Predictive Modelling of Climate Change Impacts on Disease Dynamics in Tanzania

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This thesis is dedicated to:

Mum, Janet.

&

Nan, Kath.

For being inspirational role models, and instilling in me the values of passion, self-belief and true grit.

Thank you.

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List of abbreviations

ACT	Artemisinin Combination Therapy
AFMm	Affordable Medicines Facility for malaria
AQ	Amodiaquine (antimalarial)
CHIKV	chikungunya virus
CQ	Chloroquine (antimalarial)
DEMETER	Development of a European Multi-model Ensemble System for seasonal to Inter-annual prediction.
DMC	Disease Model Cradle (University of Liverpool)
EALLJ	East African Low Level Jet
EARS	East African Rift System
ECMWF	European Centre for Medium-Range Weather Forecasting
ERA	ECMWF Reanalysis
ESA	European Space Agency
ENSO	El Niño Southern Oscillation
EOCHA	Earth Observation for Climate-related Health risk in Africa
GCM	Global Circulation Model
ITCZ	Inter-Tropical Convergence Zone
ITN	Insecticide Treated Net
IPCC	Intergovernmental Panel for Climate Change
JJAS	June, July, August, September
LLIN	Long-Lasting Insecticide treated Net
MAM	March, April, May
MAP	Malaria Atlas Project (University of Oxford)
MDAST	Malaria Decision Analyst Support Tool

MJO	Madden-Julian Oscillation
MO	Met. Office
MoHSW	Ministry of Health and Social Welfare (Tanzania)
mRDT	malaria Rapid Diagnostic Testing
NATNETS	National Insecticide Treated Nets programme
NASA	National Aeronautics and Space Administration
NBS	National Bureau of Statistics (Tanzania)
NCAR	National Centre for Atmospheric Research
NDVI	Normalised Difference Vegetation Index
NEO	NASA Earth Observation
NOA	North Atlantic Oscillation
NOAA	National Ocean and Atmospheric Administration
NWP	Numerical Weather Prediction (model)
OND	October, November, December
PPP	Public Private Partnership
PROVOST	Predictability Of climate Variations On Seasonal to inter-annual Timescales
QAACT	Quality-Assured Artemisinin Combination Therapy
RCP	Representative Concentration Pathway
ROC	Relative Operating Characteristic
SAO	Southern Atlantic Oscillation
SOI	Southern Oscillation Index
SP	Sulfadoxine Pyrimethamine
SST	Sea-Surface Temperature
TNVs	Tanzanian National Voucher scheme

TZS	Tanzanian Shilling
UCC	Universal Coverage Campaign
UNDP	United Nations Development Programme
UNPD	United Nations Population Division
USAID	United States Agency for International Development
USD	United States Dollars
WHO	World Health Organisation
WMO	World Meteorological Organisation

Abstract

Climate and the environment are key determinants impacting various aspects of disease transmission, including lifecycle, survivability and prevalence. Recent changes in both the long-term climatology, and short term El Niño events are impacting the spatial distribution of disease, increasing the number of people being at higher risk of contracting fatal diseases. These changes are particularly detrimental in developing countries, where socioeconomic conditions hinder access to disease prevention and treatment.

This thesis explores climate, environment and disease interactions using multiple epidemiological modelling methodologies to develop an informative framework within which disease risk can be assessed, to aid decision-making. Statistical analysis of the impact of extreme events indicate that El Niño has a significant impact on the Tanzanian climate, which differs by location. Spatial modelling results demonstrate that by 2050 under RCP 8.5 mean malaria risk will initially reduce by 4.7%, which then reverses to an increase of 8.9% in 2070. Overall, analysis indicates increases in mean malaria risk. Biological modelling indicates that the predicted increases in malaria risk are likely a result of the reduction in time taken to complete the sporogonic and gonotrophic cycles due to increasingly optimum environmental conditions. The novel approach applied here contributes the development of a new model in environmental epidemiology.

This thesis concludes that epidemiological modelling results could be beneficial in aiding decision makers to prepare for the impact of climate and environmental change, with a recommendation to continue research in this area with a particular focus on understudied and developing countries.

Declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or institute of learning.

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Chapter 1 : Introduction and aims

1.1 Background

Tropical diseases are those which are prevalent and unique to tropical regions, defined as those between the tropics of Capricorn (23 30’ °S) and Cancer (23 30’ °N). Historically, these diseases have been located as such due to suitable climate and environment conditions, which support and drive a plethora of diseases. Changes in climate, and subsequently, environmental conditions, have resulted in many tropical diseases emerging outside of historic altitudinal boundaries, alongside re-emerging and re-surging within previous known limits (Pathirana, 2013).

Climate and environmental changes are identified as responsible for the emergence of diseases outside of previously known boundaries, and increasing mortality in current areas (Parham and Michael, 2010; Altizer et al., 2013). This becomes increasingly apparent during El Niño conditions, where increases in epidemic outbreaks in sub-Saharan countries have been observed (Kilian et al., 1999; Kovats et al., 2003). Whilst the underlying biological and ecological determinants of infectious tropical diseases are increasingly well understood, the impacts of climate change on the epidemiological transition of diseases remain unclear, and are becoming increasingly important in epidemiological research (Khormi and Kumar, 2015).

At present, it is estimated that 13 million deaths will be attributed to infectious diseases, the majority of which will be caused by just a few pathogens and parasites: among the 1400 currently recognised (Dye, 2014). Vector-borne diseases are anticipated to play a large role in the changing distribution of disease as shown in figure 1.1 (IPCC, 1995). However, the specific impact of climate change on tropical diseases remains unclear, particularly in comparatively understudied countries which currently possess a high disease burden, such as Tanzania in East Africa.

Disease	Vector	Population at risk (million)[1]	Number of people currently infected or new cases per year	Present distribution	Likelihood of altered distribution
Malaria	Mosquito	2,400[2]	300-500 million	Tropics and Subtropics	Highly likely
Schistosomiasis	Water snail	600	200 million	Tropics and Subtropics	Very likely
Lymphatic Filariasis	Mosquito	1 094[3]	117 million	Tropics and Subtropics	Likely
African Trypanosomiasis (Sleeping sickness)	Tsetse fly	55[4]	250 000 to 300 000 cases per year	Tropical Africa	Likely
Dracunculiasis (Guinea worm)	Crustacean (Copepod)	100[5]	100 000 per year	South Asia, Arabian Peninsula, Central-West Africa	Unknown
Leishmaniasis	Phlebotomine sand fly	350	12 million infected, 500 000 new cases per year[6]	Asia, Southern Europe Africa, Americas	Likely
Onchocerciasis (River blindness)	Black fly	123	17.5 million	Africa, Latin America	Very likely
American Trypanosomiasis (Chagas disease)	Triatomine bug	100[7]	18 million	Central and South America	Likely
Dengue	Mosquito	1,800	10-30 million per year	All Tropical countries	Very likely
Yellow Fever	Mosquito	450	more than 5 000 cases per year	Tropical South America Africa	Likely

1. Top three entries are population-prorated projections, based on 1989 estimates.
2. WHO, 1994.
3. Michael and Bundy, 1995.
4. WHO, 1994.
5. Ranque, personal communication.
6. Annual incidence of visceral leishmaniasis; annual incidence of cutaneous leishmaniasis is 1-1.5 million cases/yr (PAHO, 1994).
7. WHO, 1995.

Highly likely Very likely Likely Unknown

GRID Arendal UNEP
GRAPHIC DESIGN : PHILIPPE REKACEWICZ

Source: Climate change 1995, Impacts, adaptations and mitigation of climate change: scientific-technical analyses, contribution of working group 2 to the second assessment report of the intergovernmental panel on climate change, UNEP and WMO, Cambridge press university, 1996.

Figure 1.1 - Likelihood of altered disease distribution (UNEP, n.d.).

