ENVIRONMENTAL AND SOCIO-ECONOMIC PREDICTORS OF ANTHRAX SPATIAL DISTRIBUTION IN KENYA

FREDRICK TOM OTIENO

A Research Thesis Submitted in Fulfilment of the Requirement for the Award of Degree of Doctor of Philosophy in Environmental Management of South Eastern Kenya University

2022

DECLARATION

I understand that plagiarism is an offence and I therefore declare that this thesis is my original work and has not been presented to any other institution for any other award.

Signature_____________________ Date________________

Fredrick Tom Otieno

B502/MAI/30004/2018

This research thesis has been submitted for examination with our approval as University Supervisors.

Signature_____________________ Date________________

Prof Peter G. Njuru

Department of Environmental Science and Land Resources Management,

South Eastern Kenya University

Signature_____________________ Date________________

Dr Patrick Kariuki

Geothermal Energy Training and Research Institute,

Dedan Kimathi University of Technology

Signature_____________________ Date________________

Dr John Gachohi

School of Public Health, Jomo Kenyatta University of Agriculture and Technology

Signature_____________________ Date________________

Dr Bernard Bett

International Livestock Research Institute (ILRI)

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DEDICATION

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ABBREVIATIONS AND ACRONYMS

ANN	:	Artificial Neural Network
AEZ	:	Agro Ecological Zones
AHP	:	Analytical Hierarchical Process
AR4	:	Fourth Assessment Report
ASAL	:	Arid and semi-arid areas
AUC	:	Area Under Curve
AUCROC	:	Area under the curve of the receiver operating characteristics
BRT	:	Boosted Regression Trees
CI	:	Consistency Index
CR	:	Consistency Ratio
ELETRE	:	Elimination and Choice Translating Reality
ENFA	:	Ecological Niche Factor Analysis
ENM	:	Ecological Niche Modelling
FPR	:	False positive rate
DVS	:	Directorate of Veterinary Services
GAM	:	General Additive Model
GARP	:	Genetic Algorithm for Rule-Set Prediction
GHG	:	Green House Gas
GIS	:	Geographic Information System
GPS	:	Global positioning systems
GLM	:	Generalised Linear Models
ILRI	:	International Livestock Research Institute
IPCC	:	Intergovernmental Panel on Climate Change
IQR	:	Interquartile ranges
IREC	:	Institutional Research Ethics Committee
KABS	:	Kenya Animal Bio-surveillance System
KEMRI	:	Kenya Medical Research Institute
KWS	:	Kenya Wildlife Services
RCP	:	Representative Concentration Pathway
RF	:	Random Forest
RVF	:	Rift Valley Fever

ROC	:	Receiving Operator Characteristics
PDP	:	Partial dependency plots
PH	:	Acidity or alkalinity of a solution on a logarithmic scale
MARS	:	Multiadaptive Regression Model Splines
MAUT	:	Multi-attribute Utility Theory
MAXENT	:	Maximum Entropy
MCDA	:	Multicriteria decision analysis
MCDM	:	Multiple-criteria decision-making
NDVI	:	Normalized Difference Vegetation Index
SDM	:	Species Disease Modelling
SMART	:	Simple Multi-attribute Ranking Technique
USGS	:	United States Geological Society
QGIS	:	Quantum Geographical Information System
RVF	:	Rift Valley Fever
SERU	:	Scientific and Ethics Review Unit, KEMRI
TOPSIS	:	Technique for Order of Preference by Similarity to Ideal Solution
TPR	:	True positive rate
TNR	:	True negative rate
TSS	:	True Skill Statistics
UNICEF	:	United Nations International Children Education Fund
VIF	:	Variable Inflation Factors
WHO	:	World Health Organisation

ABSTRACT

Anthrax spatial distributions and the potential driving factors remain poorly understood worldwide and in Kenya. This study aimed at establishing environmental and social-economic predictors of the spatial distribution of anthrax in Kenya through (1) determining the relationship between selected environmental and socio-economic factors on spatial distribution of anthrax through use of an ecological niche modelling framework; (2) predicting the effect of climate change on the future spatial distribution of anthrax; and (3) establishing the influence of socio-economic factors in vulnerability to anthrax. Ecological Niche Model (ENM) of boosted regression trees (BRT) algorithm was applied to predict the suitable spatial environments for anthrax under current and future climate scenarios in Kenya. The model fitted confirmed anthrax occurrences from three distinct sources of retrospective records (2011 to 2017), sporadic anthrax outbreaks (2017 to 2018) and active surveillance (2019 to 2020) against selected predictor variables to yield current and future anthrax risk maps. Finally, the underlying socio-economic vulnerability due to the risks of anthrax distribution was assessed by laying over socio-economic indicators in spatial multicriteria decision analysis to produce socio-economic vulnerability maps. The high-risk areas for anthrax outbreaks were identified predominantly in: regions around western Kenya bordering Uganda; southwestern regions bordering Tanzania and regions around central highlands of Kenya. Based on the current scenario, the number of humans affected was estimated at ~ 193,00,840 people/sq.km while that of livestock was at ~7,750,675 animals / sq.km. The important contributing predictor variables were predominantly cattle density, rain of the wettest month, monthly precipitations, soil clay, soil pH, soil carbon, longest dry season and temperature range. The anthrax highly suitable areas expanded from current to future climatic scenarios with current at 36131 km2, RCP 4.5, 40012 km2, and RCP 8.5, 39835 km2. Highly socio-economic vulnerable areas closely correlated with areas of high anthrax risk currently and into the future. At current vulnerability index > 75%, approximately 40,369,455 people were estimated to be at risk. This study results will guide risk-based surveillance and strategies for managing anthrax under One Health approach and also contributes to future research studies within Kenya and beyond.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of the study

Anthrax is a global important zoonotic disease caused by, soil-borne spore forming, Gram-positive, rod-shaped bacterium, *Bacillus anthracis* that affects livestock, wildlife and humans with widespread socio-economic impacts (Joyner, 2010; Turnbull, 2008). Even though omnivores and carnivores are infected by anthrax, they are moderately resistant (Fasanella *et al*., 2010a). Humans get infected through contact with the infected animals and their products, consuming infected meat, or inhalation of the bacterial spores. Consequently, human anthrax presents with three forms of infection: cutaneous, gastrointestinal, and inhalational, with cutaneous form accounting for more than 95% of human cases worldwide (Turnbull, 2008). Cutaneous anthrax presents when a broken skin encounters an infected material; gastrointestinal anthrax results from consuming anthrax-infected meat; and inhalational anthrax results from inhaling anthrax spores. If anthrax is untreated in humans, 20% fatality rates occur (Swartz, 2001). In addition to anthrax being of public health importance, it has recently attracted national to global security implications where it has been employed in bioterrorism (Blackburn *et al*., 2015; Fasanella *et al*., 2010a; Goel, 2015)

The persistence of anthrax is dependent on the *B. anthracis* spore survival in the environment for long periods, availability of susceptible animals, and contact between the animals and the spores during grazing (Turnbull, 2008). Spores can survive in soils for very long periods with some areas experiencing recurrent outbreaks (Smith *et al*., 2000). Spores can also remain in buried carcasses and get uncovered when such burial sites are upset. They could also be transferred via animal products of infected animals (Hugh-Jones and De Vos, 2002). (Blackburn *et al*., 2014; Dragon and Rennie, 1995). Ingestion of spores by a grazing or browsing animal initiates the cycle of anthrax infection (Turnbull, 2008), where within the infected host, the spores germinate into vegetative forms that kills the host. Then, a proportion of the *bacilli* is released into the environment with non-clotted blood; the released *bacilli* sporulates under the conducive condition in the presence of free oxygen, which then become ready to be taken up by a new host. The spores become infectious from less than one hour to many decades later to restart a new cycle.

Anthrax outbreaks are majorly influenced by factors that affect *B. anthracis* sporulation and germination including soil properties, climate, seasonality, host health and anthropogenic activities (Turnbull, 2008). Soil characteristics and properties are associated with anthrax persistence such that soils, rich in calcium and organic matter with a pH above 6.0 favour multiplication and vegetative growth cycles of *B. anthracis* (Van Ness, 1971). Climatic factors of temperature and rainfall trends, their seasonality and extremes determine anthrax outbreak distribution (Blackburn, 2010; Mwakapeje *et al*., 2019; Walsh *et al*., 2019). In addition, they indirectly affect animals' general health and their ability to resist anthrax infection (Turnbull, 2008). Changes in climate are expected to influence future transmission patterns of infectious diseases such as anthrax (Bett *et al*., 2017). While transmission of *B. anthracis* is largely environmentally mediated, spatio-temporal anthrax outbreaks patterns are influenced by prevailing socio-economic and cultural livelihoods (Lepheana *et al*., 2018; Sitali *et al*., 2017). Scavengers and necrophagous or hematophagous flies also play a significant role in the transfer and dispersal of *B. anthracis* spores (Blackburn *et al*., 2014; Dragon and Rennie, 1995). Anthrax is still common in some Mediterranean countries, small pockets of Canada, USA, certain central and south America, central Asia countries, several sub-Saharan African countries and western China (Turnbull, 2008). Sub-Saharan Africa is thought to be the geographical origin of *B. anthracis* (Keim *et al*., 1997). Kenya has had her share of anthrax outbreaks dating back to as early as 1957 (Nderitu *et al*., 2021). Despite the confirmed anthrax outbreaks in Kenya, there is still paucity of knowledge on anthrax spatial ecology and the associated risk factors that promote its long-term survival and intermittent outbreaks. Indeed, there is lack of anthrax risk map for the entire Kenya and detailed understanding of ecological risk factors that compromise targeted livestock vaccination, public education, and early detection and response in wildlife, livestock, and humans (Muturi *et al*., 2018).

Accurate geographical distribution information is necessary for informed anthrax surveillance and control strategies (Barro *et al*., 2016). This can be achieved through ecological niche model (ENM), an approach that informs investigations on the known geography or potential geographies of vectors, hosts, pathogens, or human cases at a fine spatial scale without loss of information (Peterson, 2006). The ENM relies on statistical correlations between existing species occurrences and environmental or socio-economic variables (Mischler *et al*., 2012). In the case of anthrax outbreaks, the existing species being *B. anthracis*. ENM process is only possible after data acquisition and preparation with the aid of Geographical Information Systems (GIS) and Remote Sensing (Blackburn, 2010). The occurrences' locations can be determined as centres of the study units or precisely acquired locally using Global positioning Systems (GPS). Collected data are fed into a GIS framework for spatial analysis to process and extract variables for use as inputs in ENM algorithms.

Anthrax in Kenya remains uncontrolled, in part due to lack of risk maps to identify areas vulnerable to the disease to guide surveillance and control programmes. In response, this study is the first to predict the specific geographical distribution of anthrax as a proxy of risk using ENM for the entire country. The study uniquely utilized three sources of anthrax occurrences data from historical archives in addition to passively and actively collected data. The study also identified the influencing factors to the prediction presenting in the Kenyan environment and the influencing climatic factors under multi climatic scenarios. Further the study determined the socio-economic vulnerability associated to the predicted anthrax risk. The results from this study will inform targeted risk-based surveillance and strategies for managing anthrax outbreaks in Kenya. In addition, the study will contribute to the body of knowledge on anthrax and serve as reference to future research on anthrax within and without Kenya.

1.2 Statement of the problem

Kenya has experienced recurrent anthrax clustered outbreaks in specific areas pointing to endemicity. Over the past 60 years, 666 livestock anthrax outbreaks have been reported in Kenya translating to approximately 10 anthrax outbreaks annually (Nderitu *et al*., 2021). Anthrax pauses severe disease burden, socio-economic impact, epidemic potential to Kenyans and as such, has been ranked the highest priority zoonotic disease

(Munyua *et al*., 2016). There is a possibility of some anthrax outbreak areas being unknown due to poor or unreliable reporting by livestock keepers. Futhermore, lack of integrated reporting from health and veterinary sectors on zoonoses has also been pointed to undermine tracking of anthrax outbreaks (Falzon *et al*., 2019). Persistence of anthrax and its expansion or re-emergence is expected due to influence of changes in climate. In addition, outbreaks and persistence of anthrax is exacerbated by poverty and low education levels that expose people slaughtering, selling and consuming anthrax affected meat. Despite the confirmed anthrax outbreaks in Kenya, there is still paucity of knowledge on anthrax spatial ecology or the specific geography of favouring environmental conditions or factors that promote its long-term survival and intermittent outbreaks.Furthermore, there is no anthrax risk map at the country scale and detailed understanding of ecological risk factors which hamper targeted livestock vaccination, public education, and early detection and response in wildlife, livestock, and humans. Preventing anthrax outbreaks requires that its transmission and infection be broken through practical approaches such as efficient surveillance systems which can be duly informed throug risk and vulnerability maps. The maps can be developed from curent and future scenarios predictions to guide risk-based surveillance strategies for both livestock and wildlife.

1.3 Objectives of the study

1.3.1 General objective

The general objective of the study was to establish environmental and social-economic predictors of spatial distribution of anthrax in Kenya.

1.3.2 Specific objectives

The specific objectives were:

1) To determine the relationship between selected environmental and socio-economic factors on spatial distribution of anthrax in Kenya.
2) To predict the effect of climate change on the future spatial distribution of anthrax in Kenya.

3) To determine spatially explicit socio-economic vulnerabilities to the spatial distribution of anthrax in Kenya

1.4 Research Hypothesis

The hypotheses for the research were:

$H_0$1: Specific environmental and socio-economic factors do not significantly influence the potential spatial distribution of anthrax in Kenya.

$H_0$2: Changes in climate will not significantly affect the future spatial distribution of anthrax in Kenya.

$H_0$3: Anthrax spatial distribution interacting with spatially explicit socio-economic factors do not significantly influence socio-economic vulnerability in Kenya.

1.5 Significance of the study

Due to anthrax burden, socio-economic impact, epidemic potential, and severity, valid information and knowledge on its likely outbreaks in Kenya are highly required for surveillance and subsequent control strategies. This study identifies the potential anthrax hotspot areas, the influencing risk factors and the associated socio-economic vulnerability which will aid in the necessary One Health interventions and outreach programs to the risk areas. The risk areas are presented in anthrax distribution severity maps attributed to influencing environmental and multiple climate change risk factors. Furthermore, socio-economic vulnerability severity maps due to the anthrax risks are developed to incorporate the socio-economic, demographic and health dimensions. These maps present valuable spatial information to serve as a planning and interventional tool for livestock and health sectors at national and subnational governments and non-governmental partners. The study results will precisely guide risk-based surveillance and strategies for managing anthrax outbreaks, including vaccinations and the timing of public health warnings in identified high-risk areas by specifically the Department of Veterinary Services. The identified anthrax hotspots will be ideal for investigating, in details, risk factors associated with the long-term survival of anthrax spores and outbreak occurrences.

1.6 Limitations and mitigation

Several limitations on this study were identified, however this did not invalidate the study as mitigation measures were put in place to in an attempt to minimise their negative effects.

1) The publicly available disaggregated and spatially explicit data were obtained from different sources and this may undermine data quality and accuracy at different scales. Even though there is little room for altering existing secondary data, an attempt was made to make a careful selection of data. They were from credible sources, broadly used and tested in previous similar studies, have associated metadata and being of high resolution and scale as possible for the study area.
2) The general circulation models (GCMs) climate data have inherent uncertainties emanating from individual specific parameters and functions to project the climate scenarios (Gowtham et al., 2018). This study used africlim_ensemble_v3_[base] that averages ten GCMs to reduce biases (Platts et al., 2015).
3) AUC accuracy metrics employed in model evaluation have been criticized as not optimal for ENM models accuracy evaluation (Lobo *et al*., 2008; Peterson *et al*., 2008). In this study AUC metrics were averaged from 100 ensemble runs to minimize the bias.
4) Poor reporting has been documented to underestimate anthrax outbreaks in Kenya (Abdirahim *et al*., 2019), which has got an implication on the sample size. This study employed three sources of anthrax outbreaks data in an attempt to obtain optimized the sample size.
5) There is a chance that the locations of pseudo-absences generated to represent absences might overlap with presences locations (Pearce and Boyce, 2006). The pseudo-absences in this study were generated at least 5km Euclidian distance away from any outbreak points to minimize any possible overlap.
6) In vulnerability assessment, the choice of the framework and data availability might result in a vulnerability map that is compromised and not detailed enough to capture the local disparities. In this study, an attempt was made to mitigate these challenges by adopting a vastly tested IPCC vulnerability framework and only use validated data at resolution 1 km or less to be as detailed as possible.

1.7 Scope of the study

This study evaluated the specific biogeography of anthrax in Kenya using spatial analyses and ecological niche modelling based on environmental and socio-economic characteristics of anthrax outbreak locations upscaled to cover the whole country.

Several candidate environmental and socio-economic variables associated with anthrax propagation were obtained and subjected to a rigorous selection process before the filtered variables fitted in modelling. Only confirmed anthrax outbreak cases were used. The ethics requirements adhered to ethical and compliance guidelines obtained from KEMRI Scientific and Ethics Review Unit (SERU) (Ref: KEMRI/RES/7/3/1)

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Anthrax aetiology and ecology

Anthrax is a bacterial disease caused by the spore forming *Bacillus anthracis*, a Gram-positive rod-shaped bacterium, which is the only obligate pathogen in the large genus *Bacillus* (Turnbull, 2008). *B. anthracis* formed spores are the etiological agents of anthrax. Factors that affect sporulation and germination of *B. anthracis* include environmental factors such as soil pH, temperature, water activity and cation levels. Others factors are related to the season; health of the host, insect populations and human activities (Turnbull, 2008). Anthrax affects angulate herbivorous animals (both livestock and wildlife) and humans (Turnbull, 2008; Van Ness, 1971). Humans, carnivorous and omnivorous get infected albeit with moderate resistance (Fasanella *et al*., 2010a; Turnbull, 2008).

Infection of livestock anthrax occurs through ingestion of the spores or from inoculation by biting flies (Joyner, 2010). The cycle of anthrax infection begins when grazing or browsing animal ingest the spores (Turnbull, 2008), where: within the infected host the spores germinate to produce the vegetative forms which multiply, eventually killing the host; then a proportion of the *bacilli* released by the dying or dead animal into the environment sporulate under conducive condition in presence of free oxygen, ready to be taken up by a new host from less than one hour or many decades later. *B. anthracis* spores can survive in soils for long periods of time resulting in some areas experiencing regularly occurring outbreaks (Smith *et al*., 2000). Scavenger birds such as vultures are associated with dispersal of anthrax-causing bacterial or spores to distant areas in rural environments (Turnbull, 2008). Flies also have been associated with anthrax outbreaks in endemic areas where necrophagic flies increase number of cases while haemophilic flies increase transmission in space (Blackburn *et al*., 2014; Hugh-Jones and Blackburn, 2009). **Figure 2-1** summarises the anthrax life cycle.

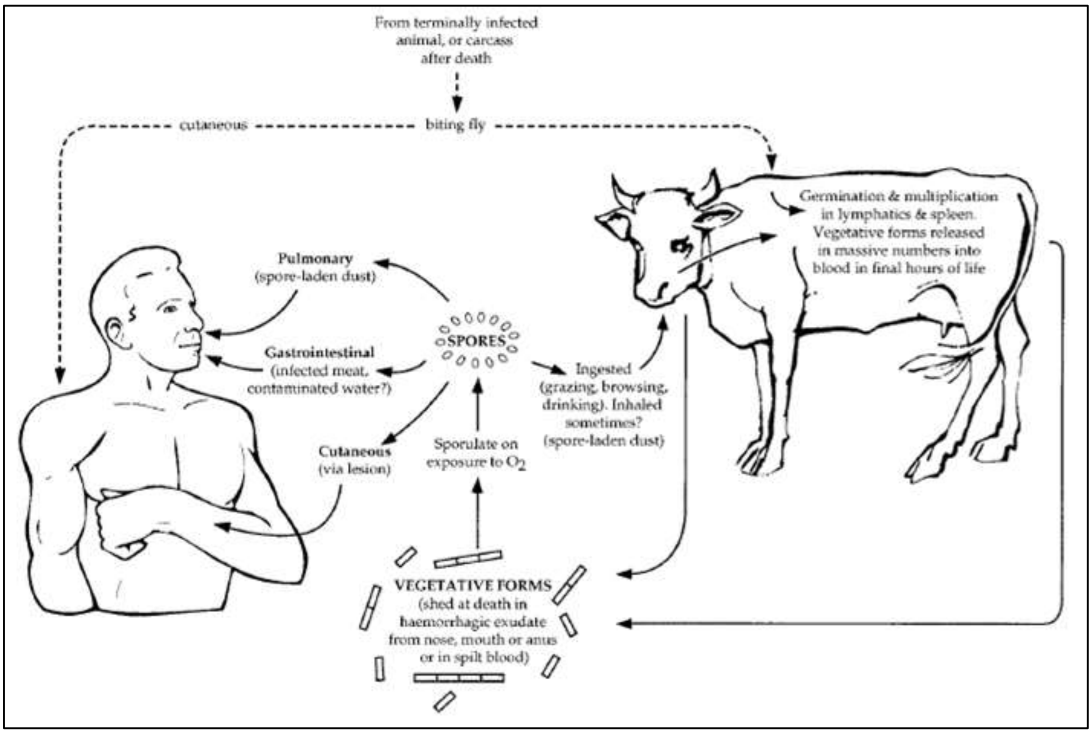

Figure 2-1: Anthrax life cycle.
(Source: Turnbull, 1998)

Humans get infected through contact with the infected animals and their products or through consuming infected meat or inhalation of spores. This presents three forms of infection namely cutaneous, gastrointestinal and inhalational. The cutaneous infection accounts for more than 95% of human cases worldwide (Turnbull, 2008). Cutaneous anthrax presents when humans' broken skin encounters an infected material, gastrointestinal, when humans consume anthrax infected meat, and inhalational, when humans inhale anthrax spores. If anthrax is untreated in humans, 20% fatality rates occur (Swartz, 2001).

Despite being a disease of antiquity, little is known about the spatial ecology of anthrax or the specific geography of environmental conditions that promote long-term survival of *B. anthracis* (Blackburn, 2006; Smith *et al*., 2000). Much has been written and hypothesized about the effects of season, rainfall, temperature, soil, vegetation, host condition and population density on the epidemiology of anthrax (Chen *et al*., 2016; Dragon and Rennie, 1995; Fasanella *et al*., 2010a; Hugh-Jones and De Vos, 2002; Saile and Koehler, 2006; Turnbull, 2008; Van Ness, 1971). However, these factors vary among locations globally, making it difficult to define a single consistent ecological description for anthrax. Furthermore, different strains of *B. anthracis* thrive in different geographic environments (Carlson *et al*., 2018; Hugh-Jones and Blackburn, 2009).

2.2 Anthrax global distribution

Anthrax outbreaks are common in several regions including in sub-Saharan Africa, south America, central Asia, Mediterranean, western China, Australia, Canada and the USA (Barro *et al*., 2016,Turnbull, 2008). A population of 1.83 billion people are estimated to live within regions of anthrax risk (Carlson *et al*., 2018). Recently anthrax outbreaks have also been reported in Arctic regions, zones previously assumed free of anthrax, due to warming temperatures thawing the permafrost (Ezhova *et al*., 2021, Stella *et al*., 2020). Interestingly, sub-Saharan Africa is thought to be the geographical origin of *B. anthracis* and has indeed reported frequent anthrax outbreaks (Blackburn *et al*., 2015; Chikerema *et al*., 2013; Driciru *et al*., 2018; Kracalik *et al*., 2017; Smith *et al*., 2000). On the eastern regions of sub–Saharan Africa, Ethiopia, Tanzania, Uganda and Kenya, have had their share in the frequent outbreaks (Assefa *et al*., 2020; *Driciru et al*., 2018; Mwakapeje *et al*., 2018, Nderitu *et al*., 2021). **Figure 2-2** shows the global distribution of anthrax occurrences from 413 countries (2015-2016). Anthrax outbreaks negatively impact public health, economies and welfare of the livestock keepers in anthrax endemic countries due to poor anthrax prevention and control programs (Vieira *et al*., 2017). Furthermore, weak surveillance systems, especially in sub-Saharan Africa, contribute to high morbidity, mortality, and socio-economic impact of anthrax (Lepheana *et al*., 2018; Muturi *et al*., 2018; Opare *et al*., 2000; Sitali *et al*., 2017). Recently anthrax has attracted global security concerns as an agent for bioterrorism (Fasanella *et al*., 2010a; Goel, 2015).

