Prosopis invaded about 2948 ha of cropland between 1988 and 2016, of which 891 ha was cleared of *Prosopis* and converted back to cropland over the same period. *Prosopis* removal is done by individual land owners or labourers. Using the estimated *Prosopis* clearing labour costs (USD 265.61 per ha per annum) (Eschen et al., 2021), together with the land-use and land-cover changes and fractional cover data, the study found that this translated to a labour cost of about USD 236,658.51, over the period (1988 – 2016). The net loss of cropland to *Prosopis* as at 2016 was about 2057 ha, which would require a about USD 546,359.77 to restore to productive farmland. Equally, the invaded pastures (2675 ha) would require a budget of USD 710,506.75 to restore to grazing lands. This scenario compounds the livelihood situation of the already disenfranchised and vulnerable inhabitants in the invaded areas of Baringo as well as other invaded lands in Kenya. Many households cannot meet the costs of managing these farmlands hence abandon them creating a further loss in livelihood.

4.3 Discussion

4.3.1 Spatial evolution of *Prosopis* invasion in Baringo

It is a well-known fact that *Prosopis* is a notorious invader and currently also branded as an ecosystem engineer (Ayanu et al., 2015; Shackleton et al., 2014) due to its ability to colonize and dominate diverse landscapes, particularly drylands (Maundu et al., 2009). However, there are significant gaps in understanding its spread rates in the affected regions and the implications on other LULC types in those regions. This study analysed the development of *Prosopis* and the concomitant changes in the LULC types present in the invaded regions in time and space using multi-temporal and multi-spectral Landsat satellites imagery. These data were supplemented by validation of LULC distribution maps with historical information available on Google Earth imagery service (Google Earth Pro, 1987) and local expert knowledge. The Random Forest classifier produced reasonably good estimations with reliable accuracies which has also been reported in other studies (Immitzer et al., 2018; Li et al., 2013, 2017; Ng et al., 2017; Reynolds et al., 2016). This provides baseline information for use as reference for long-term monitoring of *Prosopis* spread. This study covered the entire *Prosopis* invasion history, and used rigorous methods to analyse its spatio-temporal *spread* and change dynamics. The gap filled by this study is how these invasion dynamics have influenced LULC changes in the study area. This information was previously lacking but has now been filled using the findings from this study (Mbaabu et al., 2019). The use of seasonality data, particularly the dry season information was imperative to accurately separate *Prosopis* from the other co-existing vegetation and other LULC categories. However, it should be noted that this study was limited by inaccessibility to the eastern areas of Lake Baringo. The area prone to inter-ethnic conflicts and violence (Relief Web, 2017), and at the time of field data collection, access to this zone was restricted for security reasons. Therefore, ground verification (groundtruthing) was missed out for that particular zone.

A closer look at the densely invaded region (overlaid with original *Prosopis* plantations) further shows how combining multi-temporal Landsat satellite imagery and using Random Forest classifier enabled the identification and and visualization invasion processes at various scales (Figure 4.5). Both spatial and temporal patterns observed at the case study level and at smaller scales show that initially, *Prosopis* dispersed away from original plantations mainly along roads and around waterbodies or lakeshores. This shows agreement with results from Afar region in Ethiopia, where road networks and waterbodies were identified as important drivers of *Prosopis* spread (Shiferaw et al., 2019c). Then, *Prosopis* progressively moved to areas away from waterbodies, especially areas that are usually under *Vachellia tortilis* cover, grasslands, and mixed vegetation.

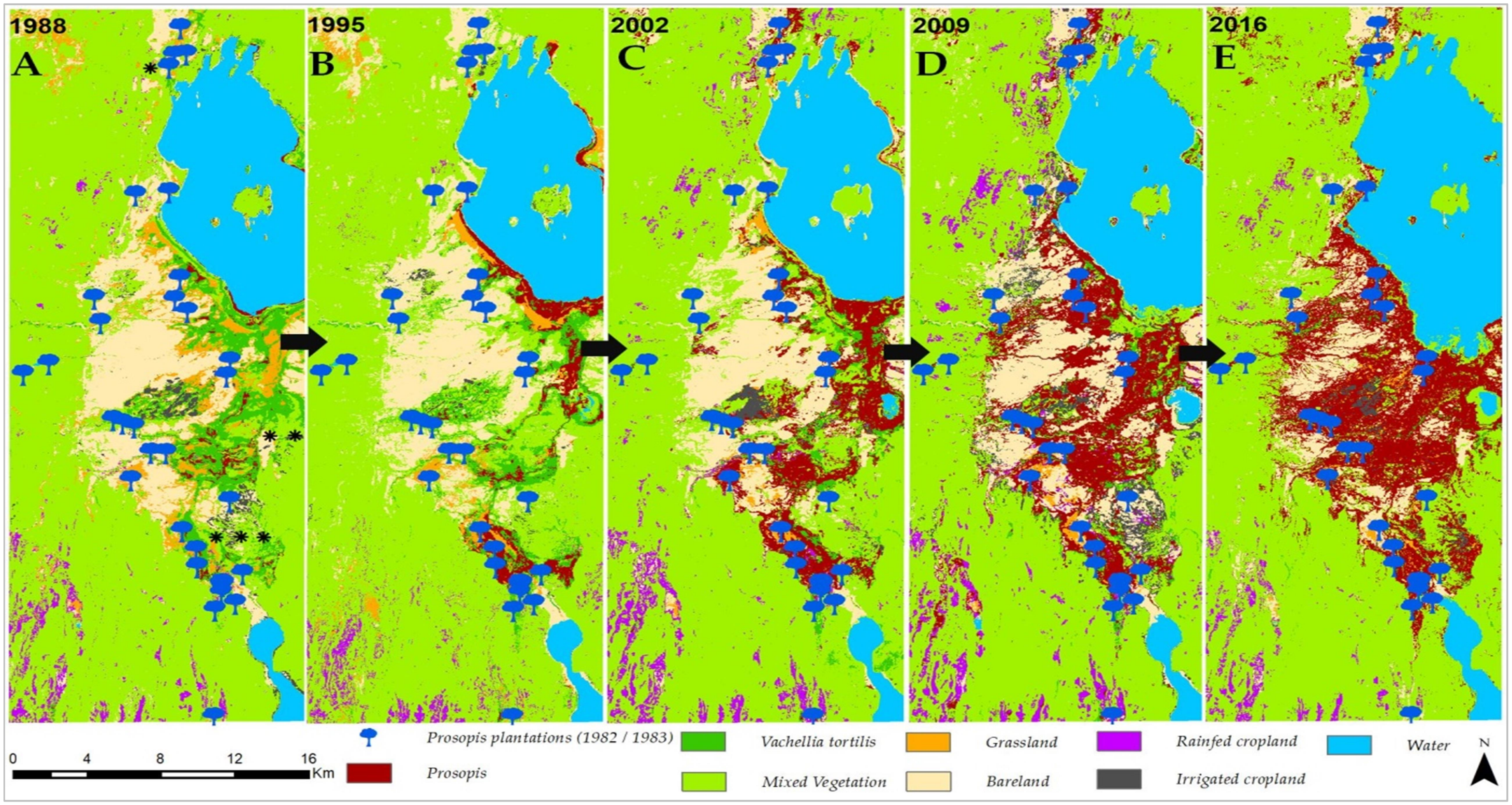


Figure 4.5 The spatial spread pattern of *Prosopis* from initial plantations in 1982 and 1983: the blue trees symbolize the initial plantations; *Prosopis* covered areas are in deep red. The sequence of LULC distribution maps visualizing a zoom view south of Lake Baringo shows the gradual increase in area under *Prosopis* cover and a general decline in most of the other LULC classes, especially grassland and *Vachellia tortilis* over time (A-E). Locations Loruk*, Logumgum** and Sandai*** are marked with a symbol in the 1988 map.

4.3.2 Spatio-temporal changes in *Prosopis* coverage

Between 1982 and 1983, *Prosopis* species were introduced in about 31 sites (Andersson, 2005) in Marigat sub-region of Baringo to rehabilitate the heavily degraded dryland and to alleviate firewood shortage (Choge and Pasiecznik, 2005; Kariuki, 1993; Maundu et al., 2009). These plantations were established along rivers, grazing areas and in irrigation schemes in order to increase their survival rate owing to the harsh climatic conditions. These zones would later become vulnerable to the invading *Prosopis* because they were zones of convergence for both animal-dispersed and waterborne seeds, as well more conducive for tree growth (Robinson et al., 2008). This study revealed a total *Prosopis* invaded area of 882 ha by 1988, which is comparable to the findings by Mwangi and Swallow (2005), who reported 739.5 ha of invaded land by 1990). *Prosopis* was estimated to increase in coverage at an annual rate of 640 ha, which is within range reported by Kyuma et al. (2016), who estimated *Prosopis* annual spread rate of around 532 ha on hillslopes and 13 to 1309 ha in the floodplains in Kajiado County, Kenya. The observed invasion distribution pattern in this study also compares with the pattern of *Prosopis* mapping conducted by Ng et al. (2017), who used higher resolution satellite imagery from Sentinel-2 and Pléiades sensors, to map *Prosopis* distribution in the same area. These findings therefore confirm that *Prosopis* is a notorious invader, which show agreement with findings from other studies in Africa (Babiker, n.d.; Meroni et al., 2017; Ndhlovu et al., 2016; Shiferaw et al., 2019c; Wakie et al., 2016). Further, these results suggest that *Prosopis* invasion is progressive and follows a regular and gradual pattern of expansion. The observed low rate of *Prosopis* expansion between 1988 and 1995 can be explained by the fact that these were the preliminary years of *Prosopis* growth, and probably not many trees had matured and produced seeds for propagation or dispersal by agents such as livestock.

4.3.3 LULC changes in the study area between 1988 and 2016

The Njemps Flats is a classic example of anecosystem undergoing exceptional changes in LULC in the recent decades (Kiage et al., 2007). It was observed that while the alien *Prosopis* coverage increased more than 20 times its coverage in 1988, LULC representing native vegetation and farmlands declined, each by over 40% of their 1988 areal estimate. This has significantly hurt the livelihood support system of the local communities such as grasslands and croplands, at an unprecedented velocity. The findings from this study uphold those of Kiage et al. (2007), on LULC changes in the same study area (around Lake Baringo) using Landsat imagery. They reported that the area under forest (which corresponds to *Vachellia tortilis* in this study), declined by 40% between 1986 and 2000. This study shows that

Prosopis encroachment took over 30% of land area that was previously under other LULC. However, besides *Prosopis* colonization, anthropogenic activities such as overgrazing, deforestation, together with human-induced climatic changes have also likely led to the LULC change dynamics observed in Baringo. Nevertheless, *Prosopis* is seemingly more ecologically adaptive than the native species (Muthana and Arora, 1983), owing to its deep root system, massive seed production and ability to survive even on nutrient-poor soils (very degraded land). Additionally, *Prosopis* severely constrains the survival of native plant species most likely due to allelopathy or competition for water, nutrients and space (Schachtschneider and February, 2013).

Over the last century, Njemps Flats has undergone marked land degradation and the observed increase in barenland from 1988 to 1995 may be treated as a continuity of this phenomena. This corroborates the findings by Kiage et al. (2007) who observed that denuded spaces increased on Lake Baringo shores between 1986 and 2000. An exacerbation of land condition in the study area was likely caused by multiple and interlinked factors such as human population growth, and consequently increases in livestock activity as pastoralism is the primary source of income for the local community (goats and donkeys increased while cattle and sheep reduced due to bush encroachment which favored browsers than grazers) (Setey, 2020) . Moreover, Baringo County experienced extremely low levels of precipitation between 1978 and 1996 (approx. annual average = 51.7 mm) which may have led to further increases in bareland.

Prosopis management by utilization (using *Prosopis* for charcoal and use of *Prosopis* pods as livestock feed) was introduced in Baringo in 2007. The findings from this study have shown that this approach has not succeeded in curtailing *Prosopis* progression. Instead, utilization leads to coppicing of several *Prosopis* stems from the originally cut mother stem, which creates impenetrable thickets and fuels further *Prosopis* spread through multiplied seed production from the coppiced trees. On the basis of successful and long-term *Prosopi*s management observed in Australia, this study proposes that effective and sustainable management of *Prosopis* in Baringo can be realized through a combination of different management methods such as mechanical, biological and chemical. Additionally, regular monitoring or surveillance of invasion risk areas and early removal of any observed *Prosopis* populations at the invasion front should be urgently considered (Shackleton et al., 2014).

4.4 Summary

By the year 2016, *Prosopis* had colonized 18,792 ha of land in Marigat. This invasion was reached through a spread rate of about 640 ha/yr between 1988 and 2016. Over the same period, the land covered by all the other LULC classes reduced, by over 40% each, of its original spatial extent in 1988. Therefore, *Prosopis* has become an additional driver of the ongoing LULC changes in Baringo, which has serious consequences on provisioning of important ecosystem services, and biodiversity. Due to the invasion of farmlands (2948 ha) and pastures (2675 ha), rural livelihoods have been grossly affected leading to food shortages, poverty, livestock deaths and high costs of clearing *Prosopis* which are additional livelihoods strains to the affected communities. These results are important in that they provide evidence upon which decisions on effective and stustainable management of *Prosopis* can be based.

At the height of *Prosopis* invasion in 2007 (Kenya Law, 2007; Little, 2019), coupled with no managenent interventions in sight, some stakeholders argued that these species could be managed / utilized for climate change mitigation. The next chapter presents findings that give insights into the soundness, feasibility and sustainability of this.

CHAPTER 5: COMPARISON OF THE IMPACT OF *PROSOPIS* INVASION VERSUS GRASSLAND RESTORATION ON CLIMATE CHANGE MITIGATION, PLANT SPECIES RICHNESS AND OTHER ECOSYSTEM SERVICES

5.1 Introduction

In this chapter, soil organic carbon stocks to one meter belowground, plant species richness, dry herbaceous biomass and key ecosystem indicator species were estimated from field measurements in five land-cover types. The variations in these parameters across the five land-cover types are analyzed and discussed.

5.2 Results

5.2.1 Soil sample characteristics per land-cover type

Soil organic carbon stocks, plant species richness and dry herbaceous biomass were compared across the five land-cover types. Further indicator species that characterize each land-cover were also analysed. Age, vegetation cover and the parameters measured in each land-cover are described in Table 5.1.

Soil Bulk density

Soil bulk density was also strongly influenced by land-cover type ($F_{4, 58} = 5.106$, $p = 0.0014$). It was highest in pristine grasslands, intermediate in restored and degraded grasslands and lowest in *Prosopis* invaded plots (Table 5.1). However, the effect of soil depth on bulk density was not consistent ($F_{3, 174} = 1.549$, $p = 0.2036$), but varied among land-cover types (with interaction effect: $F_{12, 174} = 2.482$, $p = 0.0051$; appendix 5.5). While bulk density in pristine grasslands increased with increase in soil depth, it declined or showed no consistent trend in the other land cover types (appendix 5.5).

5.2.1 Effect of soil depth and land-cover type on SOC concentration and SOC per volume

The linear mixed effect model analysis revealed that SOC concentration (i.e. %SOC) and SOC per volume of soil (expressed in g/cm^3) were significantly affected by soil depth (%SOC:$F_{3,174}$ =36.63, $p < 0.001$; and SOC per volume: $F_{3,174}$ =37.80, $p < 0.0001$) and land-cover type (%SOC: $F_{4,58}$ =4.82, $P = 0.002$; SOC per volume: $F_{4,58} = 6.15$, $P = 0.003$) (Figure 5.1 and appendix 5.1). Furthermore, the differences in %SOC and SOC per volume across land-cover types were also influenced by soil depth (interaction effect %SOC: $F_{12, 174} = 2.2609$, $p = 0.011$; interaction effect SOC per volume: $F_{12, 174} = 1.981$, $p = 0.0285$; (appendix 5.2 and 5.3). The effect of land-cover type on %SOC and SOC per volume was stronger in surface soils (0-30 cm: $F_{4, 58} = 7.718$, $p < 0.0001$) than in deeper soil layers (31-100 cm: $F_{4, 58}$

= 3.152, p = 0.0206). The highest values for %SOC and SOC per volume in the top layer were recorded in pristine grasslands and *Prosopis*-high land-cover types, while at higher soil depths, the highest values were observed in restored and pristine grassland (appendix 5.2 and 5.3). Both %SOC and SOC per volume diminished with increasing soil depth down to 1 m **(**appendix 5.1 and 5.4). Greatest declines in %SOC and SOC per volume across depth were recorded in *Prosopis*-high and pristine grasslands by 62%; 62% and 54%; 49%, respectively, while the smallest declines occurred in degraded and restored grasslands (26%; 30% and 30%; 33%, respectively). Overall, surface soils (0-15 cm) had the largest variation in %SOC and SOC per volume across land-cover types.