This chapter introduces the thesis by discussing the broader context within which this research is based, providing an overview of the quantifiable epidemiological, climatic relationships in tropical diseases and presents the challenges imposed by socioeconomic pressures on the disease ecosystem. An introduction to epidemiological modelling and its role in policy and decision guidance is also provided. It then outlines the research aims and objectives, and provides the specific scope covered within this thesis. It concludes with an outline of the overall thesis structure.

1.2 Research context

1.2.1 Determinants of disease distribution

A wide range of factors have been identified as contributing to disease prevalence. These can be split into biological and ecological factors, referring to disease bacteria, parasite and disease vector (e.g. mosquitoes) behaviour including biting rate, parasite growth rates and reproduction cycles (Hagenlocher et al., 2014; Emami et al., 2017). Climate and environmental factors provide suitable transmission conditions and habitats. This includes variables such as temperature, rainfall, humidity and associated environmental changes including standing water and vegetation. Furthermore, underlying environmental factors which support the pooling of water such as soil drainage and slope are also influential (Davidson, 1995; Raso et al., 2009). In contrast to the environmental variables highlighted, socio-economic and cultural factors including population density, human behaviour and health policy, can all modify disease distribution and prevalence depending upon the aim of the specific intervention, or lack of.

Biological variables are arguably a better understood aspect of disease transmission (Khormi and Kumar, 2015). Biological variables dictate the rate at which diseases replicate, and the intensity at which they spread (Smith et al., 2014). Key biological cycles identified as indicators of epidemic outbreaks from vector-borne diseases are identified as the sporogonic (parasitic incubation) and gonotrophic cycles (reproduction cycle) (Hoshen and Morse, 2004). Transmission vectors are poikilothermic, indicating that their temperature is controlled by external ambient temperature, which further modifies parasite incubation periods, the gonotrophic cycle and survivability (Patz et al., 1998). Furthermore, reproduction cycles often require water for egg laying (Lardeux et al., 2008). Thus, external conditions must be, at minimum, suitable for biological processes to take place, where intensity varies with increasingly optimum climatic and environmental conditions.

Climatic variables control the local environment which support these biological processes and transmission (Teklehaimanot et al., 2004). Temperature plays an influential role in supporting parasite and vector reproduction, alongside vector survivability and larvae growth. Changes in temperature reduce the time taken to complete these processes, and increase transmission potential, for example during El Niño conditions (Jones et al., 2007; Parham and Michael, 2010). Temperatures which are too high or too low reduce and cease transmission, a feature often associated with increased altitude (Bødker et al., 2003).

Transmission in sub-Saharan Africa often demonstrates seasonality associated with rainfall and humidity conditions, with a strong disease abundance relationship observed with rainfall (Chabot-Couture et al., 2014). Humidity is poorly understood in comparison to temperature and rainfall, with stronger signals observed with air-borne diseases (Cheesbrough et al., 1995; Martens et al., 1995).Increasing research is being conducted to examine humidity, including the research within this thesis.

Sustained transmission requires the presence of a human host. Proximity to humans, and subsequent human behaviour, influences exposure to disease pathogens or transmitting vectors (Silué et al., 2008). As population density increases, this supports quicker transmission via promoting parasite growth, bacteria and vector communities, contributing to disease prevalence (Ryan et al., 2015). However, human behaviour, including use of bed nets, medical treatment and natural resistance to diseases resulting from high exposure in endemic countries, plays an unquantifiable role in influencing disease prevalence (Thomson et al., 1999; Alphey et al., 2010),

1.2.2 Epidemiological and climate modelling

This understanding of the strong interactions between biological and climatological variables has led to concerns surrounding the potential impact of climate change on the distribution of disease (Khormi and Kumar, 2015). These relationships are understood and mathematically characterised through slight abstract variations of the epidemiological triangle depicted in figure 1.2 (Diekmann and Heesterbeek, 2000). As indicated, climate (including rainfall, temperature and humidity) plays a role in every aspect of the epidemiological triangle, impacting upon hosts (humans), environment, agent (parasites) and if the disease is vector-borne, the transmission vector.

This relationship was initially represented by Sir Ronald Ross in 1897, using a series of simple mathematical equations to represent the cycle of the malaria parasite within mosquitoes. This model is now known as the Ross model (Finley et al., 2014). As new data has become available, accompanied by technological advances, several variations and extensions of modelling methods have built upon the Ross model to represent current knowledge based upon differing biological and climatological factors (Mandal et al., 2011).

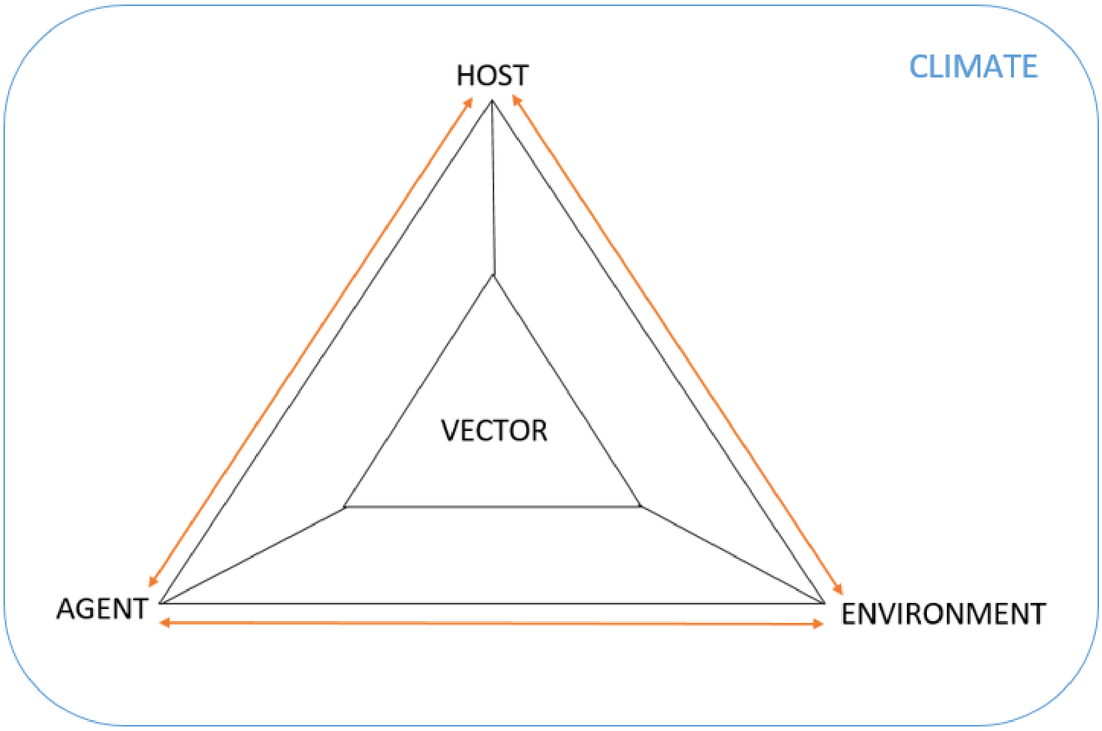


Figure 1.2 - The epidemiological triangle

Epidemiological and climate models allow for the examination of various climate, environmental and biological elements, where models range from simple deterministic mathematical models through to complex-spatially explicit stochastic and dynamic decision support systems (Khormi and Kumar, 2015). Such models have become a powerful tool in assisting health policy, and decision makers overseeing disease prevention and control (Murtaugh et al., 2017).