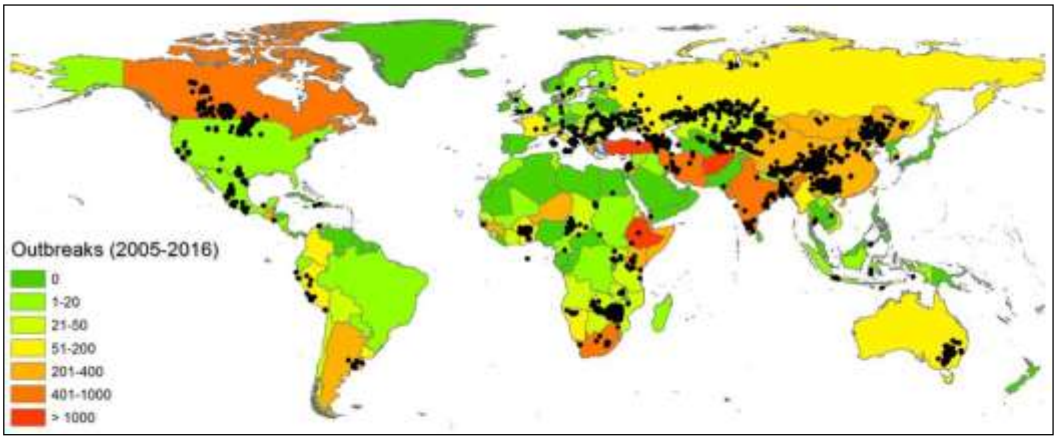

Figure 2-2: Global anthrax outbreaks of anthrax by 413 countries (2015-2016)**.** (Source: Carlson et al., 2018)

2.3 Anthrax in Kenya

Kenya has experienced anthrax outbreaks in livestock, human and wildlife both historically and in the recent past (Bett and Gachohi 2019, GIDEON, 2018; Kaitho *et al*., 2013;Muoria *et al*., 2007; Muturi *et al*., 2014, Muturi *et al*., 2018; Odhiambo *et al*., 2013). Indeed anthrax outbreaks dating back to as early as 1957 have been reported with 666 outbreaks translating to approximately 10 anthrax outbreaks annually in Kenya (Nderitu *et al*., 2021). **Figure 2-3** shows the distribution of anthrax outbreaks in Kenya (1957-2017). While anthrax appears endemic in some areas, new outbreaks have also been reported (Odhiambo, et al., 2013). Anthrax transmission in Kenyan regions (e.g., Kisumu, Marsabit, Nakuru, Narok, Isiolo and Wajir) have been attributed predominantly to human behaviours that encourage contact with infected tissues or eating infected carcasses, local knowledge about anthrax not withstanding (Abdirahim, M. A., 2018; Mbai et al., 2021; Mugo et al., 2021; Muturi *et al*., 2018). Based on the disease burden, socio-economic impact, epidemic potential, and severity, anthrax has been ranked the highest priority zoonotic disease in Kenya (Munyua *et al*., 2016). The availability of limited information undermines anthrax surveillance systems hence contribute to high morbidity, mortality, and socio-economic impact of anthrax in Kenya (Muturi et al., 2018). Kenya reports more than 10 multi-species anthrax outbreaks annually, however, risk map has been developed for the country that can help in prevention and control strategies (Muturi et al., 2018). Muturi et al., (2018) further point out that the risk map and an understanding of the ecological risk factors is necessary to promote targeted livestock vaccination, public education, and early detection and response in livestock, wildlife, and humans.

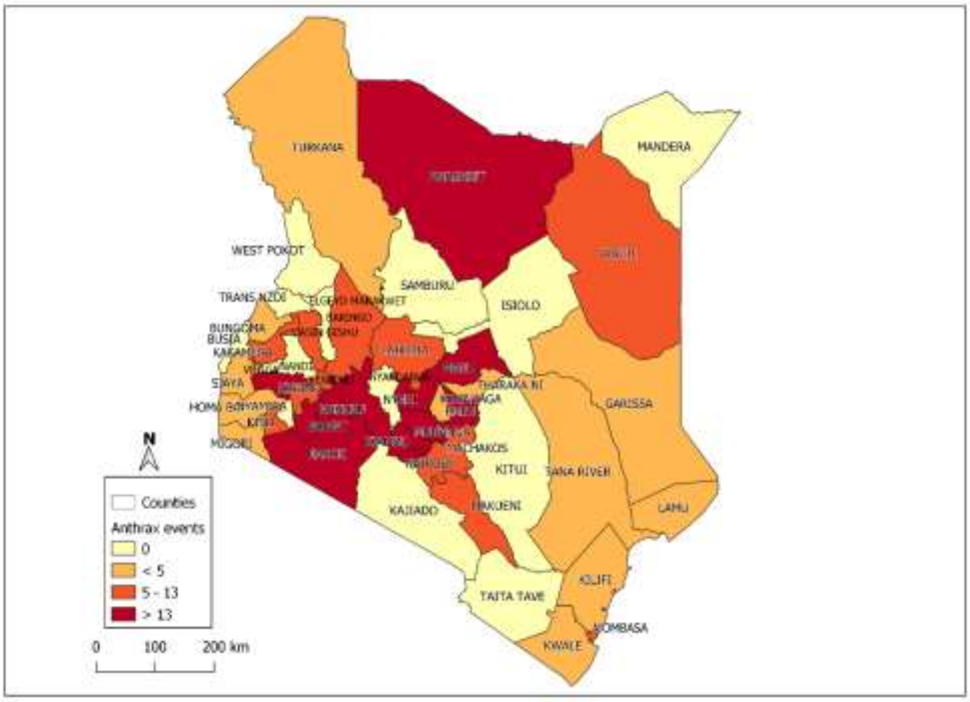

Figure 2-3: Distribution of anthrax outbreaks in Kenya (1957-2017).
(Source: author)

2.4 Anthrax and ecological niche modelling (ENM)

Joseph Grinnell brought the foundation concepts of ecological niches fore in 1917, where he postulated a niche as a part of the habitat possessing environmental conditions that enable individuals of a species to survive and reproduce, hence determining their distribution and abundance (Colwell and Rangel, 2009). Later in 1957, George Evelyn Hutchinson conceptualized duality defining a relationship between environmental and geographical space, thus providing a powerful way to model biogeographical distributions in relation to spatial environmental patterns. These theories inform ENM that is useful in predicting potential distribution of species such as *B. anthracis* in a given environment. Ecological niche modelling is a correlative model relating known occurrences with environmental variables based on conditions that meet a species' ecological requirements to predict the relative distribution (Warren and Seifert, 2011). ENM is sometimes referred to loosely as species distribution, habitat distribution, or climatic envelope model, but methods based only on geographical variables disregarding environmental correlation are not considered ENM (Peterson and Soberón, 2012; Sillero, 2011). Apart from environmental variables, socio-economic variables can also be fitted in an ENM (Hollings *et al*., 2017).

The resulting ENM distribution maps do not show actual occurrences of a species but highlight areas that have similar conditions to areas where species have occurred. Hence, it is an estimation of where a species can occur (Huijbers *et al*., 2016). Warren and Seifert (2011) outline the standard application of ENMs as 1) estimation of suitability of habitat known to be occupied by a species. 2)Suitability of habitat in geographic areas not currently occupied by a species. 3) Changes in the suitability of habitat over time due to specific scenario for environmental change. ENM has been proposed as a reliable method to identify potential anthrax outbreak risk areas for targeted surveillance strategies (Barro *et al*., 2016; Blackburn *et al*., 2017; Vieira *et al*., 2017).

The detailed description of species distribution model processes, which also applies for ENM, as they are often used interchangeably, is given by Huijbers *et al*., (2016). 1) correlation of species occurrences and measurements of environmental data with the assumption that the current distribution of a species is a good indicator of its ecological requirements. 2) Fitting the two data into a selected algorithm to estimate the probability of a species occurring in a place as some function of the environmental conditions of that place. 3) geographically projecting on a map, the model predicted species distribution. ENM employs machine learning, regression-based and rule-based algorithms. Several studies have applied selected ENM algorithms for anthrax outbreak prediction in different environments closer to Kenya and away including in Tanzania, Zimbabwe, Ghana, Australia, USA and Mexico, and China (Barro *et al*., 2016; Blackburn, 2010; Chen *et al*., 2016; Chikerema *et al*., 2013; Kracalik *et al*., 2017; Mwakapeje *et al*., 2019). Most studies applied anthrax occurrence data from historical databases, sometimes limited (Blackburn et al., 2015, Barro et al., 2016) **Figure 2-4** shows the countries where these ENM studies have been applied by 2018 while **Table 2-1** presents the descriptions of commonly applied ENM algorithms.

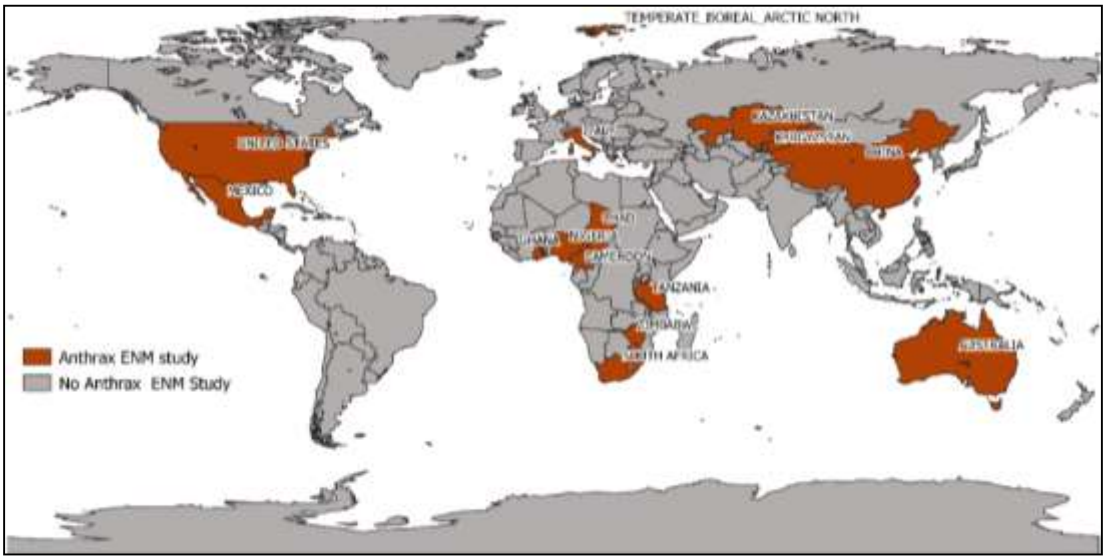

Figure 2-4: Global distribution of ENM studies (2018).
(Source: author)

ENM as a spatial distribution model broadly employs profile, regression-based and machine learning algorithms. Within the algorithms two approaches of response data, presence-absence or presence-only, are fitted. The choice of the approaches depends on data availability. When absence data is not available, the presences-only approach is applied, but pseudo-absence as absence data are generated. The pseudo-absences represent background areas from which species data are missing but might fall on presence locations (Pearce and Boyce, 2006). Randomly selected pseudo- absences are suggested to yield the most reliable distribution models (Barbet- Massin *et al*., 2012).

2.4.1 Profile algorithms

The profile models define multidimensional space from simple mathematical techniques that associate threshold distances or bounds of environmental variables to species occurrences as the potential range where species can occur. These models include: BIOCLIM, DOMAIN, Environmental Niche Factor Analysis (ENFA) and Mahalanobis distance as detailed in **Table 2-1**.

Table 2-1: Profile algorithms

Algorithms	Description	Type of data	Reference
BIOCLIM	Was the first species distribution model (SDM) package to be widely used. Uses observed presence of a species to predict suitable environments using bioclimatic envelope.	Presence-only	(Booth et al., 2014)
DOMAIN	Uses a point-to-point similarity metric to assign a classification value to a candidate site based on the proximity in environmental space of the most similar record site	Presence-only	(Carpenter et al., 1993)
Environmental Niche Factor Analysis (ENFA)	Computes suitability functions by comparing the species distribution in the ecogeographic variables space with that of the entire study area.	Presence, user pseudo-absence	(Hirzel et al., 2002)
Mahalanobis distance	Creates a multivariate mean based on the environmental conditions at the points where the species has been observed and gives a measure of dissimilarity at all other locations within the study area.	Presence only	(McLachlan, 1999)

2.4.2 Regression algorithms

Regression algorithms statistically derive estimates of the effect of environmental variables on the species distribution by constructing a function that best describes the effect of the environmental predictors on species occurrence. **Table 2-2** gives the details of the widely used regression models in species distribution modelling.

Table 2-2: Regression algorithms

Algorithms	Description	Type of data	Reference
Generalised Linear models (GLMs)	Regression-based SDM that uses occurrence and background data as dependent variables and environmental data as independent variables.	Presence, user pseudo-absence	(Elith and Leathwick, 2009)
Generalised Additive models (GAMs)	Are like GLMs but use data-defined, scatter plot smoothers to describe nonlinear responses.	Presence, user pseudo-absence	(Elith and Leathwick, 2009)
Multivariate adaptive regression splines (MARS)	Closely related to regression techniques such as GAM but has an advantage in its analytical speed and the ease of transfer of analysis results to other computational environments such as a Geographic Information System	Presence, user pseudo-absence	(Elith and Leathwick, 2007)

2.4.3 Machine learning algorithms

Machine learning algorithms model the association of species occurrences and environmental variables through experience and by the use of data. They partition data into training and testing data in modelling and evaluating the accuracy of the species distribution in association with environmental predictors. The widely applied machine learning algorithms in SDM are detailed in **Table 2-3** below.

Table 2-3: Machine learning algorithms

Algorithms	Description	Type of data	Reference
Boosted regression trees (BRT)	Combines two algorithms of regression trees and boosting, to build and fit many models and improve predictions by focusing resources on outliers.	Presence, user pseudo-absence	(Elith and Leathwick, 2017)
Random Forest (RF)	Uses a collection of tree-structured weak learners comprising identically distributed random vectors where each tree contributes to a prediction.	Presence, user pseudo-absence	(Liaw and Wiener, 2002)
Genetic Algorithm for Rule Set Prediction (GARP)	Infers correlations between environmental layers representing known species localities and a set of biotic and abiotic parameters based on defined rule sets	Presence, machine pseudo-absence (background)	(Stockman et al., 2006)
Maximum Entropy (Maxent)	Uses species presence locations and a set of environmental predictors to predict species	Presence, machine pseudo-absence (background)	(Phillips et al., 2006)

	distribution through maximum entropy density estimation.		
Artificial Neural Networks (ANN)	A relatively later introduction to species distribution modelling involving a network of simple processing elements (artificial neu-rons) that can exhibit complex global behaviour like site selection of a suitable habitat based on numerous environmental variables determined by the links between the neurons and associated functions.	Presence, user pseudo-absence	(Lek and Guégan, 1999)
Support Vector Machines (SVM)	Uses a functional relationship known as a kernel to map data onto a new hyperspace in which complicated patterns can be more simply represented.	Presence only	(Drake et al., 2006)

The selection of an ENM algorithm to apply in a specific project is not straight forward as it is difficult to identify one that should be universally applicable (Brotons *et al*., 2004). However, the type and quality of data available generally determine which modelling method will produce the best result (Steenkamp, 2013). In the context of this study, where there was no absence data, ENM of BRT algorithm was selected relative to other algorithms. Details of BRT is given in the next subsection.

2.4.4 ENM algorithm, boosted regression trees (BRT)

Boosted regression trees is an ENM algorithm that combines the strengths regression trees and boosting to build many simple decision trees adaptively (Elith and Leathwick, 2017). The BRT function **(Equation 1**) (Friedman, 2002), was developed as gradient descent boosting algorithm to estimate the weak learners.

$$f(x) = \sum_m f_{m(x)} = \sum_m \beta_{m(b(x;y_m)} \tag{1}$$

In the function, f_x is the linear predictor with β_m as the scaler representing the intercept, and $\beta_{y,}$ the coefficient values quantifying the linear effects of xy covariates. Function $b(x;y_m)$ represents individual trees with y_m as variables split values at each node and their predicted values. The β_m also represents the weights given to the nodes each tree in the collection and determines how predictions from the individual tree are combined. Gradient boosting involves two step approximation of the loss function through estimation of y_m via least square regression followed by estimation of $\beta_{m.}$

The BRT relative advantages and limitations are elucidated by Elith and Leathwick (2017) that: it handles different types of predictor variables and accommodates missing data; it has no need for prior data transformation or elimination of outliers; it can fit complex nonlinear relationships and automatically handles interaction effects between predictors; it is able to select relevant variables; and it has predictive performance that is superior to most traditional modelling methods. However, if samples are sparse in regions of the data space, its fitted functions can be noisy.

Performance of BRT model can be improved by calibrating its hyperparameters including bagging fraction, tree complexity and learning rate. Bagging fraction introduces randomness into the model by defining the proportion of data drawn at random from the original data at each step thus improving performance and reducing over-fitting. Tree complexity defines the number of nodes for each tree. Learning rate varies the contribution of each tree added to the model and is inversely proportional to the number of trees required; smaller learning rate and larger number of trees are preferable under several observations and computational time available. At least 1000 trees are enough for model fitting (Elith *et al*., 2008). In addition, BRT has in built function to reduce variables dimensionality and only fit those with relative important contribution while excluding non-important predictors when fitting trees. Recently, BRT has been considered a dominant algorithm for mapping transmission risk of infectious zoonoses (Carlson, 2020). It has been applied in previous studies in predicting the distribution of Dengue and Ebola in Colombia and Africa (Ashby *et al*., 2017; Pigott *et al*., 2014) and specifically of anthrax in China and Globally (Carlson *et al*., 2019; Chen *et al*., 2016). In studies comparing BRT to RF and GAM, BRT produced the best performance (Hollings *et al*., 2017; Martínez-Rincón *et al*., 2012).

2.4.5 ENM predictor variables

Anthrax outbreaks are associated with climatic factors of alternating heavy rainfall and drought, and high temperatures greater than 16°C (Parker, Ron *et al*., 2002). Temperatures above 15°C has been confirmed to favour multiplication and vegetative growth cycles of anthrax that can result in outbreaks (Van Ness, 1971). Fasanella *et al*. (2010a) in their laboratory culture study, further details that *B. anthracis* grows well in ordinary medium under aerobic or microaerophilic conditions, at temperature between 12 °C and 44 °C, with optimal growth at around 37 °C. Rainfall after long period of dry season is associated with a burst of growth of *B. anthracis* and spores are exposed to grazing animals feeding on newly emergent vegetation (Turnbull, 2008).

Soil characteristics and properties are also associated with anthrax persistence such that soils, rich in calcium and organic matter with a pH above 6.0 favour multiplication and vegetative growth cycles of anthrax (Van Ness, 1971). *B. anthracis* isolates were found to thrive in high calcium and high pH soils with optimal growth at soil pH of between 7.0 and 7.4 (Smith *et al*., 2000). Vertisols soil types contain alkaline pH and calcium carbonate hence suitable for germination and sporulation of *B. anthracis* (Carlson *et al*., 2019; Virmani *et al*., 1982). Concentration of organic carbon in the soils was also found to play part in spore persistence (Chen *et al*., 2016).

Landscape characteristics play a significant role in supporting environmental reservoir and propagation of anthrax. This is seen in coverage of meadow, coverage of typical grassland, topsoil, elevation from a niche study in China (Chen *et al*., 2016). Land type and vegetation are also identified as useful factors of anthrax environmental niche (Steenkamp, 2013). Steenkamp (2013) further reports low lying depressions with stagnant water, dry riverbed and hillside seeps, where organic matter accumulates during run-off to provide favourable conditions for persistence of anthrax spores. Water points where animals congregate during water scarcity periods, serve as anthrax exposure points as they might be already contaminated with anthrax spores (Hugh-Jones and De Vos, 2002).

While transmission of *B. anthracis* is largely mediated through environmental factors, socio-economic variations in affected communities exacerbate its transmission (Sitali *et al*., 2017). Further, a study in Lesotho found out that environmental and socio-economic factors have influence on the temporal and spatial pattern of anthrax outbreaks (Lepheana *et al*., 2018). Socio-economic related factors such as human development index and cattle density have been correlated to anthrax suitability (Kracalik *et al*., 2013; Walsh *et al*., 2018). Cattle density, though not a socio-economic variable per see, reflects the size of household livestock assets in an area and livestock keeping contributes to household income and welfare and to social and economic stability in rural areas (Ouma *et al*., 2003; Waters-Bayer and Bayer, 1992). Hence, cattle density has been considered as proxy for evaluating the role of socio-economic factors (Tesfaye *et al*., 2015).

The risk factors discussed above provide data for model predictor variables. Climatic, environmental and social-economic variables or proxies have been widely explored in various distribution predictive modelling to determine niche suitability for *B. anthracis* (Blackburn *et al*., 2015; Hollings *et al*., 2017; Joyner, 2010; Kracalik *et al*., 2017; Mullins *et al*., 2011; Mwakapeje *et al*., 2019; Walsh *et al*., 2019)

2.4.6 ENM evaluation

Assessing the model accuracy or performance is imperative in ENM. This is achieved via model evaluation which enables estimation of the generalization accuracy (Qiao *et al*., 2019). There exist several methods for ENM evaluation each functioning in a slightly different manner including Cohen's Kappa Statistic, True Skill Statistics

(TSS) and Area Under the Curve (AUC). Cohen's Kappa Statistic a widely used measure for the performance of models generating presence–absence predictions derived by a function based on sensitivity and specificity (Allouche *et al*., 2006). Sensitivity being the true presence normalized by sum of true presence and false absence; specificity, the true absence normalized by sum of true absence and false presence. Its drawback is being inherently dependent on prevalence which introduces statistical artefacts to estimates of predictive accuracy. True Skill Statistic is prevalence independent measure of performance measurement for SDMs where predictions are expressed as presence–absence maps. However, evaluations based on TSS may be misleading as high maximum TSS may not guarantee accurate prediction and requires a threshold (Shabani *et al*., 2018).

AUC was considered for use in this study and is discussed in more details. It is the most prominent in evaluating ENMs ability to predict the observed distributions (Peterson *et al*., 2008; Williams *et al*., 2015; Yackulic *et al*., 2013). AUC is estimated from of receiver operating characteristics curve (ROC) as a plot of false positive rate (FPR) on the x-axis against true positive rate (TPR) on the y-axis. AUC-ROC curve aids in visualizing how a classification model has performed (**Figure 2-5**). Where: TPR (sensitivity), is true positive (presence) normalized by sum of true positive and false negative (absence); True negative rate (TNR) (specificity) is the true negative normalized by sum of true negative and false positive. FPR is the inverse of TNR, (1-TNR). AUC measures model success by maximizing true positive predictions and minimizing false positive predictions such that its value less or close to 0.5 indicates poor model performance, while closer to 1 indicates closeness to good prediction (Narkhede, 2018). It possesses the advantage of being independent of subjective thresholds but also has been criticized in its model accuracy evaluation such as assigning equal weights to omission and commission errors as well as ignoring predicted probability (Guisan and Thuiller, 2005; Lobo *et al*., 2008; Peterson *et al*., 2008).

