MAXIMUM ENTROPY MODELLING OF *Parthenium hysterophorus* L. UNDER CURRENT AND PROJECTED CLIMATE CHANGE WITHIN THE MAASAI MARA ECOSYSTEM

BY

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DECLARATION

I hereby declare that this research project is my original work and has not been submitted for the award of a degree to any other university.

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(I56/89210/2016)

This research project has been submitted to the University for Examination with our approval as university supervisors.

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DEDICATION

This thesis is dedicated to my family who have tirelessly provided me with moral and financial support that gave me the strength to see it through.

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AR5	Fifth Assessment Report (AR5)
AUC	Area Under the Curve (AUC)
CABI-Africa	The Centre for Agriculture and Bioscience International
CBD	Convention on Biological Diversity
CCM4	Community Climate System Model
CO2	Carbon (iv) oxide
CSV	Comma separated values
ENM	Environmental Niche Modeling
EVI	Enhanced Vegetation Index
GHG	Greenhouse gases
GIS	Geographical Information System
GISP	Global Invasive Species Programme
GPS	Global Positioning System
HSI	Habitat Suitability Index Mapping
HSM	Habitat Suitability Modeling
HUC	Hydrologic unit code
IAPS	Invasive Alien Plant Species
IPPC	Intergovernmental Panel on Climate Change
KNBS	Kenya National Bureau of Statistics
KWS	Kenya Wildlife Service
LANDSAT TM/ETM	Landsat Thematic Mapper/Enhanced Thematic Mapper
MEA	Millennium Ecosystem Assessment
MME	Maasai Mara Ecosystem
MMNR	Maasai Mara National Reserve

MODIS..Moderate Resolution Imaging Spectroradiometer

NDVI..Normalized Difference Vegetation Index

PVM...Predictive Vegetation Mapping

RCMRD.....................................Regional Centre for Mapping of Natural Resources for Development

RCPs..Representative Concentration Pathways

ROC...Receiving Operator Curve

SDM...Species Distribution Models

SEM...Species Environmental Matching

SPOT-VGT................................Spot Vegetation

WHC...World Heritage Convention

WTO-SPS..................................World Trade Organization Agreement on the Application of Sanitary and Phytosanitary Measures

WWF..World Wide Fund for Nature

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ABSTRACT

Land managers are increasingly using Species Distribution Models (SDMs) in modeling potential geographical distribution of Invasive Alien Plant Species (IAPS). These models show current distribution and also areas prone to invasion by the species if the conditions affecting their survival are the same as those in their native areas. Therefore, species niche requirements are the basis of development of these models. Among the numerous SDMs that are in use, Maxent approach was applied in this study because it operates on presence-only data. Consequently; it is simple, fast, economical and convenient to construct meaningful species distribution models from the data that included coordinates of the IAPS. Further, GIS and Remote Sensed data that was required was easily available for extracting a set of environmental predictions that affect the fundamental and residual niches of the IAPS. These environmental predictions include precipitation, elevation and temperature for the area of study. Socio-economic factors such as wildlife population and livestock density were obtained from KWS. This study addressed one of the major IAPS that are thought to pose the highest risks to the Mara ecosystem; *Parthenium hysterophorus* L. For this study, a stratified random sampling method was used. Study area was stratified on the basis of the road network that is the main agent of IPS dispersal. Plots of 10 by 10m were set on either side of the road at every 1km travelled. GPS coordinates of the sampled *Parthenium hysterophorus* L., for use in the Maxent modelling were obtained by using an application developed by the Regional Centre for Mapping of Natural Resources for Development (RCMRD) called 'Invasive Species Mapper' available from google play store. A combination of ArcMap 10.5 and the Maxent modelling software were used to manipulate the data collected into the final product; a prediction map showing the potential geographical locations of the spread of the invasive species under study. Habitat suitability maps for the present conditions and for future were created using present environmental and socio-economic factors that impact on the growth and distribution of the IPS and extrapolated climatic scenarios of RCPs 2.6 and 8.5 for the year 2050 respectively. Results showed range expansion in the current and the projected scenarios posing imminent threat to native vegetation. Models offer a proactive management strategy for the management of IAPS.

Key words: Species Distribution Models, Maxent, Niche, IAPS, GIS, Remote sensed data, ArcMap 10.5 software, targeted sampling, prediction map, RCPs.

CHAPTER 1: INTRODUCTION

1.1 Introduction

The conservation of biodiversity within protected areas is faced by several major challenges that negatively impact on these conservation efforts. These are land cover change, habitat fragmentation and destruction, unsustainable use of the resources within, pollution, climate change and the introduction and spread of alien species. These factors are major drivers of change in terms of resources within and consequently affect ecosystem balance and health. These factors are also interrelated and together lead to massive losses in ecosystem integrity. For instance, climate change is a major agent in exacerbating the negative impacts of alien invasive species (IAS) (Rija *et al.*, 2013).

The impact of IAS is compounded by climate change as it increases the rates of establishment and spread of these IAS (IUCN, 2017). Climate change also creates new niches for IAS enabling invasibility. These ecological niches result from the environment becoming inhabitable to the native species. These species as a result reduce the resilience of protected areas to impacts of climate change. Inversely, climate change leads to the decline of an ecosystems capacity to resist invasion by IAS. Climate change and IAS should therefore always be addressed together. It is necessary that efforts to combat IAS go hand in hand with climate change policy formulation (IUCN, 2017).

The Convention on Biological diversity (CBD) describes Invasive Alien Species (IAS) as species introduced into an area thereby dispersing beyond their home range. As a result, biodiversity in the new area is affected (CBD.int, 2017). The terms non-indigenous, alien, exotic, imported, introduced, non-native, biotic invaders, colonizer and naturalized are now and again utilized reciprocally in reference to invasive species.

Scientists mostly refer to invasive alien species as non-indigenous species, rather than indigenous species. The reason for this is that the non-indigenous species tend to be aggressive in their new environments as compared to the indigenous species, enabling them to become naturalized under the prevailing conditions (Bajwa *et al.*, 2016; Richardson, 1998). According to 'Introduced Species', (2017), Invasive Alien Plant Species (IAPS) or Invasive Alien Species (IAS) are defined as non-indigenous species that establish themselves in a new area and reproduce without humans intervening; they are established species that quickly disperse to surrounding areas and, in the process, negatively impacting on the existing species therein.

It should be noted that not all non-indigenous species adversely affect their invaded environment. In fact, some indigenous species can end up noticeably invasive in a new environment. This leads us to a more precise meaning of invasive species, which incorporates both scenarios. An invasive species is therefore either an indigenous or a non-indigenous species that vigorously colonizes a specific area and adversely affects it economically, environmentally or ecologically (Bajwa *et al.*, 2016; Davis *et al.*, 2007).

Invasive Alien Plant Species (IAPS) impact on all ecosystems and are found in all taxonomic classes such as microorganisms and fungi, plants and animals. While a small number transported to new areas end up noticeably invasive, the negative effects can be broad and after some time, these increments and their effects become additive. Transportation is mainly by humans and through trade. Conservation efforts and the need to regulate the international trade in a bid to control the dispersal of these invasive alien species has arisen the need to come up with ways to identifying future invaders and come up with ways to counter their dispersal. Early detection and prediction efforts for invasive alien species management have faced several challenges. Among these are difficulties in predicting the geographical locations of spread of invasive species given that the invaders settle in new areas at different times, and difficulty in eradication of an established invader as most mitigation measures face setbacks (Davis *et al.*, 2007).

Many theories have been developed that seek to explain why some existing communities are more invasible than others. Results from field studies have been conflicting and no broad hypothesis of invasibility has yet been developed (Lonsdale 1999; Strathie and McConnachie, 2013; Williamson 1999). It is therefore far-fetched that any single hypothesis will have the capacity to represent all distinctions observed in invasibility in different areas (Simberloff *et al.*, 2000).

One major hypothesis supporting the theory of why some areas are prone to IAPS than others is the different rates of climate change observed in different areas. This is because the amount of CO_2 being released into the atmosphere is different in different areas. Excess CO_2, beyond the natural air composition limit of 0.0391%, is the main cause of climate change and is mostly released in excessive amounts into the atmosphere as a result of human activities such as burning of fossil fuels. Therefore, climate change is mainly caused by anthropogenic induced factors. These changes, both in the long run and in the short run affect ecosystems globally. One of the major effects of climate change is the impact on the spatio-temporal distribution and growth of plants. Plants are particularly greatly affected by climate change. The increasing CO_2 levels in the atmosphere results to an increase in growth and distribution of plants particularly the IPS which can better utilize the increasing CO_2 amounts. Factors that support growth and distribution of IPS are interrelated such as rates of climate change and disturbance. Local areas especially those that are ruderal in nature such as the roadsides have a marked larger population of IPS than surrounding areas. The increased plant numbers in these areas better utilize the increasing CO_2 as a result further increase in numbers. In addition to this, areas such as roadsides also are direct recipients of particulate matter (dust), sulfur oxides, nitrogen oxides, carbon monoxide and CO^2 produced from the exhaust fumes. This, as a result increases the amount of CO_2 available to IPS at these localized areas. It is important to note that IPS better utilize these gases than native plants as they have less dense tissues than native plants that assist them in utilizing CO_2 faster than native plants (Reich *et al.*, 2013). Global climate change has become unprecedented and it continues to be more unexpected by rising by at least 0.3-1.7 degree Celsius and up to an upper limit of 2.6-4.8 degree

Celsius over the 21st century (Zhang *et al.*, 2018). Many plant communities especially those with small realized niches will be threatened the most and consequently face the risk of extinction. One way of combating this foreseeable eventuality is attempting to make habitat predictions to monitor the spread of IAS thereby reducing their spread ahead of time (Zhang *et al.*, 2018).

Climate change, particularly temperature increase affects vegetation indices that measure plant density and the rate of vegetation changes in an area. Harsh climate leads to a reduction in other native vegetation cover thereby promoting growth of IAPS (Khisro, 2013). Normalized Difference Vegetation Index (NDVI) measures greenness of an area thus climate change directly impacts on NDVI. (Cord and Ro¨dder, 2011). NDVI is very useful in change detection and is useful in differentiating between classes of different components in the environment. NDVI ranges from -1.0 to +1.0. Extremely low values of NDVI that lie from 0.1 and below corresponds to sand, rocks, barren lands and snow. Values of between 0.2 and 0.3 are representative of shrub, herbs and grasslands. A range of between 0.6 and 0.8 represent temperate and tropical rainforests. This shows that the closer the NDVI value is to one the greener the vegetation and the closer the value is to 0 the stressed the vegetation of an area is. In modelling studies, NDVI is useful in detection and monitoring of changes in vegetation (Bid, 2016). Most modelling studies prefer NDVI over EVI (Enhanced Vegetation Index) but research shows that EVI is a better index as it is less affected by background features such as soil effects and saturation problems when study areas are characterized by dense vegetation. Increased CO_2 amounts in the atmosphere leads to temperature increase which increases plant productivity. Excessive CO_2 in the atmosphere promotes faster growth of IAS in comparison to native species due to their high phenotypic plasticity thus leading to the 'negative 'greening of the area. In modelling studies involving IPS, NDVI is used as an indicator to show high plant growth population in an area as a result of the negative greening of the area. Negative greening refers to the increased in NDVI values signifying lots of green vegetation in an area but in the case of IPS, the high populations of the weed leading to high NDVI recorded is inversely a negative as it is the undesirable kind of plant population growth required in an area. This detection can be useful in directing and planning for proactive conservation efforts with direction given on spatio-temporal frames where and when the negative greening is expected to be on a high (Cord and Ro¨dder, 2011).

One theory of invasibility characterized with supporting factors such as climate change induced invasions and other factors promoting invasibility can be analyzed alongside current geographical distribution of IPS to provide a clear picture of present and potential trends. The impact of climate change on protected areas is complex and determination of potential invasion on these areas is essential to protect them in the long run. This can be achieved through employing the use of Species distribution models (SDMs) such as Maxent. Maxent uses an ecosystem approach to manage the species and is more efficient than targeting individual species. It is also important to note that potential geographical distributions of IPS that can be obtained from Maxent is of paramount importance because it acts as a precautionary step towards preventing future invasions. These potential distributions are enabled by extrapolating different climate change scenarios using

Representative Concentration Pathways (RCPs). Preventing invasions is less expensive than combating established invaders. If the problem of invaders is not addressed, the world faces risk of widespread losses in agriculture, fishing sector, forestry, loss of ecosystem integrity and the economy at large will be affected (Guisan *et al.*, 2013).

1.1.1Statement of problem

Currently, biotic invaders together with human induced changes such as climate change are placed as major factors of global environmental change. If not controlled, their effects will have a toll on human survival (Simberloff *et al.*, 2000).

IAPS are considered the second biggest threat to biodiversity. Their effects are exacerbated by the increasing anthropogenic disturbances (such as changing global climate, changing land cover and shifting land uses) on natural ecosystems. Some if not most of these anthropogenic disturbances increase carbon emissions into the atmosphere which consequently lead to climate change.

Broennimann *et al.*, (2007) are of the view that the IAPS out-compete native plant species for nutrients, light, water among other resources in their home range as they cope better in disturbed rangelands and in the ever changing climatic conditions (they thrive in a wide range of environmental conditions unlike native plant species which thrive in a specific tolerable range of climatic conditions). The ecology and economic viability of the invaded ecosystem is thus negatively impacted.

Based on their findings, Cronk and Fuller (1995) acknowledged the gravity of the threat posed by invasive species on protected areas of Africa. A loss of US$1.5 trillion in form of ecological and economical costs is expected yearly as a result of damages from invasive species. This however is only a calculation based on production costs and doesn't include costs of species extinctions, loss in biological diversity and loss of ecosystem services. Including the cost of invasive species impacts on these would therefore increase this expected cost.

Increase in international trade, developments such as road and building constructions and loss of natural barriers through increase of trade facilitate easier movement thereby increasing their spread. Introduction of some species as ornamental plants has also increased their spread necessitating improved management.

Alien plant invasions therefore pose a big risk to a lot of Africa's conservation areas such as the Maasai Mara Reserve. This is diagnosed as one of the important threats to biodiversity and environment stability globally; second only to habitat loss and degradation (Guisan *et al.*, 2013; Mack *et al.*, 2000; Mungoro and Tezoo, 1999; Wilcove *et al.*, 1998).

1.1.2 Justification

Establishment of protected areas are a major component in the efforts to conserve and protect our biodiversity. Having protected areas however is not an assurance that the ecosystem within is free from any threats. Such threats include land use changes, destruction of wildlife habitats, climate change, pollution and invasion by alien species. Invasion by alien species poses a serious threat to conservation of our biodiversity in protected areas (Foxcroft *et al.*, 2013). A report by De Poorter *et al.*, (2007) showed 487 protected areas face threat by these invasive species. Invasive species threats have, however, not been widely recognized in most African countries and little information is available except for South Africa (Foxcroft *et al.*, 2013). Due to the lack of information, little is known on how the invasive species invade an area and therefore making it difficult to manage the problem (Witt *et al.*, 2017). This work focused on the MME which encompasses a protected area, the Maasai Mara game reserve.