1.2.3 Epidemiological modelling and health policy

Epidemiological models have successfully been used to inform health policy design and implementation, through the interface of science and health policy presented in figure 1.3 (Samet, 2000). Implementation of policies and the subsequent management actions, which have been guided by epidemiological models have been identified as playing a positive and critical role in reducing morbidity and mortality of epidemic outbreaks (Gu and Novak, 2005; Khormi and Kumar, 2015). However, communicating and implementing recommendations discovered from epidemiological studies face numerous barriers. Increases in big data and research methodology used is associated with increased complexity of synthesising conclusions and results, which need to be clearly communicated to policy developers to enable progression (Wardekker et al., 2008; Murtaugh et al., 2017). Thus, it is imperative that scientific studies present clear conclusions and recommendations to enable uptake of research results into policy and practice.

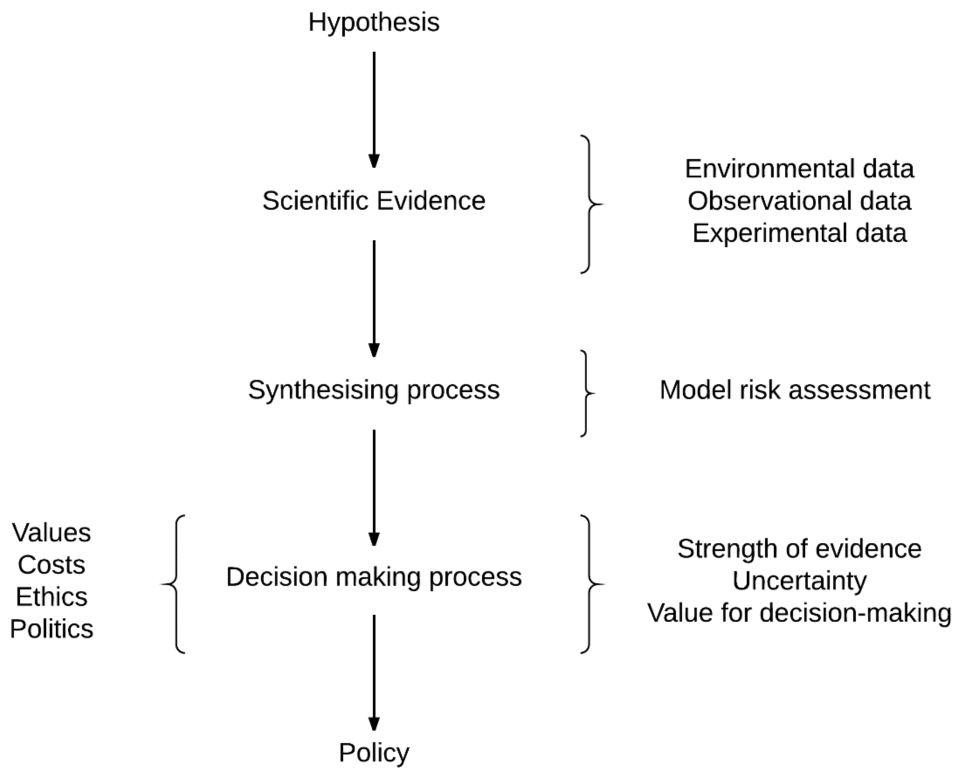


Figure 1.3 - The interface of science and health policy *(Samet, 2000)*

Organisations such as the World Health Organisation (WHO) and the Intergovernmental Panel on Climate Change (IPCC) play a crucial role in the collection and dissemination of health and climate data, guiding and funding global health policies where possible in order to provide order and support in the decision-making process (Peters et al., 2013; Smith et al., 2014b). Financing policies is a key concern and particularly challenging in developing countries, such as across sub-Saharan Africa. Where non-governmental organisations (NGOs) and impartial governmental bodies are unable to fund policies and preventions to the extent required, stakeholders can provide policy funding. However, policy makers are required to respond to the needs of the public as well as stakeholders, who provide financial backing, which can often influence the implementation of policy in a negative way and contain an element of politics (Brown et al., 2012; Mutero et al., 2014).

1.3 Research aims and objectives

The overarching research aim of this thesis is to develop a validated framework for the integration of environmental and biophysical information to support health and disease decision-making and risk modelling resulting from short and long-term climate change. This research aim is investigated through a number of associated objectives:

1. Identify key climatic characteristics and features of Tanzania, including assessing sensitivity to El Niño events.
2. Develop an environmental malaria risk model to model current and future malaria risk in Tanzania.
3. Establish the performance and predictions of a climatologically driven, dynamic mathematical-model for Tanzania.
4. Assess the validity, accuracy and usefulness for prediction of change in disease distribution and transmission for Tanzania.
5. Discuss the potential impact of socioeconomic characteristics, cultural behaviours and malaria policies on environmental model predictions.

1.4 Scope of the research

The relationship between climate change, environment and infectious diseases is large and complex. This section aims to focus the research by outlining the scope covered within this thesis.

1.4.1 The scope of climate change and epidemiological modelling

Climate change is referred to as a change in the state of climate, which can be identified (e.g. using statistical tests) by changes in the mean and/or variabilities in its properties, and that persists for an extended period of time, typically decades or longer (IPCC, 2007). This definition refers to any change in climate over a period of time, and includes both natural and human causes of variability.

This thesis will apply two epidemiological methodological approaches to build a model, examine the performance of current models, and predict disease risk based on a range of environmental, climatic and biological factors within Tanzania. These methods are:

- A weighted sum method implemented using geographical information systems (GIS)
- Dynamic mathematical-biological modelling

All model approaches include the minimum recommended climate components of rainfall and temperature, with an aim to go beyond this to include further known influential environmental variables (Chabot-Couture et al., 2014). There is currently no spatially explicit epidemiological model actively in use in guiding Tanzanian policy or actions. This will be further discussed within the context of the literature review and guiding future policy in chapter seven.

1.4.2 The scope of disease

Numerous tropical diseases are present in Tanzania, this thesis outlines three key tropical diseases which contributed to the identification of Tanzania as at risk of changing disease distribution. These diseases are malaria, bacterial meningitis, and chikungunya virus. Malaria and chikungunya are both vector-borne diseases and bacterial meningitis is an airborne disease. These diseases will be critically assessed within the literature review (chapter two) to reaffirm the identification of Tanzania as a country at high risk of climate induced changes in disease distribution. It is important to state here that malaria will be the main focus of this thesis, with bacterial meningitis examined during the climatological assessment of Tanzania only and chikungunya presented for context and awareness of the risk within Tanzania. The rationale for the focus on malaria is outlined in this section after a brief overview of the incidence of each disease in Tanzania.

Malaria (the main focus of this work) is endemic to Tanzania, and is globally, the most prevalent vector borne disease, with 214 million cases recorded in 2015, leading to 438,000 deaths (WHO, 2015c). Tanzania at present is the sixth highest contributor to the global malaria burden, with 678,207 reported confirmed cases, and 5368 deaths in 2014 (WHO, 2015c). Most deaths occur in children under the age of five, with potentially life debilitating disabilities for both adults and children that do recover from malaria. Malaria is caused by the parasite *Plasmodium falciparum*, and transmitted by mosquitoes, where multiple different species are capable of transmission (Githeko et al., 1996).

Bacterial meningitis is dominant along the “meningitis belt” which spans from Ethiopia in the east to Senegal in the west, and southward into northern Tanzania, encompassing 26 countries across sub-Saharan Africa in total. The meningitis belt does not extend into southern Tanzania at present. The largest epidemic in recent history (1996-1997), affected 250,000 people, causing 25,000 deaths and left 50,000 people disabled (Pandya et al., 2015).

Chikungunya virus (CHIKV), discovered in southern Tanzania in 1952, has gone through a period of quiescence, and there have been very few to no recorded incidences of the disease (Zhang et al., 2013). However, recent re-emergence of CHIKV cases outside of previously identified geographical boundaries, including northern Tanzania, has prompted the need for acknowledgement of this disease (Kajeguka et al., 2016). CHIKV is transmitted by a different vector to that which transmits malaria and is relatively poorly understood and understudied.