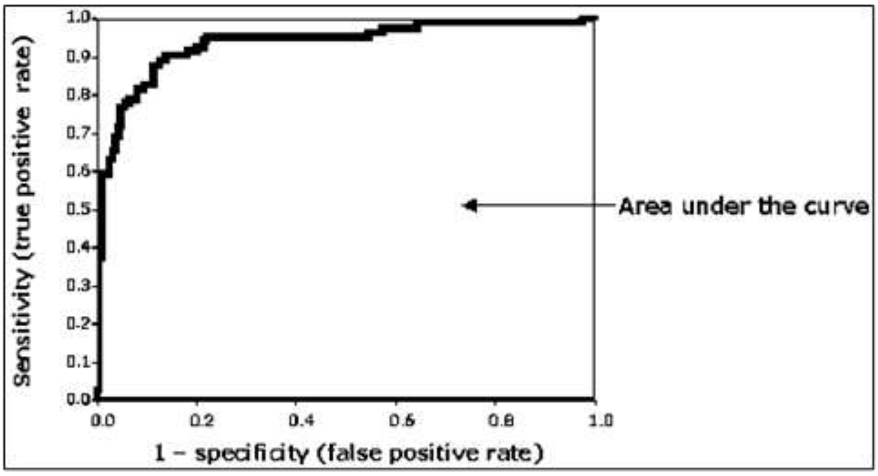

Figure 2-5: Receiver Operator Characteristic curve.
(Source: Ekelund, 2011)

2.5 Anthrax and climate change

Climate change can define livestock-human interface areas, the meeting of infected host, transmission season, the persistence and timing of an anthrax outbreak (Kangbai and Momoh, 2017). Global climate change has been reported and the direct consequences are changes in temperature, precipitation patterns and other climate variables (McMichael *et al*., 2004). Changes in air temperature have substantial effects on the epidemiology of infectious diseases such as anthrax (Bett *et al*., 2017). Intensity of precipitation and global average temperatures are projected to increase and subsequently increased prevalence of a number of infectious diseases including anthrax (Maksimović *et al*., 2017). Climate changes and its extremes also cause shifts in vegetation cover which influences anthrax transmission (Walsh *et al*., 2019), such that: animals feeding on short vegetation close to the soil are likely to ingest spores (Turnbull, 2008); and when animals consume dry and prickly vegetation, they surfer gastrointestinal (GI) tract lesions which increase chances of the ingested spores entering their bodies and causing infection (Turner *et al*., 2013). Cumulative weather extremes (prolonged droughts or rains) provide spatial and temporal factors for exposure and infection risk, and for triggering the onset of large outbreaks (Hampson *et al*., 2011). In Bosnia-Herzegovina, for example, changes in heavy springtime rains with heavy flooding, and a hot dry summer caused re-emergence of anthrax outbreaks in a region that had been free of the disease for more than two decades (Maksimović *et al*., 2017). Kenya has experienced increased climate change in the form of rising temperatures, changing rainfall patterns and increased frequency of droughts and flooding in the recent past (Njoka *et al*., 2016). This has an impact on anthrax outbreaks as a study on climate change on livestock diseases in Kenya found marked associations between anthrax outbreaks and changes in humidity, temperature; and rainy seasons (Moenga, 2010)

To examine how climate changes might influence the spatial distributions of infectious diseases over time, future global climate projections developed under different scenarios are applied (Pearson *et al*., 2006). Such climate future projections are estimated through radiative forcing climate scenarios represented by Representative Concentration Pathways (RCPs) (Van Vuuren *et al*., 2011). The climate scenarios provide four possible range of radiative forcing values in the year 2100 of greenhouse gas (GHG) emissions and atmospheric concentrations that can be applied to examine future climate change influences. In addition these climate scenarios include: stringent mitigation scenario, RCP2.6, where emissions peak in radiative forcing at ≈ 3 W/m^2 then declines before 2100; intermediate scenario, RCP 4.5, of stabilization without overshoot pathway to 4.5 W/m^2 at stabilization after 2100; intermediate scenario, RCP 6.0, of stabilization without overshoot pathway to 6 W/m^2 at stabilization after 2100; unmitigated very high GHG emissions scenario, RCP 8.5, with rising radiative forcing pathway leading to 8.5 W/m^2 by 2100 (Van Vuuren *et al*., 2011).

2.6 Anthrax and vulnerability

Anthrax burden is felt by vulnerable groups through health and socio-economic impacts. To mitigate this, vulnerability assessment is necessary to feed pragmatic decision-making processes in public health programs and disease surveillance strategies (Kienberger and Hagenlocher, 2014). Spatially explicit vulnerability assessment is important for surveillance prioritization and intervention strategies, as it incorporates additional information of other important dimensions on population to a risk map (Hongoh *et al*., 2011). A risk map (e.g., for a disease) provides important information on spatial distribution, but may be incomplete for making decisions in complex situations that cover socio-economic and demographic dimensions.

Comprehensive information can only be achieved through integrating spatially explicit methods that include the complex relationship of factors that contribute to socio-economic vulnerability.

Vulnerability is defined as the lack of resilience to uncertain hazardous events (Rass, 2006). It is not due to a single cause but a product of intersecting social processes precipitating inequalities in socio-economic status and exposures among different social groups geographically over time (Cutter *et al*., 2003; Field *et al*., 2014). While vulnerability has its roots in the study of natural hazards, it has recently received intensive research interests in several different domains including environment, socio-economic and health (Begun, 1993; Cutter *et al*., 2003; Falzon *et al*., 2019; Janssen and Ostrom, 2006; Sutherst, 2004; Turner *et al*., 2003). This implies that vulnerability is perceived in many ways by various scholarly communities (Füssel, 2007). In the environment domain, vulnerability is viewed as a means to describe and analyse the exposure and coping mechanisms of groups or individuals to environmental risks (Brouwer *et al*., 2007), while in the health domain, vulnerability is seen as the predisposition to be adversely affected by the burden of disease or risk from the likelihood of disease occurrence (Hagenlocher and Castro, 2015). In social domain. vulnerability is seen as the set of socio-economic factors that define community's ability to cope with a hazard (Brooks, 2003; Brouwer *et al*., 2007). Indeed, after exposure to a hazard, the social impacts are felt disproportionately by communities depending on their social inequalities (Cutter *et al*., 2003). Vulnerability to anthrax risk can be viewed in the context of ecology and epidemiology "disease triangle" of the host (e.g., human), Pathogen (*B. anthracis*), and environment (physical, biological and socio-economic) (Sutherst, 2004). The spread of anthrax is exacerbated by limited knowledge (augmented with attitudes and beliefs) and low income that see humans get exposed to infection risk through skinning, slaughtering dead animals or consuming infected meat (Opare *et al*., 2000; Patil, 2010). This scenario has been observed in Kenya and elsewhere in anthrax endemic countries (Chirundu *et al*., 2009; Muturi *et al*., 2018; Opare *et al*., 2000). Risk of exposure to anthrax and subsequent vulnerabilities are heightened on the poor who mostly reside in rural settings in these endemic countries (Vieira *et al*., 2017).

The prerequisite of fully capturing vulnerability is to develop a framework of risk factors and their associated measures (Moore *et al*., 2017). However, developing robust and credible measures incorporating diverse methods encompassing perceptions of risk remains a challenge (Adger, 2006). Different thematic areas bring their conceptual framework, which address similar problems and processes in different semantics to the study of vulnerability. Hence, there is no correct or best conceptualization of vulnerability that would fit all assessment contexts (Füssel, 2007). In their literature review, Moore *et al* (2017) identified seven (7) general factors influencing infectious diseases related vulnerability as demographic, health care, public health, disease dynamics, political and economic. From the social perspective, major factors identified to influence vulnerability include socio-economic status, education, population growth, rural/urban residence, medical services, beliefs and customs, and political power and representation (Cutter *et al*., 2003).

There exists several approaches of vulnerability assessment from household to population-level (Moret, 2014). However, the understanding of vulnerability in terms of biophysical and social perspectives is necessary to overcome the confusion arising from these different thematic perspectives (Brooks, 2003). Intergovernmental Panel on Climate Change (IPCC) frames vulnerability as a function of climate variations to which a system is exposed, its sensitivity, and its adaptive capacity (Mackay, 2008). This framework tend to reconcile biophysical vulnerability and social vulnerability (Brooks, 2003). Exposure is taken as the likelihood of humans and their environment getting affected by a dangerous climatic hazard at a location; sensitivity (susceptibility) as the predisposition of humans and their environment suffering harm due to disadvantageous climatic conditions and relative weaknesses as a result of physical, ecological, socio-economic, cultural, and institutional issues; adaptive capacity (resilience) as the enabling ability for societal response through access to or mobilization of resources to respond in coping or absorbing the exposure impacts. The IPCC framework has been widely adapted in different thematic settings, including public health (de Sherbinin, 2014; MOVE, 2020; Parker *et al*., 2019; Sutherst, 2004; Wandiga *et al*., 2010). Indeed, the IPCC climate change-oriented vulnerability framework can be adapted for public health context because public health and climate change-related vulnerabilities share similar perspectives in different terms (Ebi *et al*., 2006). Several studies assessing diseases-related vulnerability have been undertaken in East Africa and by extension Kenya mostly covering vector-borne diseases (malaria) and zoonosis (RVF), but none so far is reported for anthrax (Hagenlocher and Castro, 2015; Kienberger and Hagenlocher, 2014; Murithi *et al*., 2011; Onyango *et al*., 2016; Wandiga *et al*., 2010).

This study adapted the IPCC vulnerability framework for socio-economic vulnerability assessment concerning potential anthrax risk in Kenya where: exposure relate to the dangerous hazard (anthrax risk), precipitated by background environmental conditions and their changes, with negative impacts on communities (or sections); sensitivity reflects the weakness or predisposition of a community (or sections) to be unable to influence their response to the anthrax risk; and adaptive capacity aid a community (or sections) to cope or adapt to reduce impacts or rebound after the consequences of anthrax risk. **Figure 2-6** shows the adapted IPCC framework for estimating anthrax vulnerability.

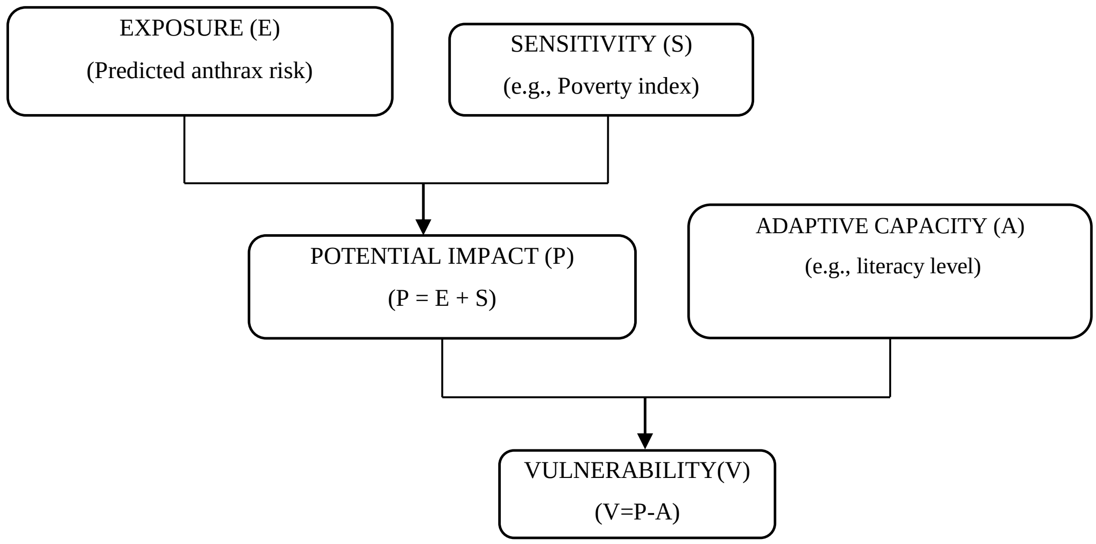

Figure 2-6: Framework for estimating anthrax vulnerability.
Adapted from IPCC framework (Mackay, 2008)

2.6.1 GIS-based multi-criteria decision analysis (GIS-MCDA)

Vulnerability to environmental hazards vary geographically over time and space among social groups. Hence its assessment involves the integration of multiple spatially explicit socio-economic and biophysical criteria to derive its patterns (Cutter *et al*., 2003; De Sherbinin *et al*., 2015). Given the potentially large set of feasible alternatives and multiple incommensurate evaluation, decision making can be complex considering the trade-offs between the social, economic, environmental and political criteria (Kiker *et al*., 2005). This necessitates objective approaches to evaluate these multiple conflicting criteria. Multicriteria decision analysis (MCDA) also referred to as multiple-criteria decision-making (MCDM) makes available the practical methods to evaluates multiple conflicting criteria for making informed decisions (Kiker *et al*., 2005). Spatial decision problems apply spatial or GIS-based multicriteria decision analysis (GIS-MCDA), which transforms and combines geographical data and decision-maker's preferences to derive decision support spatial information (Malczewski, 2006). The principle of GIS-MCDA in determining spatial vulnerability due to infectious diseases has been widely applied (Devarakonda *et al*., 2021; Hongoh *et al*., 2011; Michel, 2018). The results of GIS-MCDA in vulnerability assessment are usually vulnerability severity maps. Several vulnerability maps for east Africa and specifically Kenya have been produced for Rift Valley Fever and Malaria but none for anthrax (Hagenlocher and Castro, 2015; Kienberger and Hagenlocher, 2014; Mulefu *et al*., 2016; Murithi *et al*., 2011).

The criteria used in MCDA often have differentiated weights of contribution instead of equal ones, necessitating a determination of the relative weights. There are over 100 different MCDA criteria weighting methods that can be broadly categorised into direct (non-comparative subjective scaling or ranking) and indirect (objective comparative approaches where weights are derived from theories and mathematical model) (Guarini *et al*., 2018; Odu, 2019). The most frequently applied methods include Analytical Hierarchical Process (AHP), Multi-attribute Utility Theory (MAUT), Elimination and Choice Translating Reality (ELETRE), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Simple Multi-attribute Ranking Technique (SMART). The methods strengths and limitations are extensively elucidated in (Velasquez and Hester, 2013). The AHP is an easy-to-use method with pairwise criteria comparison hierarchal structure that can easily adjust to fit different sized problems with minimal data. However, due to the nature of comparisons for rankings and the addition of alternatives at the end of the process it could present final rank reversal. The MAUT incorporates risk preferences and uncertainty into multi criteria decision. Its major advantage is taking uncertainty into account but it requires incredible amount of data in its every procedural step. The ELETRE deals with outranking relations to mitigate ranking alternatives from the best to worst through pairwise comparisons among alternatives considering each criterion separately. It takes into account uncertainty and vagueness but its processes and outcomes are not easy to explain. The TOPSIS method applies a Euclidean distance technique to rank preferences by similarity to the ideal solution but the use of Euclidean distance does not consider the correlation of attributes. The SMART is the simplest variant of MAUT method that has the ability to convert weights into actual numbers by permitting a hierarchical tree shaped structure of criteria. It is simple and allows easy intuitive weight allocation but its framework is complicated. The decision on selection of an appropriate weighting method is a challenging task given each method has its strengths and limitations. The AHP was selected for this study for being easy to implement and not being data intensive. It is further detailed in the next section.

2.6.2 Analytic hierarchy process (AHP)

AHP is a general theory of measurement applied to compute ratio scales from both discrete and continuous paired comparisons based on actual measurements, preferences or feelings (Saaty, 1987). It employs a nonlinear hierarchical framework to derive the importance of each criterion relative to the other criteria (Abdelkarim *et al*., 2020). It has been widely applied and specifically in assessing disease vulnerability (Ali and Ahmad, 2019; Federici *et al*., 2016; Lima *et al*., 2018). The steps of AHP follow: 1) defining the problem; 2) structuring criteria and sub-criteria; 3) developing hierarchical pair-wise comparison matrices based on the fundamental scale (**Table 2-4**), calculating eigenvalue, eigenvector, consistency index, and consistency ratio; 4) weighting all elements through estimation of the relative weights, checking the consistency, and obtaining the overall rating.

Table 2-4: The Saaty's fundamental rating scale

Importance	Explanation
1	Equal importance
3	One of the criteria is of moderate importance with respect to the other
5	One of the criteria is of high importance with respect to the other
7	One of the criteria is of very high importance with respect to the other
9	One of the criteria is extremely important with respect to the other
2–4–6–8	Intermediate values used between the previous weights in numerical comparison

2.6.3 Vulnerability analysis (GIS-MCDA and AHP)

After the multi-criteria layers are standardised, they are subjected to analytical hierarchical process to assign relative weights before the now standardised and weighted criteria layers are subjected to spatial analysis of weighted overlays to derive the final vulnerability layer. **Figure 2-7** shows this framework of integrating GIS-MCDA and AHP in generating a vulnerability map.

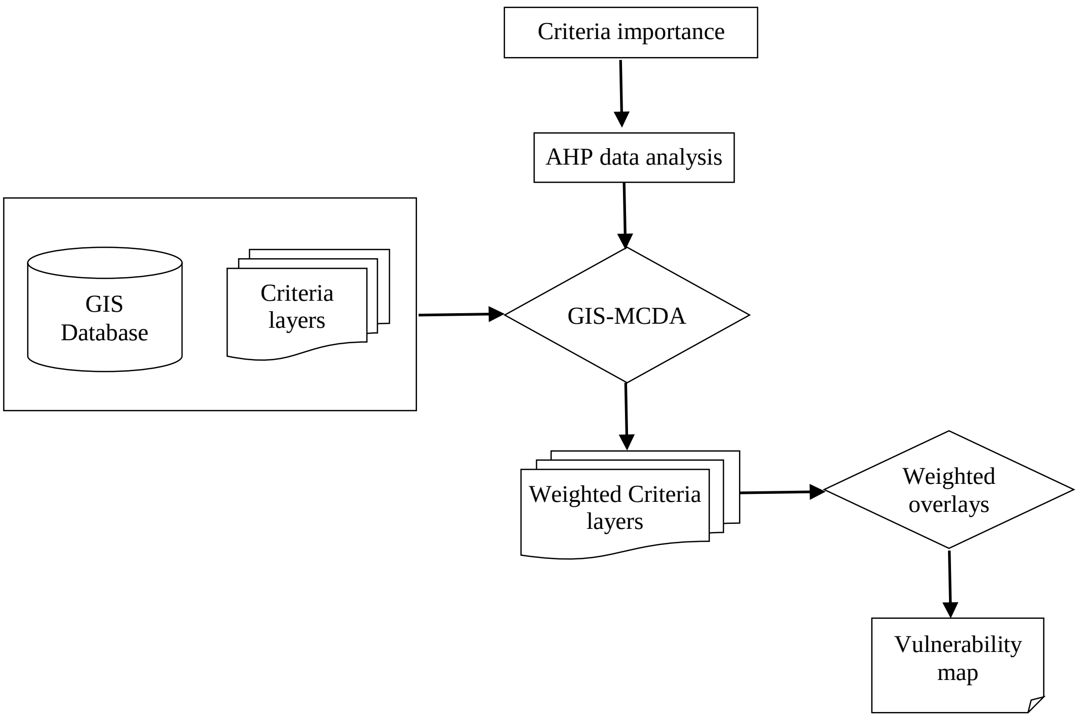

Figure 2-7: GIS-MSDA and AHP in generating vulnerability map

2.7 Summary and Knowledge Gaps

Anthrax is an important zoonotic disease globally that affects mostly herbivores and humans even though carnivorous and omnivorous get infected with moderate resistance. Anthrax has recently attracted global security concerns as an agent for bioterrorism. The cycle of anthrax infection is influenced by environmental factors however, human behaviours and socio-economic status can exacerbate its transmissions. Despite the various studies undertaken, there is limited knowledge on spatial ecology of anthrax and that little agreement exists on the roles played by these factors in the incidence of the disease. Furthermore, different strains of *B. anthracis* thrive in different geographical environments.

Anthrax is also a problem Kenya where there have been recurrent outbreaks since 1957 affecting livestock, human and wildlife. Anthrax outbreaks have negatively impacted public health, economies and welfare of the poor livestock keepers in Kenya becoming the highly prioritized zoonotic disease. Despite the confirmed anthrax outbreaks in Kenya, there is still paucity of knowledge on anthrax spatial ecology or the specific geography of favouring environmental conditions or factors that promote its long-term survival and intermittent outbreaks. Furthermore, there is weak surveillance systems, and poor anthrax prevention and control programs in Kenya partly attributed to limited information. Anthrax spatial distribution and the promoting risk factors have been studied in other countries including neighbouring Tanzania, but none has been undertaken for the entire Kenya. As such, there is lack of anthrax risk map for the entire Kenya to aid in policy actions on surveillance and control programs.

Spatial distribution of anthrax can be determined through Ecological Niche Modeling (ENM) that estimates suitable environmental habitats for a species (such as *B. anthracis*) from known occurrence locations. ENM is considered a reliable method to identify potential anthrax outbreak risk areas for targeted surveillance strategies and has been applied in varied environmental conditions from several countries in including Africa, USA and China. These studies mostly applied occurrence data from passive surveillance, as opposed to active surveillance, which might present data quality challenges. While some isolated ENMs on anthrax have been undertaken for some specific counties in Kenya, no study covered the whole country.

Global climate changes are projected to alter prevalence and geographic ranges of infectious diseases such as anthrax. The prevalence and geographic ranges of anthrax in Kenya are expected to change due to recently experienced increased rising temperatures, changing rainfall patterns and increased frequency of droughts and flooding. To examine how climate changes might influence the spatial distributions of infectious diseases over time, future global climate projections (e.g., RCP 4.5, RCP 8.5) developed under different scenarios are applied. There exists no spatial niche study for entire Kenya associating anthrax distribution to climatic changes.

While spatial distribution of anthrax provides proxy information on the risk, it may be incomplete for making decisions in complex situations that cover socio-economic and demographic dimensions. Thus, vulnerability assessment is recommended for surveillance prioritization and intervention strategies because it incorporates additional information of other important dimensions on population to a risk map. There exists no socio-economic vulnerability assessment map on exposure to anthrax risk in Kenya.

2.7.1 Conceptual framework

Environmental, climatic and socio-economic variables are associated with survival and persistence of anthrax. They serve as independent variables directly associated with anthrax occurrence (as dependent variables) in defining anthrax distribution under current and future climate change scenarios. There are moderating and mitigating variables which somewhat indirectly influences possible anthrax occurrences. Anthrax distribution serve as a proxy to anthrax risk in defining socio-economic vulnerability associating with socio-economical and health factors. **Figure 2-8** shows the conceptual framework of the relationship between independent, dependent, moderating and intervening variables.

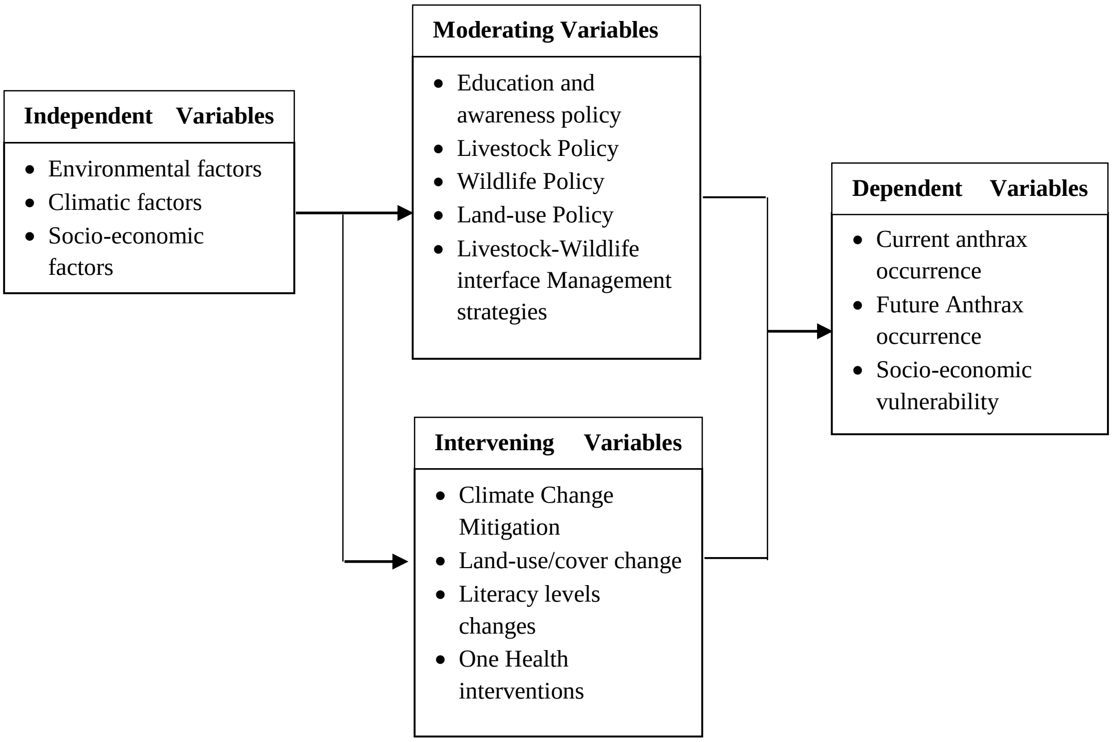

Figure 2-8: Direct and indirect variables in anthrax distribution and vulnerability.