5.2.2 Total Soil Organic Carbon Stock

Total SOC stock to 1 m depth was strongly affected by land-cover type ($F_{4,\ 58} = 5.532,\ p < 0.0001$), with pristine grasslands having the highest total SOC stock (49.76±2.28 t C ha^{-1}), followed by restored grasslands (44.68 ±3.77 t C ha^{-1}), high *Prosopis* densities (40.05 ±1.28 t C ha^{-1}), low *Prosopis* densities (36.99 ±2.51 t C ha^{-1}) and degraded grasslands (31.52±3.04 t C ha^{-1}) (Figure 5.2A). Moreover, the total SOC in degraded grassland was significantly lower than in pristine (-37%) and restored grasslands (-29%), while total SOC recorded in both low and high *Prosopis* cover densities did not differ from any of the other land-cover types (appendix 5.6).

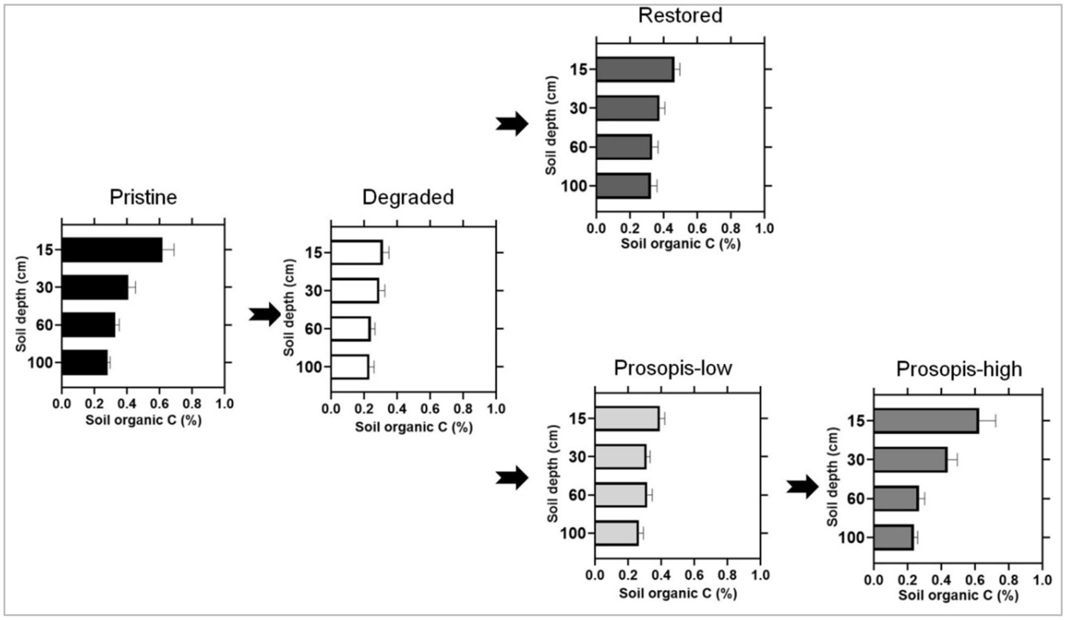


Figure 5.1 Soil organic carbon concentration (%SOC) measured for the five land-cover types and four soil depth increments. Error bars represent standard errors. "*Prosopis*-low" and "*Prosopis*-high" means ≤ 30% and ≥ 80% *Prosopis* fractional cover, respectively. The arrows are used hypothetically and represent conversion from one land-cover state to the next over time.

Table 5.1 Sampling sites attributes and mean (Standard Error) of the various parameters per land-cover type. The land-cover types sharing a letter are not significantly different at $\boldsymbol{\alpha} = 0.05$. Age estimations were done using a combination of information sources and criteria such as literature review (Anderson, 2016; Kiage and Liu, 2009; Little, 1992), time series maps for the study area – outputs from objective 1 (Mbaabu et al., 2019), and consultations with key informants (*already listed in section 3.2.1.1*). Vegetation cover was estimated using *Prosopis* fractional cover map for *Prosopis* plots, together with LULC maps and field observations for the other land-cover types.

Land-cover	**Age (years)**	**Vegetation cover (%)**	**n**	**% SOC 0-100 cm**	**Bulk density (g cm^{-3})**	**SOC per volume (g cm^{-3})**	**Total SOC t ha^{-1} 0-100 cm**	**Species Richness /225 m^{2}**	**Herb. Biomass (g m^{-2})**
Pristine	> 70	> 80	10	0.091 (0.005)	1.37 (0.02)	0.0053 (0.0006)	49.76 (2.28) *c*	18.30 (0.58) *c*	1281.7 (213.01) *b*
Degraded	> 70	< 5	16	0.064 (0.005)	1.26 (0.03)	0.0031 (0.0003)	31.52 (3.04) *a*	8.62 (1.19) *a*	147.3 (42.92) *a*
Prosopis-low	10 - 15	< 30	12	0.077 (0.005)	1.21 (0.02)	0.0037 (0.0004)	36.99 (2.51) *ab*	12.67 (1.03) *bc*	59.9 (16.88) *a*
Prosopis-high	25 - 35	> 80	10	0.083 (0.006)	1.20 (0.03)	0.0043 (0.0005)	40.05 (1.28) *abc*	9.40 (0.95) *ab*	5.7 (1.20) *a*
Restored	25 - 35	> 80	15	0.089 (0.006)	1.26 (0.02)	0.0044 (0.0004)	44.68 (3.77) *bc*	9.40 (1.37) *ab*	678.0 (85.36) *b*

5.2.3 Plant species richness and land cover-specific indicator species

In total of 81 different plant species were observed from the 63 sampling plots representing the five land-cover types. Plant species richness per plot significantly varied among the five land-cover types ($F_{4, 58} = 8.656$, $p < 0.0001$). It was nearly twice as high in pristine grasslands than in degraded grasslands (Table 5.1; Figure 5.2B). Plant species richness was lower in degraded grassland than in pristine grasslands and low density *Prosopis* areas, but did not vary from high density *Prosopis* and restored areas. Plant species richness in low density *Prosopis* areas did not also vary from that recorded in pristine grasslands (appendix 5.7). Four indicator species typical of three dominant land-cover types in the study area were identified: *Portulaca oleracea* (degraded grassland), *Cynodon dactylon* and *Waltheria indica* (pristine grasslands), and *Cenchrus ciliaris* (restored grasslands) (Table 5.2). There were no plant species associated with (characteristic) of *Prosopis* invaded areas.

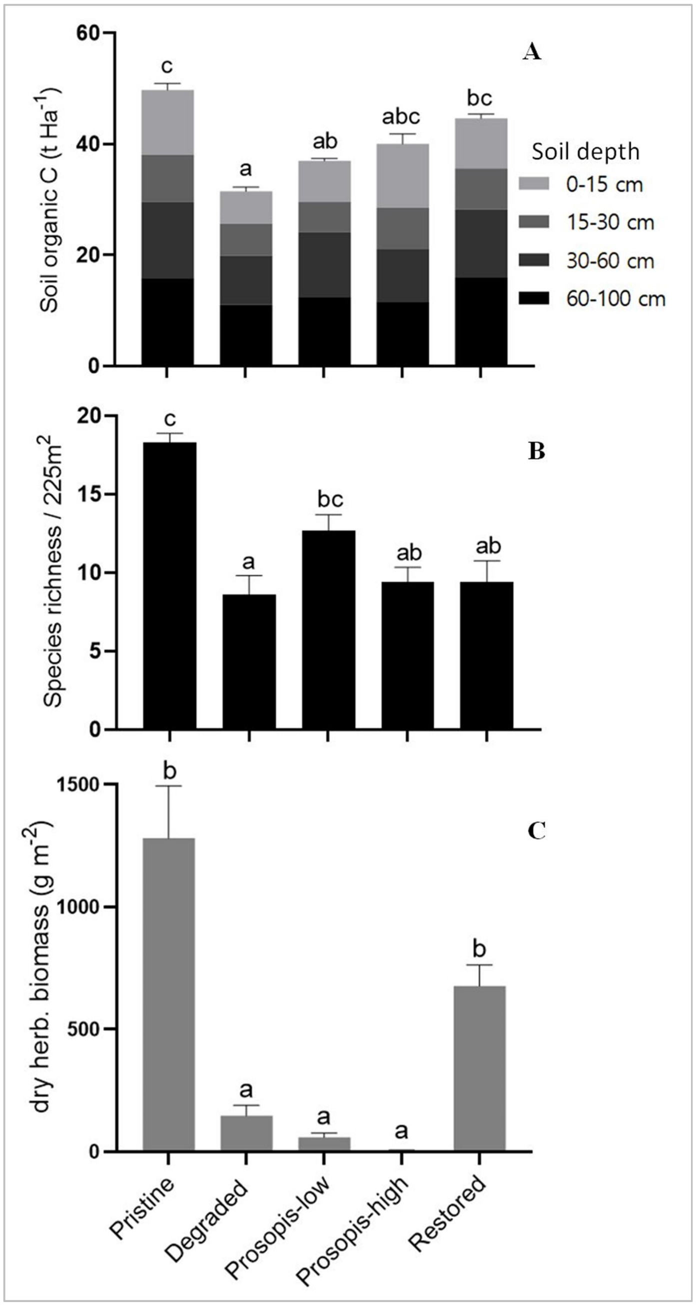


Figure 5.2 A-C Estimated Total soil organic carbon in tonnes per hectare at four soil depth increments from surface to 1 m below ground (A), species richness per plot (225 m^2) (B) and weight of dry herbaceous vegetation g m^{-2} (C), shown for the five land-cover types. The error bars indicate standard errors. The land-cover types sharing a letter are not significantly different at α = 0.05. Land-cover types with a combination of letters e.g. abc means that the value of the parameter in that land-cover type is not significantly different from the other categories with a combination of letters of individual letters that make the group. That is "abc" is not significantly different from "a", "b", "c", "ab", "ac", and "bc".

Table 5.2 Indicator species characteristic of three land-cover types, indicator value and number of plots containing species in the five land-cover types. Significance level ($\alpha = 0.05$).

					Number of plots containing species				
Indicator species	Lifeform	Land-cover	Indicator value	*p-value*	Pristine	Degraded	*Prosopis*-low	*Prosopis*-high	Restored
Portulaca oleracea	Annual	Degraded	0.08	0.02	0	12	2	0	2
Cynodon dactylon	Perennial	Pristine	0.05	0.05	10	0	7	0	2
Waltheria indica	Perennial	Pristine	0.05	0.04	10	0	0	0	1
Cenchrus ciliaris	Perennial	Restored	0.09	0.03	3	7	3	0	14

5.2.4 Herbaceous biomass

Dry herbaceous biomass differed significantly among land-cover types ($F_{4,58} = 33.97$, $p < 0.0001$). It was almost six times higher in pristine grassland than in degraded or sparsely invaded areas, and over 200 times higher than in densely invaded areas (Figure 5.2C). Herbaceous biomass in pristine and restored grasslands did not substantially differ from each other (appendix 5.8).

5.3 Discussion

5.3.1 Soil Organic Carbon stocks at depth

Corroborating with results from similar studies assessing SOC (%SOC and SOC per volume) at different soil depths (Bhojvaid and Timmer, 1998; Jobbágy and Jackson, 2000; Torn et al., 1997), both variables declined with increase in soil depth across all the land-cover types. Most reductions in SOC per volume occurred from 0-15 to the 15-30 cm depths, similar to observations made by Torn et al. (1997) on the Hawaiian Islands. Nonetheless, with regard to total SOC per ha, our results corroborate other studies in grasslands that showed deeper soils can in fact store substantial amounts of SOC (Jobbágy and Jackson, 2000; Ward et al., 2016). For instance, 59.6% of the total SOC found in pristine grassland soils were stored between 30 and 100 cm depth. These values closely match with the findings by Lal et al. (2018), that globally, ~55% of the SOC to 1 m depth exists below 30 cm depth. Jobbágy & Jackson (2000) used global datasets of soil profiles and estimated that in grasslands, the amount of SOC stored in the second and third meters was 43% of that stored in the first meter. The significant storage of SOC in deeper soil layers across all the land-cover types considered in this study underscores the importance of estimating SOC from soil samples beyond the usual threshold of 30 cm belowground (Gross and Harrison, 2019; Ward et al., 2016).

5.3.2 Soil organic carbon across different land-cover types

The total SOC values estimated in this study for pristine and restored grasslands to 1 m depth (49.76 and 44.68 t C ha^{-1}, respectively) are slightly lower than those reported by Adams et al. (1990) for savanna, and scrub woodland biomes (54 and 60 t C ha^{-1}, respectively), but within the reported FAO-UNESCO soil unit range of 42 – 62 t C ha^{-1} estimated for Xerosols (Batjes, 1996). The SOC values of *Prosopis* invaded areas (both in low and high density areas) were within the range of estimated SOC values for low and dense *Prosopis* cover in the native range in Texas, USA (Geesing et al., 2000).

While long-term variation in organic carbon storage in soils is mostly determined by factors influencing soil formation, geology and climate, (Adams et al., 1990; Torn et al., 1997), changes in LULC are influential over shorter periods (Batjes, 1996; Lal, 2018). For instance, the total and vertical distribution of SOC is affected by plant functional groups with varying allocation of photosynthates to aboveground and belowground sections of plant parts and with different root structure (Batjes, 1996; Jobbágy and Jackson, 2000). The findings in this study show that degradation of native vegetation in Baringo landscape and the subsequent re-establishment of new vegetation have caused major fluctuations in total SOC stocks and SOC profiles to 1 m belowground. Foremost, total SOC stock in degraded grasslands was 37% lower than that estimated in pristine grasslands. This is substantially higher than that reported by Dlamini et al. (2014) in a worldwide review of degraded grasslands in arid and semi-arid regions (-16%). However, studies in South Africa reported losses of SOC stocks which were comparable or even higher than those reported in this study. Some of these studies include work by Dlamini et al. (2014) who reported 79% and 42% SOC losses in grasslands with <5% and <50% vegetation cover, respectively in KwaZulu-Natal Province, and Baer et al. (2015) who reported 56% SOC losses in the South African veld due to grasslands cultivation. In East Africa, Ritchie (2014) modeled the impact of grazing intensity on SOC storage in Serengeti National Park in Tanzania, and predicted that SOC values increase at moderate grazing intensities but then rapidly decline with high grazing intensities.

Notable differences in total SOC stocks were also observed between degraded and restored grasslands, where, 30 years of grassland restoration led to substantial increases in SOC in all soil depth increments. During COP21, the ‘4 per 1000 – Soils for Food Security and Climate’ initiative was launched to promote climate change mitigation through yearly increases in soil organic carbon by 0.4% in the top 30-40 cm of grasslands, farm lands, and forest soils (4p1000, 2018; Minasny et al., 2017). The difference between restored grasslands (3 decades old) and degraded grasslands in this study translates to about 1.4% ([SOC in restored grasslands – SOC in degraded grasslands]/years since restoration started) average increase in total SOC annually, in both the top 30 cm and in the top 100 cm, which is markedly above the set threshold value of 0.4% of the ‘4 per 1000’ initiative. The higher values of yearly increase in this study corroborate with the findings by Corbeels et al. (2019), that SOC accumulation rates under sustainable agriculture and systems under multiple strata agroforestry are in fact relatively higher than the set threshold value of 0.4%. In other African drylands, increases in SOC stocks after restoring degraded grasslands have also been recorded by Chaplot et al. (2016); 33% increase within two years of NPK fertilization and livestock exclosure in KwaZulu-Natal Province, South Africa) and by Oduor et al. (2018); 27% increase in 3 to >20 years old grassland exclosures in West Pokot, Kenya). Notably, 17 of the 20 countries globally with > 70% of grassland area are located in Sub-Saharan Africa (White et al., 2000) and almost 25% of the same region is categorized as ‘heavily degraded’ (Vågen et al., 2005). Therefore, sustainable grassland management is crucial for impactful

SOC buildup in SSA owing to the extensive areal coverage of this ecosystem as it potentially offers considerable climate change mitigation opportunities.