This thesis will focus on malaria due to the high scope of endemicity, morbidity and mortality currently present throughout Tanzania, with further consideration applied to malaria being identified as highly likely to experience changes in disease distribution (section 1.1, figure 1.1). Bacterial meningitis will be examined in a climatic context due to periodic epidemic (non-endemic) presence which has high morbidity and mortality rates in northern Tanzania only, thus impacting a smaller population. As such this will be included in a baseline climate assessment and provide recommendations for this disease only and will not be modelled. Concerns with chikungunya virus will be highlighted due to concerns of re-emergence within Tanzania, but due to the understudied nature and low admissions related to the disease and differing transmission vector to malaria, only the literature will be critically assessed to highlight and provide further context for the impact of climate change on changing disease distribution with climate change.

1.4.3 The scope of socio-economics, demographics and policy in disease transmission

This thesis will assess the role of dominant individual socio-economic determinants within the context on the impact of human behaviour on health risk (Vasilj et al., 2014). This will include the demographic distribution of population including both population density and investigate total populations at risk of changing disease distribution as a result of climate change. The impact of individual circumstances will also be outlined and discussed, for example access to healthcare, education, age, gender, occupation and wealth have all been identified as influential variables in disease transmission. This will be discussed in a deductive manner based on the literature as the impact of socioeconomic relationships are at present, unquantifiable on an individual level. Attempting to measure the relationships and total impact of all socioeconomic and demographic factors would not be possible at present.

Tanzania is a developing country with an estimated total population of 48.8 million as of 2015 (NBS, 2016). Population density is not evenly spread. Overall the country's population density is 51 (people per sq. km). However, regions such as Dar es Salaam have a much higher population density of 3.133 people per sq. km (NBS, 2013a). Higher population densities contribute to allowing disease to spread quickly, although also allow prevention methods and treatment to be facilitated for easier (Agwanda and Amani, 2014). The country has a diverse social structure, with percent of population below the basic needs poverty line ranging from 4.1% in Dar es Salaam, to 21.7% in other urban areas, reaching a maximum of 33.3% in rural areas. The last recorded country average is 28.2% of residents below the basic needs poverty line as of 2012 (NBS, 2016).

This thesis will examine health policies currently implemented within Tanzania, alongside proposed initiatives which are implemented by the Ministry of Health and Social Welfare (MOHSW). At present, many health initiatives implemented by the MOHSW centre around malaria prevention, as a result of its consistent clinical presence and high contribution to disease burden on the country (30%). These will be discussed in detail, and the impacts these policies have on population health explored.

1.4.4 The geographical scope: Study area

Tanzania is situated on the East African coastline, between longitudes 29° and 41° east and latitudes 1° and 12° south, bordering; Kenya, Uganda, Rwanda, Burundi, Democratic Republic of Congo, Zambia, Malawi, Mozambique and the Indian ocean (figure 1.4) (NBS, 2016). Tanzania encompasses the mainland (883,600 km^2) and the islands of Zanzibar, Pemba, Mafia, Ukerewe and Unguja. Tanzania mainland is the focus of this thesis, and will be referred to as Tanzania. Tanzania is situated in the Great Lakes region of Africa and includes Lake Victoria, Tanganyika, Nyasa, Rukwa and Eyasi within its borders.

Tanzania's topography is varied in elevation, ranging from 0 meters above sea level (masl) to the highest mountain summit (Mt. Kilimanjaro) at 5,895 masl. Tanzania's elevation varies considerably due to two branches of the East African rift system running through Tanzania, and an elevated central plateau. Elevational outlines can be observed in figure 1.4. Variability in elevation has been identified as a key variable in changing disease distribution, where previously unaffected areas at high elevation have begun to see transmission as a result of climate change (Githeko et al., 2000). Thus, Tanzania is a suitable case study country. In addition, countries located in East Africa, including Tanzania, are comparatively understudied in epidemiology and climatology in comparison to West Africa. This thesis will adopt a spatially explicit approach and all of Tanzania mainland will be included. Some regions may be highlighted for further analysis within specific chapters where the suitability of this will be discussed there.

Figure 1.4 - Location map of Tanzania, including key features and elevation *(Sémhur, 2014)*.

1.5 Research approach

This PhD thesis research adopts a predominantly quantitative approach. It utilises environmental modelling, epidemiological modelling and climate modelling. A range of GIS-based techniques are also applied, utilising geospatial data. Bespoke R code is also applied to perform statistical analysis which is used to verify theories and draw conclusions. A systematic and deductive approach is employed when assessing literature, and conclusions drawn from discussions focused on socioeconomic and policy interactions.

1.6 Thesis layout

This chapter introduced the scope and topic of the research, overarching research aims and objectives and identified a suitable region for analysis. The following chapters include:

- Chapter two critically reviews the key literature which underpins the context for this research. This includes an investigation of the key themes in this research, climate and climate change, climate and epidemiological modelling, disease dynamics and socioeconomic and health policy in Tanzania. This provides an in-depth review of relationships and interactions.
- Chapter three provides an overview of Tanzania's climatology and a statistical assessment of the sensitivity of Tanzania's climate to El Niño events. This addresses research objective one, and a paucity in the research since the sensitivity of Tanzania's climate to changes during El Niño events are currently under assessed.
- Chapter four presents the development of a spatially explicit weighted sum environmental risk model. This model is then used to forecast malaria risk under current and future climate conditions. Analysis of risk to populations

living in high risk areas at present and in the future, is undertaken with a view to aid policy makers. This chapter addresses research objective two.

- Chapter five assesses the changing biological conditions for malaria under future climate conditions using a climate driven dynamic mathematical-biological model. This chapter addresses research objective three.
- Chapter six provides a summary of the main conclusions drawn from the empirical work presented in chapters three, four and five.
- Chapter seven presents analysis of the role of non-physical socio-economic and population interactions on disease and how this modifies disease ecosystems beyond the drivers that can be physically modelled. This addresses research objectives four and five. Conclusions drawn from the work conducted in this thesis are then presented, summarising the contribution to knowledge, and providing recommendations for further research, policy and practice.

Chapter 2 : Literature review

2.1 Introduction

Climate is a key component affecting a disease life cycle and transmission. Tanzania’s climatic variability provides suitable living and transmission conditions for a host of diseases within the country (Tanser et al., 2003; Altizer et al., 2013). Recent evidence suggests a significant change in the dynamics of diseases affected by climate, including malaria, chikungunya and bacterial meningitis (Hoshen and Morse, 2004; Zhang et al., 2013). This review aims to provide an overview of the key climatic influences on Tanzania, including a critical discussion of the evidence supporting past and future climate change as well as outlining current climatic conditions and inter-annual variations. The impact of Tanzania’s varied and unique climate is then discussed in the context of disease presence and transmission, outlining how altering conditions are influencing changing disease dynamics through direct climatological impacts as well as indirectly through environmental change. Finally, the social and economic changes and challenges faced within Tanzania will be discussed, highlighting key features of health infrastructure, provision and accessibility. This will be reviewed in the context of climate and environmental change and the impact of this on health and health provision.

2.2 Climate

Climatic variables such as temperature, rainfall and humidity have a profound effect on a variety of both vector based and airborne diseases. These parameters provide suitable living and transmission conditions for a range of “tropical” based diseases as a result of disease vectors’ biological sensitivity to environmental conditions (Tanser et al., 2003; Altizer et al., 2013). Large-scale synoptic weather patterns such as El Niño and La Niña facilitate epidemics indirectly through affecting transmission vectors such as the mosquito and directly through diseases such as cholera. Equatorial Africa experiences a high burden of disease in coincidence with climate elements, of which rainfall varies considerably over space and time (Basalirwa et al., 1999). Generally, rainfall distributions can be associated with large scale synoptic activity; for example the low level convergent winds in the Inter Tropical Convergence Zone (ICTZ) and somewhat with that of the El Niño Southern Oscillation (ENSO) despite the limited understanding of climate dynamics surrounding the Indian Ocean (Basalirwa et al., 1999; Elliott and Kipfmueller, 2010). However, in East Africa the impact of mesoscale systems induced by regional characteristics such as large water bodies and topographic features results in increasingly variable rainfall patterns.