CHAPTER THREE

3.0 METHODOLOGY

3.1 Study area

The study area covered the entire Kenyan boundary. Kenya is divided into two major levels of administrative units, county and sub-county giving 47 counties and 290 sub-counties. A county is made up of two (2) or more sub counties while a sub county is are made up of a varying number of wards between three (3) to nine (9) wards. The terrain of Kenya varies from the lowest point at sea level on the Indian ocean to the highest point at Mt Kenya (≈5,197 meters) and comprise low plains that rise into central highlands bisected by the Great Rift Valley. **Figure 3-1** shows the map of Kenya and its elevation.

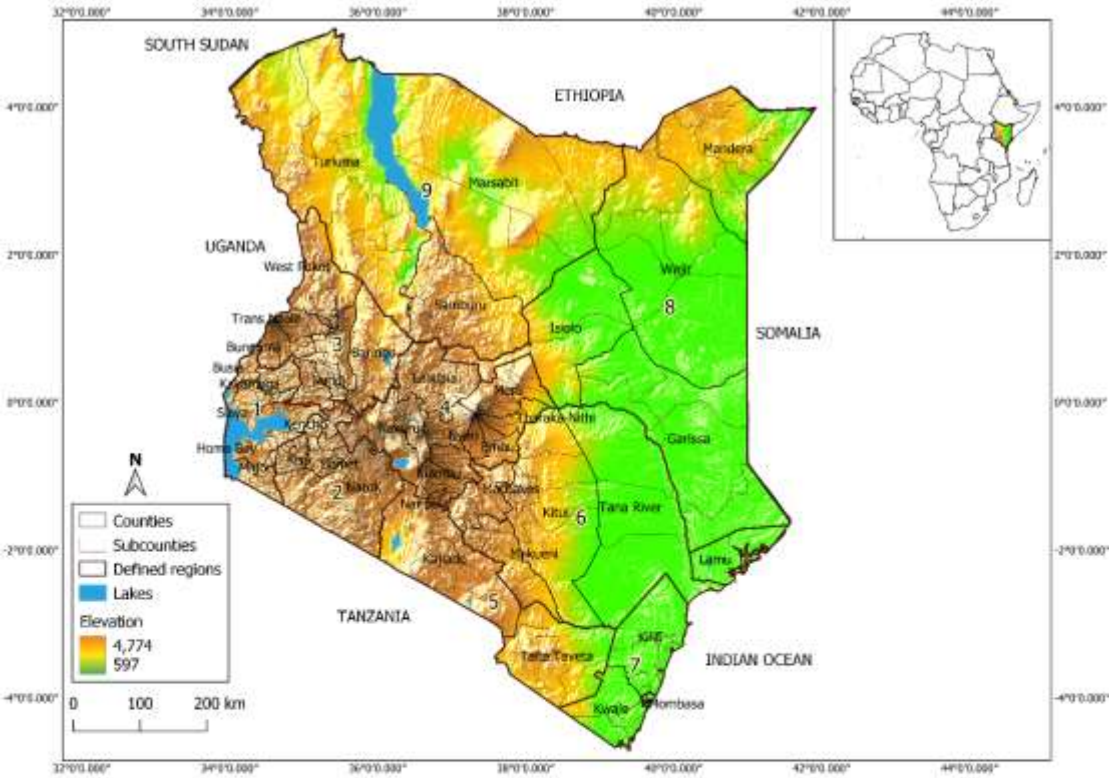

Figure 3-9: Map of Kenya showing administrative units and their elevations. *Defined regions 1 – 9 arbitrarily represent important regions for describing the predicted distribution of anthrax: 1) Lake Victoria basin; 2) Southwestern; 3) western; 4) central; 5) Southern 6) Eastern; 7) Coastal; 8) Northeastern; 9) Northern.* (Source: author)

The longterm climate conditions in Kenya vary from humid tropical, along the coast to temperate and sub-tropical inland and hot and dry in arid and semi-arid areas in the mainland areas. Generally most parts of Kenya experience a bimodal seasonal pattern with the long rains season observed between March and June, and short rains between September and December (World Bank Group, 2021). Mean temperatures generally vary with elevation, although there has been increased variability in temperature in the recent years, with estimated increase of 1.0 °C since 1960 at an average rate of 0.21°C per decade (World Bank Group, 2021). Mean annual precipitation has been recorded at 699.00 mm between 1991 and 2020 and its distribution has become more intense and less predictable (McSweeney *et al*., 2008; World Bank Group, 2021).

Kenya is among the developing countries with 46% of the population living below the poverty line (Ikiara,2009). Livestock production in Kenya constitutes 47% of the agricultural GDP where arid and semi-arid areas (ASALs) boast of high pastoral beef livestock production. In contrast, high potential areas support dairy livestock farming due to readily available fodder and pastures (Food and Agriculture Organization, 2017). Most poor livestock keepers reside in remote and rural areas (Thornton *et al*., 2003)

3.2 Study design

This study was cross-sectional on anthrax outbreaks concerning risk factors based on retrospective outbreaks records, sporadic outbreaks field characterization and active outbreaks surveillance. Historical data were based on regular validated outbreak reports from the Directorate of Veterinary Services (DVS) covering 2011 to 2017. Field characterisation was undertaken following spontaneous anthrax outbreaks that were reported between 2017 and 2018. Active surveillance was undertaken at the ward level in the randomly selected 18 study counties between 2019 and 2020 through mobile telephone transmission. The sampling process for selecting the counties for active surveillance was through:1) random selection of four sub-counties within each of the five collapsed agroecological zones (AEZs) of humid, high and medium potential, semi-arid, arid, very arid, and desert. 2) Identification of the counties where each of these 20 sub-counties fell. To increase the geographical spread of the study the rest of the sub-counties were included in the selected county in an oversampling strategy. Twenty (20) counties were anticipated, but four sub-counties fell in two separate counties in the process of random sampling. Therefore, the final number of counties dropped from 20 to 18. **Figure 3-2** shows the 18 study counties, their AEZ and the anthrax occurrences.

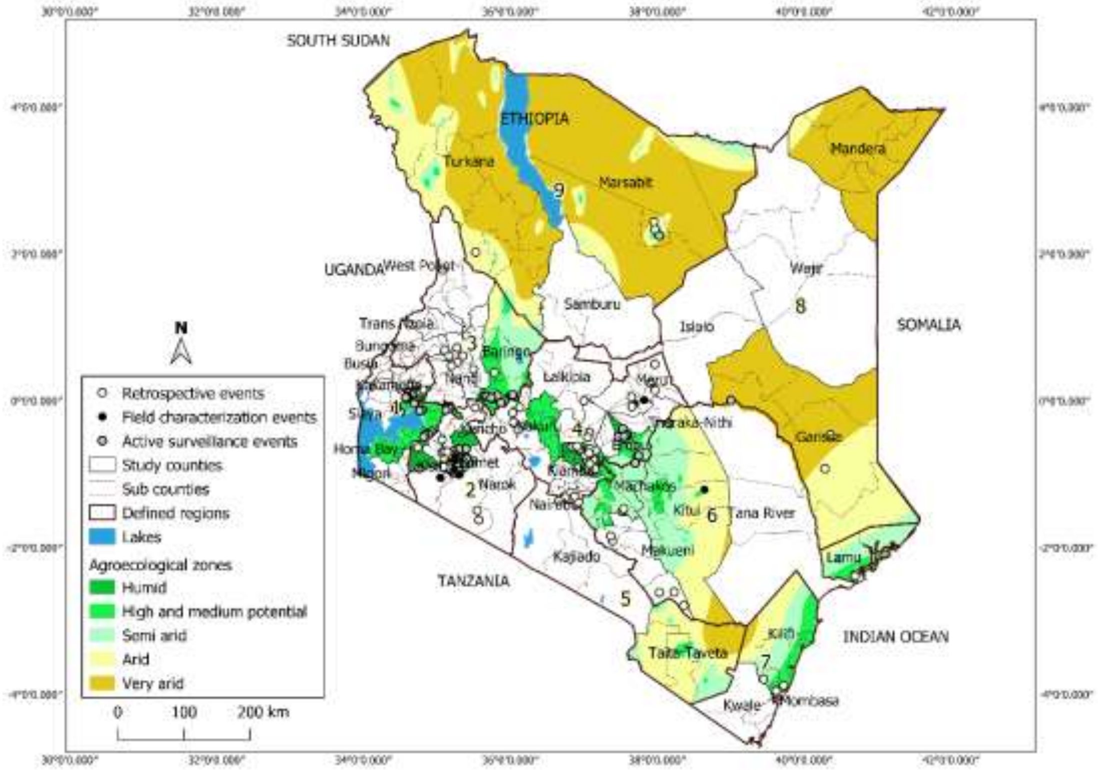

Figure 3-10: Study counties anthrax events and their Agroecological zones (AEZs). *White dots, outbreaks from retrospective records; black dots, outbreaks from field characterisation; grey dots, outbreaks from active surveillance.* (Source: author)

3.3 Prediction of potential anthrax distribution

Prediction of the distribution of anthrax was done by applying Ecological Niche Model (ENM). ENM fits occurrence data as responses against several predictor variables. These are detailed as follows:

3.3.1 Occurrence data

Variables from occurrence data served as the model response**.** A database of geo-referenced anthrax outbreaks data was constructed from retrospective records (n = 86) covering 2011 to 2017; sporadic outbreaks field characterization (n=13) covering 2017 to 2018; and active surveillance data (n=119) covering 2019 to 2020. These data were structured into comma-separated file in Microsoft Excel (2016) and converted to GIS format in QGIS 3.16 (QGIS Development Team, 2014).

3.3.2 Predictor variable selection

Publicly available spatially-explicit climatic, environmental and socio-economic data, documented to influence anthrax spatial distribution, were obtained from online repositories and additional data generated from spatial analyses (**Appendix 1, Appendix 2**). The data were subset to the Kenyan boundary and re-sampled to 250 m resolution and extracted as candidate predictor variables (all available variables before selection of final model predictor variables). The spatial analyses were done under QGIS and R 4.0.3 (R Core Team, 2018) with packages "rgdal", "raster", "sp" (Bivand *et al*., 2013; Hijmans, 2020; Pebesma, 2018).

The candidate predictor variables were subjected to variable selection process to reduce dimensionality and multicollinearity through Variable Inflation Factors (VIF) at a correlation cut-off of VIF < 10. VIF measures the amount of multicollinearity in multiple regression variables by regressing the variables against each other, VIF values, greater than one, indicate coefficient variance higher than expected with zero collinearity (Thompson *et al*., 2017). Choice of VIF cut-off threshold is debated by most researchers however, values above ten are generally considered highly correlated (O'brien, 2007). In the process of deriving the predictor variables, some collinearity was expected, and thus applying VIF <10 was considered appropriate in achieving a parsimonious model. The VIF process was achieved with R package 'usdm'(Naimi, 2015), which yielded the final predictor variables.

3.3.3 Model building and evaluation

Presences (n=178) were retained after spatial thinning to ensure that there was 1:1 presence point to predictor pixel overlap to limit autocorrelation. An equal number of pseudo-absence points as absences were randomly generated at least 5km Euclidian distance away from the presence points to represent true absence as possible. This is recommended for optimal model performance for classification techniques (Barbet-Massin *et al*., 2012). The presence and absence points were combined, and predictor variables were extracted through spatial analysis raster value extraction to construct model variable space with “raster” and “sp” R packages. The variables were partitioned into 75% for model training and 25% for model evaluation. They were thereafter fitted in ENM model of BRT algorithm of ‘gbm’ R package with ‘gbm.step’ extension (Ridgeway *et al*., 2013). The “gbm.step” hyperparameters were calibrated to obtain the best exploratory predictive performance under different bagging fraction (bag.fraction), learning rate (learning.rate), tree complexity (tree.complexity), maximum tree (max.trees) based on the minimum predictive error. The final ‘gbm.step’ was set to fit the training data with tree.complexity = 5, learning.rate = 0.001, bag.fraction = 0.5, max.trees = 2500. Model predictions comprising 100 runs, was thereafter performed yielding 100 predictions which were averaged to obtain the final anthrax distribution prediction. In addition, confidence interval maps at lower, 2.5%, and upper, 97.5%, were generated. Each model run performance was evaluated using AUCROC (area under the curve of the receiver operating characteristics) curve as it is the most frequently preferred among ENM prediction evaluation methods. AUC for each experiment was realized through “ROCR” R Package (Sing *et al*., 2007), and results averaged across all experiments to obtain the overall AUC metric. Final predictions were dichotomized as high risk (or not) at Youden index threshold. Youden Index is a frequently applied summary measure of the Receiver Operating Characteristic curve that enables the selection of an optimal threshold value (Fluss *et al*., 2005). The importance of the contribution of each predictor variable to anthrax distribution was derived via influence plots. Also, the graphs of marginal influence for each predictor variable on the mean prediction probability when other variables are kept at their average was derived via partial dependency plots (PDP) with “pdp” R package (Greenwell, 2017). The R code for the ENM processes is given in **Appendix 3**.

3.3.4 Hypothesis testing

Logistic regression model was applied to test any significant association between the dependent variables and the independent variables with significance level set at 0.05

Where: if any of the Null hypothesis that a regression coefficient = 0 is valid; the corresponding variable is statistically insignificant in the logistic regression model. Any p-value for a variable less than 0.05 is considered significant. Logistic regression model was implemented through General Linear Model (GLM) of binomial (link = "logit") under R 4.0.3 (R Core Team, 2018).

3.3.5 Specific predictions under current and climate change scenarios

The preceding methodology pathway of data preparation, variable selection, model building and evaluation was applied with different selected predictor variables in modelling for the first and the second study objectives: 1) determining the relationship between selected environmental and socio-economic factors to the spatial distribution of anthrax; 2) predicting the influence of climate change on future spatial distribution of anthrax. In the first modelling case, environmental and socio-economic candidate data (**Appendix 1**) (n= 41) were processed and subjected to VIF variable selection retaining 18 final independent variables (see the variable selection process in the preceding subsection 3.3.2). The selected variables were fitted and ran in the BRT modelling and evaluation process. In the second case, only bioclimatic (current and future projection), elevation and slope data (**Appendix 2**) (n=71) were used because other data lack future scenario data while elevation (used to derive slope) remains constant into the future. The current climate data covered (1970-2000) while future scenarios were projections for Mid-century (2041-2070) data, africlim_ensemble_v3_[base] (Platts *et al*., 2015). The data were subjected to VIF variable selection retaining ten (10) final variables fitted for BRT modelling and evaluation process. The initial BRT model was run with the current climate variables. Thereafter, the resultant model was run separately for future scenarios, RCP 4.5 and RCP 8.5, by substituting the current climate variables with the corresponding RCP 4.5 and RCP 8.5 variables. The two future scenarios were selected for modelling, to compare an intervention and a non-intervention scenario of GHG emissions. The number of human and livestock affected were estimated through spatial overlay of population density (Tatem, 2017) and livestock density (Gilbert *et al*., 2018) with the dichotomized current anthrax distribution.

3.4 Socio-economic vulnerability to anthrax risk

Socio-economic vulnerability concerning potential anthrax risk were determined by first defining the vulnerability framework, obtaining and processing data to derive criteria, determining each relative criterion weight in the vulnerability framework, and finally undertaking weighted spatial overlays to derive the vulnerability and its domain maps.

3.4.1 Vulnerability framework

The IPCC AR4 vulnerability framework (**Equation 2)** was adapted to assess the socio-economic vulnerability due to potential anthrax distribution as proxy for anthrax risk. Vulnerability assessment was undertaken with the spatial criteria following GIS-MCDA workflow (**Figure 3-3**).

$$\mathbf{V = E + S - A} \qquad \mathbf{(2)}$$

(Where: V, vulnerability; E, exposure; S, sensitivity; A adaptive capacity)

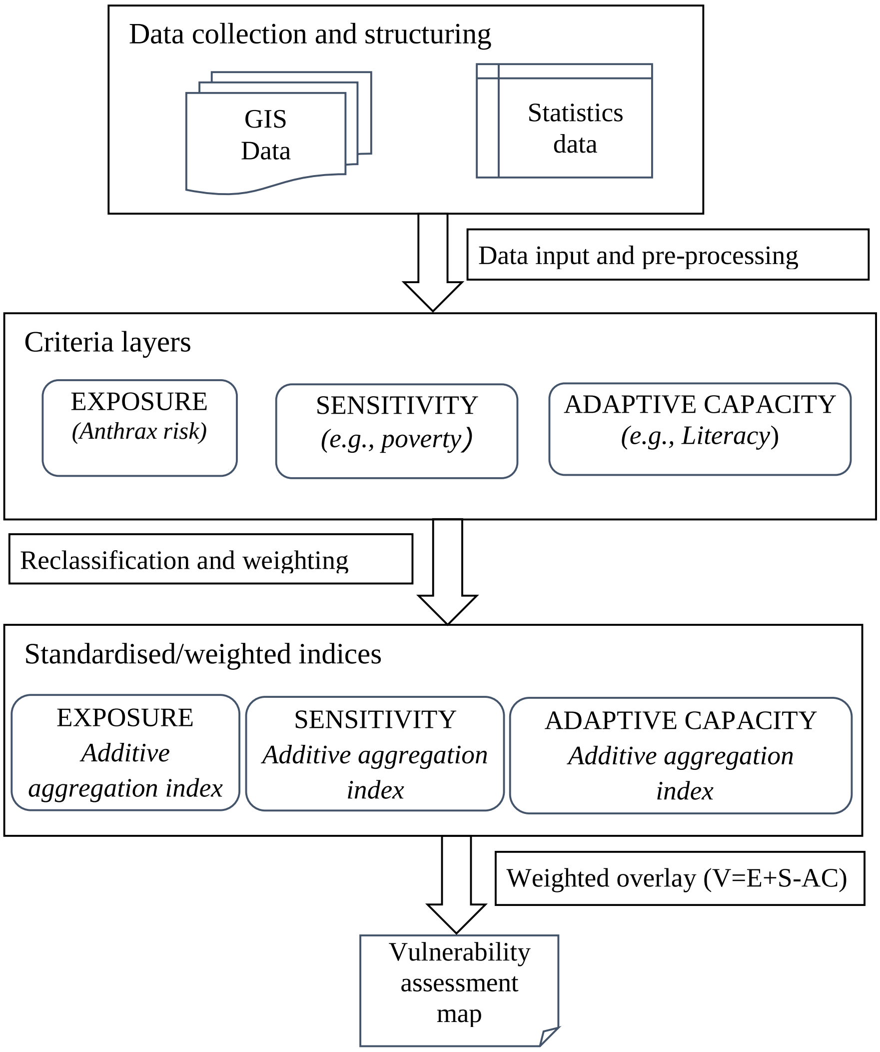

Figure 3-11: Vulnerability assessment processes based on GIS-MCDA approach.

3.4.2 Vulnerability assessment data processing

Environmental, demographic, economic and health criteria documented to influence vulnerability due to diseases risk and specifically for anthrax were identified through literature review (Carlson *et al*., 2019; Moore *et al.*, 2017; Opare *et al.*, 2000; Sitali *et al*., 2017). Seven (7) datasets for the criteria spatially varying across the study area were obtained from online repositories (**Table 3-1**). Data selection was guided by data being publicly available, most current, spatially explicit, and having a coverage of the whole study area at high to medium spatial resolution. The seven datasets for the criteria were land use cover, population density, multidimensional poverty index, literacy level, income GINI index, severe wasting prevalence and infant mortality rate. Their relationships with anthrax risk are further described:

1) Land use cover defines the cover or use on land at a given time period. Rural areas land covers refer to geographic areas located outside urban areas which have been documented to predominantly host poor livestock keepers in anthrax endemic countries and are associated with anthrax vulnerability (Carlson *et al*., 2019; Chikerema *et al*., 2013; Doganay and Metan, 2009);
2) Population density is the number of people per square kilometre and the higher it is, the more increased susceptible people get exposed to *B. anthracis* contact thereby increasing human anthrax incidence risk (Kanankege *et al*., 2019; Munang'andu *et al*., 2012);
3) Multidimensional poverty index estimates the proportion of people per grid square living in poverty. High poverty levels have been associated with anthrax outbreaks as it may induce or determine human activities that exacerbate anthrax spread such as lack of required regular vaccination or consumption of infected meats (Chikerema *et al*., 2012; Sitali *et al*., 2017);
4) Literacy level estimates the proportion of women of age 15-49 per square grid that are classed as literate. Low literacy levels indicate lack of knowledge or awareness about anthrax risk caused by limited or no education and encouraging ill-informed behaviours towards handling of infected animals, consuming infected meat, disposal of carcasses or adherence to regular vaccination (Chikerema *et al*., 2012; Sitali *et al*., 2017);
5) Income GINI index estimates degree of income inequality among individuals or households that indicates the individual purchasing power. Low income may contribute to consumption of infected meat and limited or non-adherence to regular necessary livestock vaccinations (Carlson *et al*., 2019; Opare *et al*., 2000);
6) Severe wasting prevalence indicates acute malnutrition due to acute food shortages. Acute food shortage may present lack of access to meat protein encouraging easy consumption of available anthrax infected meat (Lehman *et al*., 2017);
7) Infant mortality rate indicates the number of children who die before their first birthday for every 1,000 live births and generally indicates status of physical health of a community. It may indicate poor or limited medical care in a community

leading to lack of treatment, which may increase human case-mortality or fatality rates (Li *et al*., 2017).

Table 3-5: List of indicators for vulnerability to anthrax outbreaks

Type	Indicator	Description	Source	Spatial resolution
Environment	Land use cover	Geographic areas located outside urban areas (2015).	Reclassed from Land use CCI land cover from: http://www.esa-landcover-cci.org/?q=node/164	300m
Socio-economic/ demographic	Population density	Estimated population density per grid square (2020).	https://www.worldpop.org/geodata/summary?id=46997	1km
	Multidimension Poverty Index	Multidimensional Poverty index of proportion of people per grid square living in poverty (2008).	https://www.worldpop.org/geodata/summary?id=1262	1km
	Literacy level	Proportion of women of age 15-49 per square grid that are classed as literate (2009).	https://www.worldpop.org/geodata/summary?id=1261	1km
	Income GINI index	A measure of income inequality per county (2015).	https://data.humdata.org/dataset/kenya-income-gini-coefficient-per-county	
Health	Severe Wasting prevalence	Global Under-5 Child growth Failure (2019).	https://cloud.ihme.washington.edu/s/Q7eg2wgdmaSFbHt	5 km
	Infant mortality rate	The number of children who die before their first birthday for every 1,000 live births (2015).	https://sedac.ciesin.columbia.edu/data/set/povmap-global-subnational-infant-mortality-rates-v2/data-download	1 km

To derive the criteria layers, data were converted to common grid referencing system (WGS 84) at a resolution of 250m (being the highest resolution) and transformed into standard indicators through reclassification based on four (4) quantile thresholds (i.e.,

≤0.25, >0.25 ≤0.5, >0.5≤ 0.75, >0.75) for anthrax risk levels: 1) low risk; 2) moderate risk; and 3) high risk; 4) very high risk respectively, through QGIS symbology function. The criteria served as inputs to vulnerability domains where exposure was fed with predicted anthrax distribution (derived in sub section 3.2.1); sensitivity and adaptive capacity were input with the corresponding environment, demographic and health criteria. Criteria covering policy and institutions e.g., governance, health service provision were not included as there were no spatially explicit data available by the time of this study. **Table 3-2** shows the criteria per component, their quartile classes and ranks.