The *Prosopis*-low and the *Prosopis*-high density areas exhibited intermediate levels levels of total SOC stocks which neither of total SOC stocks which neither differed significantly from those of pristine nor restored grasslands nor those of degraded grasslands. SOC stocks present in pristine and restored grasslands tended to be even higher than those in *Prosopis* invaded sites. In part, this may be due to the fact that organic matter content in grassland soils is at least twice as high as in forests because grassland ecosystems add organic organic matter to top soil from both above-ground (from annual biomass decay) and roots (NRCS, 2014). Grass species *Cenchrus ciliaris* and*Cynodon dactylon*, which characterize restored and pristine grasslands, respectively, have deep root systems extending up to 200 cm into the soil profile (CRC Weed Management, 2008; Mnif and Chaieb, 2009). Specifically, *C. ciliaris*, the main grass species broadcasted in the Rehabilitation of Arid Environments Charitable Trust (RAE Trust) grassland restoration project, is reported to grow 60-100 cm long roots within 4-16 months after broadcasting (Mashau, 2010).

Previous studies in the pristine and in the invaded range revealed that the impact of invasion by woody species such as *Prosopis* on SOC stocks depends on the local context. A negative correlation between precipitation and changes in SOC content after grasslands were encroached by woody plants were reported by Jackson et al. (2002) and Mureva et al. (2018), where wetter sites lost and drier sites gained SOC. Because the overall losses of SOC at the wetter sites were large enough to offset increases in carbon from plant biomass, Jackson et al. (2002) suggested that assessments that are targeting and relying on carbon growth from woody plant invasions for balancing greenhouse gas emissions may be flawed. This study has demonstrated that the effect of *Prosopis* invasion on SOC stocks also depends on the ecological context. For instance, if *Prosopis* invades an already degraded site, then SOC increases are likely, particularly in the upper 30 cm of the soil. On the contrary, if *Prosopis* encroaches restored or pristine grasslands, it probaly will have no impact or potentially a negative effect on SOC stocks. *Prosopis* invasion into grasslands increases C stored in aboveground plant biomass, but C stocks in plant biomass in *Prosopis* invaded ecosystems is lower than the SOC pool in the upper 30 cm of the soil and considerably lower than the SOC pool down to 100 cm (Figure 5.2; appendix 5.9) (Birhane et al., 2017). Furthermore, C stocks in aboveground plant biomass are more exposed to losses from biomass harvesting, fire, and other site disturbances (Grace et al., 2006; Mwangi and Swallow, 2008), than soil C stocks. Notably, the sum of carbon values from both soils and plant biomass of plots under high Prosopis (*Prosopis*-high) cover densities was lower than that of pristine grasslands plots.

Prosopis invasion in an already degraded lands in Baringo added SOC mainly to the surface soil (the top 30 cm), which translates to about 65% and 55% of the total SOC in *Prosopis*-high and *Prosopis*-low density plots, respectively. This effect can be attributed to the fact that *Prosopis* trees present two unique rooting systems – the main taproot and a dense network of very extensive lateral roots (Heitschmidt et al., 1988). Mature *Prosopis* stands exhibit taproots that are associated with multiple small roots at depths of ~ 100 cm (Heitschmidt et al., 1988), while the lateral roots are mainly in the upper 30 cm of the soil profile (Yoda et al., 2012).

5.3.3 Grassland management to optimize carbon sequestration, biodiversity and ecosystem services

Grassland ecosystems provide numerous benefits to society, including agricultural production and indirect ecosystem services such as climate and water quality regulation, and plants for medicinal purposes and pollination services (White et al., 2000) among others. Fundamentally, grasslands are perhaps one of the most invaluable biomes for ecosystem service provision, yet also the most threatened by human activities and perturbations (Gibson, 2009). Globally, there is a continued loss in grasslands owing to land-use changes or degradation arising from unsustainable grazing or invasion by exotic species, which undermines their ability to provide ecosystem services and support biodiversity (Parr et al., 2014).

In Baringo County, multiple factors such as human population increases, unsustainable grazing management, land-use changes, and communal land onwership, have caused considerable degradation of grasslands, which is negatively affecting biodiversity and the provisioning of numerous ecosystem goods and services (Anderson, 1989; Anderson and Bollig, 2016; Johansson and Svensson, 2002). *Prosopis* species continue to spread into valuable land in Baringo and other similar regions in SSA (Shiferaw et al., 2019a), especially in croplands and protected areas. Recent research has shown that in both Baringo, Kenya and Afar Region of Ethiopia, > 30% of the grasslands that were present about 40 years ago, have been colonized by *Prosopis* (Mbaabu et al., 2019; Shiferaw et al., 2019c).

Sustainable land use in Baringo, and other similar and threatened landscapes in Sub-Saharan Africa, to restore multiple functioning of the ecosystem (Manning et al., 2018), while also meeting the needs of diverse stakeholders dependent on them remains a challenge. This is because, there are potential trade-offs between certain ecosystem services and biodiversity, or among ecosystem services. Carbon sequestration programs that promote afforestation in tropical grasslands and savannas cannot be assumed to offer net benefits for conservation or for provision of ecosystem multifunctionality (Chisholm, 2010; Dickie et al., 2014). For instance, Abreu et al. (2017) demonstrated that fire suppression in savannas of the Brazilian Cerrado increased carbon stocks but was also associated with severe losses in biodiversity. Similarly, *Prosopis* invasion into degraded grasslands in Baringo has increased carbon stocks and provided wood, but simultaneously suppressed biodiversity across multiple trophic ecosystem levels (Linders et al., 2019), and increased mosquito densities (Muller et al., 2017). It also reduces pasture for livestock (Linders et al., 2020), water (Dzikiti et al., 2013; Le Maitre et al., 2020), adversely affects tourism (Shackleton et al., 2014) and limits access to water, croplands, pastures, and fishing points (Weber, 2003). High consumption of water by *Prosopis* in arid and semi-arid regions is an issue of great concern, as it reduces groundwater recharge, thus negatively affecting household water availability in the invaded ecosystems (Dzikiti et al., 2013).

The findings from this study show that SOC stocks replenishment through restoring degraded grasslands is achievable within a period of about 20–30 years and does not compromise the existence of biodiversity or provision of ecosystem services. Additionally, restoration of grasslands also increased fodder to almost the level of pristine grasslands, a key ecosystem service for the livestock-dependent livelihoods of millions of pastoralists occupying grasslands in SSA. These results also agree with the results by Mureithi et al. (2016), that restored grasslands in Baringo, which were managed as communal enclosures, provide household income through livestock sales, harvested hay and grass seeds. Moreover, and in contrast to *Prosopis* encroachment, grasslands restoration does not interfere with ground water availability or water access (Dzikiti et al., 2013; Le Maitre et al., 2020), thus, grassland restoration does not aggravate climate change effects in these ecosystems.

In Baringo, three decades of grassland restoration was insufficienct for restoring plant diversity. Partly, this may be due to the long-standing land degradation witnessed in the study area (Kimosop et al., 2007) and a probable depletion of the soil seed bank due to denudation.

In the Afar Region of Ethiopia, experiments targeting grassland restoration on *Prosopis* cleared land resulted in re-establishment of species-rich communities within the short term (Megersa, unpubl. results). *Prosopis*-low density plots tended to have higher species richness than degraded, restored and areas with high *Prosopis* invasion. This is because, at low *Prosopi*s densities, *Prosopis* trees may provide shade for seasonal plants to grow underneath their canopies. However, annual plants do not provide the same ecosystem service as perennial plants such as *Cenchrus ciliaris*, because they do not build up extensive below-ground biomass, while their above-ground biomass dries up when the rains recede. Moreover, the velocity at which *Prosopis* proliferates rapidly generates high cover densities which suppress the understory vegetation. Species richness in *Prosopis*-invaded habitats significantly diminishes once *Prosopis* has reached cover densities of ~ 50% (Linders et al., 2019). This has been linked to competitive exclusion of the slow-growing shade-intolerant herbaceous savanna species by *Prosopis* species, either due to its allelopathic effects of *Prosopis* or through competition for water and nutrients (Hoffmann et al., 2012).

5.4 Summary

The findings show that restoration of degraded grasslands in the semi-arid regions of Baringo County, Kenya, is at least as effective as encroachment by the invasive *Prosopis* tree in replenishing SOC pool. Grassland restoration for thirty years increased SOC pool to almost the level of pristine grasslands. Additionally, and in contrast to woody alien *Prosopis* encroachment, grassland restoration also promoted fodder for livestock production, thus avoiding carbon-fodder trade-offs. However, recovery of plant biodiversity requires more time and/or promotion of grassland management interventions which also target restoration of the characteristic biodiversity. These findings signify the need to incorporate relevant evidence in decision-making and that use of native species should be given priority during restoration of degraded landscapes.

Further, following from the findings in objective one where *Prosopis* invasion led to significant loss of valuable native biodiversity (*Vachellia tortilis*), the modeled impacts of climate change on the current and future habitat of *Prosopis* and its associated impacts on *Vachellia tortilis* habitat are presented in the subsequent chapter 6.

CHAPTER 6: MODELING THE IMPACT OF CLIMATE CHANGE ON SUITABLE HABITAT FOR *PROSOPIS* AND *VACHELLIA TORTILIS*

6.1 Introduction

In this chapter, suitable / unsuitable habitat for *Prosopis* and *Vachellia tortilis* were modelled under different climate change scenarios using SDM approaches and a suite of climate change models. The analysis covered a much larger area (study extent covers 18 counties) than the focus in objective one and two (Baringo County and Marigat Sub-County, respectively) (see section 3.1.1). The suitable habitat for both species were analyzed, compared and discussed.

6.2 Results

6.2.1 Predictive performance of individual SDMs on species occurrences

The predictive performance on the two species occurrences were compared between climate models trained with presence and pseudo-absence response data by applying two species modeling algorithms. The two SDM algorithms showed prowess in their ability to predict suitable / unsuitable habitats for both species in the current and future climate, with reasonable accuracies (Table 6.1). With the two considered model performance evaluation metrics (TSS and AUC), model performance did not seem to vary either between the species, climate scenarios or time. TSS ranged between 0.53 and 0.59 for *Prosopis* (AUC: 0.98 and 0.99) and between 0.52 and 0.61 for *Vachellia tortilis* (AUC: 0.98 to 1.000). Notable variations in model performance between the two SDM algorithms were observed where; RF model predictions had higher TSS scores than BRT. Conversely, BRT predictions had slightly higher AUC scores than RF. Because of this, ensemble models were then generated from the two predictions (RF and BRT) for current and future climate for each species (see schematic diagram Figure 3.8). Furthermore, use of ensembles (an aggregation of more than one model) is highly recommended in species distribution studies (Rew et al., 2021), as this produces more reliable estimates. Therefore, for brevity, only ensemble results are further presented and discussed in this study.

Table 6.1 Model prediction accuracies (AUC and TSS) for *Prosopis* and *Vachellia tortilis* presented for BRT (left) and RF (right) SDM algorithms, under current and future climate scenarios. The grayed out columns indicate information that applies to both (left and right) extremes of the table.

BRT SDM algorithm predictions							**RF SDM algorithm predictions**		
Accuracy		**Output**	**Climate scenario**	**Climate data (Model)**	**Year**	**Species**	**Output**	**Accuracy**	
AUC	**TSS**							**AUC**	**TSS**
0.998	0.532	Prediction1.tif	Current	WorldClim	1970-2000	*Prosopis*	Prediction7.tif	0.988	0.593
0.998	0.527	Prediction2.tif	Current	Bioclims-Uni-Bern	1970-2000	*Prosopis*	Prediction8.tif	0.989	0.589
0.999	0.533	Prediction3.tif	Future RCP8.5	MPI-ESM-LR	2041-2060	*Prosopis*	Prediction9.tif	0.991	0.586
0.998	0.537	Prediction4.tif	Future RCP8.5	CNRM-CM5	2041-2060	*Prosopis*	Prediction10.tif	0.991	0.589
0.999	0.532	Prediction5.tif	Future RCP8.5	INMCM4	2041-2060	*Prosopis*	Prediction11.tif	0.991	0.593
0.998	0.532	Prediction6.tif	Future RCP8.5	Uni-Bern	2071-2100	*Prosopis*	Prediction12.tif	0.990	0.591
1.000	0.522	Prediction13.tif	Current	WorldClim	1970-2000	*Vachellia tortilis*	Prediction19.tif	0.982	0.584
1.000	0.531	Prediction14.tif	Current	Bioclims-Uni-Bern	1970-2000	*Vachellia tortilis*	Prediction20.tif	0.981	0.598
1.000	0.543	Prediction15.tif	Future RCP8.5	MPI-ESM-LR	2041-2060	*Vachellia tortilis*	Prediction21.tif	0.995	0.607
0.999	0.532	Prediction16.tif	Future RCP8.5	CNRM-CM5	2041-2060	*Vachellia tortilis*	Prediction22.tif	0.997	0.609
1.000	0.533	Prediction17.tif	Future RCP8.5	INMCM4	2041-2060	*Vachellia tortilis*	Prediction23.tif	0.991	0.606
0.999	0.519	Prediction18.tif	Future RCP8.5	Uni-Bern	2071-2100	*Vachellia tortilis*	Prediction24.tif	0.989	0.601

6.2.2 Suitable habitat assessment under current and future climate change scenarios

The current and future predicted suitable (green areas) / unsuitable (gray areas) habitats are displayed for the various models for both species (Figure 6.1A and 6.1B). Visually, all the models (maps) show consistencies in the spatial distribution pattern of predicted suitable habitat for both species, the areal variations across time and models notwithstanding. Notably, current predictions for *Vachellia tortilis* appeared to be more spatially knit with Uni-Bern data as opposed to the more noisy distribution with the WorldClim data (see also Figure 6.2A and B).

In the current climate, predictions with the WorldClim data estimate a higher potential suitable habitat for both *Prosopis* and *Vachellia tortilis,* respectively (863,703 ha and 1,641,856 ha) than predictions with the Uni-Bern data (693,739 ha and 1,363,908 ha) (Table 6.2). In the future climate, potential suitable areas for *Prosopis* growth were highest with the CNRM model at 933,012 ha and lowest with the Uni-Bern model at 703,307 ha. However, for *Vachellia tortilis*, MPI model predicted the highest potential suitable areas at 2,066,531 ha while the lowest predictions were observed with the Uni-Bern model at 1,142,924 ha.

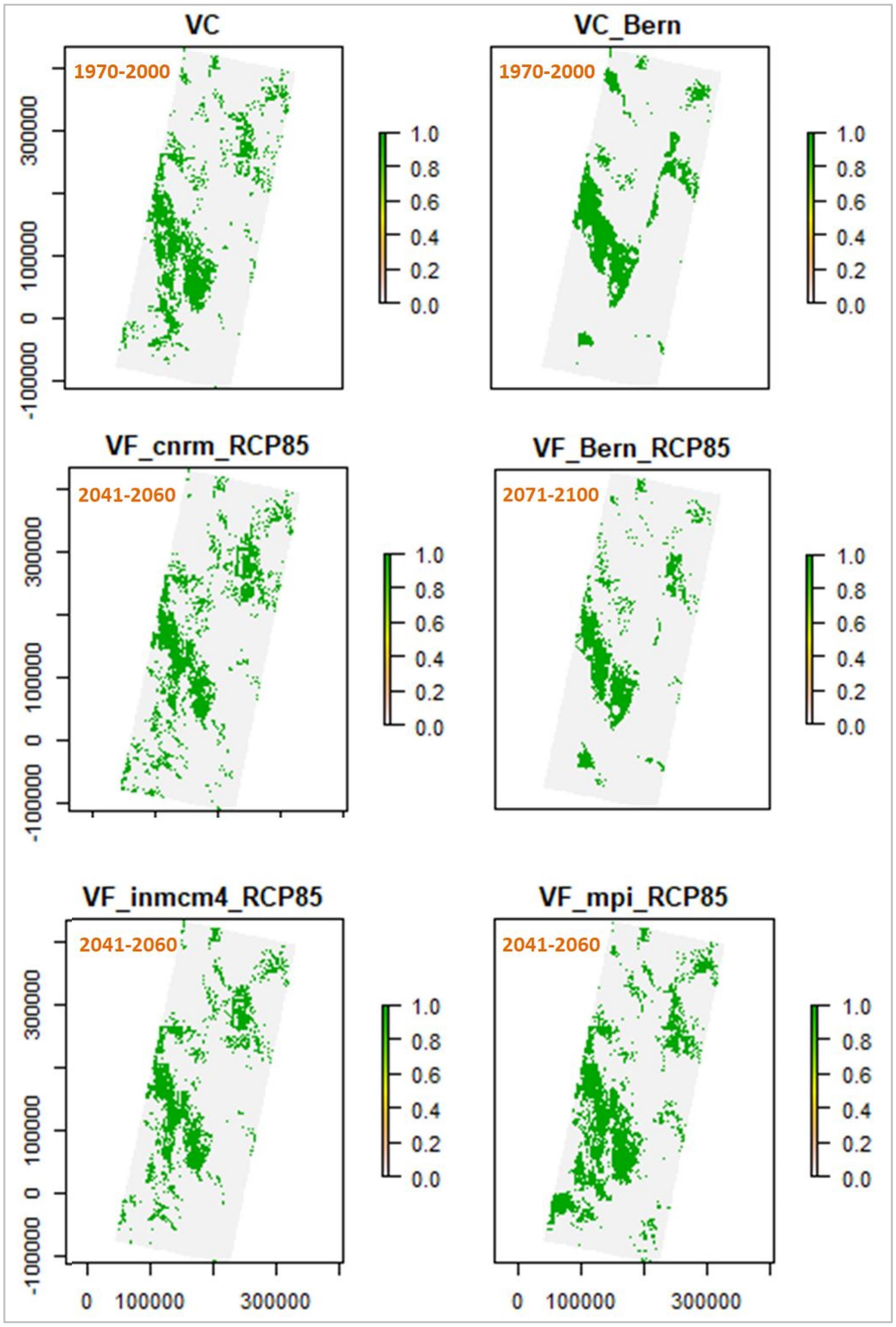


Figure 6.1A Ensemble binary predictions for the potential suitable habitat for *Vachellia tortilis* under the current and future climate. Ensembles were generated from the respective BRT and RF predictions. VC and VC_Bern = *Vachellia tortilis* suitable habitat under current climate using WorldClim and Uni-Bern data, respectively; VF = *Vachellia tortilis* suitable habitat under future climate using WorldClim and Uni-Bern datasets for the models indicated and RCP85. Maps are projected to UTM Zone 37N.