2.2.1 Current climate

Rainfall is considered the most significant climate parameter within Africa, with Tanzania experiencing two different rainfall regimes. Northern Tanzania is characterised by two annual maxima, the first lasting March until May (long rains) and the second from October to December (short rains) (Kijazi and Reason, 2005; Mapande and Reason, 2005). The processes which drive these mechanisms remain poorly understood as multiple contributors have been identified from a range of published research (Anyamba et al., 2002; Hendon et al., 2007). The bimodal pattern is largely driven by the ITCZ, subtropical anticyclones, African jet streams and global scale systems such as the El Niño/Southern Oscillation (ENSO), the Madden-Julian Oscillation (MJO) and to a lesser extent the Quasi-biennial Oscillation (QBO) (Kabanda and Jury, 1999; Mutai et al., 2000; Anyah and Semazzi, 2004). The most influential factors, including the unique influences of Tanzania's local topography on the distribution and onset of rainfall are also considered.

On average, total annual rainfall ranges from 200mm to 1000mm over most parts of the country (Basalirwa et al., 1999; Timiza, 2011; Griffiths et al., 2013). Some areas, particularly the coastal and northeastern and inland southwestern parts can see over 1500mm of rainfall with up to 3690mm being recorded in the southwestern highlands (Timiza, 2011; TMA, 2014). The lowland central region experiences significantly less rainfall, receiving the lower values of approximately 500mm (TMA, 2014).

Mean annual maximum temperatures range from 25°C to 32°C, with minimum averages ranging from 5°C to 20°C with the highland regions experiencing the colder temperatures in comparison to the lower lying regions (Timiza, 2011; TMA, 2014). A summary of climatological zones and their rainfall and temperature statistics is shown in table 2.1. Figure 2.1 shows the geographical location of each of the discussed zones in table 2.1.

Table 2.1 - Rainfall and temperature statistics in the eight climatological zones of Tanzania. Source: TMA (2014).

S/N	Climatological Zone	Mean Annual Rainfall (mm)	Mean Monthly Max. temperature (°C)	Mean Monthly Min. temperature (°C)
1	Lake Victoria Basin (Mara, Kagera, Mwanza and Shinyanga)	1128	29.0	15.4
2	Nort Eastern Highlands (Kilimanjaro, Arusha and Manyara)	786	33.1	8.3
3	North Coast (Dar es Salaam, Zanzibar, Tange, Pemba and part of Morogoro)	1268	32.4	18.2
4	Southern Coast (Mtwara and Lindi)	1180	32.4	18.2
5	South (Ruvuma, Songea and Mahenge)	1169	26.0	15.9
6	South Western Highlands (Mbeya, Iringa, Ruvuma, part of Rukwa, and part of Morogoro)	776	26.6	5.3
7	Central (Dodoma, Singida and part of Tabora)	630	31.1	13.7
8	Western (Kigoma, part of Rukwa and part of Tabora)	1105	30.3	16.5

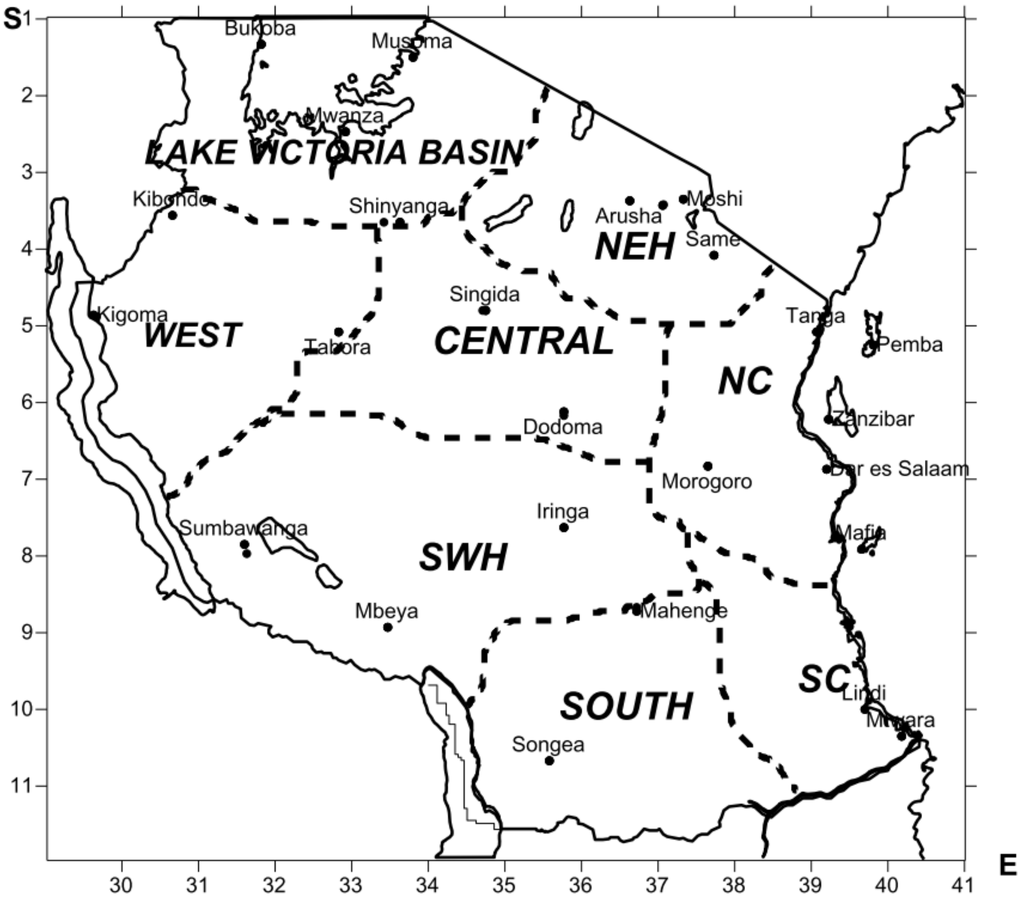


Figure 2.1 - Climatological Zones of Tanzania. Source: TMA, 2014.

2.2.2 Evidence of past climate change

When assessing changes over the long-term trend, several changes in climatic parameters have been observed. McSweeney et al. (2010) undertook an analysis of change in Tanzanian climatic parameters since 1960 as part of the United Nations Development Programme (UNDP). Statistical analysis of observations of precipitation over Tanzania demonstrate significant decreasing trends in annual, JJAS and MAM rainfall. This conclusion is supported by studies conducted by Hulme (1992; 1996), Dore (2005) and others, which concluded that extreme events, particular droughts, have become increasingly common. The greatest change was seen in the southern most regions of Tanzania, decreasing a total of 4.8mm a month per decade since 1960 (McSweeney et al. 2010; Hulme 1992; Dore, 2005).

Evidence published by McSweeney et al. (2010) shows that mean annual temperature for Tanzania was observed to increase by 1°C since 1960, averaging 0.23°C per decade with the most rapid increases seen in January and February and the slowest in June, July, August and September. This is further supported by the World Meteorological Organisation (WMO) who report similar increases in overall temperature when compared to the long term mean (IPCC, 2014; WMO, 2015). However this reported change in temperature has not occurred uniformly across Tanzania with some areas experiencing greater change in comparison to others (IPCC, 2014; TMA, 2014).