Table 3-6: Criteria class ranks based on defining anthrax risk level

Component	Criteria	Quartile classes	Ranks
Exposure	• Predicted anthrax distribution	<= 0.3 0.3 - 0.6 0.6 – 0.8 > 0.8	1 2 3 4
Sensitivity	• Population density	< = 2.6 2.6 - 12.2 12.2 - 46.9 > 46.9	1 2 3 4
	• Poverty index	< = 0.59 0.59 - 0.79 0.79 - 0.89 > 0.89	4 3 2 1
	• Land cover use	1. Grassland/shrubs 2. Agriculture 3. Forest 4. Urban/water/bare areas	4 3 2 1
	• Severe wasting prevalence	< = 0.65 0.65 - 1.10 1.10 - 1.91 > 1.91	1 2 3 4
	• Infant mortality rate	< = 31.81 31.81- 33.62 33.68 - 34.62 34.62	1 2 3 4
Adaptive capacity	• Literacy level	<= 0.19 0.19 - 0.36 0.36 - 0.39 > 0.69	4 3 2 1
	• Income GINI index	< = 35.35 35.35 - 42.40 42.40 – 49.45 > 49.45	4 3 2 1

3.4.3 Determination of relative weights

Differentiated weights to individual criteria based on their considered strength of contribution to vulnerability to anthrax risk informed by literature review and expert elicitation was determined through analytical hierarchical process (AHP). The process was based on pair-wise comparisons of criteria as each criterion is compared to another criterion at the same time leading to pair-wise matrix comparison. The steps of AHP followed: 1) calculating and normalizing eigenvector of relative importance from matrix pair-wise comparisons; 2) determination of average of relative weights; 3) calculating consistency index and consistency ratio; and 4) obtaining the overall weights. The relative weight was intended to be achieved with consistency ratio (CR) < 0.1 as an indicator for acceptable limit of results consistency. Details of the AHP process are outlined in **Appendix 4**.

3.4.4 Spatial weighted overlay

The derived weights per criteria (in subsection 3.4.3 above) were used in weighting the individual criteria index within each vulnerability component. Additive aggregation index per component was derived from individual component criteria indices where applicable. Finally, spatial weighted overlay analysis via algebraic expression raster calculations using Equation (1) was performed in QGIS resulting in socio-economic vulnerability index map to predicted anthrax risk. Three scenarios of vulnerabilities were derived based on exposures from predicted anthrax distribution at current and future climate scenarios of RCP 4.5 and RCP8.5 with the assumption that the criteria for sensitivity and adaptive capacity will remain constant into the future. The derived vulnerability maps were further overlaid with the population density layer to estimate the number of people that can be potentially at risk. Further, the contribution of each criterion to the vulnerability index was evaluated by discarding one criterion at a time while keeping all other settings constant in deriving component composite indices then determining the interquartile ranges (IQR) as detailed in (Kienberger and Hagenlocher, 2014). The size of IQR indicates the influence of a criterion on the vulnerability index where the higher the IQR, the larger its relative contribution (Lung et al., 2013).

CHAPTER FOUR

4.0 RESULTS

4.1 Anthrax distribution prediction and the influencing factors

A number of candidate biophysical and socio-economic related variables showed significant association with anthrax occurrences at $p < 0.05$ hence, the Null hypothesis (H0) that: "specific environmental and socio-economic factors do not influence the potential spatial distribution of anthrax in Kenya" was rejected at 95% confidence level. VIF process was subjected to 41 candidate variables to reduce multicollinearity and dimension selecting predictor variables (n=18) at VIF<10 for final BRT model fitting (**Table 4-1).**

Table 4-7: Final predictor variables fitted in BRT niche model

Theme	Variable	Units
Climatic	Annual Average Relative Humidity	%
	Length of longest dry season	months
	Temperature Seasonality	°c
	Rainfall wettest month	mm
	Palmer Drought Severity Index	index
	Potential evapotranspiration	mm
Edaphic	Calcic Vertisols	%
	Clay content	mass fraction (%)
	Haplic Calcisols	%
	Haplic Vertisols	%
	Silt content	mass fraction (%)
	Soil organic carbon density	kg/m3
	Soil pH	pH
	Soil Moisture	m^3/m^3
	Soil texture	factor
Others	Cattle density	animals/90km^2
	Enhanced vegetation index	index
	Slope	degrees

4.1.1 Predicted anthrax distribution

The predicted potential distribution of anthrax in Kenya was achieved with a test mean AUC of ≈0.8 ± 0.001 (**Figure 4-1**). Areas predicted as being suitable for anthrax occurrence varied across Kenya from probability of very low (0) to very high (0.9). The proportion of the study area predicted with suitable probability for anthrax at cut-off of Youden index > 0.75 was 22% of the study area. **Figure 4-2** presents the mean predicted anthrax distribution maps and its lower (2.5%) and upper (97.5%) confidence interval maps giving the certainty degree on the predicted distribution. The highly suitable regions were predominantly in the western, south-western, central and upper-eastern. Peripheral areas to these regions and along the coastal strip had suitability probabilities ranging between 0.4 and 0.6. Predicted lower suitability for anthrax outbreaks at probability < 0.2 were predominantly in the northern, north-eastern and lower-eastern regions tending to coastal region. The number of humans affected is estimated as ~ 19,300,840 people/sq.km while that of livestock, as ~7,750,675 animals / sq.km.

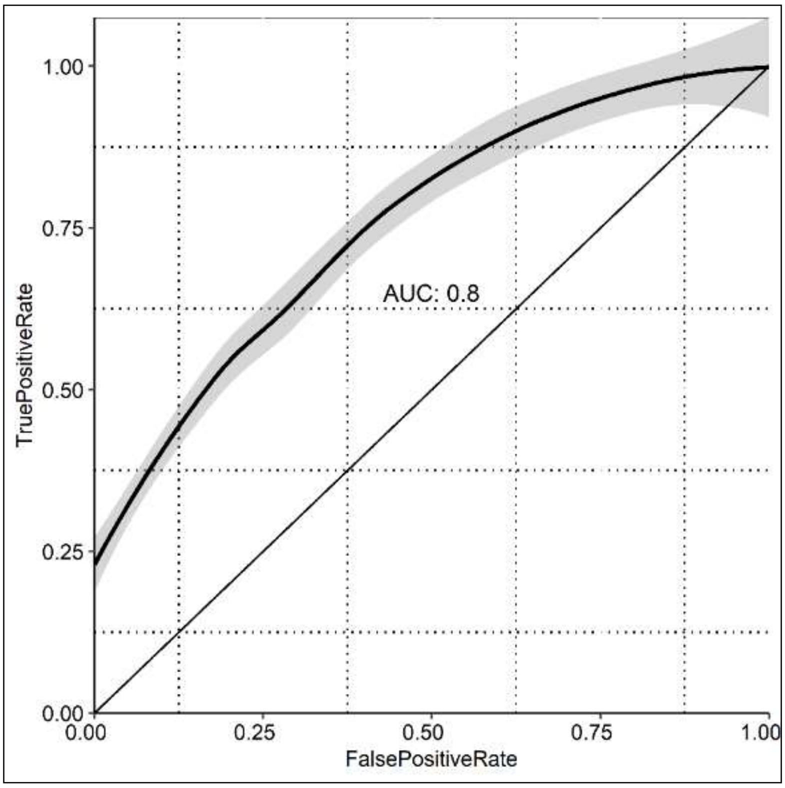

Figure 4-12: Mean AUC-ROC curve from 100 model runs in anthrax distribution prediction.

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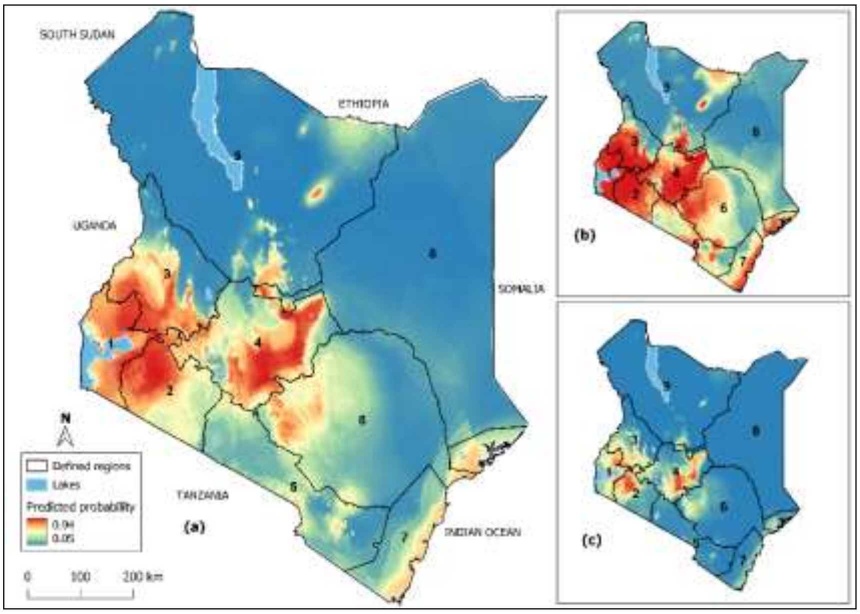

Figure 4-13: Predicted geographic distribution of anthrax in Kenya. *(a) mean prediction (b) the upper 97.5% and (c) the lower 2.5% confidence intervals.* (Source: author)

The predicted high suitability areas were also observed in areas adjacent to wildlife national parks and game reserves including Nairobi, Nakuru, Mount Kenya, Mwea, Mount Elgon and Marsabit National Parks, and Masai Mara National Reserve (**Figure 4-3**).

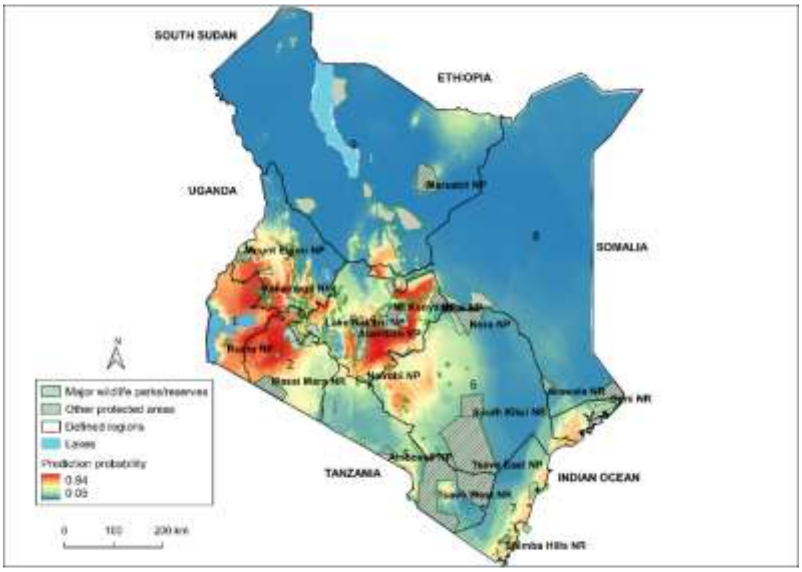

Figure 4-14: Wildlife protected areas versus the predicted anthrax distribution in Kenya.
(Source: author)

4.1.2 Relative influence of the variables

Relative influence measures the importance or usefulness of a predictor variable in a model represented by the average increase in prediction error when a given predictor is permuted. Relative influence for each predictor variable to the distribution of anthrax across the 100 BRT experiments in order of importance ranked cattle density at the top and Haplic Calsisol as the last among the 18 predictor variables (**Figure 4-4**).

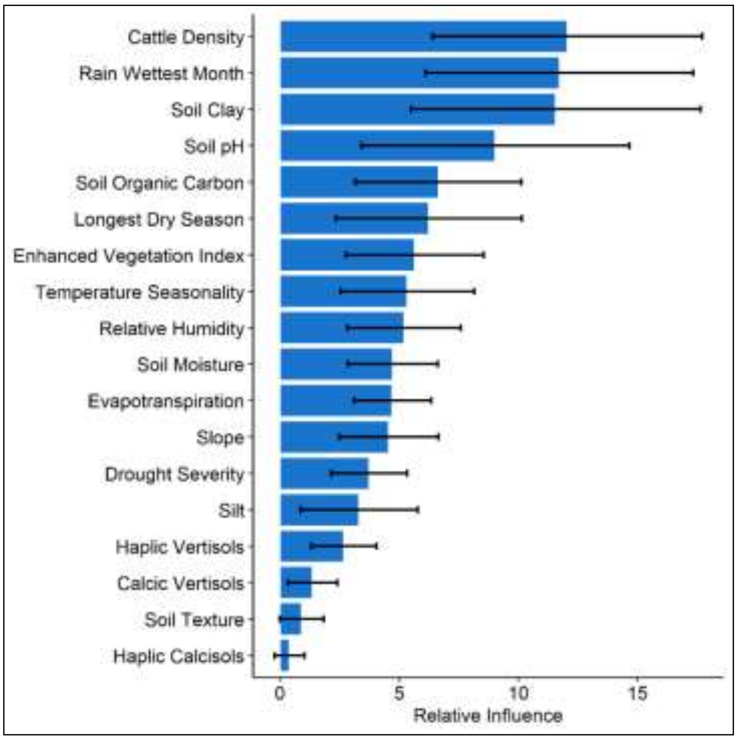

Figure 4-15: Influence of each final variables in the prediction of anthrax distribution in Kenya.
Error bars represent variability across an ensemble of 100 model runs.

4.1.3 Marginal effects of the variables

The marginal effects of each variable on anthrax prediction probability, while keeping all other variables at their average are illustrated by Partial Dependency Plots (PDP) (**Figure 4-5**). In general, the PDPs are non-linear, non-monotonic and exhibit thresholding for positive or negative correlation with anthrax prediction probability. Interpretations that can be drawn from these plots are as follows. Positive increase of variables with increasing prediction probability is observed for some variables.

Climatic factors: increased rainfall of the wettest month (between ≈ 200 and ≈400 mm); increased longest dry season above ≈ 6 months; low temperature seasonality (≈ 6 - ≈10 °c), which is in the range of limited seasonal temperature variation; high relative humidity above ≈ 60%; drought severity window (between ≈ -7 and ≈ -5 indices), which is in the extreme range of dry season). Edaphic factors: high percentage of soil clay content (≈30 – ≈ 45%); gently increased soil organic carbon below ≈300 kg/m^3; low silt content less than ≈20 mass fraction (%); increasing Haplic vertisols; Calcic vertisols above ≈6%; soil texture narrow window (≈4 - ≈5 factors) and above ≈6 factors; and Haplic Calsisols above 10%. Other factors: high cattle density above ≈5000 animals; enhanced vegetation index less than 0.3 (representing shrub and grassland); and low to gentle slopes below ≈300 degrees.

On the other hand, there are windows of negative correlation with increasing anthrax prediction probability observed with some variables including: Climatic (longest dry season between 3 and 6 months, evapotranspiration above ≈1600mm, high drought severity above ≈ -5 index); edaphic (low soil pH less than ≈7, increasing soil moisture, silt content between ≈20% and ≈40%, soil texture below ≈ 4 and (≈5-≈6) factors, Haplic Calcisols below ≈10%); Others (enhance vegetation index above 0.3, high slopes above ≈300 degrees).

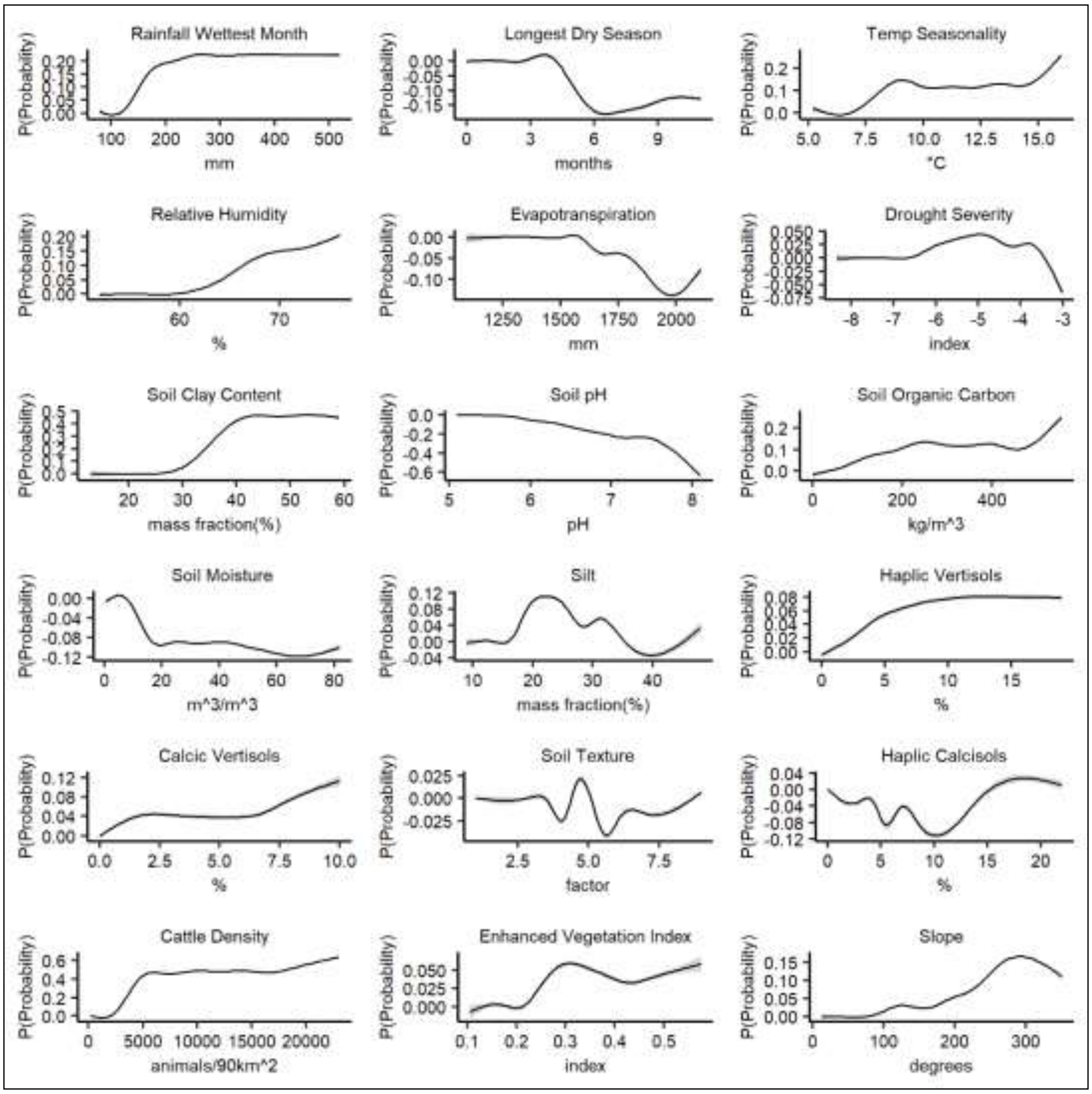

Figure 4-16: Marginal effects on the mean prediction probability of potential anthrax distribution by each variable across the 100 model runs.

4.2 Anthrax distribution as influenced by multi climate changes

To select parsimonious non-correlated final model variables, VIF<10 was applied filtering the candidate current climatic variables (n=27) to nine (9) independent predictor variables finally fitted in the BRT model (Table 4-2). The influence of each the selected variables across 100 experiments ranked in order of importance, identified precipitation of wettest month as the top ranked and temperature seasonality as the last among the 10 selected predictor variables as shown in **Figure 4-6**.

Table 4-8: Variables fitted for climate scenarios niche modelling

Variable	Unit
1.Precipitation of wettest month	mm
2.Temperature Seasonality	°c
3.Annual temperature range	°c
4.Length of longest dry season	months
5.Potential evapotranspiration	mm
6.Mean precipitation of October	mm
7.Mean precipitation of December	mm
8.Mean precipitation of February	mm
9.Mean precipitation of July	mm
1(Slope	degrees

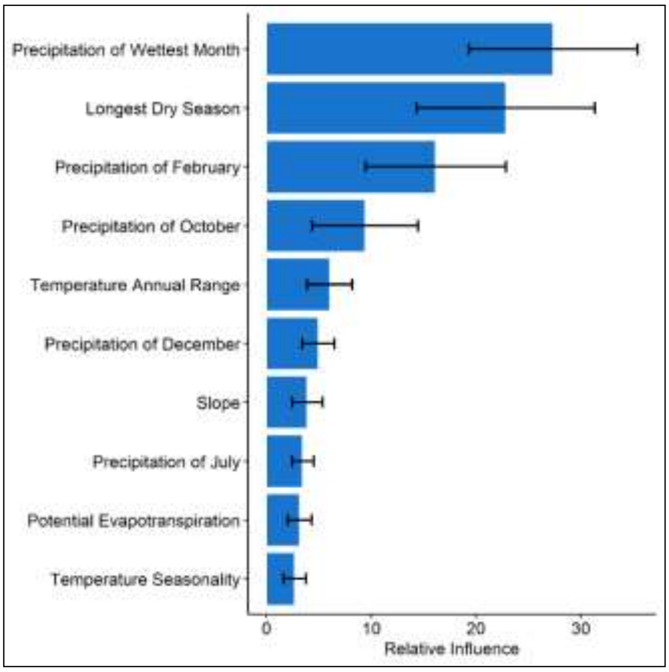

Figure 4-17: Influence of each final climate variables in the prediction of anthrax distribution in Kenya under current scenarios.
Error bars represent variability across an ensemble of 100 model runs.

4.2.1 Predicted anthrax distribution under multi-climate scenarios

The mean prediction of the likely distribution of anthrax in Kenya based on 100 BRT replicate experiments from the current climate scenario was achieved with a mean test AUC of 0.9 ± 0.004 (**Figure 4-7**). The subsequent predictions for future scenarios were projected to the geographical landscape based on the current BRT models. **Figure 4-8** shows the anthrax distribution prediction with probability from very low (0) to very high (0.93) for the three climate scenarios of current, RCP 4.5 and RCP 8.5. For all the three scenarios, high prediction probability areas were identified in western, Lake Victoria, central, south-western, and eastern regions of Kenya while lower suitability areas were identified in northern and north-eastern regions. When dichotomised at Youden index of 0.75, (**Figure 4-9**), the predicted areas show highly suitable areas for anthrax for the three scenarios were predominantly restricted in: western, Lake Victoria and central regions of Kenya. The highly suitable areas generally expanded with the future scenarios with current at 36131 km^2, RCP 4.5, 40012 km^2, and RCP 8.5, 39835 km^2. Lower suitability at a probability of < 0.2 was predicted for the eastern region further from central Kenya, the southern eastern region bordering Tanzania, coastal region away from Indian ocean and northern as well as, and north-eastern region.

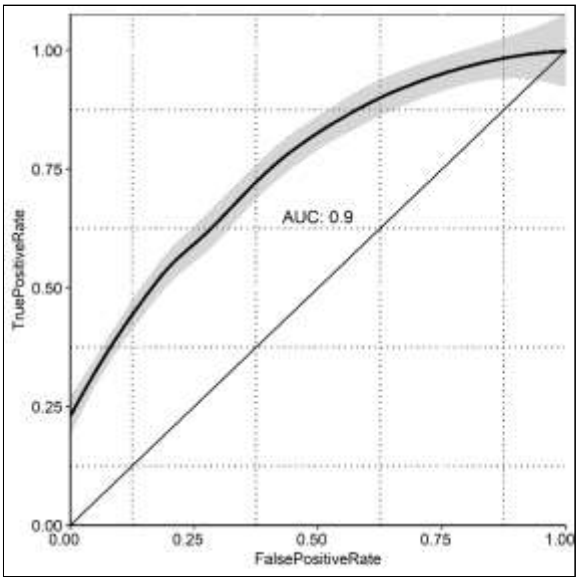

Figure 4-18: Mean AUC-ROC curve from 100 model runs in anthrax distribution prediction due to climate change modelling.