Most studies that have been done in biodiversity protection against IAPS have focused on reactive management where area surveys are done after these species have spread and established themselves and they therefore, concentrate their efforts in controlling them. Proactive management of invasive plant species where prevention is given more weight is less expensive and less effort is required as compared to reactive management. It entails predetermining areas prone to invasion and preventing this before they spread to these areas. Use of SDMs forms part of proactive management (Guisan *et al.*, 2013).

Currently, only a few tools such as time series maps and SDMs are effective and efficient in providing information on invasions by biotic invaders. For instance, Elton's (1958) application and use of time series maps clearly showed the extent of spatial distribution of biotic invaders on a temporal scale. SDMs use sets of algorithms to match sets of environmental data to areas species are not found at the moment thus forms methods of identifying potential areas where the species might thrive. Maxent, an SDM that was used in this study begins from identifying presence data of species in the area of interest. It functions to show resource managers which areas should be surveyed more closely in the future and therefore provide basis for early detection and conservation initiatives (Phillips *et al.*, 2008).

Maasai Mara is one of the finest tourist destinations and is home to one of the Seven Wonders of the World; the Great Wildebeest Migration. It is also an important biodiversity hotspot and a source of revenue to the local area and to Kenya as a whole. Therefore, it was important that this study was conducted to ensure the ecosystem's integrity is ensured by efficiently managing IAPS that are problematic.

1.1.3Significance of the study

This study sought to identify areas that face potential risk of invasion in order to increase surveillance on these areas as a way of controlling the IAS. The study also sought to form a benchmark for more SDM studies in Kenya as much work hasn't been done on this subject. This study also aimed on adding on to the information database that seeks to aid resource managers and government authorities when formulating sustainable development and protected area management strategies in Kenya.

1.1.4 Research questions

1. Which variables affect the environmental niches of *Parthenium hysterophorus* L.?

2. How do the variables affect the current geographical distribution of *Parthenium hysterophorus* L.in MME?

3. How do different climate change scenarios affect the future potential geographical distribution of *Parthenium hysterophorus* L.in MME?

1.1.5 Research objectives

1.1.5.1 General Objective

1. To determine the impact of environmental variables on the current and potential geographical distribution of *Parthenium hysterophorus* L. invasive plant species using Maxent SDM Approach.

1.1.5.2 Specific Objectives

1. To identify the environmental variables that affect the niches of *Parthenium hysterophorus* L.

2. To determine the effect of these variables on the current geographical distribution of *Parthenium hysterophorus* L.

3. To extrapolate future potential climate change scenarios and their effects on the distribution of *Parthenium hysterophorus* L.

1.1.6 Research Hypothesis

1. The distribution of *Parthenium hysterophorus* L. is not influenced by its response to specific environmental variables

CHAPTER 2: LITERATURE REVIEW

IAPS pose significant threats to an ecosystem. They affect ecosystem integrity by affecting the ecosystem functioning and despite this, they have not been given the attention they require. These threats cause deterioration of the rangeland and among the numerous resultant impacts include those on the health of humans, grazing and migrating animals therein. The IPS impact on migrating animals in turn affects the main economic activity of such rangeland areas, tourism. Most works done have been on inventory of these species and consequently control measures such as biological control methods have been implemented. Witt *et al.,* (2017) reported that in the Serengeti-Mara ecosystem and the adjoining conservancies, 245 alien plant species were encountered. Out of these, 212 were said to have been intentionally introduced into the reserve and 51 species had naturalized into the areas. Twenty-three (23) of these naturalized species were considered invasive species. Six of these found within the ecosystem, near lodges and the ecosystems surroundings where human populations exist were found to be of greatest risk to conservation efforts in the area. These were *Prosopis juliflora, Opuntia stricta, Chromolaena odorata, Lantana camara, Tithonia diversifolia*, and *Parthenium hysterophorus* L. All of these are known to be aggressively invasive and have the potential to substantially reduce the ability of rangelands to support the grazing of animals, and several have other impacts, being toxic, or having an ability to affect the health of livestock or wildlife.

The Mara ecosystem faces greatest risk of invasion particularly from the west where these species were abundantly found. This study therefore sought to address one of the six IPS that are thought to pose the highest risks, *Parthenium hysterophorus* L. It has been recorded in several regions in Africa that they pose greatest threats to the environment and especially to the Serengeti-Mara ecosystem (Illori *et al.*, 2010; Maundu *et al.,* 2009; McConnachie *et al.*, 2011; Shackleton *et al.*, 2017).

2.1 Nature of dispersal of *Parthenium hysterophorus* L.

There are several modes of dispersal of *Parthenium hysterophorus* L. One way in which the species can be moved includes dispersal by nature. Numerous studies (Bajwa *et al.*, 2016; Navie *et al.*, 1996; Taye *et al.,* 2002) have shown that *Parthenium hysterophorus* L. possesses the ability to be moved by forces of wind and floods. In addition to this, the species can also be biotically dispersed by both doth domestic and wild animals. These animals possess the ability to move the seeds from one place to another in the course of their movement (Bajwa *et al.*, 2016).

Parthenium hysterophorus L .can also be dispersed via accidental introduction. Numerous vectors can accidentally lead to introduction of the species in novel areas. Such vectors include humans, animals, various forms of transport such as cars and bicycles and machinery such as construction machinery that can move infested soil from infested areas to non-infested novel environments. This therefore explains why disturbed areas such as sites of constructions, areas next to buildings and along the roads are favorable sites for infestation (Bajwa *et al.*, 2016).

Human induced factors for introduction is another mode of dispersal as seen when people intentionally introduce the species in new areas although with ornamental intentions for use in floral bunches or as green manure (Bajwa *et al.*, 2016).

The fate of plant immigrants to an area is usually different. A few live on the risks of persistent and stochastic forces, and a small fraction end up naturalized. In turn, a few naturalized species do turn out to be invasive. There are numerous reasons why a few alien species prosper: a few break out from threats by their natural enemies in their native areas; others are aided by human-triggered disturbance that disrupts native species in the invaded area. Many invasions are enabled by cultivation, accidental movements that foster immigrant populations until they are self-perpetuating and uncontrollable (Simberloff *et al.*, 2000).

Regardless of the reason, biotic invaders can in lots of instances cause extensive environmental harm. Plant invaders can affect the fire regime, nutrient cycling, hydrology, and energy budgets in a native ecosystem thereby affecting the native plant species (Simberloff *et al.*, 2000).

In the event that the species surroundings are sufficiently comparative to its native range, IAPS might survive and replicate. They first subsist at low densities making it difficult for them to reproduce. This however changes with time. For a species to end up plainly invasive, it should effectively out-compete local life forms, spread through its new surroundings, increase its numbers and damage biological communities in the new home range. In brief, for a non-native species to be considered invasive, it must arrive, survive and flourish (Bajwa *et al.*, 2016).

Biological communities that have been invaded by alien species might not have the common predators of alien invasive species in their ranges that would ordinarily control their population. Local biological communities that have experienced human-disturbances or influences are regularly more prone to invasions in light of the fact that there is less competition from local species (due to their inability to thrive well in the disturbed home range) (Simberloff *et al.*, 2000).

Numerous traits have been singled out by scientists as predictors of invasive capacity of vegetation in new surroundings. Some of these traits are based on growth and reproduction. These consist of the following: Capacity to reproduce both asexually as well as sexually, rapid growth, early sexual maturity, high reproductive output as well as the capability to disperse offspring broadly. Other traits include: Tolerance of a wide range of environmental conditions, high phenotypic plasticity or pliancy (capacity to modify growth to match current conditions), the ability to thrive on several food types and allelopathy (production of chemical compounds which make the surrounding soil uninhabitable, or inhibitory, to other competing species) (Day *et al.*, 2003).

While IAPS possess all these attributes that enable them to successfully invade and outcompete native species thereby thrive well relative to the native species, the invasion of an environment by new species is impacted by three factors: the quantity of propagules entering the new area (propagule weight), the attributes of the new species, and the susceptibility of the area to attack by new species (invasibility) (Foxcroft *et al.*, 2013; Londsale, 1999). Invasibility is a developing property of an environment, the result of several factors, including the area's climatic conditions, the proneness of the area to disturbance and competition among the inhabitant species (Lonsdale, 1999). Invasibility may likewise be influenced by biotic interactions such as herbivory, predation and mutualism (Crawley 1987; D'Antonio *et al.*, 1992; Foxcroft *et al.*, 2013; Lonsdale 1999; Marler *et al.*, 1999).

After successful invasion of IPS in a new area, a lag phase in the detection of the IPS is however observed during population growth of invaders. This lag phase can be attributed to inability to detect isolated populations or even slight growth in population (Crooks *et al.*, 1999). It is of paramount importance that better information on potential invasions is made available. This would provide better insights on also on-going invasions and therefore provide better tools for policy making by resource managers as well as aid in further research to add on the existing scientific information. This can be referred to as natural resource monitoring. Monitoring entails collecting information though sampling. It is done repeatedly to determine changes in the status of natural resources. Monitoring can be used to assess whether management actions are effective in meeting objectives set in efforts to control IAPS. Monitoring is used to discover new populations, examine invasiveness by determining changes of population sizes with time, find out the impacts of IAPS on the ecosystem processes of an area and to measure achievement of quality control practices for example during road construction, that are supposed to avert the introduction and dispersal of IAPS in an area.

Through monitoring efforts, there are various recorded reports on the effect of invasive species on biodiversity and the environment at large (D'Antonio and Vitousek, 1992; Foxcroft *et al.*, 2013; Richardson, 1998). The intrusion of habitats by non-native species is a worldwide trend with major impacts on environmental, financial and social frameworks (Bajwa *et al.*, 2016; Dukes and Mooney 1999; Pimental *et al.*, 2000; Vitousek *et al.*, 1996; Williamson 1999). Countries and the international communities at large have been reacting to this danger with different workshops, meetings and research activities intended to comprehend, avert, and oversee species intrusions (Williamson, 1996). Thus, governments and appropriate conservation agencies such as World Heritage Convention (WHC) have expanded protection endeavors trying to rescue biodiversity. Conferences and research efforts have been established by various countries to avert and oversee control of species invasions (Bid, 2016; Richardson, 1998; Williamson, 1996).

Protection endeavors by state agencies like World Wide Fund for Nature (WWF) have also been established. International conventions, protocols and treaties have been put in place with the aim of dispensing dangers to biodiversity thereby enhancing their conservation. The 1992 Convention on Biological Diversity (CBD) sought to conserve biodiversity by controlling invasive alien species which pose threats to biodiversity. The Global Invasive Species Programme (GISP) was established in 1996 to sensitize nations on threats posed by invasive species in our environment. Each and every one of these courses of action is a marker of worldwide concern that invasive species are a genuine risk to biodiversity (Bid, 2016; Richardson, 1998).

Around 40 international policy tools, most of which are legally binding tackle several issues connected to invasive species. CBD is the most comprehensive in coverage. Trade tools for example the International Plant Protection Convention (IPPC) and the World Trade Organization (WTO) agreement on the Application of Sanitary and Phytosanitary Measures (WTO-SPS) have limited coverage but are of economic and political value (Smith *et al.*, 2008). These legally binding international conventions acknowledge that prevention is better than cure. It is easier and cheaper and more environmentally friendly to prevent the establishment and spread of IAPS than to mitigate their effects as well as invest in methods of controlling those IPS (Zimmermann *et al.*, 2004).

The Global Invasive Species Programme (GISP) acknowledges that among other needs it was necessary to have an inventory of invasive species to model and map the paths and distribution of these species, to assess their threat and to create models to be used in their management (Smith *et al.*, 2008). Basic biological knowledge must be combined with evolving technologies and tools for prevention and management of invasive alien species (CBD, 2017). The committee acknowledges the need for early detection and rapid response of the invasive species using appropriate technologies. Article 8 (h) of the CBD requires its parties to 'Prevent the introduction of, control or eradicate those alien species which threaten ecosystems habitat or species' (CBD, 2017).

Threats of invasive species are of global importance as seen in the global context of Millennium Ecosystem Assessment (MEA). It acknowledges the threat of invasive species alongside climate change as key factors leading to destruction of the ecosystems well-being. It also emphasizes on the fact that their effects are hard to reverse. It acknowledged that their effects were on the rise in most ecosystems, being highly catalyzed by growth in trade. Invasive species affect biodiversity conservation efforts and agricultural productivity, forestry, trade among other sectors of the economy. MEA also acknowledges habitat degradation as a factor of increase in the spread of invasive species. Degraded ecosystems are less likely to overcome invasion by the alien species (Smith *et al.*, 2008). A case study of disturbance promoting the establishment of invasive species was seen following the hurricane Katrina in 2005. It provided growth of establishments of the invasive species *Triadica sebifora*, the Chinese fallow tree of the coastal areas in southern USA (Pile *et al.*, 2017).

Kenya's development programme, the Kenya vision 2030, launched in the year 2008, recognizes the importance of conservation of wildlife due to its important role in the country's economy and its social and cultural significance. Wildlife habitats also play key ecosystem functions and contribute to a country's economy in sectors of energy, water, health, fisheries, livestock and agriculture. Vision 2030 aims to conserve wildlife and prosperity through conservation of wildlife habitats, their corridors and dispersal areas. Protected Areas are at the heart of wildlife conservation. However, wildlife moves beyond them in search for vital resources. Corridors function to connect habitats thereby enabling survival of wildlife as they enable them to access critical resources for example water, pasture, and breeding areas and to evade predators. Kenya has recognized the importance of needed advancement in conservation and management of resources as seen in the Kenya Wildlife Conservation and Management policy of April 2017 in which one of the policy statements was to strive to establish a scientifically robust programme that would provide a check on the spread of the invasive species (Conserving Connectivity – Protecting Wildlife Corridors and Dispersal Areas in Kenya, 2017). It is therefore essential to provide a foundation or a new approach to monitor these invasive species for instance by employing use of GIS and species distribution models.

The National Strategy and Action Plan for management of Invasive Alien species was launched by KWS in 2013 with the intention of combating serious threats posed by alien invasive species on our protected areas. Prof Judi Wakhungu, the then cabinet minister of Environment and natural resources in Kenya emphasized on the need to review legislations regarding the management and control of invasive species in order to reduce their growing impacts on the ecosystems. She further acknowledged the contribution of the expanding international trade and human impacts as a vector of the spreading invasive species all over the world. Mr. Kiprono, the then Director at the Kenya Wildlife Service reiterated the initiative would aim to improve on research, education, and control and management activities of invasive species and also focus on protected areas and adjoining community lands (Pugh, 2013).

According to a report by Tu (2009), the best method of controlling invasive species is to prevent their establishment because they are difficult to control once they are established. All these tools show that employing the use of tools that aid in preventing establishments are therefore the best approach in dealing with IAPS.

2.2 History, environmental requirements and impacts of *Parthenium hysterophorus* L.

Parthenium hysterophorus L. (Asteraceae), an annual herb from tropical US, is now a menace in rangelands and farmlands in no less than 34 regions in Africa, Asia, Australia and other continents (Adkins and Shabbir, 2014). The species is allelopathic, killing native plant species (Van der Laan, 2007), such as native grasses in Kruger National Park (Van der Laan, 2007). The weed has significantly reduced stocking rates in Queensland, Australia (McFadyen, 1992) and in India (Jayachandra, 1971). *Parthenium hysterophorus* L. causes health complications such as dermatitis and allergies to people who touch it. Similar effects are also experienced by livestock and wildlife who come into contact with it (Patel, 2011). Ninety percent of the farmers inside the lowlands of Ethiopia deem *Parthenium hysterophorus* L. to be the most threatening weed in their grazing lands (Tamado and Milberg 2004). Figure 1 below shows images of *Parthenium hysterophorus* L.*:*

Figure 1: Photograph of Parthenium hysterophorus L.