2.3 Environment

The unique combination of Tanzania's landscape and climate forms a range of environments throughout the country. Tanzania is situated in the Great Lakes region of Africa, with the mainland containing five identified major lakes and rivers covering 61.5 sq/km within its borders, with the largest being Lake Victoria (table 2.2) (NBS, 2013b). These lakes form part of the East African Rift System (EARS) which runs through Kenya into Tanzania, splitting into three branches following western, central and eastern trajectories (figure 2.2) (Mattsson, 2009; Mulibo and Nyblade, 2016). The presence of a tectonic rift system has led to three key elevational features throughout Tanzania, predominantly the southeast mountain range, north-west mountain range (containing mount Kilimanjaro), and the Tanzanian plateau which contains the crater highlands to the north including the Ngorongoro crater (Mattsson, 2009). The topographical complexity contributes to providing a range of environments from low-elevation coastal regions to mountainous forest up the slopes of Mount Kilimanjaro.

Table 2.2 - Coverage of major lakes and smaller water bodies on mainland Tanzania *(NBS, 2013b)*

Major lakes	**sq.km**
Victoria	34.9
Tanganyika	13.4
Nyasa	5.6
Rukwa	2.8
Eyasi	1.0
Other water bodies on land mass (Small lakes, dams, rivers, etc.)	3.8
Total	61.5

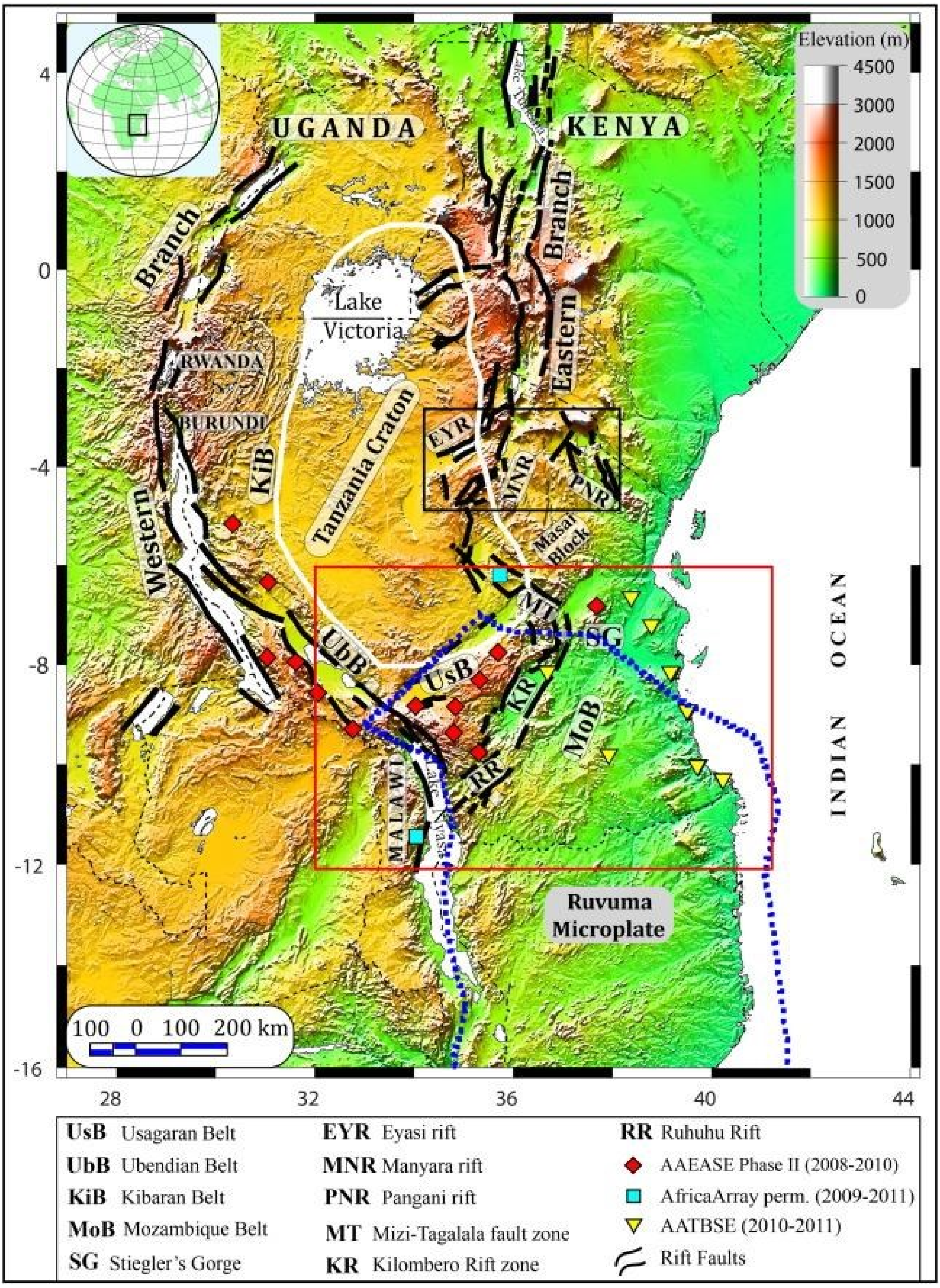


Figure 2.2 - Topographic map of East Africa showing the regional geology, including the Tanzania Craton (bold outline), the Proterozoic mobile belts surrounding the craton, the major Cenozoic rift faults and the three rift segments of the Northern Tanzania Divergence Zone (NDTZ). Seismic stations are also shown *(Mulibo and Nyblade, 2016)*.

As a result of complex tectonic activity, the underlying geology and mineral composition is equally complex, however locational patterns are discernible (figure 2.3). Coastal regions are predominantly underlain by fluvial sand, gravel, silt and limestone (Government of Tanganyika, 1955). The plateau region is underlain by a mix of plutonic rocks such as granite compounds and terrestrial sediments such as sand and gravel. The Kilimanjaro region is underlain by a mix of volcanic bedrock and Archean sediment and rock, such as marble and graphite (Fishwick and Bastow, 2011). Lake Victoria is underlain by a plutonic bedrock, consisting mostly of granite variates. Southern Tanzania, possesses elements of the Archean sediment bedrock and Mesozoic era continental and marine sandstone (Government of Tanganyika, 1955; Mulibo and Nyblade, 2016). Bedrock factors are important to consider in the context of soil drainage and water pooling, which are discussed in the context of malaria in chapter four (Patz et al., 1998; Githeko et al., 2000).

There is a distinctive variation in vegetation coverage throughout Tanzania as shown in figure 2.4 and accompanying legend in figure 2.5. Vegetation distribution can be observed to loosely follow underlying bedrock formations. Coastal areas (with the exception of artificial human settlements) are dominated by a mix of forestry and rain fed croplands. The Tanzania craton (surrounding Lake Victoria) is covered by cropland and open grassland (Mulibo and Nyblade, 2016). The southern regions (including southern highlands) are covered by a mix of forestry and shrub land, with increasing density of forest upslope with the exception of highly elevated peaks as is clear on Kilimanjaro (Duane et al., 2008). The western region of the Tanzanian plateau exhibits a greater mix of crop land, shrub land and open broadleaf forest. Vegetation coverage shifts with the movement of the rainfall seasons, however rainfall explains only half the variability in vegetation in the unimodal regime regions, with more links to vegetation coverage in the bimodal regime (Timiza, 2011).