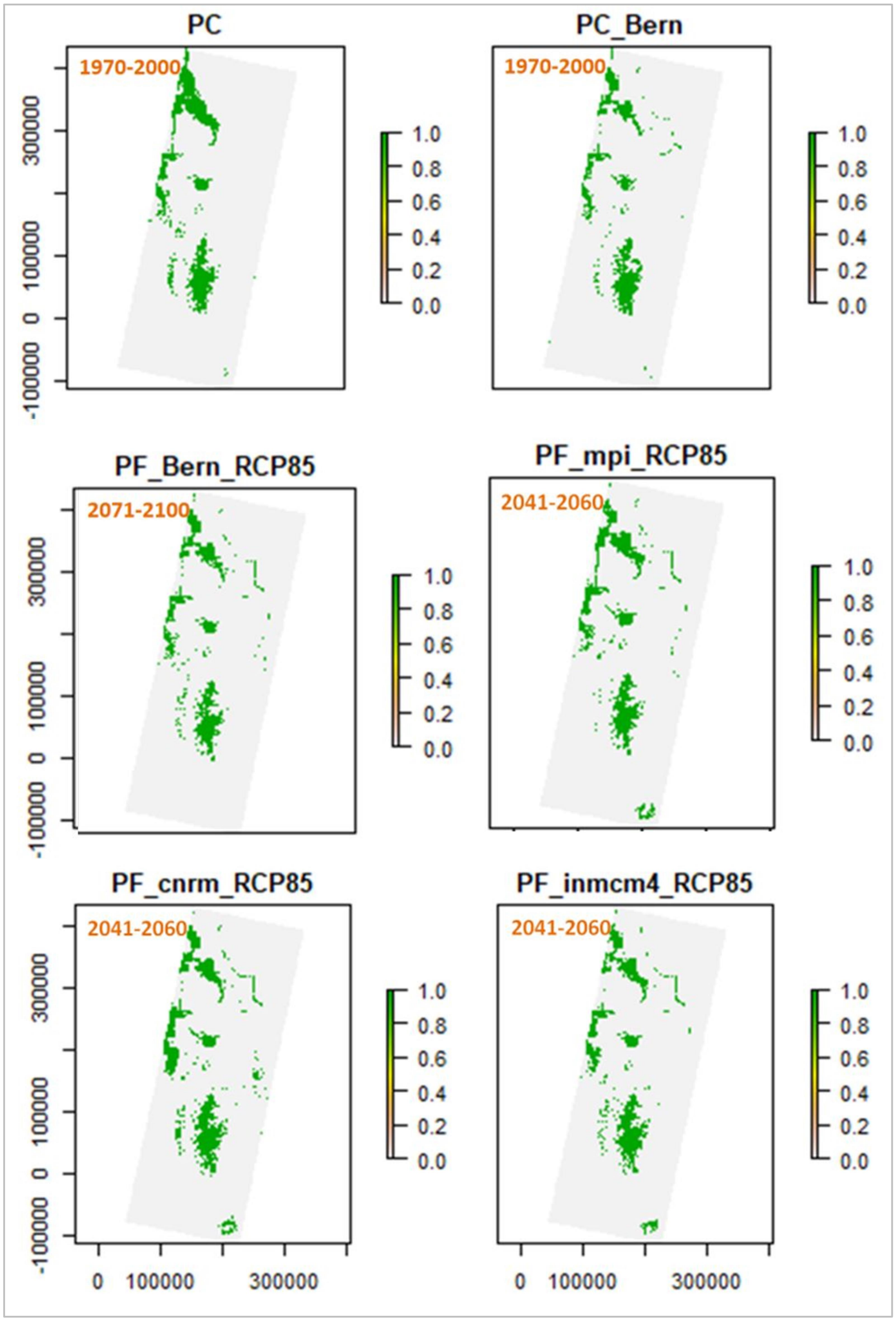


Figure 6.1B Ensemble binary predictions for the potential suitable habitat for *Prosopis* under the current and future climate. Ensembles were generated from the respective BRT and RF predictions. PC and PC_Bern = *Prosopis* suitable habitat under current climate using WorldClim and Uni-Bern data, respectively; PF = *Prosopis* suitable habitat under future climate using WorldClim and Uni-Bern datasets for the models indicated and RCP85.

Table 6.2 Potential suitable habitat changes between current and future climate for *Prosopis* and *Vachellia tortilis*. Two trajectories for analyzing habitat suitability changes are used; 1) current SDM (WorldClim) predictions minus all the four future predictions, and 2) current SDM (Uni-Bern) predictions minus all the future predictions. "S. Area" = study area

		Current climate		Future climate					
Species	Dataset	Area (Ha)	% S. Area	Model	Area (Ha)	% S. Area	Net change (Ha)	% Change	Change type
Prosopis	WorldClim	863703	9.0	cnrm	933012	9.7	-69309	-8.0	expansion
				Inmcm4	822653	8.6	41050	4.8	contraction
				mpi	820030	8.6	43673	5.1	contraction
				Uni-Bern	703307		160396		contraction
	Uni-Bern	693739	7.2	cnrm	933012		-239273		expansion
				Inmcm4	822653		-128914		expansion
				mpi	820030		-126291		expansion
				Uni-Bern	703307	7.3	-9568	-1.4	expansion
Vachellia tortilis	WorldClim	1641856	17.1	cnrm	1717987	17.9	-76131	-4.6	expansion
				Inmcm4	1535772	16.0	106084	6.5	contraction
				mpi	2066531	21.6	-424675	-25.9	expansion
				Uni-Bern	1142924		498932		contraction
	Uni-Bern	1363908	14.2	cnrm	1717987		-354079		expansion
				Inmcm4	1535772		-171864		expansion
				mpi	2066531		-702623		expansion
				Uni-Bern	1142924	11.9	220984	16.2	contraction

Mapped habitat distribution changes in response to climate change between the current and future binary SDMs revealed both habitat expansion and contraction for both species across all future climate models under RCP8.5 scenario for 2050 and 2085. Net habitat changes were estimated by calculating the areal difference between the predicted suitable habitat in the present time (current climate) and the predicted suitable habitat in the future time (Table 6.2). This analysis was done by simulating two pathways of change: 1) by estimating habitat changes using predictions from WorldClim data (present SDM minus each of the four future SDMs i.e. cnrm, inmcm4, mpi and Uni-Bern), and 2) in the same way, by estimating habitat changes using current predictions from Uni-Bern data (Table 6.2). The latter attempt was based on the assumption that, probably, it is possible that predictions in the current climate using Uni-Bern dataset were more realistic for the study area as opposed to the WorldClim dataset. This is because Uni-Bern dataset was modeled on a relatively smaller spatial scale – exclusively for the East African climate. Therefore, they have finer resolution as compared to datasets provided by WorldClim which are modeled at a global scale - hence more coarse resolution. Another assumption (in regard to simulation 1), is that the predicted future habitat under Uni-Bern provides more reliable estimates for the same reason of smaller spatial scale consideration. However, the findings presented on the basis of these simulations should be treated with caution because of the temporal mismatch between the future time climate datasets: WorldClim – near future (2041-2060), and Uni-Bern – distant future (2071-2100).

In simulation pathway 1, *Prosopis* suitable habitat is expected to contract as projected by three models (inmcm4, mpi and Uni-Bern) and expand under cnrm predictions. In the same simulation, *Vachellia tortilis* suitable habitat would expand under cnrm and mpi, and shrink under inmcm4 and Uni-Bern. In simulation 2, projected suitable areas for *Prosopis* would expand under all the four future model datasets. The same (expansion) would happen for *Vachellia tortilis* with an exception of contraction observed under Uni-Bern model (Table 6.2).

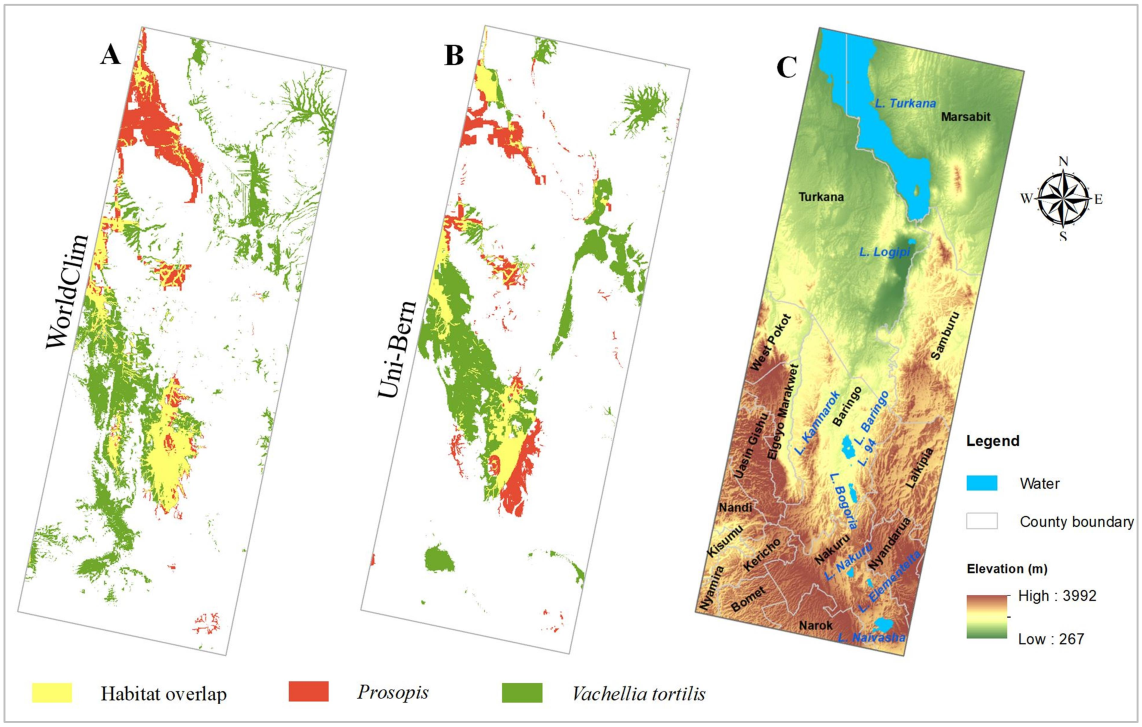
6.2.3 Projected habitat comparison between *Prosopis* and *Vachellia tortilis*

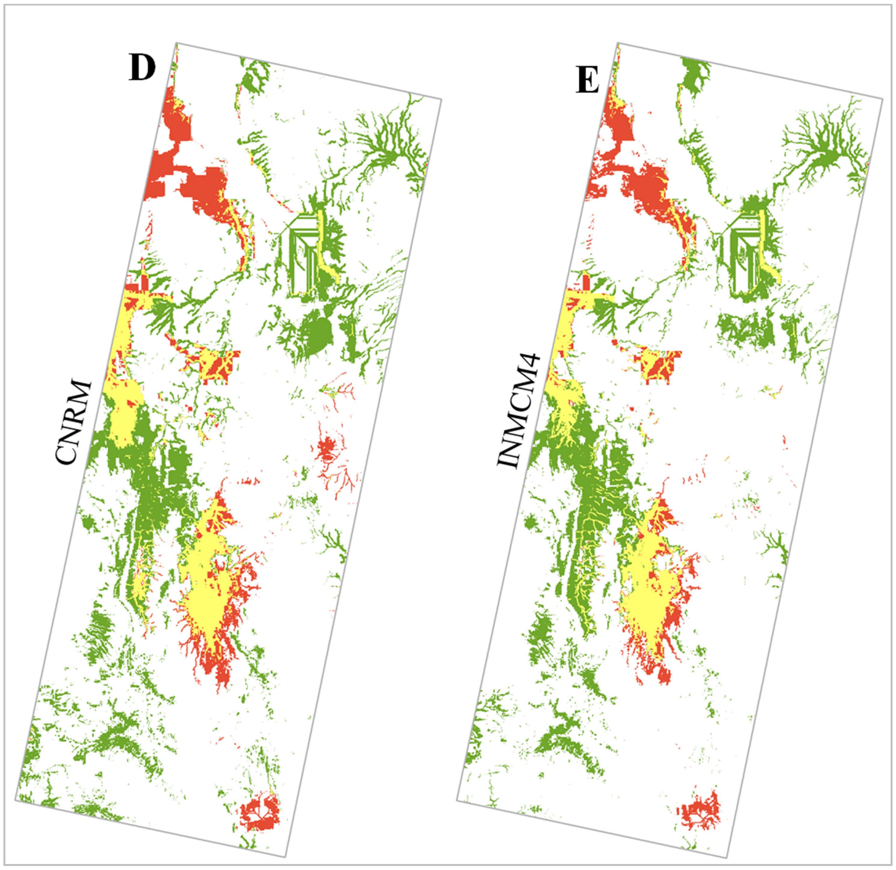
Although both species generally tend to co-occur in the currently known presence locations in the study area, their predicted habitat suitability has revealed spatial differences between them. For instance, in the current climate, both models consistently predict that areas to the west and southwest of Lake Turkana and around Lake Baringo as probable for *Prosopis* occurrence. The same distribution pattern is also observed for *Prosopis* in the future climate as all the four models predict *Prosopis* expansion along rivers and around lakes Bogoria, Nakuru and Naivasha, suggesting that water is an important variable influencing its distribution (Figure 6.2). With this kind of spatial pattern, the counties hosting a sizeable share of *Prosopis* suitable habitat both in the current and future climate include Turkana, Baringo, Nakuru and West Pokot (Figure 6.2C).

On the other hand, although both species show potential co-existence around Lake Baringo, there is a stark contrast in predicted occurrence around Lake Turkana. While *Prosopis* suitable habitat tends towards the west and southwest of the lake, *Vachellia tortilis* prefers areas to the north, east and southeast. Furthermore, in both climates, both models coherently predict (although more pronounced in the WorldClim / CMIP5 models than Uni-Bern model) substantial suitable habitats for *Vachellia tortilis* in Baringo, West Pokot, Elgeyo Marakwet, Nakuru, Kericho, Marsabit, Samburu and Kisumu counties (Figure 6.2C).

Generally, in both climate scenarios, higher elevation areas (> 1000 m) are substantially suitable for *Vachellia tortilis* but nearly devoid of *Prosopis* suitable habitat. However, exceptions to this have been observed with all the models predicting probability of *Prosopis* occurrence at elevations of about 1500 m along rivers (e.g. Rivers Turkwel and Kerio) and around settlements such as Ortum and Sebit in West Pokot County. Potential pockets of suitability have also been observed at elevations about 1700 m in East Pokot and even higher grounds at 2100 m within Lake Naivasha basin. This further confirms that water is a key factor that influences *Prosopis* habitat.

Subtle variations between model predictive performances were observed. For instance, the Uni-Bern model was able to capture *Prosopis* suitable habitat along the eastern shores of Lake Turkana which are not visible in the WorldClim model output (Figure 6.2B). On the other hand, all the WorldClim data-based models captured potential *Prosopis* habitat around Lake Naivasha, which the Uni-Bern data-based models missed.