Parthenium hysterophorus L. establishes itself in almost all environments due to their ability to withstand almost any of the prevailing conditions and its high phenotypic plasticity/pliancy abilities. This IPS thrives well in a wide range of temperatures, with a preferred mean annual temperature range of 10-25 degrees Celsius. The weed also prefers a mean maximum temperature of warmest month of about 30-40 degrees Celsius and mean minimum temperature of coldest month of 2-12 degrees Celsius. It also thrives well in all soil types that range from sea level to an altitude of 2500m. It however prefers soils of poor drainage such as clay soils. The IPS also prefers an average annual rainfall amount of 500mm although it can still tolerate less rainfall and easily adapts to high saline levels in the soil. It thrives in <60mm of rainfall in its driest month but it thrives best at an Upper limit of 2400mm of rainfall recorded in an area per annum (Day *et al.*, 2003).

It is a common misconception that IAPS cannot invade relatively undisturbed (anthropogenic disturbance) ecosystems such as MME because they offer some form of resistance to invasion. However, a study conducted by Te Beest, *et al.*, (2015) showed that spread and thriving of *Chromolaena odorata* in in the grasslands of Hluhluwe-lmfolozi Park in South Africa was due to disturbances at relatively small areas that provide suitable micro site characteristics that support growth and spread of these IAPS in the long run. It is however important to note that even though all invasive plants generally react to disturbance in the same way, responses to disturbance by different IPS differ among species and it is also dependent on their life stages (Orban *et al.*, 2021)

2.3 Species Distribution Model

Species Distribution Modeling is otherwise known as Environmental Niche Modeling (ENMs), Models of Suitable Environmental Conditions, Species Environmental Matching Models, Predictive Vegetation Mapping (PVM), Predictive Habitat Distribution Modeling, Habitat Suitability Index Mapping (HSI), Habitat Suitability Modeling (HSM), and Niche Modeling among others. These terms are used to evaluate between environmental variables and known species occurrence, and uses that information to identify space where populations could potentially occur. Modeling uses information about the spatial environmental characteristics of an area, such as land cover type, temperature range, precipitation, human pressure and any other variable that can explain the physical and anthropogenic environment of that location, to determine how the occurrence of a species is affected by these characteristics and then makes spatial predictions on potential habitats for the species in question.

There have been a variety of papers on evaluation of modeling techniques used in predicting future species distribution (Phillips *et al.,* 2006). Basically, species distribution models target to provide habitat suitability maps for species.

Holcombe *et al.,* (2007) used GIS in predicting future and modern-day habitat distribution for the invasive cane toad (*Bufo marinus*) using predictive future and modern-day environmental parameters. From his studies, he discovered that the cane toad had invaded the entire range of its suitable habitat. He modeled his study using the Species Environmental Matching (SEM) version and six-digit Hydrologic unit code (HUC). Relevant data used was obtained from public records.

According to Baldwin (2009), Maxent is based on a machine learning response, designed to make response from incomplete data. An estimation is arrived at, for the most uniform distribution (maximum entropy) of sampling points in comparison to background locations. The maximum entropy algorithm converges to the maximum entropy probability distributions since it is deterministic; therefore, the resultant output represents how well the model fits the location data than would a uniform distribution.

In this Study, the Maxent model was selected because of its high suitability for predicting the distribution of plant invasive species in the MME. The suitability of this model is supported by presence-only data (occurrence of invasive species). According to Phillips *et al.,* (2008), even though most SDMs focus on both presence and absence data to give a clear and complete picture of a habitat, Maxent is still mostly preferred in SDMs studies because it relies on presence-only data but can also incorporate historic presence data if available. It is important to note that Presence-absence models cannot confirm the absence of a species in the past even if it can provide presence- absence data in the present. Therefore, indulging in absence data in the present and not including that of the past is incomplete. It should, however, be noted that one advantage of Maxent is it can be run using current presence location data only. The background points generated by Maxent are usually pseudoabsences that are used to compare against the acquired presence locations. These background points hold equal chance of being sampled. In addition to this, Maxent is also of an advantage as it removes the need to obtain absence data that would be otherwise difficult to adequately sample due to the large areas involved in modelling. Also, Maxent requires few locations for the presence data to construct useful models. Out of the presence data collected, 70% of the data is used as training data of the model that is used to create predictive models while the remaining 30% is used as test data that is necessary to assess the accuracy of the model. Another reason for the model's suitability is the ease of acquiring a set of environmental predictions required, such as precipitation and temperature for the area of study. Maxent output includes an Area Under the curve (AUC) test statistic that measures a model's performance fitness. It ranges from 0-1. The closer the AUC tends to 1 the better the model performed. Other advantages associated with it include its ease of use and running the model and the presence of a jackknife feature which enables us to test the variable importance between the different variables. Using the jackknife feature, Maxent runs an individual test for each variable and compares this to the other variables (Yi *et al.,* 2016). This feature is also known as the 'leave one out feature'. A model with all the variables can be created, a model excluding one variable can be created and a model created by excluding each variable in turn can also be obtained. This serves to show which variable mostly impacts on the existence of an IAPS in an area. The feature shows statistical significance of each variable in the model (Yost *et al.,* 2008). Another feature of Maxent is the heuristic test or the analysis of percentage contribution of variables feature. It also provides variable contribution or importance of the different variables. The impact of the variables on the model is shown by response curves created by the model for each variable. It is important to note that the Jackknife feature provides us with variable importance after considering each variable independent of the other while the heuristic test doesn't not take this consideration and the product is usually affected by a compounded effect of the variables. Maxent also accommodates use of limited data and allows for use of both continuous and categorical data (Phillips *et al.,* 2006). Maxent computes statistical analysis through AUC and using a threshold to come up with a binary prediction in which the unsuitable conditions are represented as those below the threshold while those above the threshold represent suitable conditions. Maxent is run using iterations from which averages are produced for all the models. The Statistical significance of the models in prediction are given by the binomial test of choice provided by Maxent (Phillips *et al.,* 2006). Such an example, as used in his study was the minimum training logistic threshold rule which was used to provide the p value for the test at 95% confidence interval of a one tailed test. The p values are 1-sided p values as suitable areas of IPS are either above or below the threshold, as influenced by the prevailing environmental conditions. This threshold means that all sites that are at least as suitable as the least suitable site in your training set are considered suitable.

The statistical machine learning model or software shows the relationship or impact of the independent variables (environmental information) on the dependent variables (species present in an area). Species environmental matching models are thus directly related to the ecological niche concept. The ecological niche concept entails both the fundamental niche and the realized niche. The fundamental niche refers to abiotic or the environmental variables that affect a species habitat and thus the habitat's suitability to the survival of the species. The realized niche in addition to environmental variables incorporates the biotic interactions that are indirect indicators for habitat suitability. These indirect indicators include the land use in an area. Other explanatory variables or indirect indicators include proximity to roads and rivers, human and wildlife populations, degradation status, livestock density, altitude, soil type and bioclimatic data. These explanatory variables are chosen based on studies that chose specific variables that reflect "the three main types of influences on the species" (Giusan and Zimmermann 2000). The three main types of influences on the species are limiting elements that have a bearing on the ecophysiology of a species such as extreme temperatures, natural or anthropogenic interferences, and resources such as energy used by the alien plant species and finally variables that denote biotic interactions. Quantifying this is not possible thus proxies are used to denote their impact on the growth and distribution of IPS. For instance, wildlife, livestock and human population numbers are proxies for disturbance while proximity or distance to water sources such as rivers is a proxy of several factors such as soil water content moisture proxy, propagule pressure and human induced disturbance (Simpson, 2011).

Maxent method of modeling species distribution has experienced some shortcomings over the years. Philipps and Dudick (2008) are of the view that one main drawback is the possibility of over-fitting, limiting the ability of the model to come up with independent data. This is because it may not generalize appropriately. To correct this, there is a parameter in the Maxent software called the regularization multiplier that limits the complexity of the model and generates a less localized prediction. Another drawback to Maxent is biases in occurrence localities. A solution to this is given by Arnold *et al.*, (2014) who are of the view that these biases can be minimized by using remotely sensed data rather than field-based observations only.

2.3.1 Environmental, social and bioclimatic data

In modelling studies, explanatory variables such as NDVI are used to give information about the existence and possible spread of IPS. Other variables include climate change, wildlife and livestock densities, land cover changes, roads and river networks among others (Bajwa *et al.*, 2016).

Bioclimatic data used in the Maxent model was obtained from WorldClim. WorldClim refers to climatic information of the world provided at spatial resolution of 1km^2 from which information for use in GIS and modelling can be derived. Bioclimatic predictors are important as they represent three main aspects of climate namely: annual climatic conditions, seasonal mean climatic conditions and intra-year seasonality. Observing climate over several time periods is of paramount importance when determining the additive effects of climate change on species distribution in the present, past and predicted future states. This criterion is important as climate change impacts on the growth and development of species and subsequently the distribution of species (O'Donnell and Ignizio, 2012). For current scenario, data from the years 1960-2000 was used. For projection, year 2050 data was used. All these variables had a spatial resolution of 1km^2. The Community Climate System Model (CCSM4), a climate model from which information on the earth's climate in the past, present and future provided the data for current climatic scenarios and future projections. The CCSM4 was used by the IPCC in its Fifth Assessment Report (AR5) in 2014. In this report, a greenhouse emission trajectory, also known as Representative Concentration Pathways (RCPs), was adopted. These RCPs are used for climatic modelling and provide possible future climatic scenarios. The fundamental principle behind RCPs is the amounts of emissions of greenhouse gases (GHG) into the atmosphere resulting from anthropogenic factors leading to climate change. Out of the four possible RCPs scenarios, RCP 2.6, RCP 4.5, RCP 6, and RCP 8.5, only two, that is, RCP 2.6 and RCP 8.5 were used for the year 2050. RCP 2.6 denotes the lowest (GHG) concentration pathway, while RCP 8.5 symbolizes the extreme GHG concentration pathway. This difference is based on the possible range and intensity of different human activities that lead to varying GHG emissions. A change in temperature even by a degree affects the distribution of all plant species and it specifically favors IPS as they better cope in these new conditions (Lockwood *et al.*, 2007).

Table 1: AR5 on global warming increase (Degree C) projections

Scenario	**Mean and likely range**	
	2046-2065	**2081-2100**
RCP 2.6	1.0 (0.4 to 1.6)	1.0 (0.3 to 1.7)
RCP 4.5	1.4 (0.9 to 2.0)	1.8 (1.1 to 2.6)
RCP 6.0	1.3 (0.8 to 1.8)	2.2 (1.4 to 3.1)
RCP 8.5	2.0 (1.4 to 2.6)	3.7 (2.6 to 4.8)

(IPCC, 2014)

Current climate information was used as baseline information for mapping of the IPS and tempro-spatial modelling was obtained from WorldClim version 2.0.

Other than bioclimatic data, data on vegetation indices, land-cover change and habitat types, etc. are also useful in the Maxent model and can be obtained from Remote sensed data. Landsat images can be easily obtained from online sources (Njago, 2013). Landsat imageries are preferred over other imageries such as SPOT and IKONOS owing to their high spectral resolution of seven bands. This aids in distinguishing between the different land uses. Most records on environmental information such as soil type also useful for Maxent can be obtained from online sources or records obtained from organizations such as CABI-Africa. Most vegetation indices such as NDVI, are obtained from MODIS and SPOT-VGT (VITO, n.d.). This study initially considered all the 19 bioclimatic variables and environmental and social variables such as livestock density, wildlife density, human population of the study area, landcover changes, soils, elevation, proximity to water habitat type which is a proxy for realized niche (Simpson, 2011) and MODIS variables, NDVI and EVI. Livestock density and wildlife densities were obtained from Kenya wildlife Service (KWS) for the year 2018.

2.3.2 Multicollinearity tests and variable selection

It is important to note that though important, some variables cannot be run together in Maxent. The environmental and social variables should be tested for multicollinearity to determine the final variables that should be run on Maxent in order to avoid overfitting the model. There are variables that impact on the distribution of a species in the same way and as a result could overfit the model leading to correlation (Philipps and Dudick 2008). Collinearity of variables is a problem because it reduces the statistical power of SDMs. Therefore, collinearity among variables reduces the effectiveness of an SDM in accurately predicting the potential geographical distribution of IPS (Júnior *et al.,* 2018).

Pearson's correlation coefficient (r) is used to measure the degree of association between perceived correlated variables. The coefficient ranges between -1 and +1. There are several degrees of correlation in which values that tend towards +1 indicate perfect positive correlation in which both variables positively increase while values that tend towards -1 indicate perfect negative correlation in which both variables positively decrease while a 0 indicates lack of a relationship between the variables (Solutions, n.d.).

According to Júnior *et al.,* (2018), in the case where variables tested give a product r>0.7, one variable has to be excluded as it contains information adequately represented in the other. This would increase the risk of overfitting the model. In this case, the researcher's discretion should be used to decide on which variable to use. For instance, representing altitude and rainfall should be avoided. Their direct relationship would result into the problem of correlation. Landcover changes are represented by vegetation indices. Degradation of forests obtained from land cover change symbolizes landcover changes thus indicating unnecessary correlation when used alongside vegetation indices. Other anthropogenic disturbance proxies such as livestock density, wildlife density and human population numbers can also be tested to measure the degree of collinearity.

CHAPTER 3: STUDY AREA, MATERIALS AND METHODS

The Maasai Mara Ecosystem (MME) (fig. 2 below) is made up of the Mara triangle, the Maasai Mara National Reserve (MMNR) and adjacent community conservancies and group ranches that are privately owned. The ecosystem is part of the larger Mara-Serengeti and is found adjacent north of the Serengeti National Park in Tanzania. The main conservation area is the Maasai Mara National Reserve and the surrounding ranches are buffer zones (Witt *et al.*, 2017). It was established in 1948 as a wildlife sanctuary and was named after the local inhabitants in the area, the Maasai people.