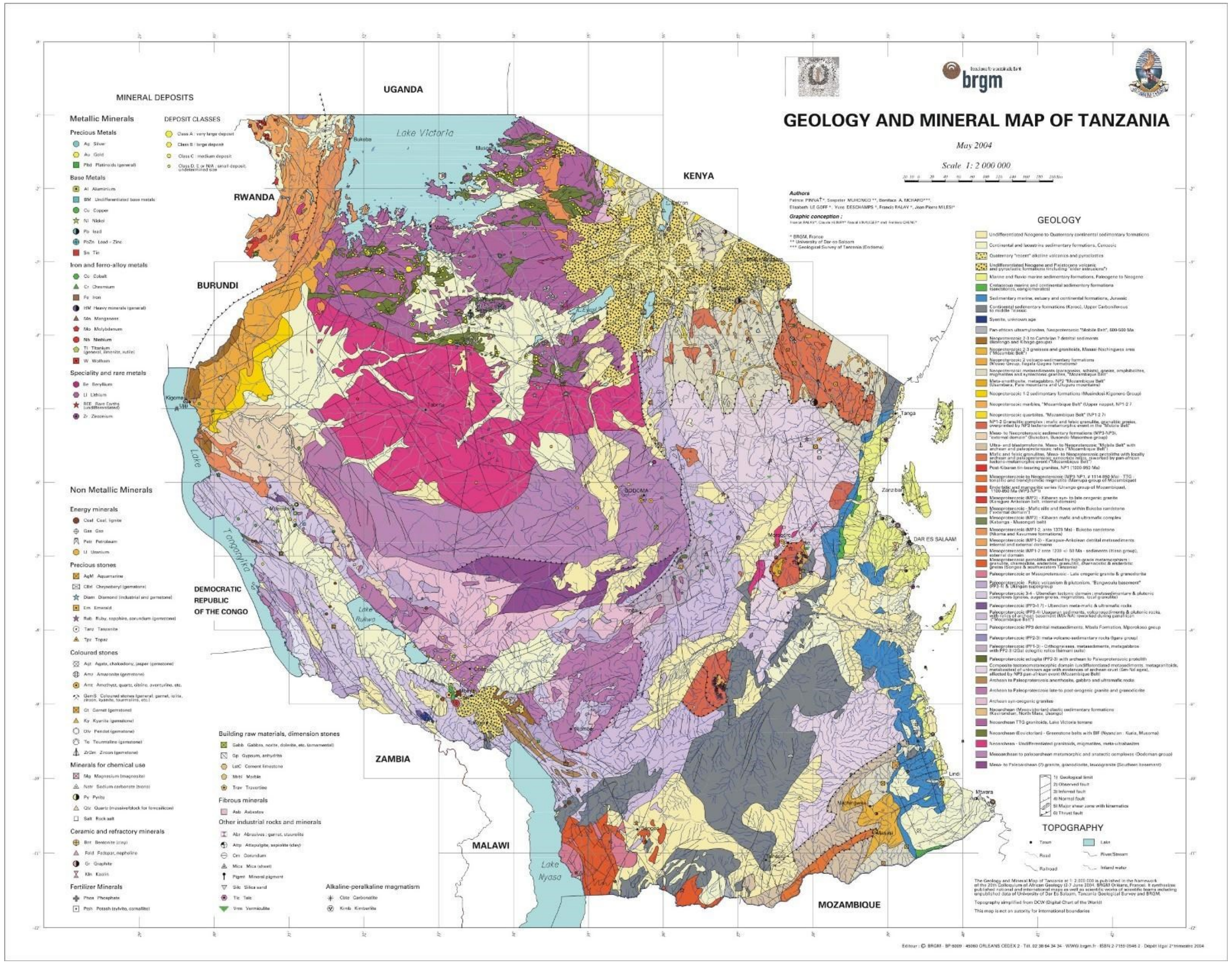


Figure 2.3 - Geology and mineral map of Tanzania (Geological Survey of Tanzania, 2004)

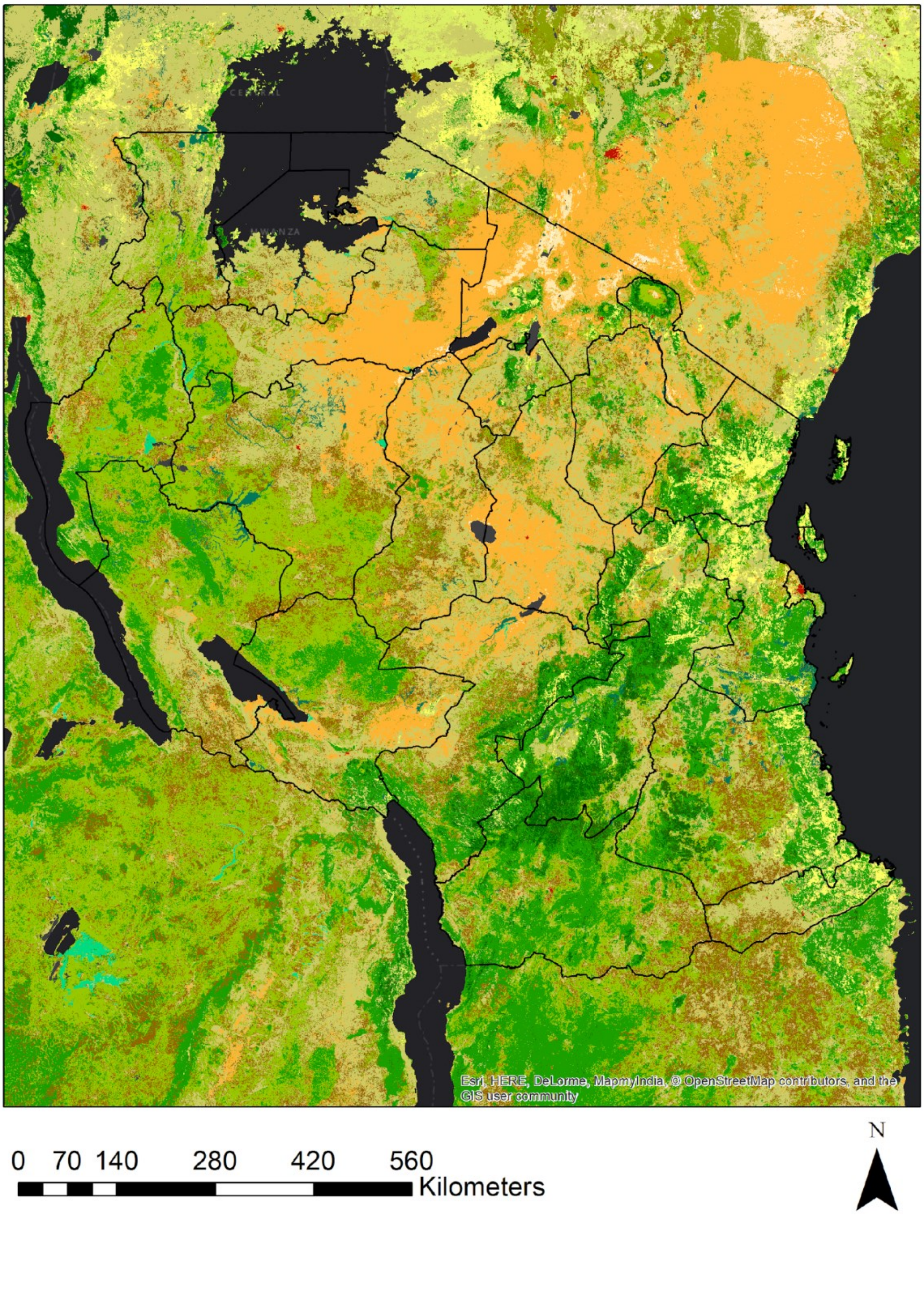


Figure 2.4 - ESA GlobCover, high resolution land use map of Tanzania *(ESA, 2009)*.