A
WorldClim
B
Uni-Bern
C
L. Turkana
Marsabit
Turkana
L. Logipi
West Pokot
Samburu
Elgeyo Marakwet
Baringo
L. Kamnarok
L. Baringo
L. 94
Uasin Gishu
Laikipia
L. Bogoria
Nandi
Kisumu
Kericho
Nakuru
L. Nakuru
Nyandarua
L. Elementaita
Nyamira
Bomet
Narok
L. Naivasha
N
W
E
S
Legend
Water
County boundary
Elevation (m)
High : 3992
Low : 267
Habitat overlap
Prosopis
Vachellia tortilis


D
CNRM
E
INMCM4

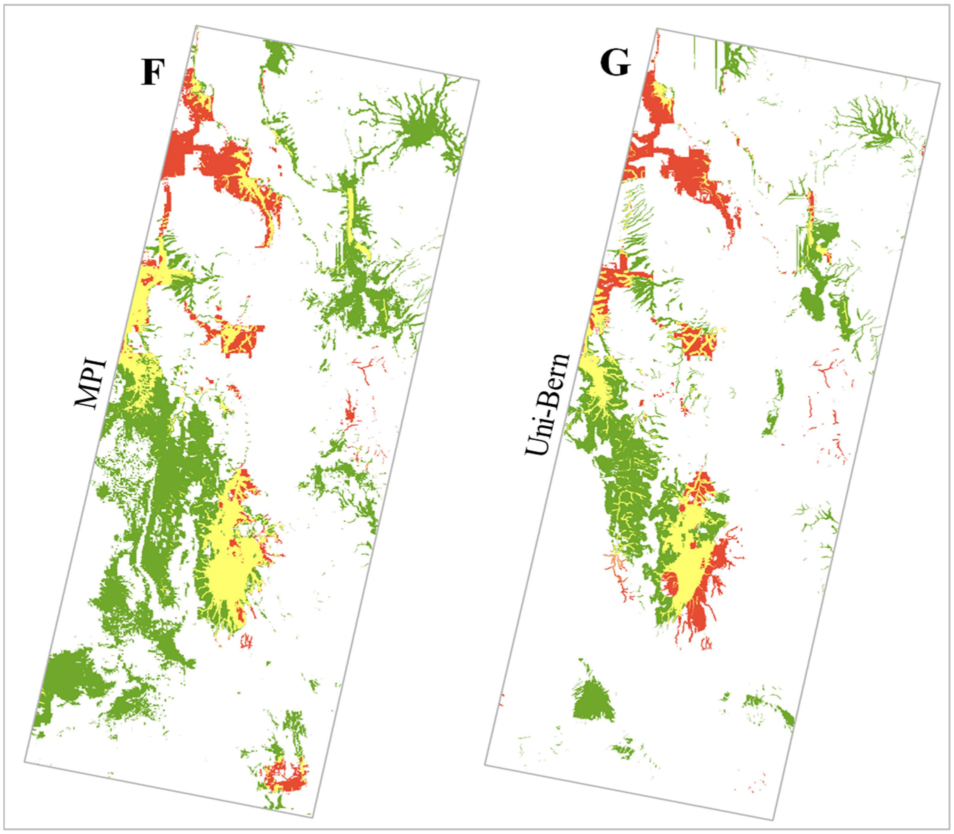


Figure 6.2A-G Distribution of predicted suitable habitat overlap for *Prosopis* and *Vachellia tortilis* in the current (WorldClim and Uni-Bern) and future climates for three CMIP5 GCMs (WorldClim) and Uni-Bern.

Habitat overlap occurred in areas with converging low elevation, floodplains, and relatively high anthropogenic disturbance. A comparison of habitat overlaps revealed that in the current climate, the habitat overlap was 28.0% and 24.6% for WorldClim and Uni-Bern models, respectively (Table 6.3). In the future climate, habitat overlap ranged from 23.5% (mpi model) to 29.7% (inmcm4 model). Highest and lowest habitat overlap areas occurred in mpi (484,787 ha) and Uni-Bern (317,537 ha), respectively. The spatial distribution pattern of habitat overlap was consistent across all the models.

Table 6.3 Suitable habitat overlap area estimates in hectares (ha) for *Prosopis* and *Vachellia tortilis* under future climate change (2041-2060 and 2071-2100) shown for the three CMIP5 GCMs (WorldClim) and Uni-Bern.

	Current Climate		**Future Climate**			
Suitable habitat	**WorldClim**	**Uni-Bern**	**cnrm**	**inmcm4**	**mpi**	**Uni-Bern**
Prosopis (ha)	863703	693739	933012	822653	820030	703307
Vachellia tortilis (ha)	1641856	1363908	1717987	1535772	2066531	1142924
Habitat overlap (ha)	459174	336088	475832	455706	484787	317537
Habitat overlap (%)	28.0	24.6	27.7	29.7	23.5	27.8

6.2.4 Potential refugia for *Vachellia tortilis* conservation and *Prosopis* invasion threat

Spatially, there was congruence among models in presenting climate refugia for *Vachellia tortilis* with potential areas ranging from 10% to 14% of the total study area (Figure 6.3). Mpi and Uni-Bern models had highest and lowest refugia areas at 1,337,949 ha and 917,146 ha, respectively (Table 6.4). Because *Prosopis* is an aggressive invader, it is estimated with consonance among all the four models that over 30% of the predicted refugia area for *Vachellia tortilis* will be lost to *Prosopis* invasion in future. The average potential refugia area at risk of *Prosopis* invasion ('areas of vulnerability) was estimated at 382,469 ha representing ~34% of the mean suitable refugia area i.e. average of the four models.

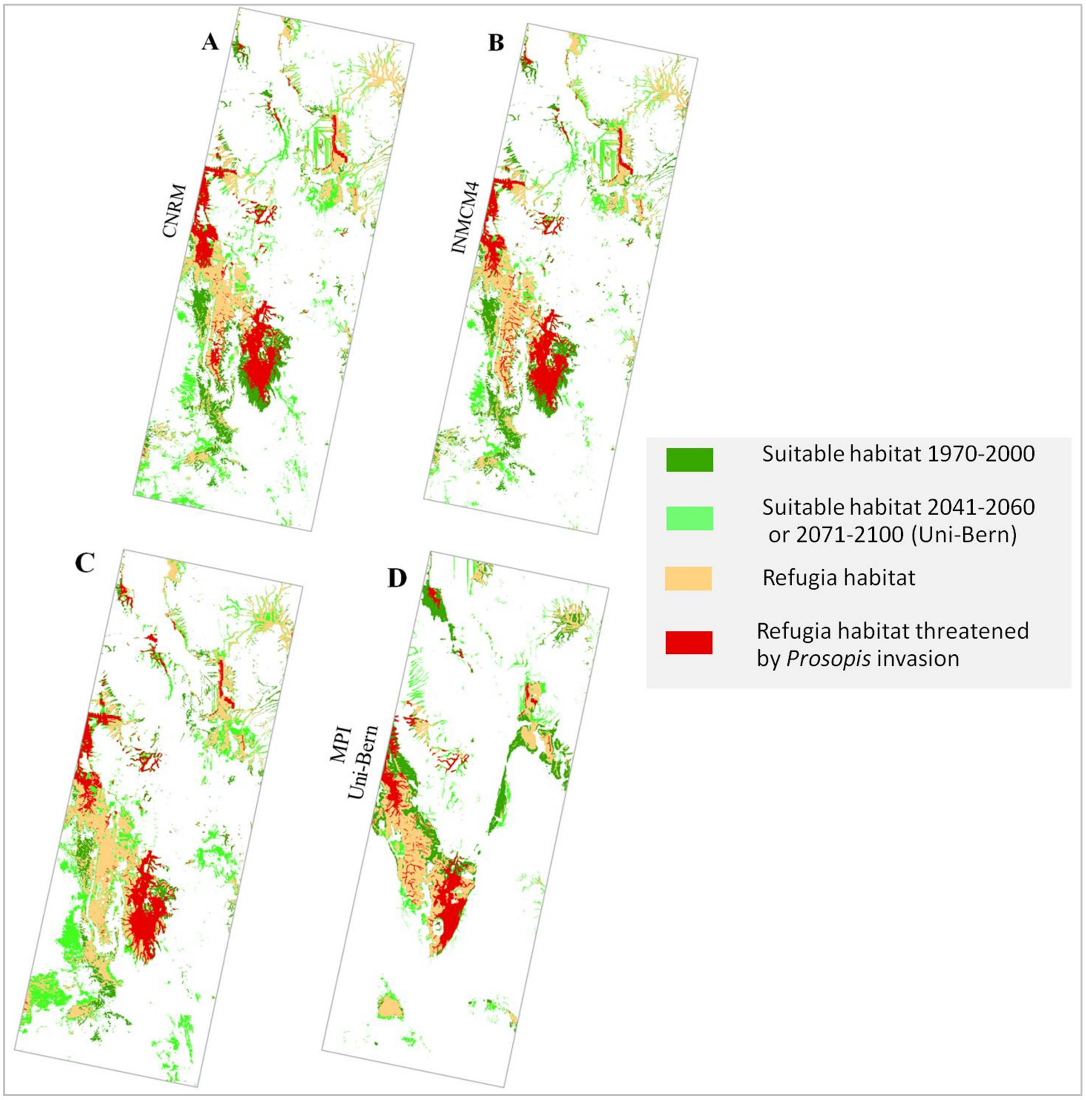


Figure 6.3A-D Spatial distribution of potential climate refugia for *Vachellia tortilis* visualized together with potential *Prosopis* suitable habitat layer.

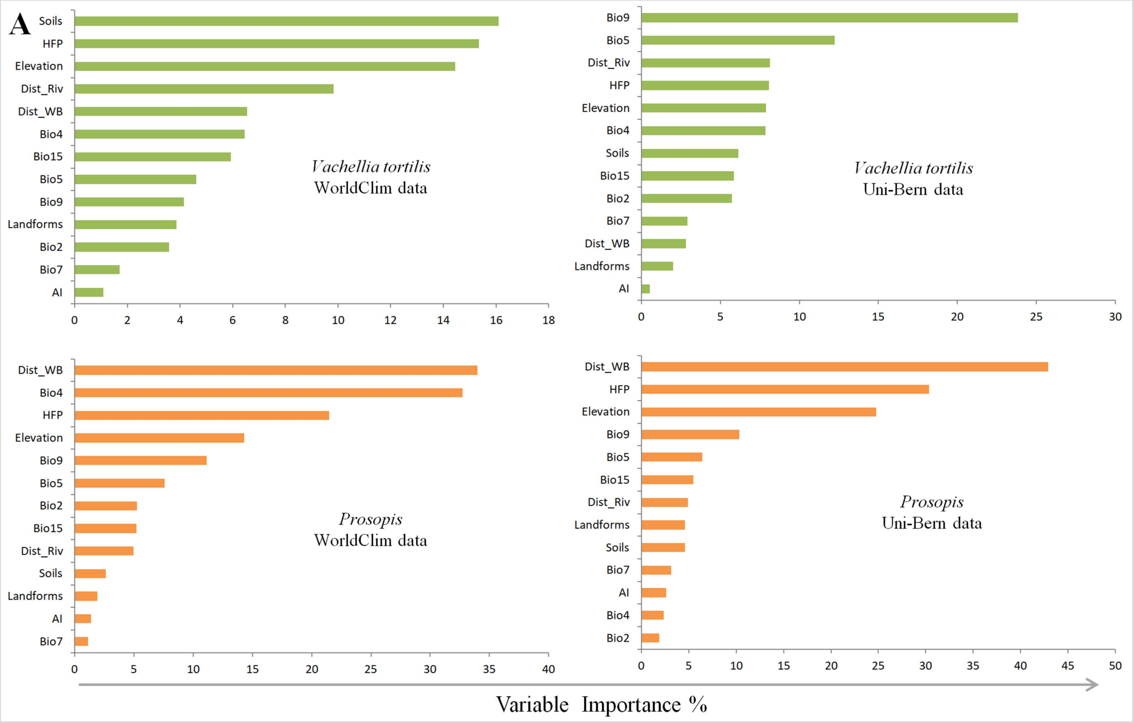
Table 6.4 Potential refugia habitat for *Vachellia tortilis* and the proportion at risk of invasion by *Prosopis*.

Model	Year	Refugia habitat (ha)	% Study area	Refugia under *Prosopis* threat (ha)	Potential refugia loss (%)
Cnrm	2041-2060	1157660	12.1	423991	36.6
Inmcm4	2041-2060	1138040	11.9	414670	36.4
Mpi	2041-2060	1337949	14.0	409661	30.6
Uni-Bern	2071-2100	917146	9.6	281552	30.7

6.2.5 Relative importance of environmental variables

Variable relative influence graphs (Figure 6.4A and 6.4B) revealed the contribution of each environmental variable in influencing the probability of each species occurrence. Variable contributions differed considerably between the two species. Suitable habitat for *Prosopis* were highly influenced by proximity to water bodies, human footprint index, bio9 (mean temperature of driest quarter), elevation and bio5 (maximum temperature of warmest month). In the current climate, the predicted habitat using the WorldClim data also presented bio4 (temperature seasonality) as contributing relatively more than the other bioclimatic variables, while with the Uni-Bern data, bio9 outperformed bio4. Aridity index, bio2 (annual mean diurnal temperature range), soils, landforms and bio7 (temperature annual range) were found to be least important in influencing distribution of potential *Prosopis* habitat, with all contributing less than 5% to the models.

Landscape factors (soils, elevation and distance to rivers) and anthropogenic pressure (human footprint) are the principal candidates in determining the potential suitable habitat for *Vachellia tortilis*. While soils and bio2 ranked among the least important factors for *Prosopis* habitat (Figure 6.4), they emerged among the most influential predictors for *Vachellia tortilis* distribution. In the same vein, while distance to water bodies was paramount for potential *Prosopis* habitat, it was inconsequential for *Vachellia tortilis*. The insignificant variables for *Vachellia tortilis* were aridity index, landforms and distance to water bodies. The common denominator variable important for both species was human footprint (HFP), which averagely contributed about 15% and 30% to *Vachellia tortilis* and *Prosopis* models, respectively. Generally, landscape variables and human footprint are more influential than climatic variables in predicting potential habitat for both species under both climate scenarios. However, climatic variables seemed more important than landscape variables under the Uni-Bern model of *Vachellia tortilis* habitat both in the current and future climate. Seemingly, the few influential climatic variables are those that measure temperature regime such as bio9, bio5, bio7 and bio4. Rainfall (precipitation seasonality – bio15) moderately influenced both species habitat across all the models but exhibited stronger influence on *Vachellia tortilis* habitat under the Uni-Bern model in the future climate.