3.1 Study Area

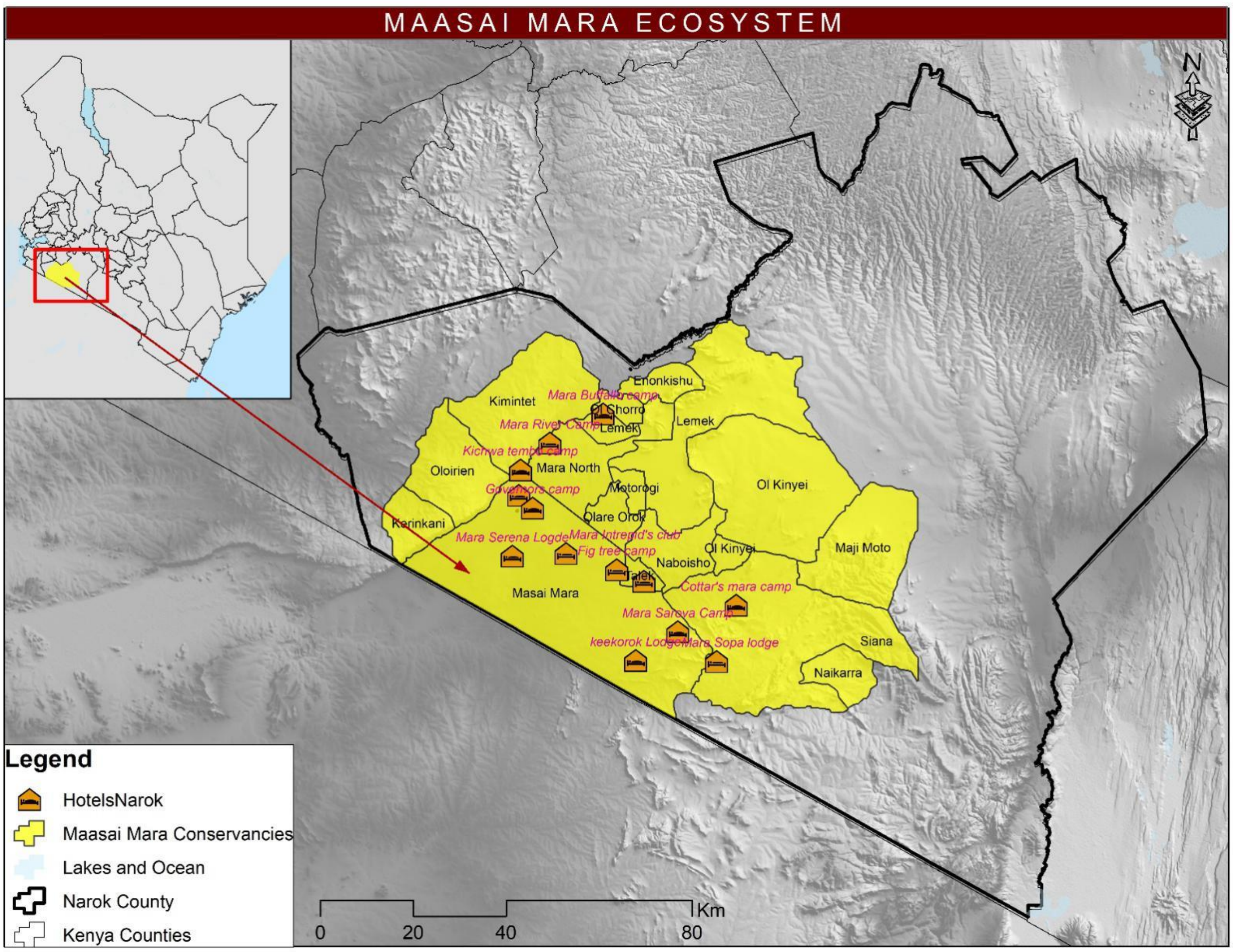

Figure 2: Map of Maasai Mara ecosystem showing the conservancies in the area and some of the camps/accomodations found therein

The mean annual rainfall received in the area is approximately 1000mm, characterized by a short rainy season between October and November and a relatively long rainy season between the months of March and May. Vegetation cover in the MME is mainly savanna grassland interspersed with patches of woodland (Acacia), riverine forests inselbergs, wetlands and bushy thickets (Witt *et al.*, 2017).

The MME is characterized by rapid vegetation changes. The naturally occurring scattered bushes, grasses and herbs, forest and woodlands are fast being changed into agricultural lands. The group ranches/conservancies that surround the reserve and are either communal lands or privately owned have their main land-use being cultivation and pastoralism. The grasslands and woodlands outside the reserve, in these conservancies are greatly affected by extreme anthropogenic disturbances as these areas are increasing subjected to overgrazing by cattle, increased cultivation, among others. Other forms of disturbance experienced in these areas include the resident wildlife present in the area and the migrating wildebeests which graze in these private lands during the dry season. These animals also function to maintain the grassland vegetation in the area (Witt *et al.*, 2017).

Rapid land use changes have been observed through the years in the ecosystem particularly the conservancies as seen from the expanding farm lands which are increasingly, over the years, being highly mechanized and subjected to the use of numerous inorganic fertilizers. Other forms of land use in the area include the expansion of small scale settlements (Witt *et al.*, 2017).

Due to the ever increasing disturbances, the MME faces an increasing risk of invasion by numerous IPS. Native grasses that provide food for animals in the area are rapidly being replaced by IPS. Up to 245 alien plant species have been documented in the area. Out of these, 212 were said to have been intentionally introduced into the reserve and 51 species had naturalized into the areas. Twenty-three (23) of these naturalized species were considered invasive species. Six of these found within the ecosystem, near lodges and the ecosystems surroundings where human populations exist were found to be of greatest risk to conservation efforts in the area. These were *Prosopis juliflora, Opuntia stricta, Chromolaena odorata, Lantana camara, Tithonia diversifolia*, and *Parthenium hysterophorus L.* (Witt *et al.*, 2017).

The MME is well renowned for its abundant and diverse assemblages of wild ungulates, and for the seasonal migration of herds of wildlife. They graze on the fresh grass after the rains and later move on. These animals include the wildebeest, zebras, Thomson's gazelles, African buffalo, Topi, black rhinoceros, giraffes, eland and elephants. Their movement is cyclic as the animals rotate between grazing in the Mara National Reserve and its conservancies in Kenya and the Serengeti National Park. These herbivores movement is followed by the big cats such as leopards, lions and cheetahs. Vultures and hyenas also follow the migration. The migrating animals cross the Mara River where crocodiles and hippos are found. They migrate to Kenya to graze and mate in the months of June to August/September but return to Serengeti in October to November to graze as the grass of the Mara regrows during the short rains of Kenya in October to November. The Mara River is also a major source of water in both the Maasai Mara ecosystem and the Serengeti National Park (https: simple.wikipedia.org wiki Masai_Mara). The greater wildebeest migration has attracted many developments in the area dating back from the 1960's. Several tourist lodges, roads and tracks, camp sites, residential areas for staff working within the MME have been constructed in the area (Witt *et al.*, 2017).

3.2 Materials and Methods

The sampling points of this study were as shown in figure 2 below;

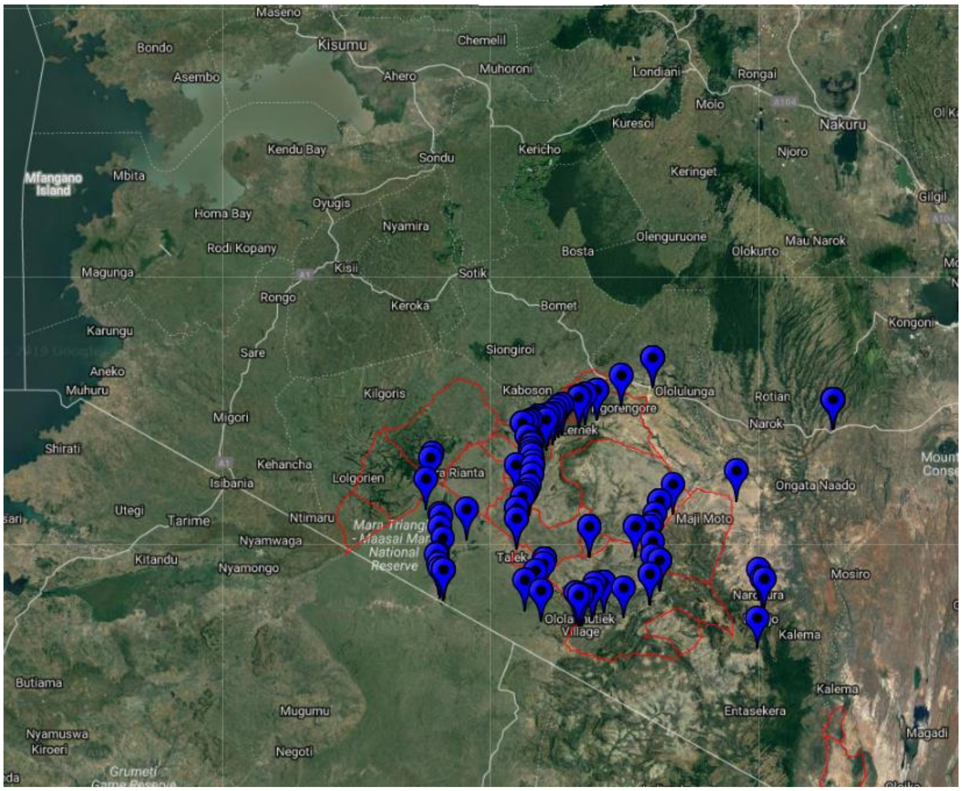

Figure 3: Satellite map showing terrain of the sampling points within the MME

(Adapted from http: mobiledata.rcmrd.org invspec index.php)

The current distribution of *Parthenium hysterophorus* L. in the Maasai Mara ecosystem was determined by recording the geographic coordinates (presence points) of species observations. A total of 110 *Parthenium hysterophorus* L. samples were recorded in October 2018 in the Maasai Mara Ecosystem as shown in figure 3 above. Among the areas sampled included the Maasai Mara National Reserve, the Mara triangle, Siana, Lemek, Motorogi, Maji Moto, Olarro, Oloirien, Kerinkani, Naikarra, Kimintet, Talek, Mara North, Naboisho, Enonkishu and Ol Chorro conservancies. An application developed by the Regional Centre for Mapping of Natural Resources for Development (RCMRD) called 'Invasive Species Mapper' available from google play store was used to obtain species coordinates. The offline application automatically saves data and sends the bulk data on species geographical coordinates to the server in RCMRD once field work is completed. The data sheet is then downloaded at the organization upon request. For this study, a stratified random sampling method was used. Study area was stratified on the basis of the road network that is the main agent of IPS dispersal. These major and minor roads were 10km of Ololaimutia gate road up to Ngoswani market from which 60 points were taken; 5km stretch of the Mara bridge road to the Kenya-Tanzania border on which 25 points were taken; 5km of the Serena wildebeest crossing to Mara Bridge from which 25 points coordinated recordings were taken.

These areas are characterized by impact of disturbance be it anthropogenic or animal-induced such as along roads and rivers, next to built up areas such as hotels, migratory routes and animal pools.

According to Wabunyele *et al.,* (2014), studies of the distribution of IPS should be predominantly along road networks for landscape studies. Wabunyele also reiterated on the importance of this purposive study due to the growth characteristics of IAPS, where they mostly grow in disturbed areas in order to achieve the best, meaningful results for the research work. This fact is based on the availability of long-distance agents of dispersal in the form of vehicles that move within the ecosystems. Therefore, most of the observations were made along roads and river networks. In addition to the road and river network being readily available conduits of dispersal, they also possess, the characteristic of being primary sites of disturbance, otherwise known as ruderal areas. These ruderal areas serve as suitable microhabitats of IPS thus ensures that all the different aspects of the landscape are captured in the research work in order to provide an accurate representation of the landscape. Other than roads, footpaths and rivers, other microhabitats that were sampled included livestock grazing areas, areas of high population densities such as the hotels and homes found in and around the conservancies. These are areas that have been affected in one way or the other by a human activity that leads to a form of disturbance in the area. In addition to this, sampling of IPS at landscape level is best done along roads as other methods can be very expensive due to the large areas covered and it can be time consuming (Kosaka *et al.,* 2010).

From the Ololaimutia gate road, field plots of 10m by 10m, 200m apart on either side of the road, were placed at every 1km travelled. This distance was suitable because the spatial resolution for most of the environmental variables that were used are provided at 1km^2. This method was used to prevent recording of duplicate coordinates thereby reducing spatial autocorrelation. Interval between plots was subjective. Previous studies by Thapa *et al.,* (2018) used 5-10km intervals but he acknowledged that shorter intervals are best to serve as an accurate representative of all suitable microhabitats. Although Maasai Mara ecosystem is predominantly flat, a short interval was used relative to the Thapa *et al.,* (2018) study and other studies due to a relatively smaller total area of study and also to ensure the best results are obtained giving consideration to any possible existing microhabitat features. Other microhabitats such as burnt areas and areas affected by livestock stocking were also sampled for IAPS. It is important to note that Maxent can generate useful models from little data as it generates random background points for analysis thus there is no set bare minimum/threshold.

Other data, though not required for modelling was also collected to better understand the landscape and coverage by the IPS in the area hence only estimates were obtained using the 'Invasive Species Mapper' application. Such data included the species abundance. The species abundance was categorized as; single, scattered, dense monoculture and scattered dense patches was denoted when collecting data. A plant point for single plant infestation represented a small area having one or a few plants irrespective of the density of the whole area. Scattered type of plant abundance was characterized by individual plant species widely spaced in the plot area. Dense monoculture referred to a large collection of the species covering the plot area growing very close together forming a continuous pattern while scattered dense patches referred to groups of closely growing species found at some distance from each other forming a pattern. An estimate of invasive species coverage in % was also done and the estimated canopy closure recorded. This canopy was provided as an estimate as no measurements were done but the canopy of the plant was assessed relative to the plot area. Trace canopy closure was a representation of less than 1 per cent, low canopy closure was represented by 1 to 5 per cent, Moderate canopy closure was represented by an estimate of between 5.1 and 25 per cent and lastly a high canopy closure of 25.1 to 100 per cent represented a total closure (Simpson, 2011). Other data that was recorded using the application included an estimate of the size of the area of infestation, habitat type, land ownership, area accessibility, location description and scenic photograph. These details were recorded for each *Parthenium hysterophorus* L. plant sampled.

3.2.1 Variable selection and Modelling Approach

Bioclimatic data used in the Maxent model was obtained from worldclim. WorldClim contains climate data obtained by interpolation of climate station records from 1950–2000. Wordclim data was used to obtain current and future climatic scenarios for both present and future projections. Nineteen (19) bioclimatic variables were downloaded (WorldClim, n.d.). These variables were:

BIO1 = Annual Mean Temperature
BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3 = Isothermality (BIO2 BIO7) (* 100)
BIO4 = Temperature Seasonality (standard deviation *100)
BIO5 = Max Temperature of Warmest Month
BIO6 = Min Temperature of Coldest Month
BIO7 = Temperature Annual Range (BIO5-BIO6)
BIO8 = Mean Temperature of Wettest Quarter
BIO9 = Mean Temperature of Driest Quarter
BIO10 = Mean Temperature of Warmest Quarter
BIO11 = Mean Temperature of Coldest Quarter
BIO12 = Annual Precipitation
BIO13 = Precipitation of Wettest Month
BIO14 = Precipitation of Driest Month

BIO15 = Precipitation Seasonality (Coefficient of Variation)
BIO16 = Precipitation of Wettest Quarter
BIO17 = Precipitation of Driest Quarter
BIO18 = Precipitation of Warmest Quarter
BIO19 = Precipitation of Coldest Quarter

Socio-economic factors such as population density data was obtained from Kenya National Bureau of Statistics (KNBS) while wildlife density and livestock density were obtained from Kenya Wildlife Service (KWS). Extraction of this socioeconomic data for use was done in Arcmap using the density function, point density specifically. NDVI data was obtained from MODIS. The NDVI of the 12 months of 2018 were extracted to provide an NDVI time series. The extraction tool in the Spatial Analyst tools in Arcmap was used. An extraction to points was done in order to get the value associated with every sampling point. The extract values to points feature was used (ArcMap, n.d.). All remote sensed data was available at $1Km^2$ resolution. Pearson's correlation coefficient (r) is a measure the degree of association between perceived correlated variables. This was used to measure variable importance and used to determine variables that would fit the model. Livestock density, wildlife density and human population numbers were tested for collinearity. Elevation and rainfall were also tested.