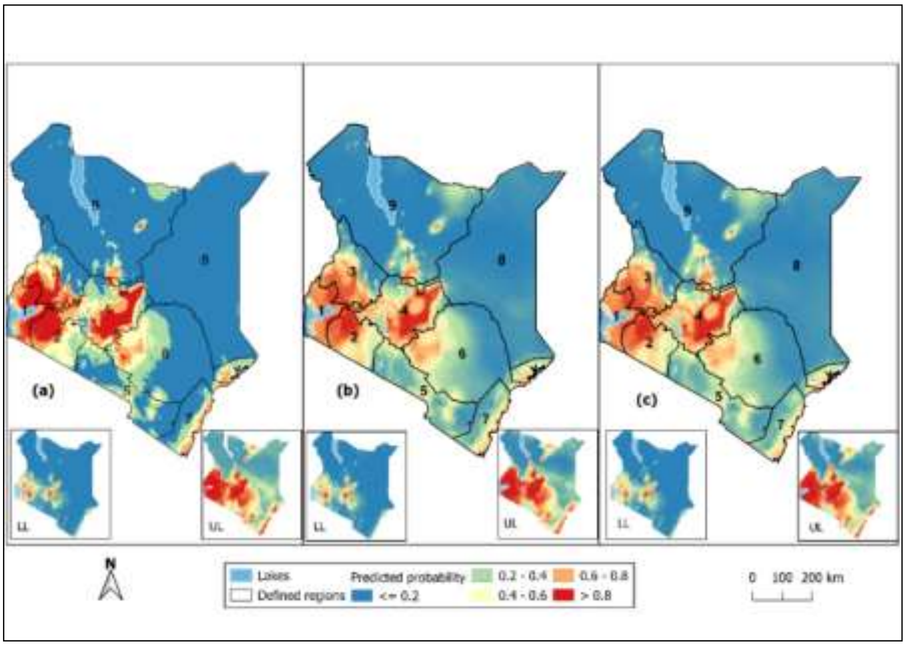

Figure 4-19: Relative predicted distribution of anthrax for Kenya under multiple climate scenarios.
(a), current; (b), RCP 4.5; (c) RCP 8.5. (Source: author)

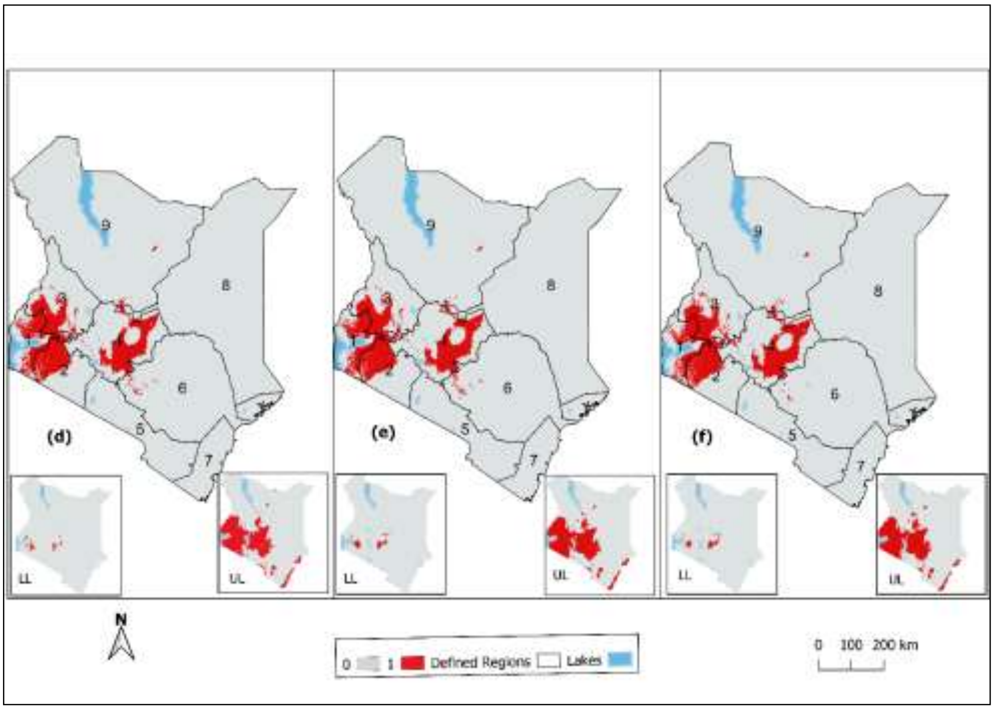

Figure 4-20: Dichotomised maps of predicted anthrax distribution at Youden index ≥ 0.75 suitability.
Climate scenarios: (a), current; (b), RCP 4.5; (c), RCP 8.5. Highly suitable areas are shown in red colour and less suitable in grey colour.
(Source: author)

4.2.2 Change in potential anthrax distribution

An increase in risk is identified in portions of the areas that already had high-risk predictions and also in areas that had not shown previous high-risk predictions (**Figure 4-10**), even though the areal coverages are relatively smaller for RCP 4.5 than RCP 8.5. These regions with an increase in anthrax risk include central region bordering central highlands; western regions bordering Uganda; and northern regions around rift valley escapement towards Lake Turkana. On the other hand, risk reduction was identified for both future scenario predictions in small patches of western, central, coastal and southwestern regions.

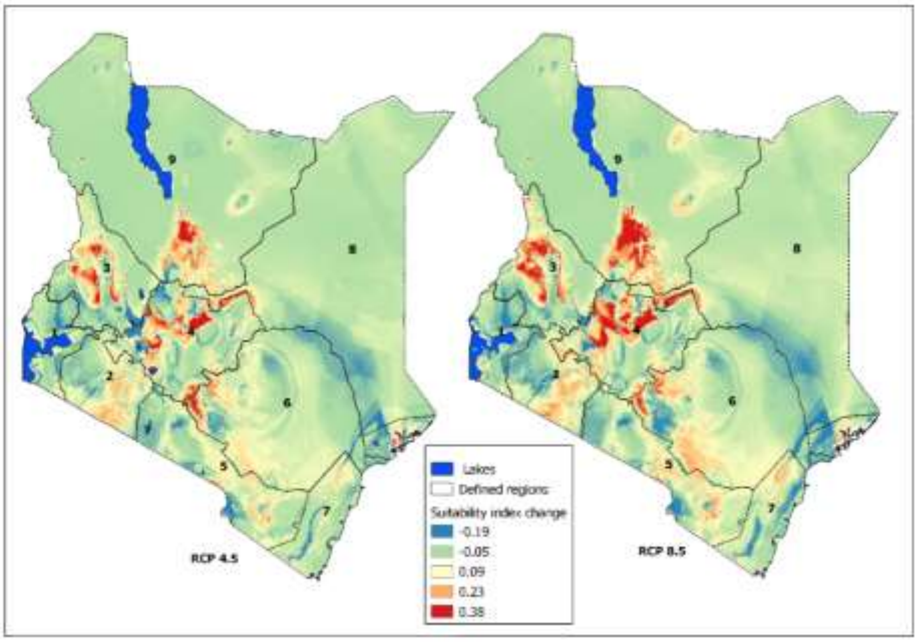

Figure 4-21: Changes in predicted anthrax risk in Kenya under RCP 4.5 and RCP 8.5 climate scenarios.
Red areas show the increase in risk while blue areas the decrease.
(Source: author)

The association between the anthrax occurrences and changes in the climate change variables of RCP 4.5 and RCP 8.5 future climate scenarios from current scenario exhibited cases of $p < 0.05$, thus, H0 that: "Changes in specific climate parameters will not affect the future spatial distribution of anthrax in Kenya" was rejected at 95% confidence level. Changes in expansion, reduction (loss) and stability (no-change) were realized in the predicted anthrax distributions due to the three climate scenarios.

The total expansion areas realized across the climate scenarios made up 0.9% of the study area (≈580,367 km^2), total areas of reduction were 0.4% and total areas of no-change were 6%. In addition, the distribution exhibited a northward shift from current to RCP 8.5 prediction as shown by the deviation ellipse (see **Figure 4-11**).

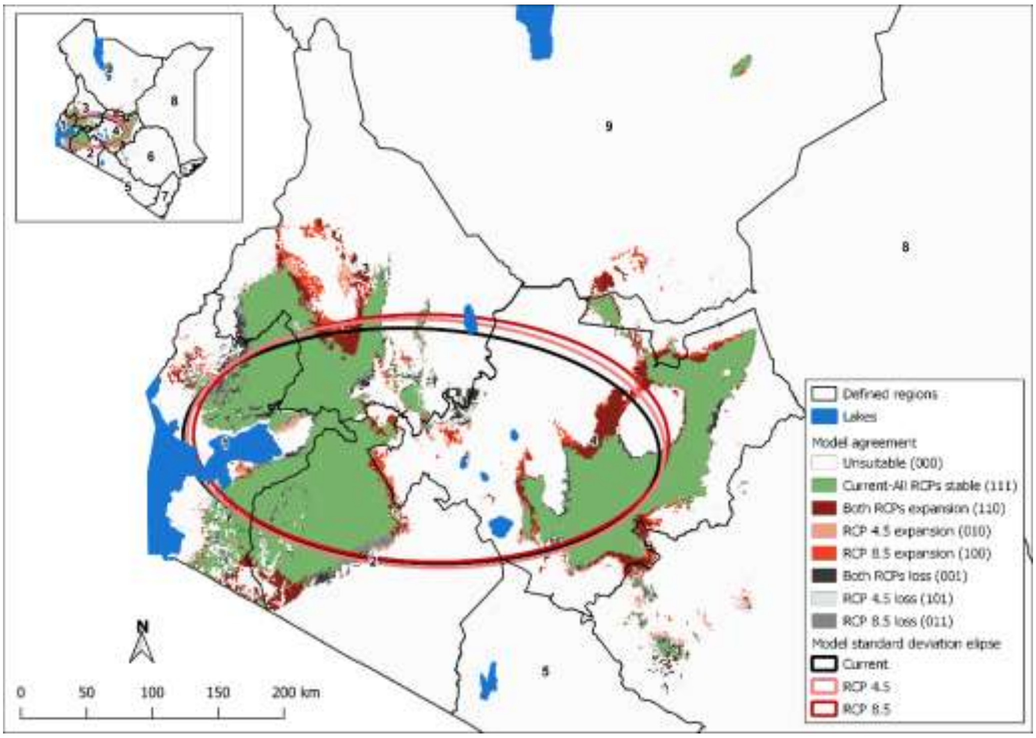

Figure 4-22: Potential anthrax distributional changes and shifts in Kenya under RCP 4.5 and RCP 8.5 relative to current climatic scenario.
(Source: author)

4.2.3 Marginal effects of the climate scenario variables

Partial dependency plots (PDP) of effect of the climate variables on the mean prediction probability of potential anthrax are presented in **Figure 4-12.** The relationships between the climatic variables and the anthrax prediction probability were nonlinear, multimodal and exhibited thresholding effect. Positive association of increasing variables with probability of anthrax suitability were observed for: increased precipitation of wettest month between ≈150mm and ≈200 mm; precipitation of February (≈20 – ≈50 mm); precipitation of October (≈20 - ≈ 100 mm); precipitation of December (≈30 - ≈50 mm); annual temperature range between ≈15 °C and ≈20 °C; precipitation of July (≈0 - ≈100mm); and potential evapotranspiration from ≈1500 mm to ≈1750 mm. On the other hand, increased longest dry season between ≈3 months and ≈6 months, temperature seasonality from ≈1°C to 1.3 °C were associated with decreasing anthrax prediction probability. Slope exhibited a constant relationship before a constant drop after 85 degrees with the prediction probability.

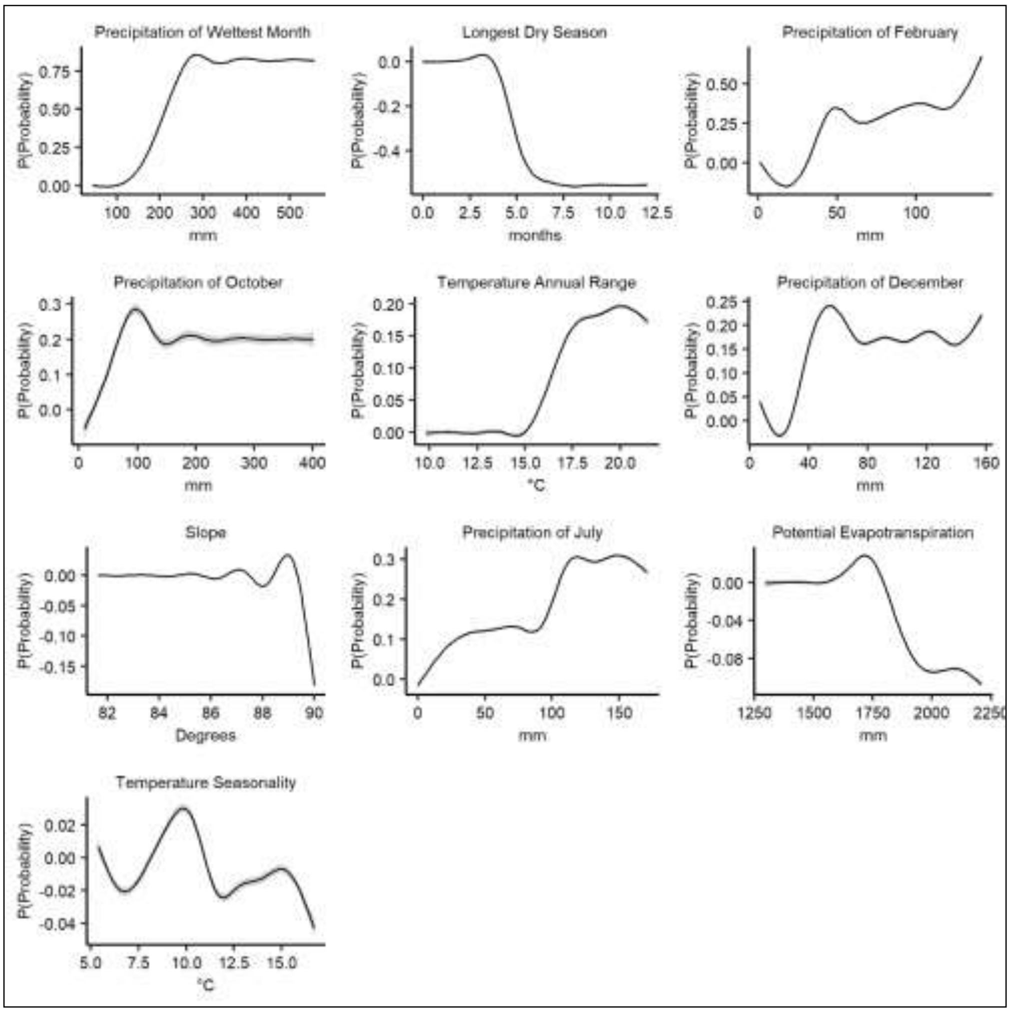

Figure 4-23: Marginal effects plots of climate variables on the mean prediction probability of potential anthrax distribution.

4.3 Socio-economic vulnerabilities due to predicted anthrax risk

4.3.1 AHP relative weights

The pairwise criteria comparison matrix (**Table 4-3**) was constructed and applied in obtaining the relative criteria weights (Normalised Eigenvector). The criteria weights were determined with a consistency ratio of 0.03, which indicates acceptable limit of consistency as it is less than 0.1. Among the selected criteria, predicted anthrax distribution came out as the most critical and population density as the least.

Table 4-9: Pairwise Comparison Matrix and Weights of the Criteria. *AN, predicted anthrax distribution; LC, land cover use; LL; literacy level; PI, poverty index; PD, population density; IG, Income index; SP, Severe wasting prevalence; IM, Infant mortality rate*

	AN	LL	PI	IG	LC	SP	IM	PD	Weights
AN	1	2	2	2	3	2	3	7	0.24
LL	0.5	1	2	2	3	3	3	7	0.21
PI	0.5	0.5	1	1	3	2	3	5	0.15
IG	0.5	0.5	1.0	1	3	2	2	7	0.15
LC	0.3	0.3	0.3	0.3	1	2	2	3	0.08
SP	0.3	0.3	0.5	0.5	0.5	1	2	3	0.07
IM	0.3	0.3	0.3	0.5	0.5	0.5	1	3	0.06
PD	0.1	0.1	0.2	0.1	0.3	0.5	0.3	1	0.03
Total	3.0	6.0	6.5	10.2	13.0	16.0	25.5	32	1.000

Mean eigen value (hmax) = 8.315; Consistency Index (CI) *= 0.45;* Consistency Ratio *(CR) = 0.03*

4.3.2 Assessment of socio-economic vulnerability

The association of vulnerability values as dependent variables and values of standard scaled predicted anthrax distribution interacting with other vulnerability criteria as independent variables exhibited significance at $p<0.05$. Hence, Null hypothesis that “anthrax spatial risk interacting with spatially explicit socio-economic factors do not influence socio-economic vulnerability in Kenya” was rejected at confidence level of 95%. Varying socio-economic vulnerability due to exposure to potential anthrax risk in four quantile classes (low, moderate, high, very high) were suggested across entire Kenya for current scenario. Very high vulnerability areas, above 75% quartile range (index > 1.0), were identified predominantly in the western, Lake Victoria Basin, central, south-eastern and upper eastern regions. In addition, small isolated patches of very high vulnerability were identified in northern, north-eastern and the coastal regions. Areas with low vulnerability below 25% quartile range (index < 0.5), were identified predominantly in parts of northern, north-eastern, eastern and southern regions tending to the Kenyan coast. The areas with very high vulnerability also host the larger portion of the Kenyan population. Based on the estimated total number of people per 100 m grid-cell (Tatem, 2017), the population at risk within the high vulnerability area (index > 75%) is ≈40,369,455 people. **Figure 4-13** shows the severity of socio-economic vulnerability in Kenya at current scenario.

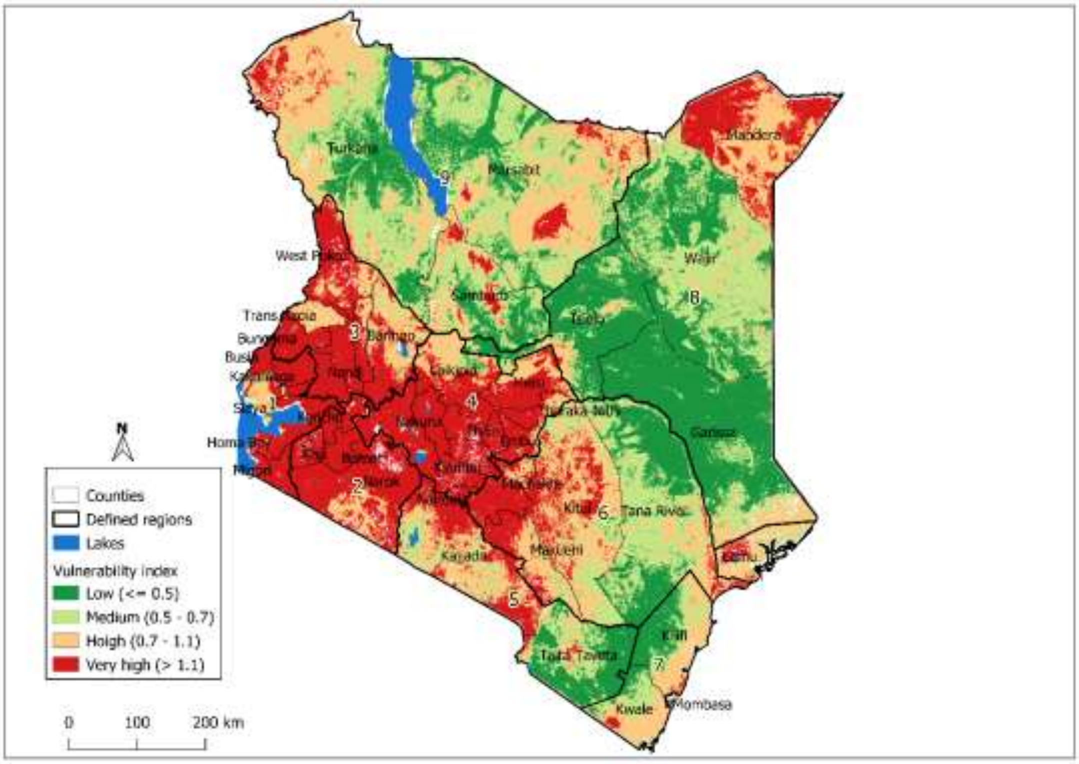

Figure 4-24: Map of socio-economic vulnerability to anthrax risk in Kenya at current scenario.
Red colour, very high risk; green colour, low risk.
(Source: author)

Similar varying socio-economic vulnerability patterns were observed for future scenarios as in current scenario, however, with areal expansions as influenced by the climate changes i.e., ≈181,559 km^2 for current scenario, ≈185,124 km^2 for RCP 4.5, and ≈185,345 km^2 for RCP 8.5 assuming sensitivity and adaptive capacity criteria remain constant into the future. **Figure 4-14** shows the relative vulnerability across the country for current and future scenarios.

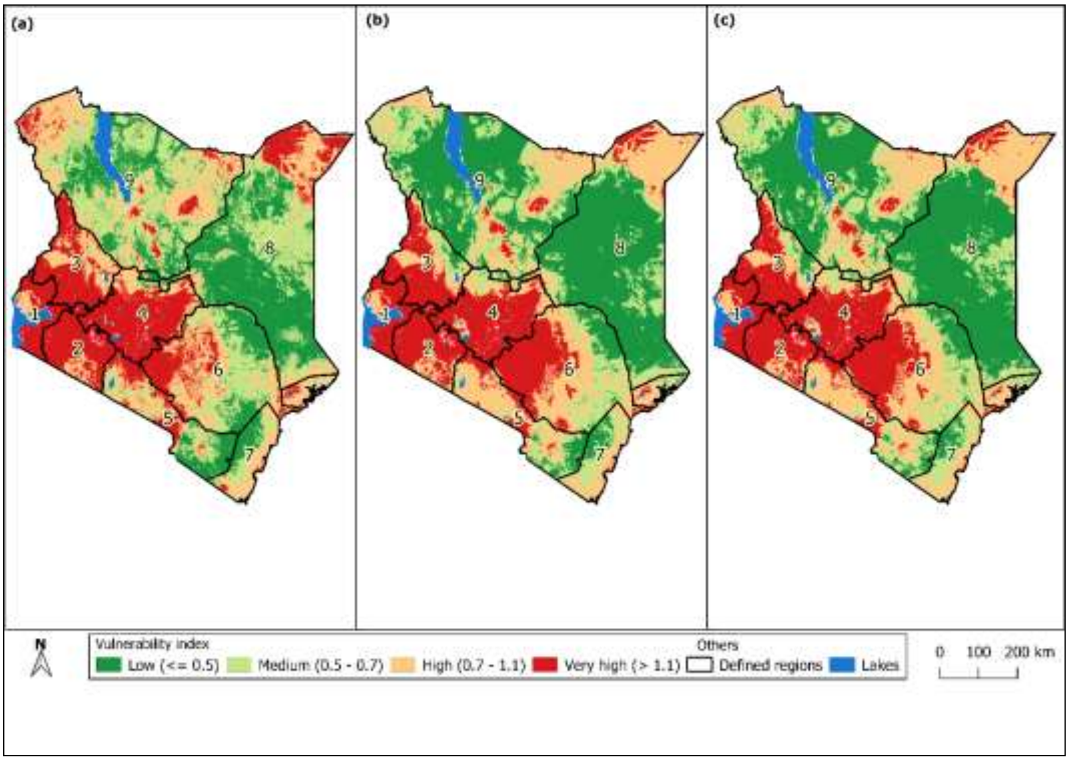

Figure 4-25: Maps of socio-economic vulnerability to anthrax risk under multiple climatic scenarios.
(a)current climate scenario; (b), future climate scenario, RCP 4.5; and (c), future climate scenario, RCP 8.5. (Source: author)

Separate maps from sensitivity and adaptive capacity based on the aggregated composite indices from their individual criteria indices concerning anthrax risk were produced as shown in **Figure 4-15**. The areas identified for low to moderate risks resulting from low sensitivity and high adaptive capacity due anthrax exposure, are predominantly in similar areas as those previously predicted for high anthrax distribution. Conversely, high sensitivity and low adaptive capacity indicating high risks areas due to anthrax exposure are identified in northern and north-eastern regions areas with low predicted anthrax distribution.