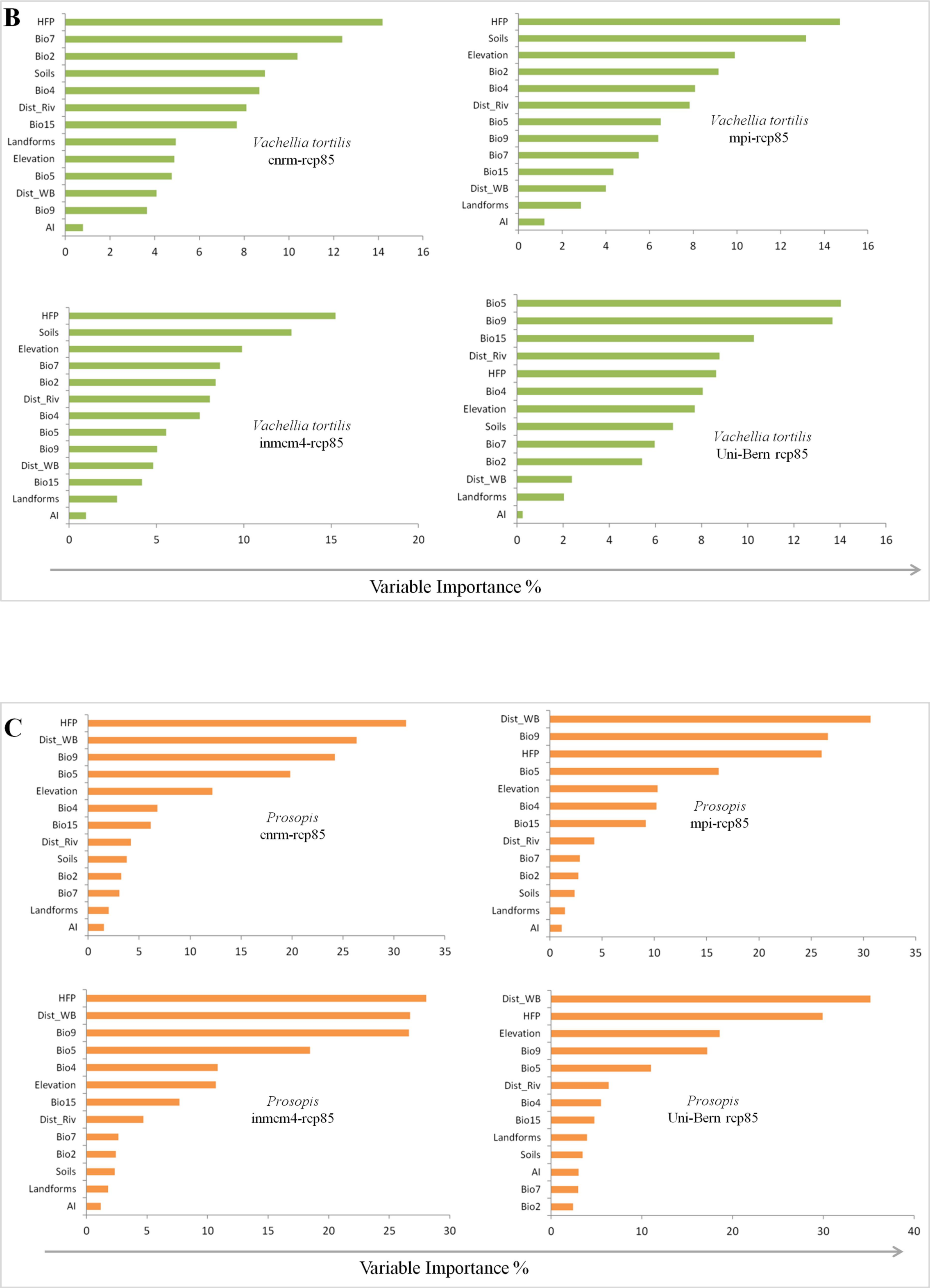


Figure 6.4A-C The relative importance (%) of environmental variables on the distribution of each species in the current climate (A), future climate – *Vachellia tortilis* (B) and future climate –*Prosopis* (C). The abbreviated variables are Bio2 (annual mean diurnal

temperature), Bio4 (temperature seasonality), Bio5 (maximum temperature of warmest month), Bio7 (temperature annual range), Bio9 (mean temperature of driest quarter), Bio15 (precipitation seasonality), Dist_Riv (weighted minimum Euclidean distance to rivers), Dist_WB (minimum Euclidean distance to buffered waterbodies), AI (aridity index), and HFP (global human footprint index) (Table 3.6).

6.3 Discussion

6.3.1 Suitable habitat for *Prosopis* and *Vachellia tortilis* under current and future climate

Under the current climate, the global model (WorldClim) predicted a slightly higher *Prosopis* suitable habitat (9% of total study area) than the regional model (Uni-Bern) which predicted 7.2% suitability (Table 6.2). In the future climate, one global model (CNRM – for 2050) and the regional model (Uni-Bern for 2080) predicted an increase in *Prosopis* suitable habitat from the current conditions at 9.7% and 7.3%, respectively (Table 6.2). On the contrary, two global models (Inmcm-4 and MPI – both for 2050 projections) predicted a decrease in *Prosopis* suitable habitat, both predicting 8.6% suitable habitat (Table 6.2). These predictions closely corroborate the results by Sintayehu et al. (2020), who modeled *Prosopis* distribution dynamics in Africa for both current and future climate scenarios RCP4.5 and RCP8.5 for 2050 and 2070 using the improved 5th version of the atmosphere-ocean General Circulation Model. They estimated that under the current climate, 11.4%, 7.4% and 5.6% of Africa has low, moderate and high suitability to *Prosopis juliflora,* respectively. Specifically, they observed that most suitable areas will occur in the eastern Africa region with Kenya listed among the countries falling under high *Prosopis* suitability (Sintayehu et al., 2020). A similar recent study in Eastern Africa predicted that nearly 17% of Kenya is currently suitable for *Prosopis* (Eckert et al., 2020). In the future climate, *Prosopis* suitability will expand in the study area as revealed by the CNRM and Uni-Bern models in this study, a similar pattern of projections was reported in previous studies (Eckert et al., 2020; Ng et al., 2018; Sintayehu et al., 2020). Sintayehu et al. (2020) projected *Prosopis* expansion over Africa through 2050 and 2080. In this study, areas suitable for *Prosopis* will increase by 8% by 2050 as predicted by the CNRM model and by 1.4% by 2080 as predicted by Uni-Bern model. Declines in suitable areas by 2050 (by 4.8% under Inmcm4 and by 5.1% under the MPI model) were recorded.

In this study, *Prosopis* suitability tended towards lowland areas surrounding water bodies such as lakes Turkana and Baringo, and along rivers such as River Turkwel. This potential habitat distribution pattern was also observed by Eckert et al. (2020) for Eastern Africa, suggesting that water is a key determinant factor of *Prosopis* habitat, similar to observations in other studies (Dakhil et al., 2021; Ng et al., 2018; Schachtschneider and February, 2013). However, it was also observed that in contrast, despite water presence, areas to the southeast, east and northeast of Lake Turkana as well as around Lake Bogoria remained largely unsuitable for *Prosopis*. This suggests that *Prosopis* habitat is probably influenced by interplay of multiple factors at site. The observed unsuitability may be attributed to differences in soil conditions brought about by sediments deposited by water at the late stages of the river. Clay content has been found to substantially increase the invasion risk of *Prosopis juliflora* thereby positively influencing habitat suitability (Dakhil et al., 2021). Because of the influence of rivers Turkwel and Kerio (draining into Lake Turkana) and River Waseges-Sandai (draining into Lake Bogoria), the southwest and west of Lake Turkana and northern tip of Lake Bogoria show high *Prosopis* suitability. This is in tandem with the already observed mapped *Prosopis* distribution in those areas as reported in previous studies (Mbaabu et al., 2019; Muturi et al., 2013, 2009; Ng et al., 2016a). It is however noted that, this study's prediction (lack of *Prosopis* suitability around Lake Turkana) contrasts the findings in a similar study in the study area (Eckert et al., 2020). Visual comparisons of their *Prosopis* suitable habitat generated for eastern Africa region present *Prosopis* suitable habitat in larger areas to the south east, east and northeast of Lake Turkana. These model differences may be attributed to the choice of predictor variables included in the models for the two separate studies. Specifically, it is noted that Eckert et al. (2020) did not include edaphic-related variables such as soil or landforms which were included in this study. Although soil did not contribute significantly to our prediction models, incorporating soil-related variables in the models showed better performance and produced more accurate predictions - similar observations were reported by Dakhil et al. (2021). Furthermore, Kumar et al. (2009) points out that provided climatic conditions are suitable, edaphic-related factors can set the ecological limits that restrict species distributions.

It was also determined that both minimum Euclidean distance to waterbodies and human footprint index (HFP) contributed more than 50% in determining *Prosopis* habitat, mirroring previous findings (Eckert et al., 2020; Ng et al., 2018). This implies that humans and their associated human-environment interactions greatly shape habitat suitability for *Prosopis*. However, a contrasting finding was reported by Dakhil et al. (2021), who modeled the global invasion risk of *Prosopis juliflora* at biome level, by running MaxEnt algorithm on three different clusters of predictors: 1) climate, 2) climate + soil, 3) climate + soil + human. They determined that human influence did not have a significant contribution on *Prosopis* potential distribution. Site suitability may also be limited by certain factors at play at the landscape level that were probably not investigated in this study such as alkalinity, soil depth and ground water table, but these data are largely scarce or not available particularly for our modeling scale. For instance, for both current and future climate conditions, it was observed that landforms, aridity index and temperature annual range (bio7) together explained less than 5% of the global climate models predictions. Climatic factors that greatly explained *Prosopis* habitat suitability both under current and future climate conditions were temperature seasonality (bio4) and temperature of the driest quarter (bio9), similar to observations in other studies (Dakhil et al., 2021; Eckert et al., 2020; Ng et al., 2018).

The results further show that high *Prosopis* habitat suitability tended towards the currently *Prosopis*-invaded locations, an observation that was also reported in previous studies (Sintayehu et al., 2020). This is because, areas neighboring *Prosopis* plantations usually become the first victims of invasion owing to their proximity and a likely traversing of non-invaded locations by dispersal agents such as livestock or seed transportation during flood events.

For *Vachellia tortilis*, the global (WorldClim) and regional (Uni-Bern) models predicted suitable habitat of 17.1% and 14.2% of total study area, respectively, under the current climatic conditions. In the future climate (2050), both CNRM and MPI predicted an increase in *Vachellia tortilis* suitable areas at 17.9% and 21.6% of the study area, while Inmcm4 predicted the lowest and decreased suitable habitat at 16.1% (Table 6.2). This represents an increase in habitat suitability by 4.6% and 25.9% for the two models (in order), respectively, of the suitable area under the current conditions. The regional model predicted a decrease in suitable habitat from the current conditions at 11.9%, representing habitat contraction of 16.2%. An expansion of *Vachellia tortilis* habitat has also been reported in Africa (Mechergui et al., 2021). They modeled the current and future potential distributions of *Vachellia tortilis* under climate change in Tunisia for 2050 and 2070 using MaxEnt species distribution model. Their estimated rate of increase (6.22% by 2050 RCP8.5) in suitable habitat compares to our estimate with the Inmcm4 model (increase by 6.5% by 2050 under the same climate scenario).

In contrast to *Prosopis*, that is spatially limited to lowland areas, *Vachellia tortilis* suitability tended even towards highland areas within the counties of West Pokot, Uasin Gishu, Nandi, Elgeyo Marakwet, Nakuru, Kericho, Bomet, Laikipia, Samburu and Marsabit. This observation is not surprising as elevation appeared among the most influential variables in determining suitable habitats for *Vachellia tortilis*. Furthermore, soils and HFP contributed substantially to *Vachellia tortilis* habitat (Figure 6.4).

Model outputs showed a substantial overlap in the predicted suitable habitats for both species at (model average) 26.3% and 27.1% for current and future climate, respectively **(**Figure 6.2). Although both species tend to co-occur in lowland zones, it is evident from this study that the native *Vachellia tortilis* has a wider climate envelope than *Prosopis* species, suggesting that *Vachellia tortilis* could benefit from this in the face of adverse climatic conditions. It was also interesting to find pockets of suitable *Prosopis* habitat in very high elevation areas of up to 2100 m a.s.l, but locations at close proximity to water. These findings suggest that water is the most important factor in delimiting *Prosopis* habitat (Figure 6.4), and that the two species respond differently to habitat water conditions. Of the three global climate models considered in this study, the MPI model predicts a warmer and drier climate over the eastern Africa coast including Madagascar and Mozambique (Eckert et al., 2020; McSweeney et al., 2015). This model predicted an expansion by 25.9% in *Vachellia tortilis* suitable habitat with reference to the current climate conditions and a decrease by 5.1% in *Prosopis* suitable habitat, suggesting that the predicted drier climate over this region may restrict future expansion of *Prosopis*, but promote native *Vachellia* expansion.

6.3.2 Climate refugia for *Vachellia tortilis*

These results indicate that refugia areas of varying sizes (depending on the models) will exist at least up to 2050 or 2080. Potential refugia areas ranged between 10 to 14% of the total study area across the four models. These zones present potential areas where actions, efforts and resources need to be targeted for conservation of *Vachellia tortilis* which is currently threatened by *Prosopis* species (Figure 6.3). On the other hand, if conservation measures are not taken up early enough, these refugia areas present areas of vulnerability and 30% of the refugia is at high risk of *Prosopis* invasion by 2080. This is because *Prosopis* has been widely reported as an aggressive invader in previous studies, usually engineering invaded ecosystems (Ayanu et al., 2015; Mbaabu et al., 2019; Ng et al., 2017).

6.3.3 Performance of global and regional climate models in predicting potential suitable habitats

A comparative assessment of the models shows an expansion of suitable habitat for both species in the current climate. However, the global climate model predicts a slightly larger suitable habitat (*Prosopis*: 9% vs. 7.2% and *Vachellia tortilis* 17.1% vs.14.2%) for both species under both climates than the regional model. Although the models were consistent in their projections from current to future climates, they showed slightly conflicting results with regards to habitat suitability in the future climate. For example, while CNRM (global model) and Uni-Bern (regional model) showed that *Prosopis* habitat would expand from current to future climate, the two other global models (Inmcm4 and MPI) showed that *Prosopis* habitat will decrease in future. Similarly, for *Vachellia tortilis*, both CNRM and MPI predict habitat expansion while Inmcm4 and Uni-Bern predict habitat contraction. These differences in model performances could largely originate from the differences in the individual model performance characteristics (McSweeney et al., 2015). For example, the global model classifications were: CNRM model - satisfactory but an outlier, MPI – satisfactory and Inmcm4 – significantly biased (Table 3.5).

6.4 Summary

Using two SDMs and four climate model datasets, this study predicted potential (current and future) suitable habitats for *Prosopis* and *Vachellia tortilis* within a semi-arid landscape in rift valley Kenya. Species distribution models revealed that climate warming will have profound effects on species geographic ranges of both alien and native species. Climate models predict both habit expansion and contraction. The adverse effects (habitat encroachment) of invasive plant species on native biodiversity will equally persist in the face of the envisaged climatic changes. Over 30% of the predicted suitable habitat for *Vachellia tortilis* was also predicted as suitable for *Prosopis*, an indication of possible *Prosopis* invasion into these habitats in future. The key strategies for mitigating further spread of invasive alien plant species and their negative effects include prevention of introductions, early detection and rapid response, as well as controlling their spread (Bellard et al., 2013; Fernandes et al., 2019). In order to achieve this, anticipating invasive alien plants in future distributions is essential for promoting pre-emptive and adaptive management decisions and actions. These findings therefore provide the requisite baseline information regarding future invasion of the two species.

CHAPTER 7: SYNTHESIS, CONCLUSIONS AND RECOMMENDATIONS

7.1 Synthesis

The analysis and monitoring of landscape changes over time and in space is important for promoting sustainability of global ecosystems amid global environmental changes. These changes are strong indications of anthropogenic disturbance on landscapes occurring at fine scale e.g. species level or coarse scale e.g. at global level (Alphan, 2017). Some of the causes of landscape changes include fire, agricultural expansion and intensification, population increase, land fragmentation, climate change, pollution, technological development, globalization, and biological invasions (Bürgi et al., 2004; Tesfamariam et al., 2018). Landscape changes have implications on ecosystems, biodiversity, livelihoods and economies (Bürgi et al., 2004), hence should be carefully assessed and monitored to inform effective management decisions (Alphan, 2017).

Despite the multiple documented negative impacts of grassland degradation on ecosystems and livelihoods e.g. (Han et al., 2020; Luo et al., 2023; Tiscornia et al., 2019; Xiao et al., 2022), and the recent studies to understand the impacts of invasive species (Bekele et al., 2018b; Dzikiti et al., 2013; Linders et al., 2020, 2019; Mooney, 2005; Muller et al., 2017; Pejchar and Mooney, 2009; Shackleton et al., 2017b, 2019), grasslands – particularly tropical savannas - are still exposed to degradation. In particular, invasive weedy plants continue to spread at unprecedented rates, compromising ecosystem services provisioning which immensely hurts ecosystems, economies and livelihoods, with a likely exacerbation by climate change. Yet, there remain barriers to policy formulation and decision making that can guide effective alien plant species management and sound sustainable ecosystem restoration solutions. These barriers are in part due to lack of reliable information regarding invasive plant species spread, as well as paucity of local and context-specific data on impacts. Due to the scarcity of these relevant data, coupled with pressing impacts on communities, the urgent need for solutions has led to implementation of strategies that aren't informed by evidence. For example, the model of *Prosopis* management by "utilization" implemented in Kenya and Ethiopia was not based on any scientific evidence, and there were no known studies providing evidence regarding the efficacy of the model to curtail further spread of the invasive plant.