With the resultant variables from the collinearity analysis, Maxent model was run. These variables were wildlife density, distance to roads, land use and landcover change in addition to the 19 bioclimatic variables and NDVI. Maxent software (version 3.3.3k) was downloaded (http: www.cs.princeton.edu ~schapire Maxent). The software provides an estimate of probability of occurrence of an IAPS in an area. The probability ranges from 0 to 1, the former indicating lowest occurrence probability while the latter showing highest probability of presence in an area. The software has a feature referred to as the Area Under the Curve (AUC) or the Receiving Operator Curve that is used to measure the accuracy of the prediction that results from running the model. In addition to this, this feature is also used to validate the resultant model (Chitale *et al.*, 2014). The AUC values range from 0-1. Values that are within the range of 0.2-0.5 are low, those that lie within the range of 0.5-0.7 are considered as moderate while the values that are within the range of 0.7-1.0 are referred to as high. The model produces an AUC value from splitting the occurrence datasets into two. Seventy percent (70%) of the occurrence data is used as training data while the remaining thirty percent (30%) is used as test data, otherwise known as validation or evaluation data. This validation data is used by the software to calculate statistical analysis or statistical significance of the model (Thapa *et al.,* 2018). The Maxent model involves other data preparation; using several other software other than the Notepad. These are MS Excel, ESRI ArcGIS and python. The processes for data preparation are: Cleaning data and producing comma separated values (.csv) from invasive species occurrence coordinates in an excel spreadsheet, modifying environmental layers to be the same extent (geographic bounds and cell size), converting environmental rasters to ASCII format, then loading all this information into the Maxent software and running the model. Next, the Maxent outputs are interpreted and finally, conversion of

Maxent's ASCII output to a raster is done. This gives the final product; a prediction map showing the potential geographical locations of the invasive species under study. Further analysis is conducted to extract finer details and explanations for components of the results are arrived at (Phillips *et al.*, 2006).

The current and future climatic data used to run the model was obtained at the highest available resolution of $1km^2$. The climatic data used for current scenario was from the years 1960-2000. For projection, year 2050 data was used. All these variables had a spatial resolution of $1km^2$. RCP 2.6 and RCP 8.5 were used and as mentioned earlier, RCP 2.6 denotes the lowest (GHG) concentration pathway, while RCP 8.5 symbolizes the extreme GHG concentration pathway. The difference is based on the possible range and intensity of different human activities that lead to varying GHG emissions. In order to achieve uniformity of variables, using a tool as simple as notepad, the geographic extent of the all non- climatic variables (wildlife density, distance to roads, land use and landcover change and NDVI) were modified to $1km^2$ at the equator , with a cell size (x, y) 0.00833, 0.00833 to match the climatic variables.

3.2.2 Image classification, combination, and analysis

Products from running the Maxent software were imported to ArcGIS 10.4 and converted into a tiff raster format before further manipulation. The resultant maps of distribution obtained from running Maxent were classified into a threshold of two groups of IPS suitability based on pixel size; unsuitable and suitable areas. Suitability of an area increased as the value tend towards 1.00. A value of around 0.50 symbolized an occurrence probability of 50%.

In addition to this, change detection maps were also produced using a feature available in ArcGIS called difference function. This function takes into account future distribution scenarios and present distribution of IAPS and the difference shows whether there will be a positive change (range reduction) or negative change (range expansion). In order to come up with the negative and positive changes, a reclassification of the maps was necessary in order to easily observe the trend of IAPS.

CHAPTER 4: RESULTS

4.1 Variable selection

A pairwise Pearson correlation using SPSS statistics analysis was done and only variables with $r \leq \pm 0.7$ were used in the final model prediction. Soil drainage was correlated to land cover change (r= 0.72), Elevation was correlated to Annual precipitation (r= 0.865), livestock density to wildlife density (r= 0.79), human population to wildlife density (r= 0.77) and land use and land cover change was also correlated to annual precipitation (r= 0.664) (no correlation) thus the decision was made to run the models using wildlife density, distance to roads, land use and landcover change in addition to the 19 bioclimatic variables and NDVI. Table 2 below shows the results of Pearson's correlation analysis.

Table 2: Pearson's correlation analysis.

Correlations (at 0.05 level, 2 tailed test)			
Variables		Pearson's correlation, r	Decision
Soil drainage	land use and land cover change	0.72	Choose 1 variable (land use and land cover change chosen)
Elevation	Annual precipitation	0.865	Choose 1 variable (Annual precipitation chosen)
livestock density	wildlife density	0.79	Choose 1 variable (Wildlife density chosen)
human population	wildlife density	0.77	Choose 1 variable (Wildlife density chosen)
land use and land cover change	annual precipitation	0.664	Use both variables

4.2 Hypothesis testing

The research hypothesis of this thesis was used to evaluate the performance of the three models. It stated that the distribution of invasive plant species is randomly distributed in the environmental space that is, the distribution of a species is not influenced by its response to environmental variables. As earlier on mentioned, Maxent computes statistical analysis through AUC and using a threshold to come up with a binary prediction of suitability. Unsuitable conditions were represented as those below the threshold while suitable conditions were represented as those above the threshold. The statistical significance of the models were given by the minimum training presence logistic threshold obtained from running the models. These p values were as follows:

Current scenario: $P_{(0.05)} = 1.396E-9$

RCP 2.6: $P_{(0.05)} = 3.092E-9$

RCP 8.5: $P_{(0.05)} = 4.1E-7$

The statistical p was less than $p_{(0.05)}$ thus the hypothesis that distribution of a species is not influenced by its response to environmental variables was therefore rejected in all the three scenarios. This means that environmental variables had a strong influence on the growth and distribution of the IPS.

4.3 Model performance (Prediction Accuracy)

The models had high test AUC values of 0.895, 0.902, 0.882 for the scenarios, current, 2.6 projection and 8.5 projection respectively as shown in table 3 below:

Table 3: Prediction accuracy of invasive species distribution modeling.

Scenario	Current	RCP 2.6 Year 2050	RCP 8.5 Year 2050
Test AUC Value	0.895	0.902	0.882

From table 3 above, the models accuracy in predicting occurrence probability was observed to be generally at a high of 80-90% as seen in the AUC values for both the current and future scenarios. The highest AUC value obtained for *Parthenium hysterophorus* L. was 0.902 for RCP 2.6, year 2050.

4.4 Response of the tested variables to habitat suitability

The breakdown of the impact of the individual predictor variables on the distribution of the IPS as provided for by Jackknife analysis of variable contribution, percentage contribution and response curves were analyzed. In the current scenario, the predictor variables with the highest percentage contribution to predicting the suitable niches were November NDVI (33.6%), Temperature Seasonality (26%), Temperature Annual Range (13.8%), Isothermality (7.6%), land use and land cover change (6.3%) and wildlife density (2.8%). Under the future climate scenarios 2.6 and 8.5, the predictor variables with the contribution to the potential distribution of IPS were Temperature Seasonality, Temperature Annual Range, Isothermality, Precipitation Seasonality (Coefficient of Variation), in both scenarios. In the RCP 2.6 scenario, percentage contribution of the variables Temperature Seasonality (26.6%), Temperature Annual Range (20.4%), Isothermality (15.2%), Precipitation Seasonality (Coefficient of Variation, 7.2%), while that of RCP 8.5 projected scenario the percentage contribution of the variables was Temperature Seasonality (26.6%), Temperature Annual Range (24.6%), Isothermality (12.9%) Precipitation Seasonality (Coefficient of Variation, 7%).

The Jackknife feature was used to analyze the input of the individual predictor variables by the increase or decrease in gain in the predictive capability of the model as each variable is either considered independently or omitted from among all the other variables.

The jackknife analysis depicted that the most important predictor variables in the current scenario, when used in isolation, and had the greatest impact on the distribution of *Parthenium hysterophorus* L. were Precipitation Seasonality (Coefficient of Variation) (0.79) followed by November NDVI (0.74), October NDVI (0.73) and Temperature Seasonality (standard deviation *100) (0.72). This indicates that these have the most information as lone variables in that order. For the jackknife analysis of the projections, the most important predictor variables, when used in isolation, and had the greatest impact on the distribution of *Parthenium hysterophorus* L. were Annual Precipitation (0.82), Precipitation Seasonality (Coefficient of Variation) (0.81) and Precipitation of Wettest Quarter (0.78) in both scenarios. This indicates that these have the most information as lone variables.
In the current scenario, the variable that upon omission led to a significant reduction in the predictive power by decreasing the AUC gain of the model was Temperature Annual Range (0.72). This variable also signifies which variable appears to have the most information that isn't present in the other variables.
The variable that least impacted on the AUC gain was distance to rivers (0.59). This shows that it provided the least amount of useful information to the model as a lone variable. For the jackknife analysis of the projections, the variable that upon omission led to a significant reduction in the predictive power by decreasing the AUC gain of the model was June NDVI (0.68) in both scenarios.

4.5 Model Application

4.5.1 Distribution Range expansion of *Parthenium hysterophorus* L. under current and projected conditions

In the current scenario, most of the suitable niches are concentrated around some conservancies but projections show that these niches will spread out to the conservancies that currently are not suitable niches while the original niches slowly become unsuitable. The model results widely predicted suitable niches areas across the MME. Based on the area calculations, current extent of the IPS was 66, 300 Ha. The total unsuitable area was at 1,977,300 Ha.

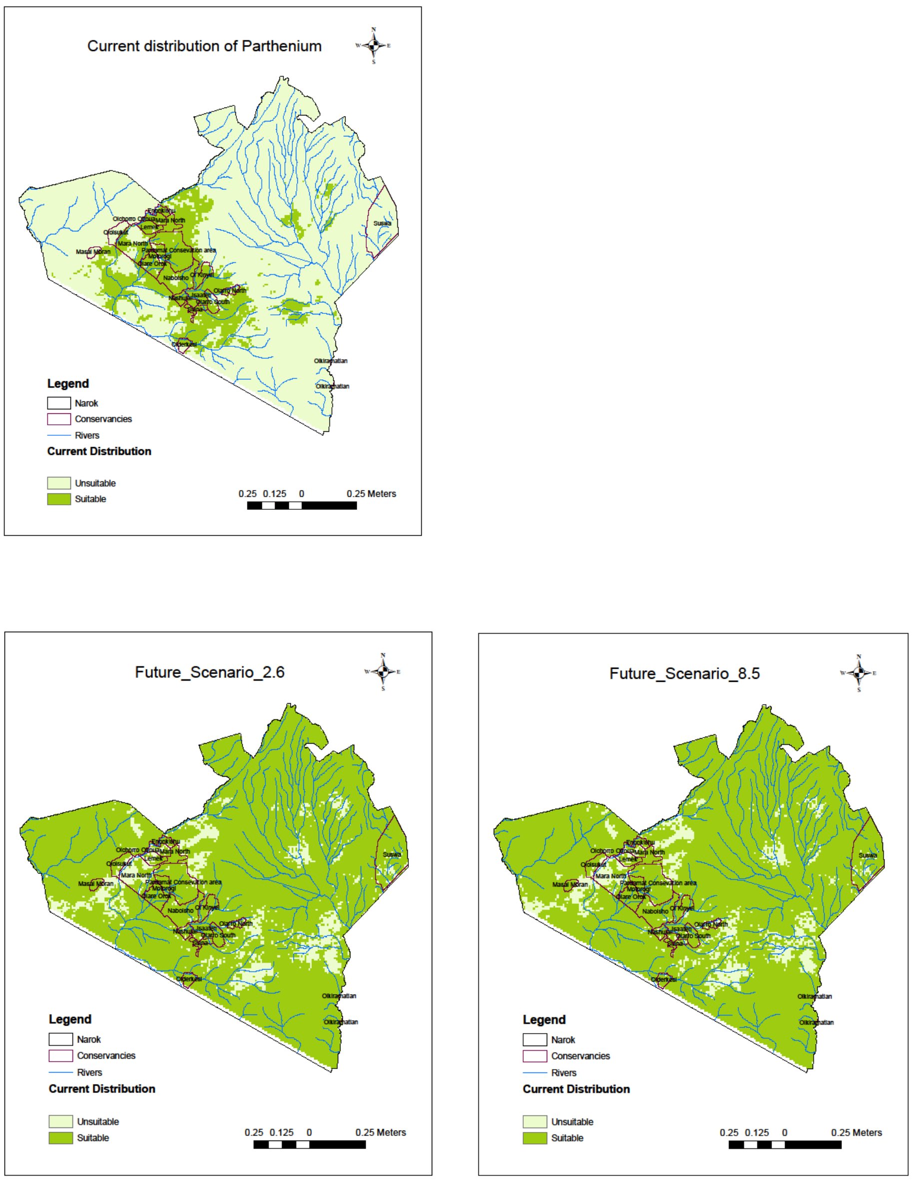

Figure 3: Habitat suitability map for current scenario and change maps for projections 2.6 and 8.5

Current distribution map of *Parthenium hysterophorus L.* distribution (Figure 3) shows the areas and conservancies that have the highest suitable niches. These are the areas with the highest potential for being heavily invaded areas; that is, are the areas of highest suitability for the IAPS. These are the upper parts of Maasai Mara National Reserve, Naboisho, Ol Kinyei, Motorogi, Lemek, Mara North, Olare Orok, Talek conservancies and some parts of Ol Chorro, Siana, Enonkishu, conservancies. The most suitable niches at the present were found in Lemek, Talek, Orok and Motorogi. The Mara River banks, road networks and Mara Bridge also presented suitable niches of *Parthenium hysterophorus* L.

4.5.2 Distribution Range expansion of *Parthenium hysterophorus* L. under projected future climate scenarios

The conservancies that were previously uninvaded (current scenario) will be invaded into from the current niches. The range expansion will be outwards from the current conservancies that extend northwards from the MMNR to the other conservancies. The Mara River banks, road networks and Mara Bridge are projected to increasingly present suitable niches of *Parthenium hysterophorus* L. From the figure above, the current scenario map shows suitable areas while the change maps provide the range expansion in areas that are anticipated in future projections from the current suitable areas. In the scenario 2.6, the expansion was predicted to an area of 906,000 Ha while in scenario 8.5, the expansion of suitable sites was predicted to 914,400 Ha.

A reduction in area of unsuitable sites was also observed in both scenarios with a total area of 1,137,800 Ha and 1,129,400 Ha recorded for RCP 2.6 and 8.5 respectively. Range expansion of suitable sites are expected to occur in the projections into novel areas outside MME, the larger Narok County. The conservancies that are projected to be hit by invasion and were not invaded significantly in the current scenario include wider areas of Ol Chorro, Enonkishu and Siana, Kerinkani, Kimintet, Maji Moto and Naikarra. The conservancies that are projected to be least affected by invasion, with least range expansion were Kerinkani, Naikarra, Maji Mojo and Oloirien.