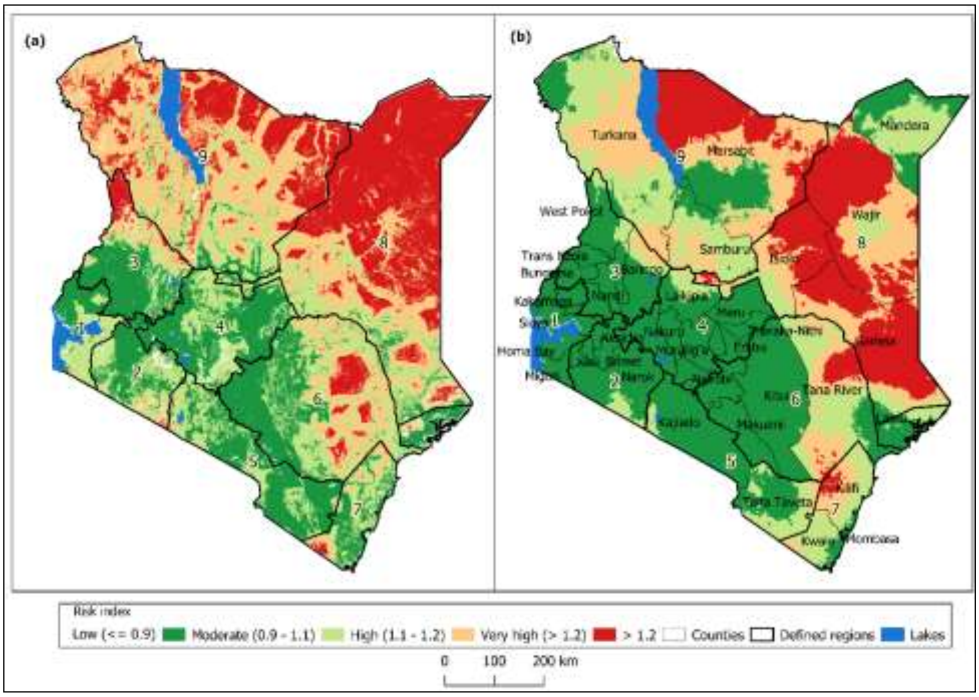

Figure 4-26: Maps of risk to anthrax exposure per vulnerability component. *(a) sensitivity and (b) adaptive capacity.* (Source: author)

Each criterion's contribution to socio-economic vulnerability index was assessed by omitting the criterion while keeping everything constant in the sensitivity and adaptive capacity composite indices derivation. Contribution assessment for exposure component was not necessary as it had only one criterion. For sensitivity composite index, the omission of Severe Wasting Prevalence gave the highest inter quartile range (IQR) of 0.15, indicating highest contribution while that of Poverty Index, the lowest at IQR of 0.11. In the case for adaptive capacity score, the omission of Income Index gave higher IQR of 0.22 compared to the omission of Literacy Level of 0.15. **Figure 4-16** presents relative boxplots indicating the resulting IQRs when a criterion is discarded in the sensitivity and adaptive capacity vulnerability components.

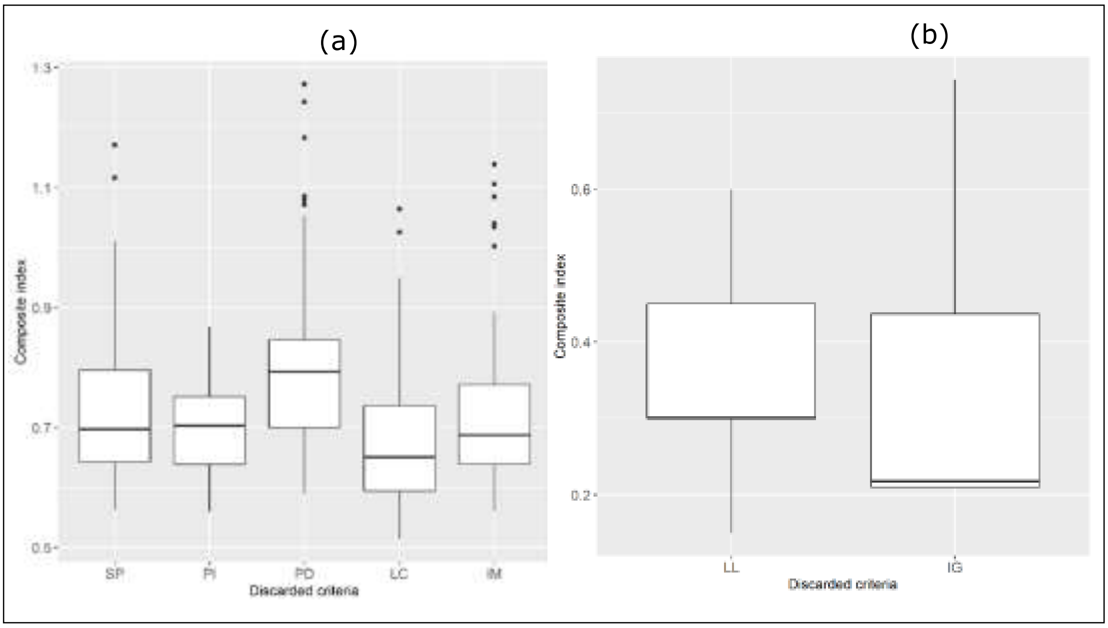

Figure 4-27: The inter quartile range for each criteria contribution to the aggregated indices of the vulnerability components.
(a)composite sensitivity index outcomes when a criterion is discarded
while other criteria are kept constant; and (b) composite adaptive capacity index outcomes. Criteria: LL, literacy level; IG, Income Index; SP, Severe wasting prevalence; PI, poverty index; PD, population density; LC, Land cover use; and IM, Infant mortality rate.

CHAPTER FIVE

5.0 DISCUSSION

5.1 Anthrax spatial distribution and the influencing factors

The predicted environmental conditions highly suitable for anthrax outbreaks were predominantly in regions around western Kenya and around Lake Victoria Basin bordering Uganda; southwestern regions around the shared Kenya-Tanzania border and running as a belt through central highlands of Kenya. This affects ~19,300,840 people per sq.km and ~7,750,675 livestock per sq.km. These predicted highly suitable areas closely include the areas previously reported with anthrax outbreaks in Kenya (Bett and Gachohi, 2019; Muturi *et al*., 2018). The areas are predominantly in poor rural settings where livelihood is mostly pastoralism and/or mixed crop-livestock agriculture (Carlson *et al*., 2019). On the other hand, low suitable areas were predicted in northern, north-eastern and lower-eastern regions towards the coastal region of Kenya, perhaps partly due to cultural frown on consumption of dead carcasses. The high and low suitability geographical distribution of the anthrax can be attributed to local environmental persistence of *B. anthracis*, the human behaviour and probably livestock movement through trade which may have disseminated *B. anthracis*, serving as a pathway for inter-region dispersion. The human behaviour being characterized by limited knowledge or awareness on the risk of the carcass handling and disposal; and consumption of infected meat as observed in Zimbabwe, Kenya and Ghana (Chirundu *et al*., 2009; Muturi *et al*., 2018; Opare *et al*., 2000). The number of people and animals at risk from anthrax outbreaks may most likely increase as the anthrax distribution in Kenya was predicted to expand with future climatic scenarios in this study The factors influencing the predicted anthrax distribution included climatic, edaphic, other environmental, topographical and socio-economic. These factors are further discussed save for climatic factors that are discussed in the climate section.

Edaphic factors including soil pH, clay content, soil organic carbon, Calcic Vertisols, Haplic Vertisols and Haplic Calcisols were suggested as other important factors in influencing to anthrax prediction, as documented in several previous studies in Tanzania, Zimbabwe, USA, China and India (Chen *et al*., 2016; Chikerema *et al*., 2013; Mwakapeje *et al*., 2019; Nath and Dere, 2016). Different soil types are reported as important in anthrax distribution prediction in different environments, but they may possess similar characteristics that support *B. anthracis* vitality and persistence (Carlson *et al*., 2018). Increasing contents of Haplic vertisols, Calcic vertisols above ≈6% and Haplic Calsisols above 10% were associated with increasing prediction probability. Vertisols and Calsisols soils are rich in calcium and pH which are confirmed to influence *B. anthracis* spore germination, growth, survival, and possibly re-sporulation in the soil (Carlson *et al*., 2019; Da Gama *et al*., 2019; Hugh-Jones and Blackburn, 2009; Virmani *et al*., 1982). In addition, soil pH marginal effect was suggested in this study to slightly increase anthrax prediction at high alkalinity window of 7 to 7.5. Studies in Ghana, and northern Hemisphere (temperate, boreal, and arctic regions) also found high soil pH indices to be associated with anthrax distribution prediction (Kracalik *et al*., 2017; Walsh *et al*., 2018). Soils with high pH > 6.1 influence *B. anthracis* spore survival (Hugh-Jones and Blackburn, 2009; Steenkamp, 2013). High percentage of soil clay content (≈30 – ≈45%) were associated with increasing prediction probability. High clay content in the soils, may accelerate flooding due to its high water-retaining capacity and resulting flooding may transport the spores to concentrate elsewhere in low lying 'storage areas' (Dragon and Rennie, 1995; Fasanella *et al*., 2013). This precipitates conducive environments for the growth of contaminated fresh forage that attracts grazing by livestock. Further, low quantity range of soil organic carbon below ≈300 kg/m3 was found to increase the probability of anthrax prediction. Another study in Kenya covering selected wildlife areas also found an association of anthrax outbreaks with soil organic carbon (Obanda et al., 2021). Soil organic matter containing soil organic carbon as the main component, support *B. anthracis* spore persistence (Dragon and Rennie, 1995; Hugh-Jones and Blackburn, 2009). Generally, soil types determine chemical composition and moisture affinity of a soil hence the potential to support *B. anthracis* sporulation and subsequent potential anthrax risk (Blackburn, 2010; Lindeque and Turnbull, 1994; Ryu *et al*., 2003).

Enhanced vegetation index was suggested in this study to have increasing association with anthrax distribution prediction similar to a study in Ghana (Kracalik et al., 2017). Interestingly, another study in Kenya taken for selected wildlife areas applying a different vegetation index (NDVI), also found an association with anthrax outbreaks (Obanda et al., 2021). The range of vegetation index less than 0.3 represents grassland and shrub, which mostly serve as grazing grounds for livestock in Africa. These grounds may get contaminated with anthrax spores and serve as anthrax infection 'time bomb' to grazers' anthrax infection. In addition, potential commingling of infected livestock in the grazing areas may lead to anthrax outbreaks. Indeed, grazing is the dominant transmission route for *B. anthracis* (Turner *et al*., 2016).

High cattle density above 5000 animals/90 km2 was suggested to have positive correlation with increasing anthrax prediction probability. Cattle density reflects the size of household livestock assets in an area and livestock keeping contributes to household income and welfare thus to social and economic status in rural areas (Ouma *et al.,* 2003; Waters-Bayer and Bayer, 1992). Hence, cattle density can be considered as a proxy to evaluate socio-economic factors (Tesfaye *et al*., 2015). Cattle density has been associated with anthrax distribution prediction by studies in China and temperate, boreal, and arctic regions (Chen *et al.,* 2016; Walsh *et al.,* 2018). While environmental conditions define *B. anthracis* niches, socio-economic variables inherent within livestock production, including livestock numbers play an essential role in the occurrence of anthrax (Sitali *et al*., 2017). Another study in Lesotho also reported that socio-economic factors, have influence on the temporal and spatial pattern of anthrax outbreaks (Lepheana *et al*., 2018). Cattle keeping in Lesotho and Kenya bear similar African socio-economic role. High cattle density may present high likelihood of exposure to anthrax infection at shared contaminated grazing and/or watering points (Clegg *et al*., 2007).

Despite applying only livestock anthrax occurrences in this study, the study revealed potential anthrax outbreak suitability in wildlife conservation areas. The suitable areas fall in wildlife conservation areas such as Nakuru National Park that have previously reported anthrax outbreaks in Kenyan (Gachohi *et al*., 2019; Muturi *et al*., 2018). At the same time low risk was suggested in Tsavo National Park and Amboseli Game Reserves which have been reported in a previous study with low anthrax outbreaks (Gachohi *et al*., 2019). This study also predicted suitable anthrax areas around the shared Kenya-Tanzanian border, suggesting a likely transboundary anthrax suitability across the larger Mara-Serengeti ecosystem. Similarly, previous studies have documented anthrax occurrences in Serengeti National Park in Tanzania with anthrax distribution predictions identifying suitable areas along the border on the Tanzanian side (Hampson *et al*., 2011; Lembo *et al*., 2011). The fringes of wildlife conservation areas are usually shared by livestock and wildlife, presenting possible bidirectional anthrax transmission interfaces as is hypothesized for bovine tuberculosis or foot-and-mouth disease (FMD) (Mohamed, 2020; Nthiwa *et al*., 2019). Inherently anthrax burden in wildlife has been underestimated due to surveillance inadequacies and difficulties (Bengis and Frean, 2014). Therefore, information on potential anthrax distribution in relation to wildlife conservation areas is valuable for conservation efforts more so for endangered species like rhinos and Rothschild giraffe inhabiting these anthrax-suitable ecosystems. Niche modelling, such as carried out in this study, provides opportunities for a better approximation of risk hotspots concerning the wildlife conservation areas.

5.2 Anthrax distribution as influenced by multi climate changes

Occurrence and distribution of anthrax is limited by various climatic factors. The climate variables found in this study to have had important contribution to the potential distribution of anthrax outbreaks included: precipitation related (rainfall of wettest month, monthly mean precipitation, relative humidity, potential evapotranspiration); temperature related (annual temperature range, temperature seasonality); and weather extremes (longest dry season, drought severity). Specific patterns of rainfall, temperature, their ranges and their seasonality have been found to influence anthrax distribution in Tanzania, South Africa, Kazakhstan, Kyrgyzstan and Siberia (Blackburn *et al*., 2017; Ezhova *et al*., 2020; Joyner *et al*., 2010; Mwakapeje *et al*., 2019; Steenkamp, 2013). In this study, precipitation level of the wettest month was suggested to have an increasing marginal effect to anthrax distribution prediction. Furthermore, monthly mean precipitation (February, July, October, December) were also suggested to have increasing marginal effect with anthrax distribution prediction probability. This implies that anthrax predicted outbreaks are associated with highly wet months of Kenya as another study in northern Kenya counties of Wajir, Isiolo and

Marsabit also associated rainfall of the wettest month with anthrax outbreaks (Abdirahim, M. A., 2018) Indeed, the precipitation months identified approximately overlaps with traditional wet months of Kenya, long rains (March-June) and short rains (September-December). The inexactness in the overlap may be attributed to shifts in wet months due to current changes in precipitation patterns associated with climate change (Njoka *et al*., 2016). Precipitation may influence anthrax outbreak by exposing buried spores to the surface, causing run-offs that disperse the spores or collecting and concentrating the spores in 'storage areas' (Dragon and Rennie, 1995).

Temperature related variables, range and seasonality, had a positive correlation with increasing anthrax distribution prediction probability. Temperature range and seasonality were suggested to positively increase with increase in distribution prediction probability. Temperature has a direct effect on *B. anthracis* sporulation and germination (Turnbull, 2008). A study in northern Kenya covering Wajir, Isiolo, Marsabit counties also found temperature seasonality to be associated with anthrax outbreaks (Abdirahim, M. A., 2018). Away from Kenya, in Zimbabwe and Ghana temperature related variables were also found to increase with anthrax suitability prediction (Chikerema *et al*., 2013; Kracalik *et al*., 2017). Extreme weather patterns related to temperature in the form of drought severity and prolonged hot dry season were also found to influence anthrax prediction in this study. Drought severity presented a positive marginal effect on anthrax prediction and so was the longest dry season but after a threshold of 6 months. Previous studies in Zimbabwe, Tanzania and Italy also associated dry seasons with anthrax outbreaks (Chikerema *et al*., 2012; Fasanella *et al*., 2010b; Mwakapeje *et al*., 2019). Prolonged hot dry season preceded by heavy rains and rains ending a period of drought are documented to influence anthrax outbreaks (Nath and Dere, 2016; Turnbull, 2008). Dry seasons decrease soil water balance and compromise forage and force herbivores to feed on the available short grass very close to potentially spore-laden soils increasing the chances of anthrax outbreaks (Turnbull , 2008). In addition, during the dry seasons, characterized by scarcity of water and forage, livestock-wildlife anthrax transmission interfaces are precipitated at grazing grounds and water points (Mwakapeje *et al*., 2018). The wet season immediately after dry seasons, characterized by increased soil water balance and sprouting grass, may expose spores to the surface with possible ingestion by herbivores (Nath and Dere, 2016).

Potential evapotranspiration and relative humidity are suggested in this study to substantially influence in anthrax prediction probability. Relative humidity showed increase with prediction probability after 60%. In a study in mainland China, relative humidity was also found to have substantial influence on anthrax suitability (Chen *et al*., 2016). Relative humidity greater than 96% supports anthrax spore germination and can accelerate spores size growth (Turnbull, 2008). Potential evapotranspiration presented a decrease with anthrax prediction probability after 1500mm. A study in India also found a threshold of a negative correlation with anthrax suitability for Priestley-Taylor α coefficient which is a derivative of potential evapotranspiration (Walsh *et al*., 2019). Potential evapotranspiration influences the microenvironment for rate and extent of sporulation of *B.anthracis* (Turnbull, 2008).

The predictions under multi climate change scenarios were suggested in this study to expand in the anthrax high-risk areas into the future. This is similar to a study on climatic influence on anthrax suitability in northern Hemisphere (temperate, boreal, and arctic regions) (Walsh *et al*., 2018). Despite the environmental differences between Kenya and the northern Hemisphere, there are commonalities in patterns of climate-sensitive infectious diseases in the tropics and Arctic (Evengård and Sauerborn, 2009). This study also suggests a northward shift towards northern Kenya in anthrax distribution with varied spatial patterns and magnitude under the two climate change scenarios similar to previous studies in Tanzania and Kenya where climate change was found to cause shift and variation in distribution patterns of Rift Valley Fever (RVF) (Bett *et al*., 2019; Mweya *et al*., 2016). Similar climatic factors of precipitation, temperature, and their derivatives influence anthrax and RVF outbreaks (Bett *et al*., 2019; Hugh-Jones and Blackburn, 2009). *B. anthracis* growth, multiplication and sporulation are dependent on favourable climatic factors of precipitation, temperature, and their derivatives (Hugh-Jones and De Vos, 2002). Furthermore, increased temperatures may suppress host immune functions (Walsh *et al*., 2018). Expansion of risk was suggested in this study to extend in small patches of northern region, areas that did not have any high-risk prediction. A study in Bosnia and Herzegovina also reported new outbreaks in areas that had not reported anthrax for more than two decades, which was attributed to changes in temperature and rainfall patterns (Maksimović *et al*., 2017). The predicted anthrax risk in these new areas may be due to changing micro-climatic conditions presented by the relatively elevated altitude of the neighbouring rift valley escarpments. Conversely, a reduction in anthrax risk was shown for both future scenario predictions in small patches of western, central, coastal and southwestern regions. The variability of anthrax risk in magnitude and spatial patterns predicted future scenarios may be attributed to future variability of climate and weather across Kenya, either increasing or decreasing climatic suitability of anthrax. Climate changes have been confirmed to alter temperatures regimes, rainfall patterns and their derivatives (Stocker *et al*., 2014), which can in turn encourage increase of anthrax outbreaks potential by altering livestock-human interface areas, the meeting of infected hosts, and transmission season of anthrax (Kangbai and Momoh, 2017). Climate changes have been experienced in Kenya and changes in temperatures, rainfall patterns, and frequency of droughts and flooding have been documented (Njoka *et al*., 2016). This can be expected to influence spatial anthrax distribution patterns in Kenya.

5.3 Socio-economic vulnerabilities due to predicted anthrax risk

Socio-economic vulnerability to anthrax risk was generated by integrating selected criteria for: environment (land use cover); demographic (population density, poverty index, literacy level and income index); and health (severe wasting prevalence and infant mortality rate). On a relative scale, the socio-economic vulnerability and its decomposed domains varied in space perhaps due a spatial variation of the underlying anthrax risks. This study suggested occurrence of socio-economic vulnerability hotspots (index > 75%) for anthrax to be predominantly around Lake Victoria basin, western, southwestern, central regions for current and future climate scenarios affecting. This may be attributed to clustering of anthrax outbreaks in the same hotspot areas (Nderitu *et al*., 2021; Otieno *et al*., 2021). The exposure domain represented by predicted anthrax distribution attracted a larger weight relative to others. This suggests that vulnerability was majorly attributed to the exposure relative to sensitivity and adaptive capacity domains. This may explain the manifestation of low vulnerability in northern, north eastern and eastern Kenya where anthrax risk is also low. Indeed, risks contributed to the vulnerability separately by sensitivity and adaptive capacity in the identified vulnerability hotspot were low. This may be attributed to the fact that these hotspots fall in medium to high agricultural potential areas where the resident communities have relatively better livelihoods as mixed farmers. This study also suggested general expansion in vulnerable areas into the future for current scenario at ≈181,559 km^2, RCP 4.5 at ≈185,124 km^2 and RCP 8.5 at ≈185,345 km^2. This may be attributed to anthrax risk which was predicted to expand from current to the future similar to a study on vulnerability to malaria risk in relation to climate change for East Africa, central Asia, China and south America (Van Lieshout *et al*., 2004). Anthrax and malaria transmissions are influenced by similarly by climatic change (Davies, D. G., 1960; Martens *et al*., 1995). The estimated population at risk within the vulnerability hotspots was estimated at 40,369,455 people, which accounts for 75% of the Kenyan population. This high percentage may be explained by the fact that these vulnerability hotspots fall in the densely populated medium to high agricultural potential areas that host 80% of the Kenyan population (FAO, 2015).

The derived individual relative contribution of each criterion in the socio-economic vulnerability were specific. Severe Wasting Prevalence was suggested to have the highest contribution within the sensitivity domain, while Income Index, the highest in the adaptive capacity domain. Severe Wasting Prevalence indicates acute undernutrition due to lack of protein diets (Dukhi, 2020). Its manifestation may predispose households to consumption of anthrax infected meat leading to increased human anthrax incidences as have been reported in Zimbabwe, Zambia and Kenya (Davies, 1982; Lehman *et al*., 2017; Mbai *et al*., 2021). In addition, low-income levels may precipitate a situation where households cannot afford meat hence lead to possible consumption of infected meat (Opare *et al*., 2000). Low income may also negatively influence the ability of households to afford regular livestock vaccination encouraging livestock anthrax outbreaks with possible spill over to humans, a scenario that has been observed in Kenya and Bangladesh (Mbai *et al*., 2021; Sarker *et al*., 2020).

5.4 Conclusions

a) The potential areas of anthrax risk and socio-economic vulnerability in Kenya under current and future climate scenarios are predominantly in western, central and southwestern regions with the influencing risk factors being related to precipitation, temperature, soil composition, vegetation index, slope and cattle density.

b) Future climatic changes by the year 2055 will lead to expansion and northward shift of anthrax risk towards northern Kenya from current to future.

c) A large proportion of the Kenyan population in high to medium potential areas are exposed to socio-economic vulnerability. The vulnerability resulting more from exposure to anthrax spatial risk relative to other criteria.