This thesis has provided reliable estimates of the spatio-temporal changes in *Prosopis* cover, and the multifaceted impacts of these changes on the ecosystem, people, and their livelihoods. In particular, *Prosopis* has proven its aggressiveness and ability to engineer invaded ecosystems by inducing changes in other land-uses and land-cover, similar to findings in other studies in Kenya (Kyuma et al., 2016; Ng et al., 2017, 2016a), Africa (Adam et al., 2017; Ayanu et al., 2015; Babiker, n.d.; Meroni et al., 2017; Rembold et al., 2015; Shackleton et al., 2015a; Shiferaw et al., 2019c) and globally (Brown and Carter, 1998; Dakhil et al., 2021; Robinson et al., 2008, 2008; Shackleton et al., 2014; Vidhya et al., 2017). As a result of these invasions, the capacity of these ecosystems to supply various ecosystem services such as fodder, food, water among others has been impaired. While *Prosopis* is considered as a conflict-of-interest species because of the derived potential benefits such as charcoal, wood and greening the ambient environment, previous studies have shown that the overall negative effects of invasion outweigh the benefits both at local and national scales (Bekele et al., 2018a; Linders et al., 2020, 2019). *Prosopis* invasion compromises rural livelihood provisioning and sustainability in invaded areas (Bekele et al., 2018b; Mwangi and Swallow, 2005), as demonstrated by the findings in this thesis, using proxies such as invasion of croplands and grazing areas, which further increases land maintenance costs beyond the reach of many households in the affected areas.

Recent discourses have oriented climate mitigation actions such as afforestation in semi-arid areas. While it is true that afforestation is one of the mechanisms for climate change mediation, our findings suggest that these assertions are potentially incorrect and ill-fated, similar to observations in other studies (Jackson et al., 2002; Parr et al., 2014). Our study provides evidence that even though *Prosopis* expansion plays a role in soil carbon sequestration, it hurts biodiversity, limits provisioning of essential ecosystem services such as livestock fodder. This is in agreement with findings in other studies on *Prosopis* inavasion in semi-arid areas (Shackleton et al., 2015a; Van Klinken and Campbell, 2009). This study finds that grassland restoration would be a more effective approach for climate change mitigation as it additionally offers markedly more other benefits such as alleviating negative effects of land degradation, promotes biodiversity and rural livelihood support.

Climate change is impacting species habitats in unprecented ways (Eckert et al., 2020; Kyuma et al., 2016). The findings in this thesis are in tandem with those from other studies that show anthropogenically induced environmental change will favour expansion of woody alien species in some areas and a contraction in other environments. This means that there will be an amplification of the negative effects associated with these invasions. One of the projected effects of future invasion is a continual replacement of native biodiversity. While some native biodiversity will likely be pushed to extinction by climatic changes, the additional threat by invasion calls for evidence informed decision. The findings in this thesis provide evidence needed for advancing decision making on management of alien invasions in the face of the current and envisaged climatic changes. This is particularly paramount since the species invades fragile ecosystems that host some of the already marginalized and vulnerable communities currently experiencing other livelihood threats.

7.1.1 Management implications of this study

Because of the expected and inevitable impacts of projected climatic changes, forecasting, quantifying and visualizing potential ramifications on species habitat across a range of plausible future scenarios is crucial for supporting conservation management and decision-making especially in the context of invasive alien species. This study attempted to support pre-emptive conservation planning by modeling, identifying and quantifying potential suitable habitats for both species as well as estimating climate refugia for *Vachellia tortilis*, to enhance biodiversity conservation. Regardless of the model, it is important to note that, these results provide predictions from four different models, hence, areas where refugia are projected under all the four climate scenarios should be treated as realistic conservation targets.

Since established populations of *Prosopis* are difficult and expensive to manage (Heshmati et al., 2019; Ng et al., 2018), strategies to prevent invasion of new areas, as well as early detection and rapid response (EDRR) should be adopted. Moreover, since *Prosopis* invasion threatens the existence of local biodiversity such as *Vachellia tortilis*, conservation strategies, efforts and resources should be prioritized in protecting the climate refugia areas for this species from likely *Prosopis* invasion in future. Furthermore, emphasis should be put to retain the suitable habitat currently occupied by *Vachellia tortilis* in order to facilitate their survival even in situations when the climatic conditions exceed the tolerance level of the species.

7.2 Conclusions

As part of this thesis, the spatio-temporal spread of *Prosopis* and its impacts on other land-uses and land-cover was assessed in Baringo County. The findings presented in chapter four have revealed that, over nearly four decades since *Prosopis* was introduced in Baringo, the species has spread from original plantations taking up valuable land such as croplands, pastures and native woodlands at a rate of 640 ha per year. This has consequently led to over

30% changes in other LULC, which is severely affecting native biodiversity and rural livelihoods.

Further, the emerging advocacy for growing trees for climate change mitigation projects has seen many tropical degraded grasslands being targeted for woody expansion in recent years, which is eliciting much debate. In order to contribute to these debates, this study further investigated and compared the effects of grassland restoration and woody *Prosopis* encroachment on soil organic carbon stocks, plant species richness and herbaceous biomass. This thesis provides evidence that grassland restoration is as effective as *Prosopis* in replenishing soil organic carbon stocks. Moreover, unlike *Prosopis* which limits fodder production and other ecosystem service provisioning, grassland restoration does not compromise herbaceous biomass productivity and supports provisioning of other ecosystem services needed to support agro-pastoral livelihoods.

Climate is a delimiting factor influencing species distributions; hence, it is expected that predicted climatic changes could have a bearing on species geographic ranges in future. In chapter six, the potential species suitability under projected climatic changes was modeled for *Prosopis* and *Vachellia tortilis,* and potential suitable habitat overlaps determined to inform conservation of native *V. tortilis*. This study demonstrates that future climatic changes will increase potential suitable habitats for both *Prosopis* and *V. tortilis*. However, over 30% of the land suitable for *V. tortilis* (climate refugia) is at a high risk of *Prosopis* invasion. Further, *Prosopis* has high affinity for areas at close proximity to water and favourable soils. This study concludes that riparian zones, irrigation canals, wetlands and lake shores are at higher risk of invasion which may limit water availability and access and further compound *Prosopis* invasion impacts on livelihoods. The livelihoods are threatened by *Prosopis* invasion and the situation will likely be exercebated by the changing climatic conditions.

7.3 Recommendations

Prosopis has been present in Kenya for more than 70 years (since 1948). Over this period, it has gradually spread throughout the country and even crossed national borders to other countries such as Tanzania. It has caused tremendous environmental damages and affected people's way of life. Yet, despite the outcry and push by affected communities for lasting solutions, the invasion continues unabated, with negative impacts accelatating with changing climatic conditions. On the basis of these findings, urgent actions on *Prosopis* management are recommended as below.

1. Management actions need to target *Prosopis* using a blend of approaches such as mechanical, chemical and biological control, because use of a single strategy alone may be too costly in the long-term, ineffective and unfeasible especially for management of naturalized *Proposis* over large areas.
2. Strategies for reversing land degradation should consider restoration of native grasslands in a mosaic of other compatible ecosystems such as forest and shrublands comprising non-invasive woody species. Moreover, promoting further spread of woody species particularly *Prosopis* should be ceased immediately.
3. Because the rapidity and velocity of climate change, coupled with the fast spread of *Prosopis* may render survival of native biodiversity intolerable, immediate protection and prioritization of *V. tortilis* conservation should be considered. Most importantly, prevention of *Prosopis* invasion into these landscapes should be treated as a matter of urgency.

These results are considered important for both National and County Governments in Kenya, particularly counties classified as arid and semi-arid (ASALs) such as Baringo, West Pokot, Samburu, Turkana, Isiolo, Tana River and Garissa, because suitability of *Prosopis* species is highest in lowland areas in these ASALs. As such, the impacts of *Prosopis* on these regions and their host communities might become even more pronounced in the future due to climate change. Therefore, prompt responses to new introductions of *Prosopis* and control of invasions should be mainstreamed in national climate change mitigation plans as well as in plans targeting invasive plant species management and biodiversity conservation.

7.4 Directions for future research

This study modeled the impact of climate change on geographic range of *Prosopis* and *V. tortilis*. Future research should be targeted in modeling the responses of other flora characteristic of savanna ecosystems to projected climatic changes. Further, a holistic landscape scale quantification of costs of land degradation and *Prosopis* invasion would be important to inform management decisions and guide restoration actions in the severely degraded and invaded areas. Furthermore, there have been claims by some stakeholders e.g. fishermen and traders that *Prosopis* has caused depletion of fish stocks in Lake Baringo. Further research should investigate the impacts of *Prosopis* on water quality and aquatic life.

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APPENDICES

Appendix 1.1 1988 Classification Accuracy Report

1988 classification		*Reference Data*														
LULC Type		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**Classified Total**	**User's Accuracy (%)**
Prosopis	**1**	101	2	0	0	0	0	0	0	0	0	20	0	0	**123**	82.1
Vachellia tortilis	**2**	7	144	0	5	0	0	0	0	0	1	2	2	0	**161**	89.4
Vachellia reficiens	**3**	2	6	131	15	0	0	0	7	23	9	2	2	0	**197**	66.5
Mixed vegetation	**4**	0	4	12	325	0	6	1	4	2	0	1	0	0	**355**	91.5
Indigenous forest	**5**	0	0	0	0	136	14	2	0	0	0	0	0	0	**152**	89.5
Plantation forest	**6**	0	0	0	10	55	779	8	0	0	0	0	0	0	**852**	91.4
Water	**7**	0	0	0	0	0	0	5999	0	0	0	0	0	0	**5999**	100.0
Rain-fed cropland	**8**	0	0	4	0	0	0	2	92	9	0	0	0	0	**107**	86.0
Bareland	**9**	0	0	0	0	0	0	0	0	164	0	0	0	0	**164**	100.0
Grassland	**10**	1	0	0	0	0	0	0	0	19	117	0	1	0	**138**	84.8
Balanites aegyptica	**11**	8	4	0	0	0	0	0	0	0	0	101	0	0	**113**	89.4
Irrigated cropland	**12**	0	0	0	0	0	0	0	0	0	0	0	45	0	**45**	100.0
Water weeds	**13**	5	0	0	1	0	0	0	0	0	0	0	0	55	**61**	90.2
Reference Total		**124**	**160**	**147**	**356**	**191**	**799**	**6012**	**103**	**217**	**127**	**126**	**50**	**55**	**8467**	
Producer`s Accuracy (%)		81.5	90.0	89.1	91.3	71.2	97.5	99.8	89.3	75.6	92.1	80.2	90.0	100.0		

Appendix 1.2 1995 Classification Accuracy Report

1995 classification		***Reference Data***														
LULC Type		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**Classified Total**	**User's Accuracy (%)**
Prosopis	**1**	135	3	0	3	2	0	0	0	0	3	14	0	10	**170**	79.4
Vachellia tortilis	**2**	4	122	0	3	0	0	0	0	0	0	13	0	1	**143**	85.3
Vachellia reficiens	**3**	0	0	113	1	0	0	0	3	4	0	0	2	0	**123**	91.9
Mixed vegetation	**4**	0	8	26	349	0	0	0	0	4	0	4	0	0	**391**	89.3
Indigenous forest	**5**	5	0	0	0	189	5	0	0	0	0	2	0	0	**201**	94.0
Plantation forest	**6**	0	2	0	4	15	795	0	0	0	0	0	0	0	**816**	97.4
Water	**7**	0	2	0	0	0	0	6527	0	0	0	0	0	0	**6529**	100.0
Rain-fed cropland	**8**	0	0	4	0	0	1	0	106	8	0	0	0	0	**119**	89.1
Bareland	**9**	0	0	2	0	0	0	0	0	181	6	0	0	1	**190**	95.3
Grassland	**10**	3	0	0	0	0	0	0	0	0	177	9	0	0	**189**	93.7
Balanites aegyptica	**11**	4	17	0	0	0	0	0	0	0	0	76	0	0	**97**	78.4
Irrigated cropland	**12**	0	0	0	0	0	0	0	0	0	0	0	37	0	**37**	100.0
Water weeds	**13**	1	1	0	0	0	0	0	0	0	0	0	0	46	**48**	95.8
Reference Total		**152**	**155**	**145**	**360**	**206**	**801**	**6527**	**109**	**197**	**186**	**118**	**39**	**58**	**9053**	
Producer`s Accuracy (%)		88.8	78.7	77.9	96.9	91.7	99.3	100.0	97.2	91.9	95.2	64.4	94.9	79.3		

Appendix 1.3 2002 Classification Accuracy Report

2002 classification		***Reference Data***														
LULC Type		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**Classified Total**	**User`s Accuracy (%)**
Prosopis	**1**	70	9	0	1	0	0	0	1	2	0	6	0	11	**100**	70.0
Vachellia tortilis	**2**	6	105	3	3	0	0	0	1	0	0	3	0	0	**121**	86.8
Vachellia reficiens	**3**	0	0	102	0	0	0	0	7	1	0	0	1	0	**111**	91.9
Mixed vegetation	**4**	0	9	31	358	0	0	0	1	3	0	2	0	0	**404**	88.6
Indigenous forest	**5**	0	0	0	0	175	0	0	0	0	0	6	0	0	**181**	96.7
Plantation forest	**6**	0	0	0	0	16	851	0	0	0	0	0	0	0	**867**	98.2
Water	**7**	0	0	0	0	0	0	6227	0	0	0	0	0	0	**6227**	100.0
Rain-fed cropland	**8**	0	0	5	0	0	0	0	91	1	0	2	0	0	**99**	91.9
Bareland	**9**	7	1	6	0	0	0	0	0	207	0	0	0	0	**221**	93.7
Grassland	**10**	0	0	0	0	0	0	0	0	2	76	0	0	0	**78**	97.4
Balanites aegyptica	**11**	24	12	0	0	0	0	0	2	0	0	107	0	0	**145**	73.8
Irrigated cropland	**12**	1	0	0	0	0	0	0	0	0	2	0	42	0	**45**	93.3
Water weeds	**13**	0	1	0	0	0	0	0	0	0	0	0	0	61	**62**	98.4
Reference Total		**108**	**137**	**147**	**362**	**191**	**851**	**6227**	**103**	**216**	**78**	**126**	**43**	**72**	**8661**	
Producer`s Accuracy (%)		64.8	76.6	69.4	98.9	91.6	100.0	100.0	88.3	95.8	97.4	84.9	97.7	84.7		

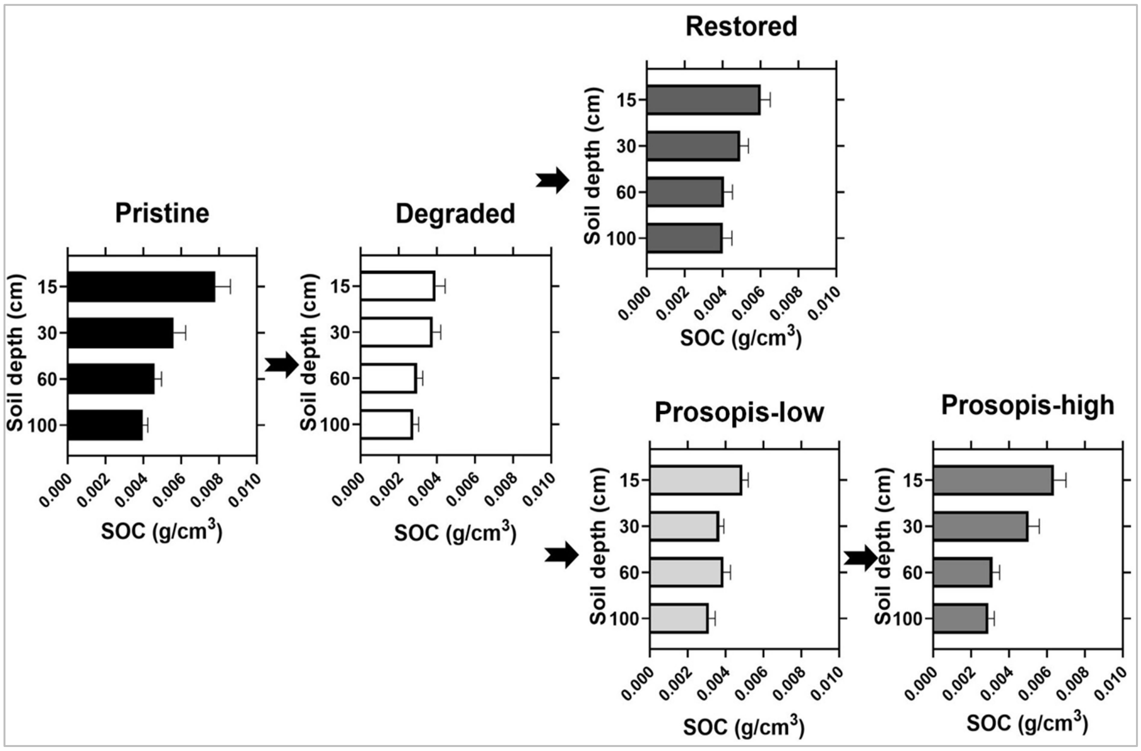
Appendix 1.4 2009 Classification Accuracy Report