CHAPTER 5: DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 DISCUSSION

5.1.1 To identify the environmental variables that affect the niches of *Parthenium hysterophorus* L.

According to *Júnior et al.*, (2018), in the case where variables tested give a product r>0.7, one variable has to be excluded as it contains information adequately represented in the other. Most data especially that of predictor variables usually have a great deal of collinearity. This collinearity can be attributed to several causes and the most notable one is usually that predictor variables which are collinear are just diverse manifestations of the same fundamental processes in the environment. As such over-representation of the same underlying process in nature should be avoided in order to get accurate results (Dormann *et al.*, 2013). A pairwise Pearson correlation using SPSS statistics analysis was done and only variables with $r \leq \pm 0.7$ were used in the final model prediction. Soil drainage was correlated to land cover change (r=0.72), Elevation was correlated to Annual precipitation (r=0.865), livestock density to wildlife density (r=0.79), human population to wildlife density (r=0.77) and land use and land cover change was also correlated to annual precipitation (r=0.664) (no correlation) thus the decision was made to run the models using wildlife density, distance to roads, land use and landcover change in addition to the 19 bioclimatic variables and NDVI to determine their impact on the current and potential geographical distribution of *Parthenium hysterophorus* L.

5.1.2 To determine the effect of these variables on the current geographical distribution of *Parthenium hysterophorus L.*

Hypothesis testing was done to determine if there was an effect of the above-mentioned variables on the current geographical distribution of *Parthenium hysterophorus* L. The results of this testing sought to reject the research hypothesis that the distribution of invasive plant species is randomly distributed in the environmental space; that is the distribution of the species is not influenced by its response to environmental variables. It therefore follows that the distribution of *Parthenium hysterophorus* L.is not randomly distributed in the environmental space. In other words, that the distribution of a species is influenced by its response to environmental variables. The null hypothesis was also used to evaluate the model performance in the current scenario. The statistical significance of the model/p value of the Minimum Training Presence Logistic threshold obtained from running the model in the current scenario was as follows:

Current scenario: $P_{(0.05)} = 1.396E\text{-}9$

The test was one tailed as we sought to determine whether the distribution of IPS will be greater or less than the threshold of suitability. The P value was set at a confidence level of 0.05 as is usually done in most biological studies. At 95% confidence interval, the models were able to distinguish between the optimal niches for *Parthenium hysterophorus* L. as influenced by environmental variables over random background points. The statistical p was less than p = 0.05 thus the hypothesis that distribution of a species is not influenced by its response to environmental variables was therefore rejected. This means that environmental variables had a strong influence on the current growth and distribution of the IPS. It is therefore evident that *Parthenium hysterophorus* L. is non-randomly distributed in the MME as a pattern of more growth and distribution in disturbed areas was observed.

This work had established that the predictor variables had a significant impact on the current growth and distribution of *Parthenium hysterophorus L.* and sought to determine to what geographical extent the suitable niches of the IPS were. These suitable niches would help to identify key areas that require urgent ecosystem management efforts to prevent current ongoing and potential degradation and loss of ecosystem integrity of the Maasai Mara ecosystem.

In the present, significant changes in environmental, social and bioclimatic conditions of MME are observed. Changes in these variables contribute immensely to the growth and spread of *Parthenium hysterophorus* L.in the ecosystem in the present. The model predicted that there would be an upward spread of invasion from the MMNR and the conservancies north to it. This would also significantly impact on the surrounding potential areas of the wider areas of Ol Chorro, Enonkishu and Siana, Kerinkani, Kimintet, Maji Moto and Naikarra that are seen to also have suitable niches. The current extent of suitable niche is represented by a total area of 66, 300 Ha. This poses imminent threat to the surrounding pastoral communities who depend on the native vegetation. The conservancies that are projected to be least affected by invasion, with least range expansion were Kerinkani, Naikarra, Maji Mojo and Oloirien. This can be attributed to the different rates of anthropogenic activities and the consequent anthropogenic induced climate change rates in the different conservancies. There is a lot of tourist activities and an observed higher rate of pastoralism in the areas with more suitable sites. More camps and lodges are seen to be in these conservancies thus more transport is seen in the area. Transport has a marked increase in the rates of released particulate matter (dust), sulfur oxides, nitrogen oxides, carbon monoxide and CO^2 produced from the exhaust fumes in the area. This information can help land managers in prioritizing proactive management strategies of IPS.

5.1.3To extrapolate future potential climate change scenarios and their effects on the distribution of *Parthenium hysterophorus* L.

The fifth IPCC reports describes extrapolated climatic scenarios of the years 2050 and 2070 under RCPs 2.6 and 8.5. This study focused on the year 2050 whereby the spread range expansion of

Parthenium hysterophorus L. was predicted to substantially increase with climate warming. This means that habitat suitability increases with warming climate.

Just like in the current scenario, this paper sought to reject the research hypothesis that the distribution of invasive plant species is randomly distributed in the environmental space; that is the distribution of the species is not influenced by its response to environmental variables, in the predictive models. The Statistical significance of the models/p values of the Minimum Training Presence Logistic threshold obtained from running the predictive models were as follows:

RCP 2.6: $P_{(0.05)} = 3.092E\text{-}9$

RCP 8.5: $P_{(0.05)} = 4.1E\text{-}7$

The statistical p of the one tailed test set at 95% confidence interval was less than p = 0.05 thus the hypothesis that distribution of a species is not influenced by its response to environmental variables was therefore rejected in the future scenarios of RCP 2.6 and 8.5. This means that the predicted environmental variables had a strong influence on the growth and distribution of the IPS.

In the coming years, significant changes in predictor variables just like in the current scenario will contribute immensely to the growth and spread of *Parthenium hysterophorus* L.in the ecosystem in the present and future. The predictive models, just like in the current scenario, showed an upward spread of invasion from the MMNR and the conservancies north to it. Some invasion to the surrounding potential areas of wider areas of Ol Chorro, Enonkishu and Siana, Kerinkani, Kimintet, Maji Moto and Naikarra will also be observed but at a larger extent compared to the current scenario with the RCP 8.5 representing the highest increase in suitable niches projected to be at a growth extent of at 914,400 Ha while that of RCP 2.6 projected expansion to be up to an area of 906,000 Ha. Just like in the current scenario, the conservancies that are projected to be least affected by invasion, with least range expansion were Kerinkani, Naikarra, Maji Mojo and Oloirien.

5.1.4 General overview

Alien species, landcover change, fragmentation and destruction, unsustainable use of the resources within ecosystems, pollution and climate change are placed as major factors of global environmental change. These factors are major drivers of change in terms of resources within and consequently affect ecosystem balance and health. The factors have frustrated conservation efforts within protected areas. They are interrelated and together lead to massive losses in ecosystem integrity. It is therefore necessary to address all of them when dealing with species distribution models to ensure an accurate representation of what is on the ground (Rija *et al.*, 2013).

Previous research findings (Thomas *et al.,* 2004) depict that species distribution and ecosystem health at large are negatively affected by warming climates. However, this does not apply to IAPS which generally thrive best under harsh conditions by coping better to the new conditions compared to native species. Lockwood *et al., (*2007) are of the view that climate change will have a direct impact on the success of establishment and spread of IAPS in a new area. Reason for this being that climate change will increase an area's susceptibility to invasion due to the resultant resource shortage as well as the area's increased competition among the indigenous plants and animals due to resource scarcity. Moreover, increased human induced climate change also has adverse impacts on species that are not able to extend from their home ranges to areas that are more conducive for their survival. In addition to this, species that have long generation periods and or cannot withstand a wide range of climatic conditions are disadvantaged and are overtaken by IPS that have these capabilities that enable them to thrive under these harsh conditions.

From the results, suitable sites are enabled with the increase in climatic variables such as Temperature Seasonality, Temperature Annual Range and Isothermality in the current scenario. Under the future climate scenarios 2.6 and 8.5, the predictor variables with the highest contribution to the projected distribution of IPS were Temperature Seasonality, Temperature Annual Range, Isothermality, Precipitation Seasonality (Coefficient of Variation), in both scenarios, RCP 2.6 and RCP 8.5. Temperature seasonality refers to determining how temperature changes in a period of one year based on the variation in averages of monthly temperatures while temperature annual range refers to a measure of variation in temperature over a certain period. This is particularly useful in species distributions and is used to determine whether this distribution is affected by ranges in adverse temperature states. Isothermality basically seeks to compare diurnal temperatures to annual temperatures. Isothermality means that a species distribution may be affected by the changes in the average monthly temperature relative to annual temperatures. Precipitation seasonality is an index that gives a sum of total precipitation of 3 months in a year that were the driest. This is useful in determining how such a factor can impact on species distributions (O'Donnell and Ignizio, 2012). These important predictor variables that shape the distribution of *Parthenium hysterophorus* L. should be monitored closely and precautionary measures should be set around them. The variables can also be put in check by controlling the anthropogenic activities that can lead to direct impacts on these variables.

Generally, the distribution of the *Parthenium hysterophorus* L.in MME is affected by long term changes in climatic characteristics over short term changes. For example, from the results, temperature seasonality affects the distribution of *Parthenium hysterophorus* L. more than isothermality (Cord and Ro¨dder, 2011).

The resultant models also showed the importance of management practices taking into account both the impacts of IAPS and climate change in their efforts to conserve native plant species and the entire ecosystems at large as they were seen to be key drivers of perpetuating the growth, establishment and spread of the IPS. As such, determining the current and potential geographical distribution of IPS is paramount and should be undertaken before any plans of controlling their establishment and spread are put in place (Margules and Pressey, 2000).

One of the Seven Wonders of the World is the Great Wildebeest migration that takes place in the Maasai Mara Reserve. The cross movement of the animals between Mara and Serengeti already provides a transmission mechanism for dispersal of IPS seeds. In addition, the mass movement also provides suitable micro habitat characteristics of disturbed regions that aid in the establishment of IAPS.

Areas where the IPS was mostly found included areas such as Ngineji market, Olmusereji market, Kishelmulyak market, built up areas such as 3km east of Zakaria camp, Mara bridge, police camps, Serena and Loita Plain hotels, schools such as Loita Kids Academy, along tarmac roads such as the tarmac road in Olaro Conservancy, in towns such as Lemek town, next to Motorogi river and along borders such as Olchoro Oruwa (refer to field data sheet in appendices). In addition, both private and community lands were found to be infested with dense monocultures observed mainly next to police camps and hippo pools. All these areas are characterized by the existence of one form or another of a human activity such as tourism and construction. For instance, construction activities can lead to movement of infested soils from one area to another thereby forming a dispersal pathway for IPS. The Mara Bridge is one area that was heavily invaded. Hippos, which are one of the main seed dispersal mechanisms for *Parthenium hysterophorus* L. have numerous hippo paths close to the bridge on which they easily disperse the seeds which are easily attached to their oily skins as a result of their tough oily red secretions ('blood sweat'). There are also numerous anthills within the MME that are also heavily infested by the IPS as a result of dispersal by grazing animals. The wild animals usually use these ant hills as watch towers to look out for predators and in the process they excrete here and the tough *Parthenium hysterophorus* L. end up germinating in these areas.

Predictive maps are essential in ecosystem management as they depict the vegetation zones that are prone to degradation and the wildlife that are likely to face adverse health impacts due to invasion. Predictive maps are therefore useful in identifying future biotic invasions and thereby provides for an opportunity of proactive management of invasive plant species where prevention is given more weight is and is a less expensive venture that requires less effort as compared to reactive management. It entails predetermining areas prone to invasion and preventing this before they spread to novel areas. Predictive modelling also offers land managers with the opportunity to discover vegetation types that face the risk of destruction due to invasion (Thapa *et al.*, 2018).

There are several Species distribution models (SDMs)/predictive models such as Maxent. Maxent uses an ecosystem approach to manage the species and is more efficient than targeting individual species. Maxent approach was applied in this study because it operates on presence-only data. Consequently; it is simple, fast, economical and convenient to construct meaningful species distribution models. Maxent output included an Area Under the curve (AUC), a test statistic that measures a model's performance fitness. It ranges from 0-1. The closer the AUC tends to 1 the better the model performed. Based on this analysis by Chitale *et al., (*2014), this model performed very well. A model's accuracy is best evaluated through AUC (Phillips *et al.,* 2006). This high AUC means that at 95% confidence interval, the models depicted their ability to highly distinguish between the optimal niches for *Parthenium hysterophorus* L. over random background points. The model's accuracy in predicting occurrence probability was observed to be generally at a high of

80-90% as seen in the AUC values for both the current and future scenarios (Table 2). The AUC values were 0.895, 0.902 and 0.882 for the scenarios, current, 2.6 projection and 8.5 projection

Other advantages associated with it include the presence of a jackknife feature which was used to test the variable importance between the different variables. Using the jackknife feature, Maxent ran an individual test for each variable and compared this to the other variables to create several individual models (Yi *et al.*, 2016). A model with all the variables can be created, a model excluding one variable can be created and a model created by excluding each variable in turn can also be obtained and this was done. This serves to show which variable mostly impacts on the existence of an IAPS in an area. The feature shows statistical significance of each variable in the model (Yost *et al.*, 2008). The jackknife analysis depicted that the most important predictor variables in the current scenario, when used in isolation, and had the greatest impact on the distribution of *Parthenium hysterophorus* L. were Precipitation Seasonality (Coefficient of Variation) followed by November NDVI and in the current scenario followed by October NDVI and Temperature Seasonality (standard deviation *100). This indicates that it has the most information as a lone variable. For the jackknife analysis of the projections, the most important predictor variables, when used in isolation, and had the greatest impact on the distribution of *Parthenium hysterophorus* L. were Annual Precipitation, Precipitation Seasonality (Coefficient of Variation) and Precipitation of Wettest Quarter in both scenarios. This indicates that these have the most information as lone variables. Another feature of Maxent is the heuristic test or the analysis of percentage contribution of variables feature. This was used to provide variable contribution or importance of the different variables. The variable with the highest percentage contribution as provided by the heuristic test, in the current scenario, was November NDVI. Under the future climate scenarios 2.6 and 8.5, the predictor variables with the contribution to the potential distribution of IPS were Temperature Seasonality in both cases. Vegetation indices such as NDVI are important in modelling studies as they are used in monitoring of changes in vegetation. It can also be described as the greenness of vegetation. This measures plant density and rate of vegetation changes and is also directly affected by climate change, particularly temperature and leads to a reduction in other vegetation cover thereby promoting growth of IAPS (Khisro, 2013). In this study, the phenological variations of *Parthenium hysterophorus* L. were detected by November NDVI. This means that in the month of November, NDVI can be used to detect *Parthenium hysterophorus* L. as at this time, the species is very green, easy to detect and easily distinguishable from other vegetation. In MMNR, the migrating animals migrate to Kenya to graze and mate in the months of June to September but return to Serengeti in October to November to graze as the grass of the Mara regrows during the short rains of Kenya in October to November. For the period leading to the short rains, the grass in Mara is grazed upon by the increasing numbers of the wildlife adversely affecting them. The short rains that are meant to regrow them cause faster growth of IPS over the native grass due to the fact that IPS are better resource utilizers. This and other traits they possess such as the capacity to reproduce both asexually as well as sexually, rapid growth, early sexual maturity, high reproductive output as well as the capability to disperse offspring broadly, tolerance of a wide range of environmental conditions, high phenotypic plasticity or pliancy (capacity to modify growth to match current conditions) and allelopathy (production of chemical compounds which make the surrounding soil uninhabitable, or inhibitory, to other competing species), deep root system means that the growth, spread and flowering of the IPS will happen before that of native grass and as a result greenness of the area, especially in the beginning of the rains, will be due to IPS (Day *et al.,* 2003). This can be used to easily identify these species in the month of November for the purposes of monitoring and control.