5.5 Recommendations

a) The developed anthrax risk and vulnerability maps should be employed by national and county governments, Kenya Wildlife Services (KWS) and partners to inform policy actions on anthrax preventions and control programs.

b) Early warning community health education and awareness campaigns should be implemented in areas where high anthrax risk and vulnerability are predicted.

c) Regular annual livestock vaccination campaigns should be targeted at the identified anthrax high risk livestock keeping areas as well as areas in proximity to wildlife conservation areas.

d) The findings in this study should inform future ecological and epidemiological research on anthrax possible outbreaks especially in pinpointed isolated spots in arid and semi-arid environments.

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World Bank Group. (2021). *Explore historical and projected climate data, climate data by sector, impacts, key vulnerabilities and what adaptation measures are being taken. Explore the overview for a general context of how climate change* *is affecting Kenya*. Climate Change Knowledge Portal. https://climateknowledgeportal.worldbank.org/country/kenya/climate-data-historical

Yackulic, C. B., Chandler, R., Zipkin, E. F., Royle, J., Nichols, J. D., Campbell Grant, E. H., & Veran, S. (2013). Presence- only modelling using MAXENT: when can we trust the inferences? *Methods in Ecology and Evolution*, *4*(3), 236–243.

APPENDICES

Appendix 1: Anti-plagiarism check results

Otieno_Environmental and socio-economic predictors of anthrax spatial distribution in Kenya

ORIGINALITY REPORT

22%	15%	15%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Fredrick Tom Otieno, John Gachohi, Peter Gikuma-Njuru, Patrick Kariuki et al. "Modeling the Potential Future Distribution of Anthrax Outbreaks under Multiple Climate Change Scenarios for Kenya", International Journal of Environmental Research and Public Health, 2021 Publication	4%
2	journals.plos.org Internet Source	3%
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4	www.esp.org Internet Source	1%
5	www.mced-ecology.org Internet Source	<1%
6	repository.up.ac.za Internet Source	<1%

link.springer.com

Appendix 2: Environment and socioeconomic data description, sources and references

	Variable	Source	Reference
1.	30 arc seconds. Priestley-Taylor Alpha Coefficient Soil-Water Balance (P-Tα)	**Trabucco *etal*, figshare:** https://figshare.com/articles/Global_High-Resolution_Soil-Water_Balance/7707605/3	(Trabucco and Zomer, 2010)
2.	0.5° resolution Relative Humidity (%)	**CRU:** https://crudata.uea.ac.uk/cru/data/hrg/tmc/	(New *et al*., 2002)
3.	30-arc seconds digital elevation model (m)	**USGS:** https://earthexplorer.usgs.gov/	(USGS, 1996)
4.	Slope (°)	Spatial analysis derived from GOTOPO30	Derived by author
5.	1km resolution Mean annual temperature (° C*10)	**University of York, AfriClim:** https://webfiles.york.ac.uk/KITE/AfriClim/GeoTIFF_30s/baseline_worldclim/	Platts *et al*., 2015)
6.	1km resolution Mean temp warmest quarter (° C*10)		
7.	1km resolution Mean temp coolest quarter (° C*10)		
8.	1km resolution Mean annual rainfall (mm)		
9.	1km resolution Rainfall wettest month (mm)		
10.	1km resolution Precipitation of Driest Month (mm)		
11.	1km resolution Rainfall seasonality (mm)		
12.	1km resolution Rainfall wettest quarter (mm)		
13.	1km resolution Rainfall driest quarter (mm)		
14.	1km resolution Mean diurnal range in temp (° C*10)		
15.	1km resolution Isothermality (° C*10)		
16.	1km resolution Temperature Seasonality (° C*10)		
17.	1km resolution Max temp warmest month (° C*10)		
18.	1km resolution Min temp coolest month (° C*10)		
19.	1km resolution Annual temperature range (° C*10)		
20.	1km resolution Number of dry months (months)		
21.	1km resolution Length of longest dry season (months)		
22.	1km resolution Annual moisture index (index)		
23.	1km resolution Moisture index moist quarter (index)		
24.	1km resolution Moisture index arid quarter (index)		

25.	30 arc seconds Potential evapotranspiration (mm)		
26.	4 km resolution Palmer Drought Severity Index (index)	**TerraClimate:** https://climate.northwestknowledge.net/TERRACLIMATE/index_directDownloads.php	(Abatzoglou *et al*., 2018)
27.	4 km resolution Soil Moisture (m^3/m^3)		
28.	4 km resolution Windspeed(km/hr)		
29.	1km Multidimension Poverty Index	**Worldpop:** https://www.worldpop.org/geodata/summary?id=1262	(Tatem, 2017)
30.	1km Income GINI index	**HDX:** https://data.humdata.org/dataset/kenya-income-gini-coefficient-per-county	(Gini, 1936)
31.	250m resolution Soil organic carbon density (depth 0 cm) (kg/m3)	**ISRIC:** https://files.isric.org/soilgrids/data/recent/	(Hengl *et al*., 2017)
32.	250m resolution Clay content (0-2 micrometer) at depth 0.00 m (mass fraction %)		
33.	250 m resolution Soil texture fraction at depth 0.00 m (factor)		
34.	250 m resolution Silt content (2-50 micrometer) at depth 0.00 m (mass fraction %)		
35.	250m resolution sand content (50-2000 micrometer) depth 0.00m (mass fraction %)		
36.	250 m resolution Soil pH x 10 in H2O at depth 0.00 (Index*10)		
37.	250 m resolution Calcic Vertisols WRB class (%)		
38.	250 m resolution Haplic Vertisols WRB class (%)		
39.	250 m resolution Haplic Calcisols WRB class (%)		
40.	5 arc-minute Gridded Livestock Density (animals per km2	**HAVARD, Dataverse:** https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GIVQ75	(Gilbert *et al*., 2018)
41.	250 m resolution Enhanced vegetation index (index)	**AfSIS:** http://africasoils.net/services/data/remote-sensing/land	(Didan, 2015)

Appendix 3: Current and future climate data description, sources and references

	Variable	Source	Reference
1.	30-arc seconds digital elevation model (m)	**USGS:** https://earthexplorer.usgs.gov/	(USGS, 1996)
2.	Slope (°)	derived from DEM through Spatial analysis	Derived by author
3.	1km resolution Mean annual temperature (° C*10)(current, RCP 4.5, RCP 8.5)	**University of York, AfriClim:** https://webfiles.york.ac.uk/KITE/AfriClim/GeoTIFF_30s/	(Platts *et al*., 2015)
4.	1km resolution Mean temp warmest quarter (° C*10) (current, RCP 4.5, RCP 8.5)		
5.	1km resolution Mean temp coolest quarter (° C*10)(current, RCP 4.5, RCP 8.5)		
6.	1km resolution Mean annual rainfall (mm) (current, RCP 4.5, RCP 8.5)		
7.	1km resolution Rainfall wettest month (mm) (current, RCP 4.5, RCP 8.5)		
8.	1km resolution Precipitation of Driest Month (mm) (current, RCP 4.5, RCP 8.5)		
9.	1km resolution Rainfall seasonality (mm) (current, RCP 4.5, RCP 8.5)		
10.	1km resolution Rainfall wettest quarter (mm) (current, RCP 4.5, RCP 8.5)		
11.	1km resolution Rainfall driest quarter (mm) (current, RCP 4.5, RCP 8.5)		
12.	1km resolution Mean diurnal range in temp (° C*10)(current, RCP 4.5, RCP 8.5)		
13.	1km resolution Isothermality (° C) x10 (current, RCP 4.5, RCP 8.5)		
14.	1km resolution Temperature Seasonality (° C*10)(current, RCP 4.5, RCP 8.5)		
15.	1km resolution Max temp warmest month (° C*10) (current, RCP 4.5, RCP 8.5)		
16.	1km resolution Min temp coolest month (° C*10) (current, RCP 4.5, RCP 8.5)		
17.	1km resolution Annual temperature range (° C*10) (current, RCP 4.5, RCP 8.5)		
18.	1km resolution Number of dry months (months) (current, RCP 4.5, RCP 8.5)		
19.	1km resolution Length of longest dry season (months) (current, RCP 4.5, RCP 8.5)		
20.	1km resolution Annual moisture index (index) (current, RCP 4.5, RCP 8.5) (current, RCP 4.5, RCP 8.5)		

21.	1km resolution Moisture index moist quarter (index) (current, RCP 4.5, RCP 8.5)		
22.	1km resolution Moisture index arid quarter (index)		
23.	30 arc seconds Potential evapotranspiration (mm) (current, RCP 4.5, RCP 8.5)		
24.	30 arc seconds Mean monthly precipitation (current, RCP 4.5, RCP 8.5)		
25.	30-arc seconds Monthly 2-metre air temperature (current, RCP 4.5, RCP 8.5)		
26.	30-arc seconds Monthly average of daily maximum temperature (current, RCP 4.5, RCP 8.5)		
27.	30-arc seconds Monthly average of daily minimum temperature (current, RCP 4.5, RCP 8.5)		

Appendix 4: R script for ENM of BRT

```
library(maps)
library(sp)
library(rgdal)
library(raster)
library(rgeos)
library(maptools)
library(mapdata)
library(gbm)
library(dismo)
library (ResourceSelection)
library(dplyr)
library(tidyverse)
library (SDMPlay)
library(spatstat)
library(xlsx)
library (MASS)
library(spatialEco)
library(pROC)
library(randomForest)
library(boot)
library (Hmisc)
library(verification)

memory.limit(size=40000)# sets ample RAM for model runs to avoid bail out

#Input data preparation
####################

# access data storage folder
#--------------------------------
inputs<- ("C:/RF_data/Inputs") #data path
setwd(inputs)

#Read spatial data
#----------------------
studarea_bnd <- readOGR("historicalCentWestSouthSubs_bnd.shp")
kenya1<-readOGR("kenya1.shp")# used to provide uniform CRS
projcrs <- crs(kenya1)
maskedbnd<- readOGR("historicalWestSouthSubsLess5kmbuff.shp")# create 5km mask
around presences.
plot(maskedbnd)

#read occurrences-presence CSV
#------------------------------------
anthrax_occurences <- read.csv ("occurrence69Points.csv",header=TRUE, sep=",")
anthrax_occurences <-anthrax_occurences[,3:4]
head(anthrax_occurences)

#accessing and stacking the raster files
#--------------------------------------------
```

```
setwd("C:\\RF_data\\Inputs\\VIF\\BRT") #raster path to any predictor raster data (e.g. environmental, climate)
tifFiles <- Sys.glob ('*.tif')
predictors_anthrax <-stack(tifFiles,quick =F)

#model loop run steps
###################
set.seed(100)
mylist<-list()
bs.list <- list()
dps <- list()
nrep=100 # initialising 100 runs
for (r in 1:nrep){
  setwd("C:\\RF_data\\Inputs\\VIF\\runs_brt2")# run out put storage folder
  print(paste("run", r))
  set.seed(100)# setting reproducibility in the model runs

  #generate pseudo-absence random points
  anthrax_pseudos<-spsample(maskedbnd,n=178,"random", cellsize=5000)
  anthrax_pseudos_df<-data.frame(anthrax_pseudos)
  anthrax_pseudos_df<-anthrax_pseudos_df[,1:2]
  plot(anthrax_pseudos)

  #convert dataframes to spatial data
  anthrax_occurences_points <- SpatialPointsDataFrame (anthrax_occurences, anthrax_occurences,proj4string = projcrs)
  head(anthrax_occurences_points)

  plot(anthrax_occurences_points,Add=T)
  anthrax_pseudos_points <- SpatialPointsDataFrame (anthrax_pseudos, anthrax_pseudos_df, proj4string = projcrs)
  head(anthrax_pseudos_points)

  #partitioning data into training (75%) and testing (25%)
  #-----------------------------------------------------------------
  #For presence data
  group<-kfold(anthrax_occurences_points,10)
  prescence_train<-anthrax_occurences_points[group! =1,] #set 75% of the presence data as your training data
  prescence_test<-anthrax_occurences_points[group==1,] #set 25% of the presence data as your testing data
  #For pseudo-absence data
  group<-kfold(anthrax_pseudos_points,10)
  absence_train<-anthrax_pseudos_points[group! =1,]   #set 75% of the absence data as your training data
  absence_test<-anthrax_pseudos_points[group==1,]   #set 25% of the absence data as your training data

  #plotting training presence and absence points
  #-----------------------------------------------------
  train_ponts <- rbind( prescence_train , absence_train)
  plot(maskedbnd)
```

```
points (train_ponts)

#extracting train data from predictor raster
#------------------------------------------------
file1<-raster::extract(predictors_anthrax,prescence_train,method='simple')
outcome<-rep(1,dim(file1)[[1]])
file1<-cbind(outcome,file1)

file2<-raster::extract(predictors_anthrax,absence_train,method='simple')
outcome<-rep(0,dim(file2)[[1]])
file2<-cbind(outcome,file2)

#combine presence and absence train data
train_data<-as.data.frame(rbind(file1,file2))

# persist run train data into csv files
write.csv(train_data,
paste0(getwd(),Sep="/","trainData.csv"),row.names=TRUE,col.names=FALSE)

#extracting testing data from predictor raster
#--------------------------------------------------
pre_testdata<-raster::extract(predictors_anthrax,prescence_test,method='simple')
outcome<-rep(1,dim(pre_testdata)[[1]])
pre_testdata<-cbind(outcome,pre_testdata)
pre_testdata<-na.omit(pre_testdata)

abs_testdata<-raster::extract(predictors_anthrax,absence_test,method='simple')
outcome<-rep(0,dim(abs_testdata)[[1]])
abs_testdata<-cbind(outcome,abs_testdata)
abs_testdata<-na.omit(abs_testdata)

#combine presence and absence test data
test_data<-as.data.frame(rbind(pre_testdata,abs_testdata))

# persist run train data into csv files

write.csv(test_data,paste0(getwd(),Sep="/","testData.csv"),row.names=TRUE,col.names=FA
LSE)

#modelling and Evaluation
####################
#fitting model and selecting variables
#------------------------------------------
col<-ncol(train_data)
brt_step <-gbm.step(data = train_data, gbm.x = c(2:col), gbm.y = 1,family = "bernoulli",
tree.complexity = 5,learning.rate = 0.001, bag.fraction = 0.5,max.trees = 2500,n.folds = 10)
      #n.trees=brt_simplify_step$n.tree, type='response', format='GTiff',overwrite=TRUE)#
outputs predicted #distribution rasters.

#storing BRT run objects
#-----------------------------
```

```
  brt_step.bs <- try(gbm.step(data=train_data[sample(NROW(train_data), NROW(train_data),   replace=T),], gbm.x =c(2:col),
                          gbm.y = 1, family = "bernoulli", tree.complexity = 5, learning.rate = 0.001, bag.fraction = 0.5,max.trees = 2500,n.folds = 10,
                          verbose=TRUE, silent=FALSE, plot.main=TRUE))
  if (class(brt_step.bs) == "try-error") next
  bs.list[[r]] <- brt_step.bs
  cat("This is replicate number ", r, "\n")
  save(bs.list, file="bs.list.Rdata")
  rm(brt_step.bs)

  #storing run AUcs
  #----------------------
  AUC<-brt_step$cv.statistics$discrimination.mean
  mylist<-append(mylist,AUC)
  }
 #create AUC excel file
 #---------------------------
 write.xlsx(unlist(mylist),"AUC.xlsx")

#Get CI values
#-----------------
CI.mat <- matrix(ncol=nrep, nrow=124)
for (i in 1:nrep) { CI.mat[,i] <- predict.gbm(bs.list[[i]], newdata=train_data, n.trees=2500,
                                       type="response")
  CIs <- apply(CI.mat, 1, quantile, c(0.25,0.5, 0.975), na.rm=T)
 }

# BRT partial plots with CI
#--------------------------------
xlims=c(0,520)
partial <- plot.gbm(brt_step, i.var="CDens", return.grid=T)
plot.new()
plot(partial, type="l", main="", col="blue",ylab="", xlim=xlims, xlab="EVI", ylim=c(-0.15,0.2),
     yaxs="i", las=1, xaxs="r", cex.lab=1, tcl=0)
abline(h=0, col="red")
newx <- seq(min(train_data$CDens, na.rm=T), max(train_data$CDens, na.rm=T),len=124)

#bootstrap lines:
lines(newx, predict.gbm(brt_step, newdata=train_data, n.trees=200, type="response"), col="grey40", lwd=2,
      type="s")
matlines(newx, t(CIs), col=rgb(.2,.2,.2,.4), lwd=3, type="o", lty=c(2,1,2),xlim = xlims,ylim=c(-0.15,0.2))

#creating mean of the predictions and CIs
##################################
#Mean of Predictions
setwd("C:\\RF_data\\Inputs\\VIF\\runs_brt2")
tifFiles <- Sys.glob('*.tif')
predicted<-stack(tifFiles,quick=F)
```

```
mean_narm = function(x,...){mean(x,na.rm=TRUE)}
Predict_mean<- do.call(overlay, c(predicted, fun = mean_narm))
writeRaster(Predict_mean,filename='mean_predictBRT', format="GTiff", overwrite=TRUE)
meanPred<-raster("C:\\RF_data\\Inputs\\VIF\\runs_brt2\\mean_predictBRT.tif")
plot(meanPred)

#Upper 97.5% of predictions
setwd("C:\\RF_data\\Inputs\\VIF\\runs_brt2")
tifFiles <- Sys.glob('*.tif')
predicted<-stack(tifFiles, quick=F)
uci_narm = function(x,...){quantile(x, probs = c(0.975),na.rm=TRUE)}
Predict_uci<- do.call(overlay, c(predicted, fun = uci_narm))
setwd("C:\\RF_data\\Inputs\\VIF\\runs_brt2\\CI")
writeRaster(Predict_uci,filename='uci_predictBRT2', format="GTiff", overwrite=TRUE)
uciPred<-raster("C:\\RF_data\\Inputs\\VIF\\runs_brt2\\CI\\uci_predictBRT2.tif")
plot(uciPred)

#Lower 2.5% of predictions
setwd("C:\\RF_data\\Inputs\\VIF\\runs_brt2")
tifFiles <- Sys.glob('*.tif')
predicted<-stack(tifFiles, quick=F)
lci_narm = function(x,...){quantile(x, probs = c(0.025),na.rm=TRUE)}
Predict_lci<- do.call(overlay, c(predicted, fun = lci_narm))
setwd("C:\\RF_data\\Inputs\\VIF\\runs_brt2\\CI")
writeRaster(Predict_lci,filename='lci_predictBRT2', format="GTiff", overwrite=TRUE)
lciPred<-raster("C:\\RF_data\\Inputs\\VIF\\runs_brt2\\CI\\lci_predictBRT2.tif")
plot(lciPred)
```

Appendix 5: Application of AHP to derive criteria weights

Eight environmental, demographic, economic and health criteria were subjected to AHP process to determine their relative weights in assessing the socio-economic vulnerability to anthrax risk. The criteria included: exposure (predicted anthrax distribution (AN)); sensitivity (Land cover use (LC), Poverty index (PI), Population density, (PD), Severe wasting prevalence (SP) Infant mortality rate (IM)); adaptive capacity, (Income index (IG) and Literacy level (LL))

Criteria importance values for each criterion relative to the other criteria were determined based Saaty's fundamental scale resulting pairwise comparison matrix (**Table 1**). The assigned importance values were arrived at from literature review and expert consultations. The order of developing the comparison matrix was such that, the importance values were assigned to a criterion relative to others based on the deemed relative strength (or not) in the row cells ($i_{1\text{-}n}$, $j_{1\text{-}n}$) and reciprocal judgment values assigned in column cells ($j_{1\text{-}n}$, $i_{1\text{-}n}$) of the lower triangular matrix (cells before the diagonal cells usually contains value=1). The comparison matrix (table) was to enable calculation of λmax (eigenvalues) through initial derivation of eigenvector (relative weights). λmax values are prerequisite for the calculation of Consistency Index (CI) hence Consistency Ratio (CR). Consistency ratio indicates the acceptable limit of consistency at CR < 0.1. There exist several methods for calculating the eigenvector (relative weights). In this study, the method adapted was that of multiplying each row entry of the matrix together then taking the 8th root of the products to give approximation of the eigenvectors for each row. The process of deriving λmax values was as the following outline:

1) First, the 8^{th} root of the product of the row matrix criteria pair values was determined for the eight (8) criteria to derive eigenvector, ω.
2) Each eigenvector value was normalised with their overall sum for eigenvector values to add to one (1). Then, each matrix row value ((i_k, j_n) for the criteria pair was multiplied by the corresponding normalized eigenvector column values (e.g., row (i_1, j_1) to normalized eigenvector (cell 1) and row (i_2, j_2) to normalized eigenvector (cell 2)) then the results summed up to obtain a new vector, Aω.

3) Finally, each Aω was multiplied by the corresponding normalized eigenvector resulting eigenvalues, λmax. Mean of λmax estimates the overall eigenvalue and must be larger than the number of criteria fitted for non-erroneous calculations.

Table 1: Pairwise comparison matrix for factor criteria

	AN	LL	PI	IG	LC	SP	IM	PD	Eigenvector	Normalised Eigenvector(ω)	Aω	Eigenvalues (*λMax)*
AN	1	2	2	2	3	2	3	7	2.374	0.24	2.038	8.409
LL	0.5	1	2	2	3	3	3	7	2.100	0.21	1.777	8.290
PI	0.5	0.5	1	1	3	2	3	5	1.476	0.15	1.239	8.223
IG	0.5	0.5	1.0	1	3	2	2	7	1.463	0.15	1.235	8.269
LC	0.3	0.3	0.3	0.3	1	2	2	3	0.788	0.08	0.686	8.532
SP	0.3	0.3	0.5	0.5	0.5	1	2	3	0.733	0.07	0.621	8.299
IM	0.3	0.3	0.3	0.5	0.5	0.5	1	3	0.586	0.06	0.499	8.337
PD	0.1	0.1	0.2	0.1	0.3	0.5	0.3	1	0.275	0.03	0.229	8.164
Total	3.0	6.0	6.5	10.2	13.0	16.0	25.5	32	10.259	1.000		

Eigenvalues (λmax)

$\lambda\mathbf{max} = \dfrac{\mathbf{A\omega}}{\boldsymbol{\omega}}$ *(where: **λmax**), estimates of the eigenvalues for each matrix row; **Aω**, overall sum of row, eigenvector products; **ω**, the normalised eigenvectors)*

λmax $_{(1\text{-}8)}$ = (8.409, 8.290,8.223,8.269,8.532,8.299,8.337,8.164); mean **(λmax**) = 8.315
Mean of λmax is larger than 8 therefore there was no error in the calculations.

Consistency Index (CI)

$$CI = \frac{\lambda_{max} - n}{n-1}$$

CI = (8.3-8)/ (8-1) = 0.45 (*where: λMax,* mean **(λmax**)*; n, the count of criteria*)

Consistency Ratio (CR)

$$CR = \frac{CI}{RI}$$

= 0.45/1.41= 0.03 (*where: RI is the Saaty's random index corresponding to n in **Table 2)***
Consistency ratio of 0.03 is less than 0.1 and therefore the derived weights lie within acceptable limit of consistency.

Table 2: Saaty's random index (R) for the order of the matrix (N)

N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Appendix 6: Publications

The respective chapters of this thesis have generated the following peer reviewed publications as listed.

1. **Otieno, F.T**., Gachohi, J., Gikuma-Njuru, P., Kariuki, P., Oyas, H., Canfield, S.A., Blackburn, J.K., Njenga, M.K. and Bett, B., 2021. Modeling the spatial distribution of anthrax in southern Kenya. PLOS Neglected Tropical Diseases, 15(3), p.e0009301.
2. **Otieno, F.T**.; Gachohi, J.; Gikuma-Njuru, P.; Kariuki, P.; Oyas, H.; Canfield, S.A.; Bett, B.; Njenga, M.K.; Blackburn, J.K. Modeling the Potential Future Distribution of Anthrax Outbreaks under Multiple Climate Change Scenarios for Kenya. Int. J. Environ. Res. Public Health 2021, 18, 4176. https://doi.org/10.3390/ijerph18084176