2009 classification		***Reference Data***														
LULC Type		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**Classified Total**	**User`s Accuracy (%)**
Prosopis	**1**	179	9	0	1	0	0	0	0	3	0	32	0	5	**229**	78.2
Vachellia tortilis	**2**	12	77	0	2	0	2	0	0	0	0	5	0	5	**103**	74.8
Vachellia reficiens	**3**	0	0	108	1	0	0	0	2	4	0	0	0	0	**115**	93.9
Mixed vegetation	**4**	1	4	14	357	0	0	0	0	4	0	0	0	1	**381**	93.7
Indigenous forest	**5**	0	0	0	0	201	19	0	0	0	0	1	0	0	**221**	91.0
Plantation forest	**6**	0	0	0	1	0	809	0	0	0	0	0	0	0	**810**	99.9
Water	**7**	2	0	0	0	0	0	6309	0	0	0	0	0	0	**6311**	100.0
Rain-fed cropland	**8**	0	0	9	0	0	0	0	97	0	0	0	0	0	**106**	91.5
Bareland	**9**	8	0	4	0	0	0	0	0	204	1	0	0	0	**217**	94.0
Grassland	**10**	2	0	0	0	0	0	0	0	0	67	0	0	1	**70**	95.7
Balanites aegyptica	**11**	16	10	0	0	3	0	0	0	0	0	92	0	0	**121**	76.0
Irrigated cropland	**12**	0	0	14	0	0	0	0	0	1	0	0	54	0	**69**	78.3
Water weeds	**13**	0	0	0	1	0	0	0	0	0	0	0	0	3	**4**	75.0
Reference Total		**220**	**100**	**149**	**363**	**204**	**830**	**6309**	**99**	**216**	**68**	**130**	**54**	**15**	**8757**	
Producer`s Accuracy (%)		81.4	77.0	72.5	98.3	98.5	97.5	100.0	98.0	94.4	98.5	70.8	100.0	20.0		

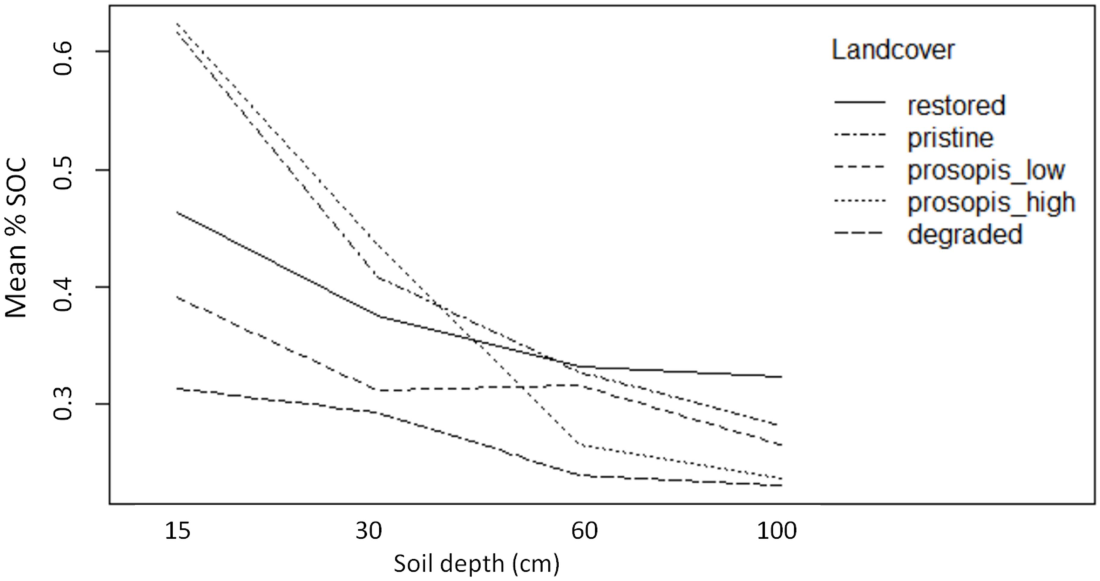
Appendix 1.5 2016 Classification Accuracy Report

2016 classification		***Reference Data***														
LULC Type		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**Classified Total**	**User`s Accuracy (%)**
Prosopis	**1**	170	19	0	0	0	0	0	0	0	4	20	1	8	**222**	76.6
Vachellia tortilis	**2**	6	53	0	1	0	0	0	0	0	0	1	0	0	**61**	86.9
Vachellia reficiens	**3**	1	0	132	4	0	0	0	1	0	0	0	16	0	**154**	85.7
Mixed vegetation	**4**	2	3	4	336	0	3	0	0	0	0	2	0	0	**350**	96.0
Indigenous forest	**5**	0	0	0	0	166	2	0	0	0	0	0	0	0	**168**	98.8
Plantation forest	**6**	0	2	0	0	5	789	0	0	0	0	0	0	0	**796**	99.1
Water	**7**	0	0	0	0	0	1	6889	0	1	0	0	0	0	**6891**	100.0
Rain-fed cropland	**8**	0	0	7	0	0	0	0	120	0	0	0	0	0	**127**	94.5
Bareland	**9**	0	0	0	0	0	0	0	0	216	2	0	0	0	**218**	99.1
Grassland	**10**	2	2	0	0	0	0	0	0	0	64	0	0	3	**71**	90.1
Balanites aegyptica	**11**	14	20	0	0	1	0	0	0	0	0	106	0	0	**141**	75.2
Irrigated cropland	**12**	1	0	0	0	0	0	0	0	0	0	0	100	0	**101**	99.0
Water weeds	**13**	3	0	0	0	0	0	0	0	0	0	6	0	132	**141**	93.6
Reference Total		**199**	**99**	**143**	**341**	**172**	**795**	**6889**	**121**	**217**	**70**	**135**	**117**	**143**	**9441**	
Producer`s Accuracy (%)		85.4	53.5	92.3	98.5	96.5	99.2	100.0	99.2	99.5	91.4	78.5	85.5	92.3		

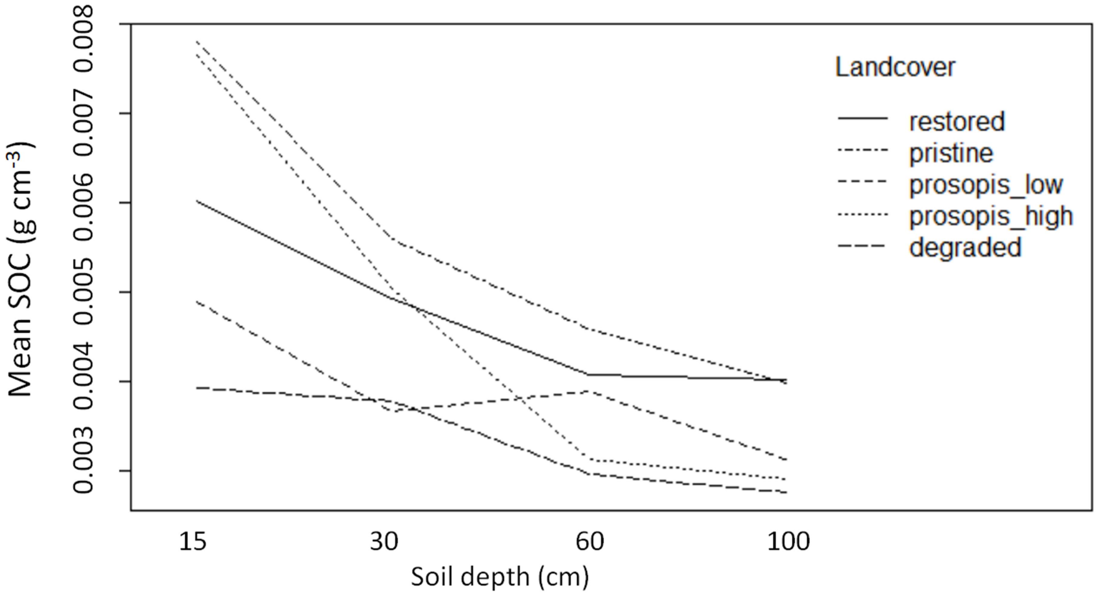
Appendix 5.1 SOC per volume (g cm^{-3}) for the five land cover types and four soil depth increments. Error bars indicate standard errors. The arrows represent a hypothetical transition from one land cover state to the next over time.



Appendix 5.2 Interaction effects of land cover type and soil depth on SOC concentration (%SOC).



Appendix 5.3 Interaction effects of land cover type and soil depth on SOC per volume (SOC g cm^{-3}).



Appendix 5.4 Effect of land cover type and soil depth on SOC concentration (%SOC). Land cover-soil depth combinations sharing the same letter do not differ significantly from each other (Tukey HSD Post-Doc test; α = 0.05).

	Num DF	Den DF	F-value	*p-value*
(Intercept)	1	174	1097.7480	<.0001
Land cover	4	58	4.8207	0.002
Soil depth	3	174	36.6325	<.0001
Landcover:soil depth	12	174	2.2609	0.011

Land cover	Soil depth (cm)	%SOC	SE	df	lower CL	upper CL	Tukey HSD
Pristine	0-15	0.5767	0.0693	58	0.3953	0.8414	f
Degraded	0-15	0.2816	0.0267	62	0.2089	0.3796	abcd
Prosopis-low	0-15	0.3772	0.0413	58	0.2671	0.5324	bcdef
Prosopis-high	0-15	0.5648	0.0678	58	0.3871	0.8241	ef
Restored	0-15	0.4483	0.0439	58	0.3292	0.6102	def
Pristine	15-30	0.3870	0.0465	58	0.2652	0.5646	bcdef
Degraded	15-30	0.2695	0.0256	62	0.1999	0.3633	abc
Prosopis-low	15-30	0.3044	0.0333	58	0.2156	0.4297	abcd
Prosopis-high	15-30	0.3967	0.0476	58	0.2718	0.5787	cdef
Restored	15-30	0.3539	0.0347	58	0.2599	0.4817	bcdef
Pristine	30-60	0.3188	0.0383	58	0.2185	0.4652	abcde
Degraded	30-60	0.2234	0.0212	62	0.1657	0.3012	ab
Prosopis-low	30-60	0.3019	0.0331	58	0.2138	0.4262	abcd
Prosopis-high	30-60	0.2456	0.0295	58	0.1683	0.3583	ab
Restored	30-60	0.3047	0.0298	58	0.2238	0.4148	abcd
Pristine	60-100	0.2786	0.0334	58	0.1909	0.4064	abcd
Degraded	60-100	0.2101	0.0199	62	0.1558	0.2832	a
Prosopis-low	60-100	0.2504	0.0274	58	0.1773	0.3535	abc
Prosopis-high	60-100	0.2273	0.0273	58	0.1558	0.3317	ab
Restored	60-100	0.2942	0.0288	58	0.2161	0.4005	abc

Appendix 5.5 Effect of land cover type and soil depth on SOC per volume (SOC g cm^{-3}). Land cover-soil depth combinations sharing the same letter do not differ significantly from each other (Tukey HSD Post-Doc test; α = 0.05).

	Num DF	Den DF	F-value	*p-value*
(Intercept)	1	174	25021.776	<.0001
Land cover	4	58	6.148	0.0003
Soil depth	3	174	37.796	<.0001
Land cover:soil depth	12	174	1.981	0.0285

Land cover	Soil depth (cm)	SOC per volume	SE	df	lower CL	upper CL	Tukey HSD
Pristine	0-15	0.0074	0.0009	58	0.0051	0.0109	k
Degraded	0-15	0.0035	0.0003	62	0.0026	0.0048	abcdefghi
Prosopis-low	0-15	0.0048	0.0005	58	0.0034	0.0068	cdfhijk
Prosopis-high	0-15	0.0069	0.0008	58	0.0047	0.0101	jk
Restored	0-15	0.0057	0.0005	58	0.0042	0.0078	ijk
Pristine	15-30	0.0053	0.0006	58	0.0036	0.0077	ghijk
Degraded	15-30	0.0035	0.0003	62	0.0026	0.0048	abcdefghi
Prosopis-low	15-30	0.0036	0.0003	58	0.0025	0.0051	abcdefghi
Prosopis-high	15-30	0.0047	0.0005	58	0.0032	0.0068	efghijk
Restored	15-30	0.0046	0.0005	58	0.0034	0.0063	bdghijk
Pristine	30-60	0.0044	0.0005	58	0.0030	0.0065	abcdefghij
Degraded	30-60	0.0028	0.0003	62	0.0021	0.0037	acef
Prosopis-low	30-60	0.0036	0.0004	58	0.0026	0.0052	abcdefghi
Prosopis-high	30-60	0.0029	0.0004	58	0.0020	0.0043	abcdefgh
Restored	30-60	0.0037	0.0004	58	0.0027	0.0050	abcdefgh
Pristine	60-100	0.0039	0.0005	58	0.0027	0.0057	abcdefghij
Degraded	60-100	0.0026	0.0002	62	0.0019	0.0035	a
Prosopis-low	60-100	0.0029	0.0003	58	0.0021	0.0041	abeg
Prosopis-high	60-100	0.0028	0.0003	58	0.0019	0.0040	abcd
Restored	60-100	0.0036	0.0004	58	0.0027	0.0049	abcdefgh

Appendix 5.6 Effect of land cover type on total SOC per unit area (t ha^{-1}). Land cover types sharing a letter are not significantly different from each other (Tukey HSD Post-Doc test; α = 0.05).

	Df	Sum of Squares	Mean Square	F-value	p-value
Landcover	4	2539	634.7	5.532	0.000766***
Residuals	58	6654	114.7		

Land cover	total SOC	SE	Asymp.LCL	Asymp.UCL	Tukey HSD
Degraded	31.52287	2.677832	24.64416	38.40159	a
Prosopis-low	36.98844	3.092094	29.04558	44.93130	ab
Prosopis-high	40.04675	3.387220	31.34578	48.74772	abc
Restored	44.67903	2.765653	37.57473	51.78334	bc
Pristine	49.75775	3.387220	41.05678	58.45872	c

Appendix 5.7 Effect of land cover type on plant species richness (number of species plot^{-1}). Land cover types sharing a letter do not differ significantly from each other (Tukey HSD Post-Doc test; α = 0.05).

	Df	Sum of Squares	Mean Square	F-value	p-value
Land cover	4	6.245	1.5612	8.656	<0.0001***
Residuals	58	10.461	0.1804		

Land cover	species richness	SE	Asymp.LCL	Asymp.UCL	Tukey HSD
Degraded	7.23	0.77	5.50	9.49	a
Restored	8.59	0.94	6.48	11.38	ab
Prosopis-high	8.97	1.20	6.35	12.66	ab
Prosopis-low	12.26	1.50	8.94	16.79	bc
Pristine	18.21	2.45	12.90	25.72	c

Appendix 5.8 Effect of land cover type on dry herbaceous biomass (dry weight g m^{-2}). Land cover types sharing a letter do not differ significantly from each other (Tukey HSD Post-Doc test; α = 0.05).

	Df	Sum of Squares	Mean Square	F-value	p-value
Land cover	4	14578	3644	33.97	<0.0001***
Residuals	58	6223	107		

Land cover	Biomass	SE	Asymp.LCL	Asymp.UCL	Tukey HSD
Prosopis-high	13.90	3.28	5.49	22.31	a
Prosopis-low	21.29	2.99	13.61	28.97	a
Degraded	23.03	2.59	16.38	29.68	a
Restored	46.73	2.67	39.86	53.60	b
Pristine	55.20	3.28	46.79	63.61	b

Appendix 5.9 Above-ground carbon stock (mean and standard error of the mean) expressed in tonnes per hectare for pristine, restored and *Prosopis* invaded areas. These were determined using dry woody *Prosopis* above-ground biomass (for *Prosopis* invaded areas) derived by applying a *Prosopis*-species allometric equation on the diameter at breast height (DBH at 0.3 m from ground) of all individual *Prosopis* trees in randomly sampled 5x5 m subplots following the methods described by Linders et al. (2020). The *Prosopis* species allometric equation was developed by Linders et al. (2020) using *Prosopis* data from Kenya by Muturi et al. (2012). For grasslands dry herbaceous biomass was used to estimate above-ground carbon stocks. For both grasslands and *Prosopis* invaded areas, a conversion factor of 0.47 was used to convert dry above-ground biomass to carbon stocks (IPCC, 2006).

Land cover	**n**	**Above-ground C (t ha^{-1})**	**Standard error**
Pristine	10	6.02	1.00
Restored	15	3.19	0.40
Prosopis-high	5	12.46	2.84
Prosopis-low	28	2.78	0.47