It is important to note that the two results; jackknife and heuristic test obtained from running Maxent results can at times be confusing. These are Jackknife analysis of variable contribution and heuristic test/analysis of percentage contribution of variables. They both serve the same purpose but can provide contradictory results. Jackknife provides us with variable importance after considering each variable independent of the other while the heuristic test doesn't not take this consideration. Results from a heuristic test can highly rank a variable over others in a different order when compared to jackknife results because that variable might have an additional correlated effect of another correlated variable assigned to it by the model. It is therefore advisable to take into account the results from jackknife as opposed to heuristic test as the former takes into account the biological role a variable play in the survival of a species while the latter just provides us with the response of a species to a variable (Ward, 2007). Knowledge of the variables with the highest significance in developing the models can also guide management strategies in controlling the role played by humans.

Present invaded areas will over time be more infested by the IPS. In addition, presently there are also more suitable niches that are yet to be invaded if measures are not taken. Under projections, the invasion range will spread outwards into novel areas as seen from figure 3. With time, the resources of these areas will be over-used by the expanding populations of the *Parthenium hysterophorus L.* species to levels that even the remaining resources cannot support the IPS even after displacing the indigenous species. As a result, the IPS will spread to neighboring non infested areas such as the minimally infested conservancies of Ol Chorro, Enonkishu and Siana, Kerinkani, Kimintet, Maji Moto and Naikarra and the larger Narok County. This spread will be facilitated by dispersal mechanisms and ever-changing climate patterns that are anticipated to be harsh as a result of increasing carbon emissions into the atmosphere as evidenced by the spread of suitable areas outside the current 'hot spots' while these areas increasingly become unsuitable for the growth and establishment of the IPS. Conservation efforts for the MME is therefore necessary and should commence at the earliest possible time before such eventuality is arrived at. Conservancies that have the highest suitable niches are heavily invaded areas of highest suitability for the IAPS are the upper parts of Maasai Mara National Reserve, Naboisho, Ol Kinyei, Motorogi, Lemek, Mara North, Olare Orok, Talek conservancies and some parts of Ol Chorro, Siana, Enonkishu, conservancies. The most suitable niches at the present were found in Lemek, Talek, Orok and Motorogi.

As seen above, the extent of the invasion in all MMR and the surrounding conservancies is set to increase with the increase projected to be higher in some conservancies than others. Better and focused planning such as use and implementing the information obtained from predictive models to control establishment and growth is therefore necessary in these hotspot areas in order to prevent spread from these areas to the neighboring conservancies and areas (Reddy, 2008).

The best way to manage IPS involves an integrated approach whereby biological, chemical and mechanical techniques are used (DiTomaso, 2000). Mechanical techniques can be employed at different life stages of establishment or growth of the IPS. For instance, upon establishment when the population is still minimal, physical or mechanical management of these species would be appropriate and easy to employ simply via uprooting process. Uprooting is best done before the plant starts flowering in order to prevent the spread of seeds. Some invasive plant species have also been controlled through flooding of the inhabited areas for short periods of time. Countries such as Australia have used fires in the past to control the IPS but this has proven to create disturbed areas that provide favorable grounds for growth of the IPS (Holman, 1981). Use of herbicides (chemical technique) and biological control methods have also proven to be beneficial in controlling these species. For instance, chemical control methods such as the use of altrazine has been used in Australia. Its usage is however, discouraged in large areas as it adversely affects the environment and is economically unviable (Paudel, 2009). The biological control method that has proven to be useful in the control and management of *Parthenium hysterophorus L.* is the use of the leaf feeding beetle, *Zygogramma bicolorata*, which is being used in Australia, India (particularly in Karnataka) and South Africa. (Strathie and McConnachie, 2013). Other biological control methods include the use of *Aphis fabae*, and *Carmenta ithacae* (Strathie and McConnachie, 2013). Studies show that effective biological management of IPS encompasses use of natural animal enemies to the IPS together with growing suppressive plants to the IPS that will suppress the growth of the invasive plant and rehabilitating the degraded areas by growing competitive native forage grasses (Adkins and Shabbir, 2014). These biological control methods, however, attack non-target species and therefore are not the best approach in controlling the IPS. For instance, *Zygogramma bicolorata,* has been observed to attack sunflowers in India (Singh *et al.*, 2017). Another approach that has proven to be beneficial in the efforts of controlling the menace of IAPS is identification of ways of putting them into economical use. For instance, the IAPS such as *Parthenium hysterophorus* L. plant biomass can be used in the manufacture of biochar. *Parthenium hysterophorus* L. can also be used to in making paper and as a component in biogas production and using its biomass in making green manure (Vithanage *et al.,* 2014).

All the above methods can be referred to as the traditional control methods that have been used in controlling the IPS. These methods, however, have proven to be harmful to the environment. Resource managers usually employ the use of these methods after IPS have become widespread and established over large geographical areas. As a result of the establishment of these IPS over large areas, these traditional methods end up being noticeably inefficient in controlling the growing populations of the IPS. The best method therefore entails preventing their establishment to avoid looking for ways to control them once they have established themselves. The use of SDMS has proven to be a great solution to this by providing target areas thereby enabling resource managers to focus their conservation efforts in these areas. These traditional methods however can be effectively used hand in areas that are minimally infested. Employing the use of these methods in the early stages means targeting smaller areas that will have minimal impact on the environment and non-target species.

A collaborative approach between all stakeholders, the research community and the communities in the affected areas is necessary to ensure prevention, early detection and necessary management and control measures of IAPS (Kannan *et al.*, 2016).

5.2 CONCLUSIONS

5.2.1 Which variables affect the environmental niches of *Parthenium hysterophorus* L.?

1. The models performed very well and the pairwise decision made to run the models using wildlife density, distance to roads, land use and landcover change in addition to the 19 bioclimatic variables and NDVI was satisfactory in depicting the impact of these variables on the current and potential geographical distribution of *Parthenium hysterophorus* L.
2. Variables such as November NDVI in the present can be used to detect *Parthenium hysterophorus* L.in the month of November as the probability of getting the IAPS is highest in this month when using NDVI.

5.2.2 How do the variables affect the current geographical distribution of these invasive plant species in MME?

1. The one tailed Hypothesis testing done to model on current geographical distribution of the IPS conclusively rejected the research hypothesis. This therefore follows that the distribution of *Parthenium hysterophorus* L.is influenced by its response to environmental variables.
2. Based on the model's results, it is evident that the indigenous vegetation, wildlife and livestock face risks of the spread and impact of IAPS under the current prevailing conditions. The model identified the areas that face the most threat such as the Mara Triangle and the reserve at large and conservancies such as Talek, Lemek and Motorigi. Special proactive management strategies should therefore be especially concentrated in such areas to ensure the prevention of depletion of resources in these areas as well as loss of the ecosystem's integrity. Employing the use of strategies such as modelling is therefore of paramount importance in enhancing conservation of natural resources.

5.2.3 How do different climate changes affect the future potential geographical distribution of invasive species in MME?

1. The one tailed Hypothesis testing done to models on the potential geographical distribution of the IPS conclusively rejected the research hypothesis. This therefore follows that the

distribution of *Parthenium hysterophorus* L.is influenced by its response to environmental variables.

2. The model's results, it is evident that the indigenous vegetation, wildlife and livestock will still face the risks of the spread and impact of IAPS under the potential impacts of the extrapolated climate scenarios. The models showed an upward spread of invasion from the MMNR and the conservancies north to it. Some invasion to the surrounding potential areas of wider areas of Ol Chorro, Enonkishu and Siana, Kerinkani, Kimintet, Maji Moto and Naikarra will in addition to the Mara Triangle and conservancies such as Talek, Lemek and Motorigi.
3. Special proactive management strategies should therefore be especially concentrated in such areas to ensure the prevention of depletion of resources in these areas as well as loss of the ecosystem's integrity. Employing the use of strategies such as modelling is therefore of paramount importance in enhancing conservation of natural resources.
4. From the results, it is evident that *Parthenium hysterophorus* L. has the potential to invade large geographical areas in a relatively short time thereby spreading its adverse impacts over large expanses. Though it has some documented uses that are beneficial, their negative impacts are far more dire that their relative importance in areas such as treating various ailments such as malaria and treating inflammations.

5.3 RECOMMENDATIONS

1. Due to time and financial constraints, this study only focused on two future climate scenarios; RCP 2.6 and RCP 8.5 for the year 2050. Further studies are necessary to determine the potential impacts of warming climates under the four climate scenarios including RCP 4.5 and 6.0 to give a more comprehensive and closer look at the potential impact of IPS if not efficiently managed
2. Further application of SDMs is necessary for the vast areas of the country that hold conservation importance to enhance proactive management of the IAPS as opposed to reactive management which has over the years proven to be more expensive and inefficient
3. There should be increased efforts to digitize some information such as road data to improve the efficiency of SDMs. Roads, as earlier on discussed, are an important dispersal agent of *Parthenium hysterophorus* L. and other IAPS thus an important element that should be considered when modelling. This can be an efficient way of determining propagule pressure through determining the distance from roads and their lengths in areas under study
4. More research can be done on how better to use *Parthenium hysterophorus* L. to treat the various ailments it is evidenced to treat. This will provide a platform of reversing its negative impacts, though at a smaller scale as its positive uses cannot match the relative negative impacts it causes to the environment.

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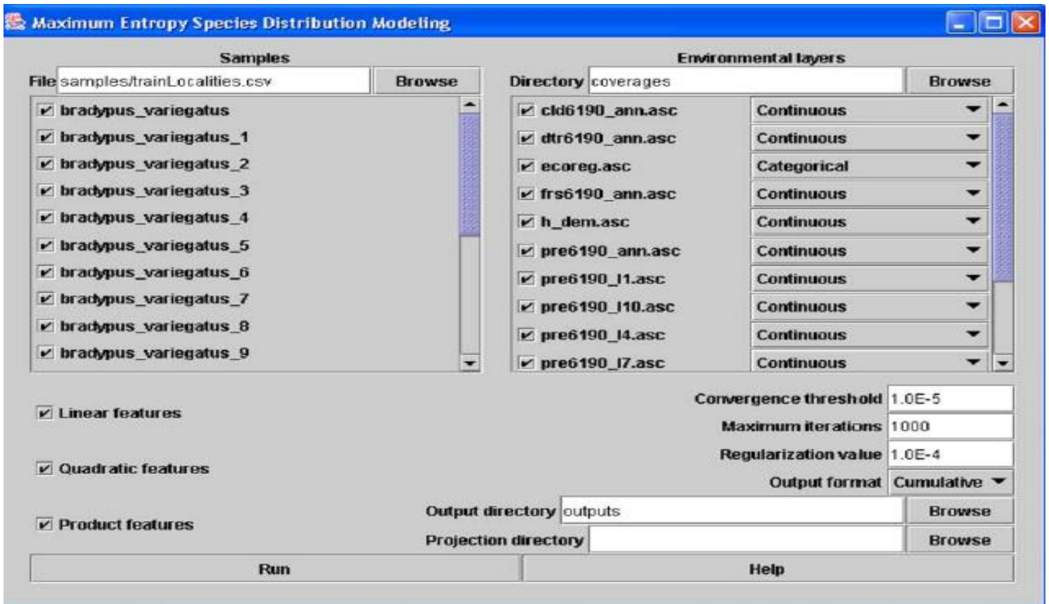
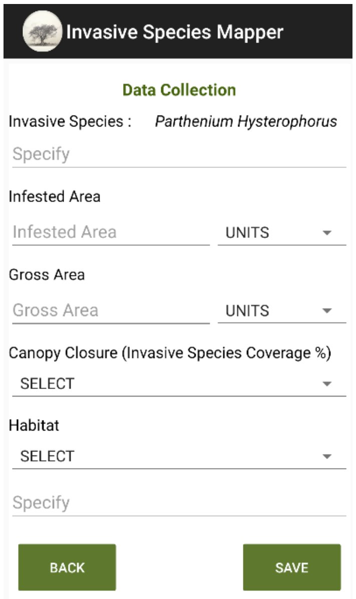
APPENDICES

Appendix 1: Maxent program user interface used to model IAPS at particular longitude and latitude locations (Simpson, 2011)



Appendix 2: Invasive Species Mapper Application

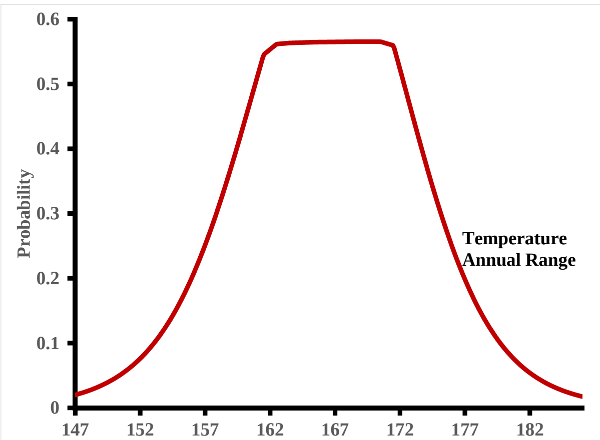


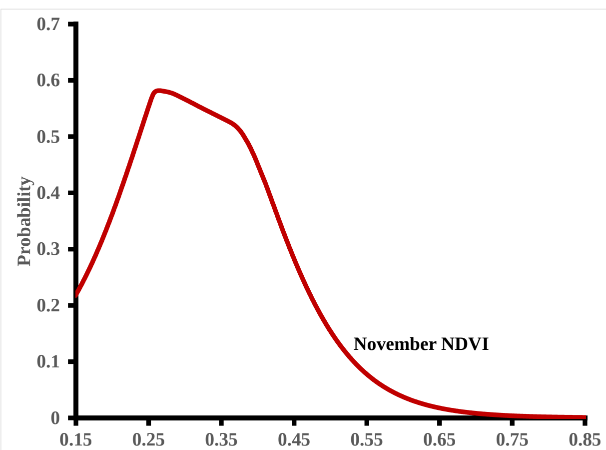
Appendix 4: Field data sheet

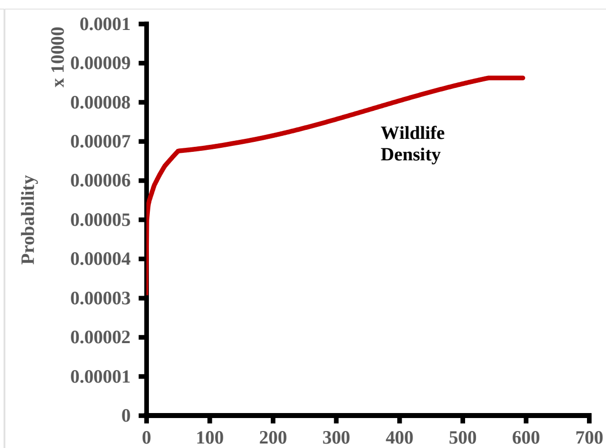
Kindly see separate attachment

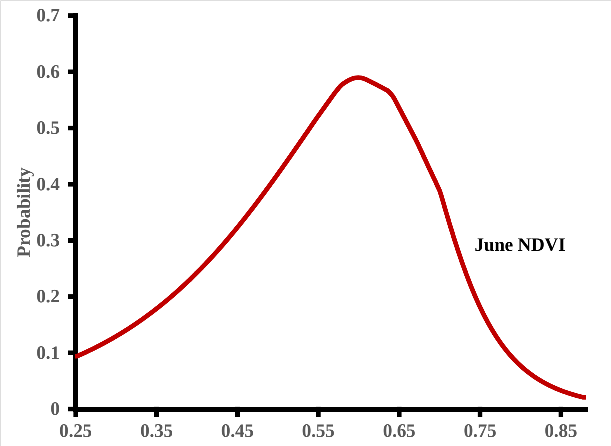
Appendix 5: Response curves- Predictor variable response curves in the current scenario: Temperature seasonality, Temperature Annual Range, November NDVI, Wildlife Density and June NDVI

Response curves function to quantify the relationship between the variables used to run the model and habitat suitability. They serve to increase the understanding of the niche requirements of the species. Temperature seasonality units in degree Celsius, Temperature annual range units in degree Celsius, Wildlife density in numbers/square kilometer





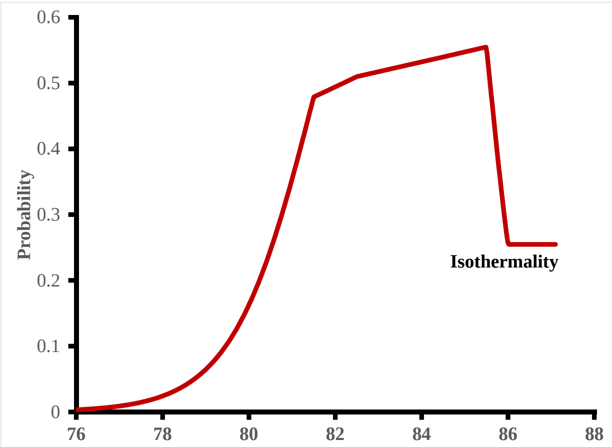


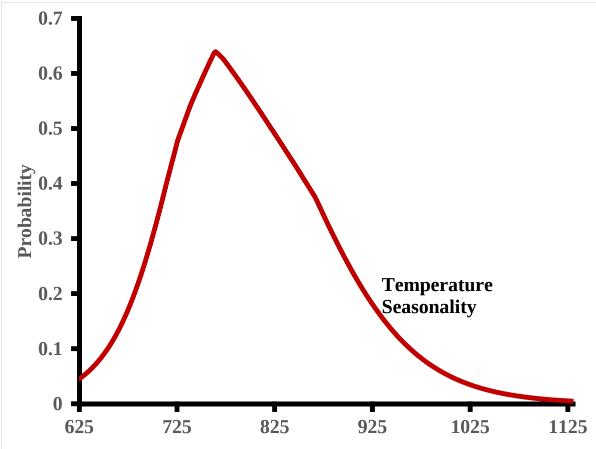


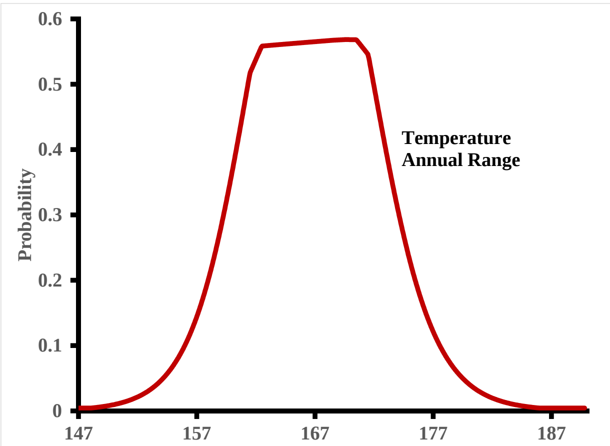
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Probability
June NDVI
0.25
0.35
0.45
0.55
0.65
0.75
0.85

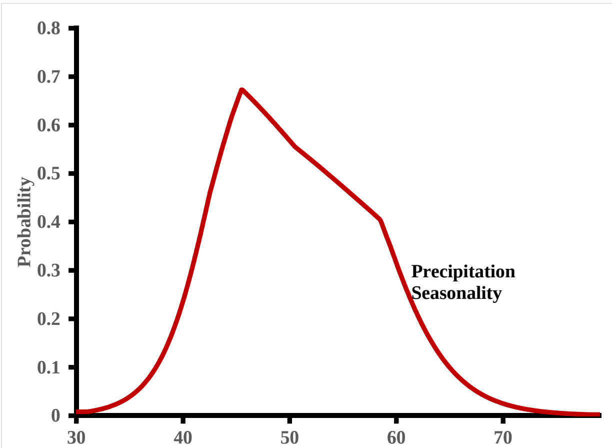
Appendix 6 : Response curves- Predictor variable response curves in the projection 2.6: Temperature seasonality, Temperature Annual Range, November NDVI, Wildlife Density and June NDVI

Temperature seasonality units is given in degree Celsius, Temperature annual range units in degree Celsius, Isothermality in percentage and precipitation seasonality also in percentage.



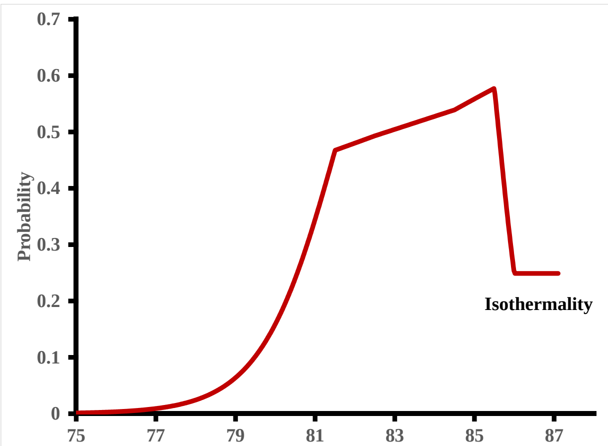


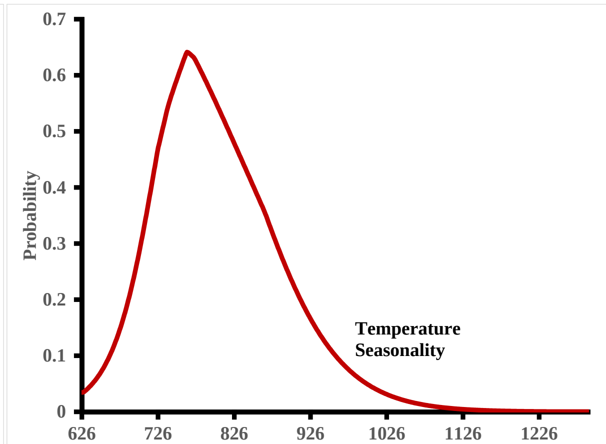


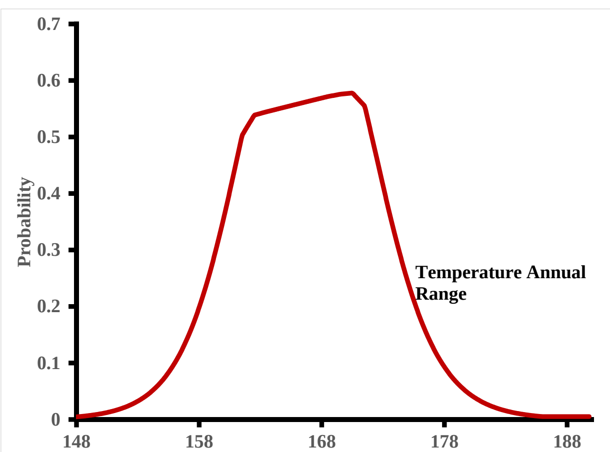


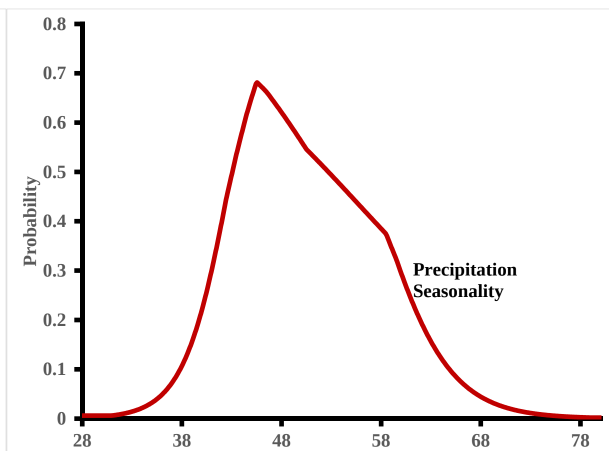
Appendix 7: Response curves- Predictor variable response curves in the projection 8.5: Temperature seasonality, Temperature Annual Range, November NDVI, Wildlife Density and June NDVI

Temperature seasonality units is given in degree Celsius, Temperature annual range units in degree Celsius, Isothermality in percentage and precipitation seasonality also in percentage.



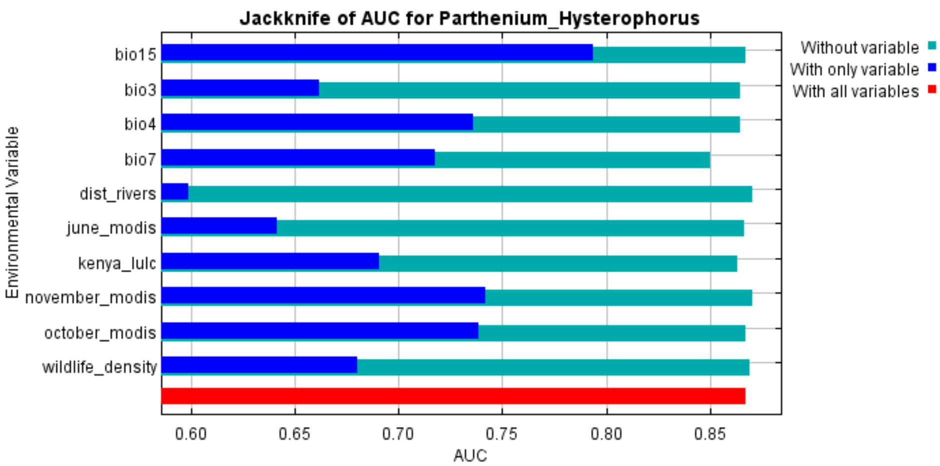






Appendix 8: Jackknife AUC results for current scenario

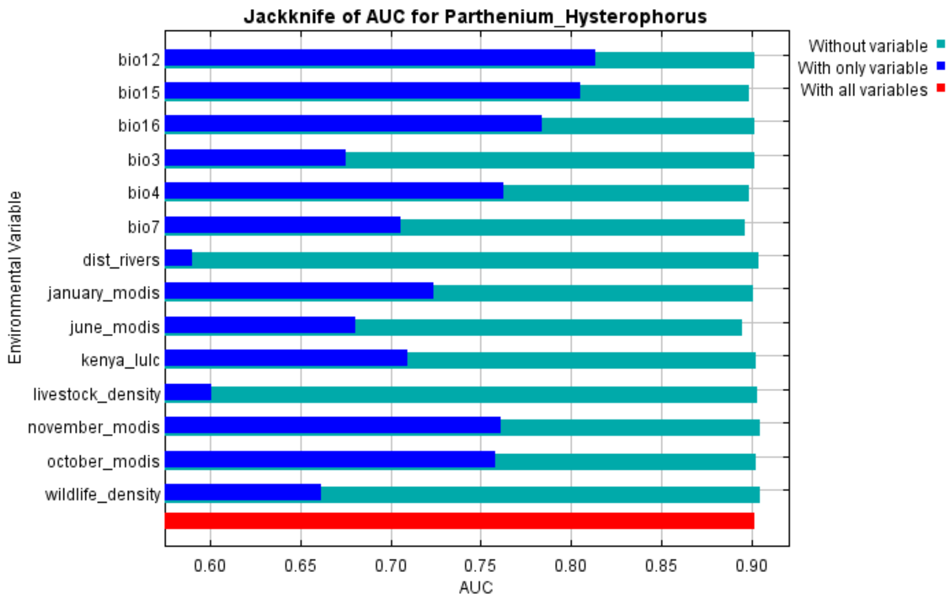
Jackknife test for AUC of the tested variables is given to show their variable importance. The values below represent an average of 25 replicate runs. AUC values that tend to 1 show model fitness and influence of a variable to model fitness is checked on the basis of its AUC value.
The dark blue bars show the variable that increases the gain of the model when used in isolation and has the most information as a lone variable. The variable that least impacts on the gain of the model is represented by the shortest dark blue bar. This variable provides the least amount of useful information to the model as a lone variable.
The light blue bars show the impact of removing the one variable on the gain of the model. The variable that decreases the gain the most when it is omitted appears to have the most information that isn't present in the other variables.
The gain of the model when all the variables are included is represented by the red bar.



Jackknife of AUC, current scenario

Appendix 9: Jackknife AUC results for projection 2.6 scenario.

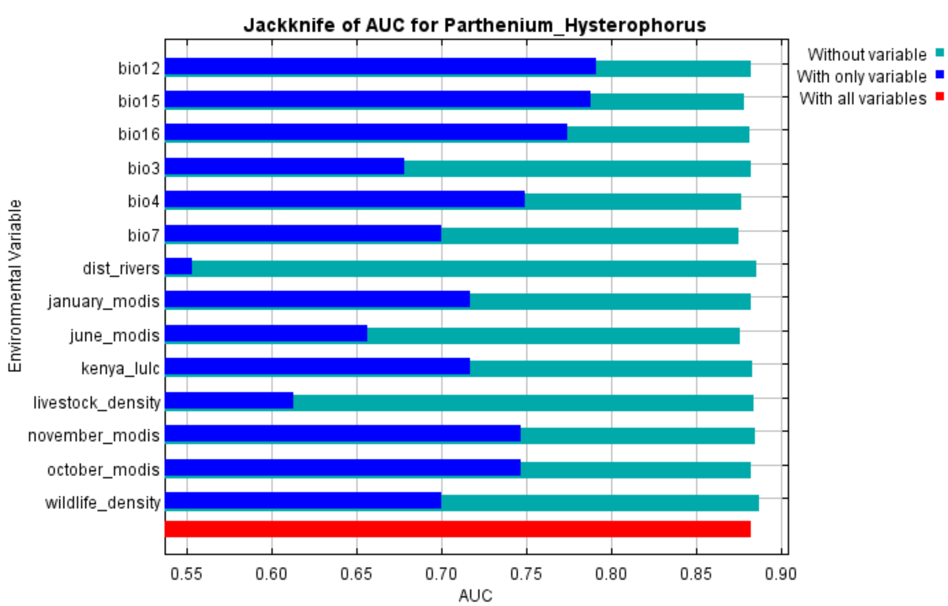
Dark blue bars show a model created from running this only variable, red bar shoes a model generated from running all the variables while the light blue ones show a model generated from excluding the one variable.



Jackknife of AUC, scenario 2.6

Appendix 10: Jackknife AUC results for projection 8.5 scenario

Dark blue bars show a model created from running this only variable, red bar shoes a model generated from running all the variables while the light blue ones show a model generated from excluding the one variable.



Jackknife of AUC, scenario 8.5