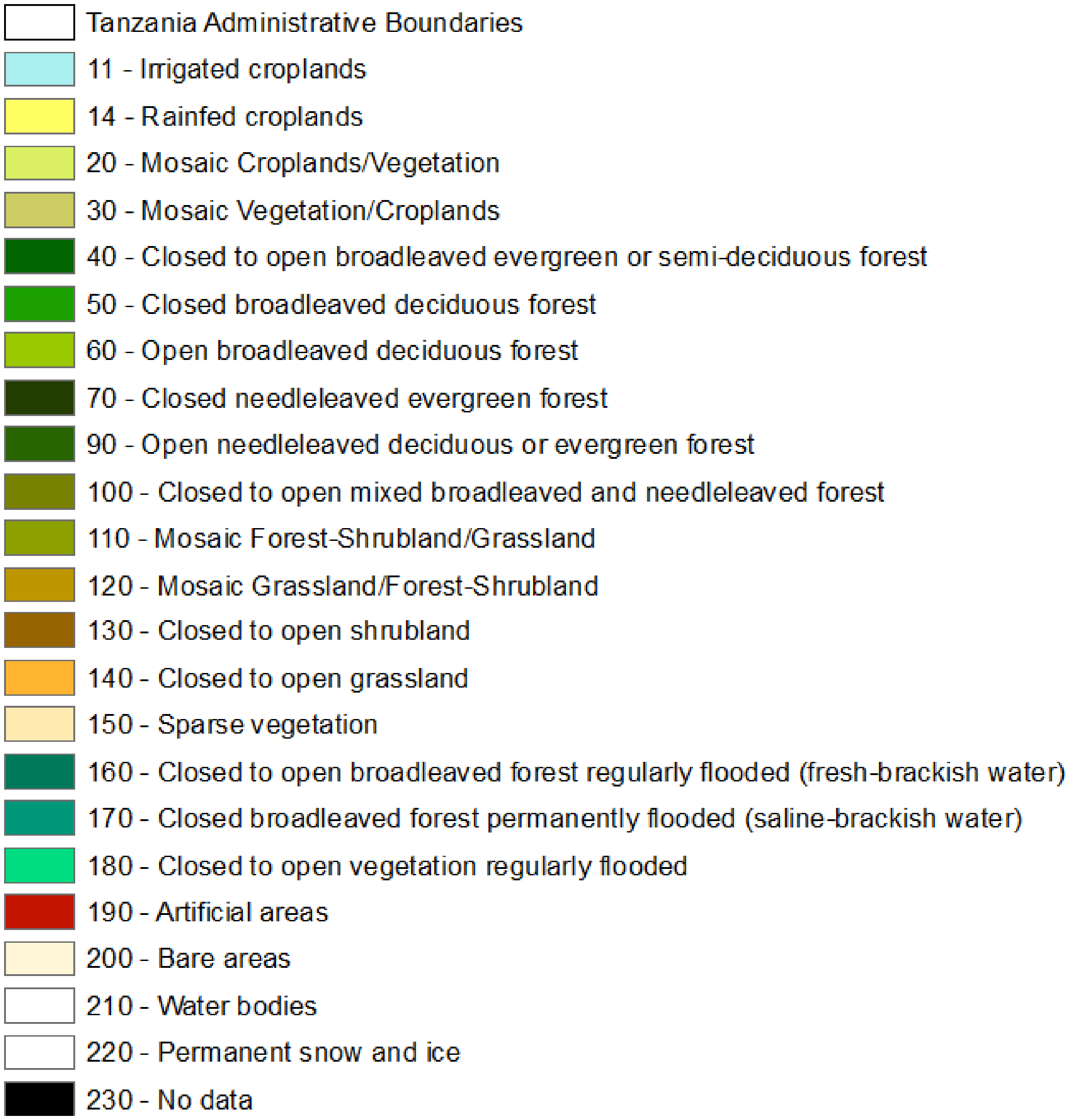


Figure 2.5 - Legend for figure 2.4 *(ESA, 2009)*.

2.4 Rainfall mechanisms

Initial examinations of the mechanics behind African rainfall variability stemmed from theory and observational studies undertaken by pioneers in teleconnection analysis such as Walker and Bliss (1932) whom demonstrated that these systems transcend latitudes having global impacts (Walker and Bliss, 1932; Nicholson, 1986). The initial evidence provided by Walker and Bliss has since been further supported by more robust studies such as that undertaken by Egger (1977) and Van Loon and Rogers (1978) whom had access to substantially more data than the former examiners (Wallace and Gutzler, 1981). Work conducted by the aforementioned has provided the basis of numerous examinations on teleconnection behaviour on both the North Atlantic Oscillation (NAO) and Southern Atlantic Oscillation (SAO), of which no major oppositions to the dynamical coupling between the northern and southern hemispheres have emerged. In general, when pressure is high above the northern Pacific, it tends to be low in the Indian Ocean spanning from Africa to Australia. These conditions are associated with lower temperatures in both hemispheres, with rainfall varying in the opposite direction to pressure (Walker and Bliss, 1932; Rasmusson and Wallace, 1983; Milesi et al., 2005; Barry and Chorley, 2010). This connection and confliction in atmospheric pressures is most clearly identified and defined by the Inter-Tropical Convergence Zone (ITCZ), a mechanism that plays a significant role in driving the equatorial climate.

2.4.1 Inter-Tropical Convergence Zone

The theoretical formation of the ITCZ began through the standard treatment of wind conditions near the equator, whereby the “trade winds” of the northern and southern Hadley convection cells blow toward the equator from the northeast and southeast in the northern and southern hemispheres respectively (Dobby, 1945; Barry and

Chorley, 2010). The meeting of the easterly moving trade winds creates a fast moving, rainfall laden low-pressure band, generally lying 6° north of the geographical equator and defining the meteorological equator (Waliser and Gautier, 1993; Hardman-Mountford et al., 2003). This fast moving band is predominantly driven by the release of latent heat stemming from the equatorial region, within which conditions (both location and band continuity) vary depending on atmospheric factors (Dobby, 1945; Fletcher, 1945). In order to provide the convective energy required, the ITCZ forms predominantly over the ocean, generally located over the warmest surface waters of at least 27.5˚C. Above this temperature threshold, organised convective activity is competitive between different regions resulting in either fragmentation or a sustained continuous ITCZ (Barry and Chorley, 2010; Schneider et al., 2014).

Upon reaching a substantial land mass, such as continental Africa, the contrasting forces exerted from the oceanic and continental pressure cells dictate the extent of ITCZ migration. Over the central Atlantic and Pacific Oceans, the ITCZ migrates between 9˚N and 2˚N in boreal winter. Over the Indian Ocean and its adjacent landmasses (including continental Africa), the ITCZ moves more significantly between the average latitudes of 20˚N in boreal summer and 8˚S in boreal winter (Schneider et al., 2014). Before the introduction of satellite technology, this considerably lower latitude ITCZ band was thought to be a commonly occurring separate entity, described as the double ITCZ. However following the assessment of satellite imagery, it has been accepted that a double ITCZ was in fact a rarity and the dip observed over the African landmass as a result of changes in convection as part of the whole ITCZ system (Hubert et al., 1969).

Extreme changes in the seasonal movement of the ITCZ can result in droughts or floods, depending on the climatic circumstances (Basalirwa et al., 1999; Indeje et al., 2000). Typically, the band of precipitation moves southward through Tanzania during October through to December, reaching the southern sections of the country in January and February before migrating during March, April and May (Basalirwa et al., 1999; Gaidet et al., 2012; McSweeney et al., 2013). This seasonal transition creates marked differences in annual rainfall distributions with defined monsoon seasons. Northern Tanzania experiences a bi-modal precipitation regime with the long rains (Masika) occurring between March and May (MAM), in conjunction with the ITCZ's northward movement. The short rains (Vuli) begin in mid-October and last until early December (OND), coinciding with the ITCZ's southward migration. Towards the central, southern and western areas of Tanzania a unimodal rainfall regime presides in association with the lowest migration point and curvature of the ITCZ band (figure 2.6) which starts from November and continues to the end of April (Zorita and Tilya, 2002; Rowhani et al., 2011; Timiza, 2011; TMA, 2014). Further detail on rainfall quantities and specific distribution can be found in section 2.2.1.

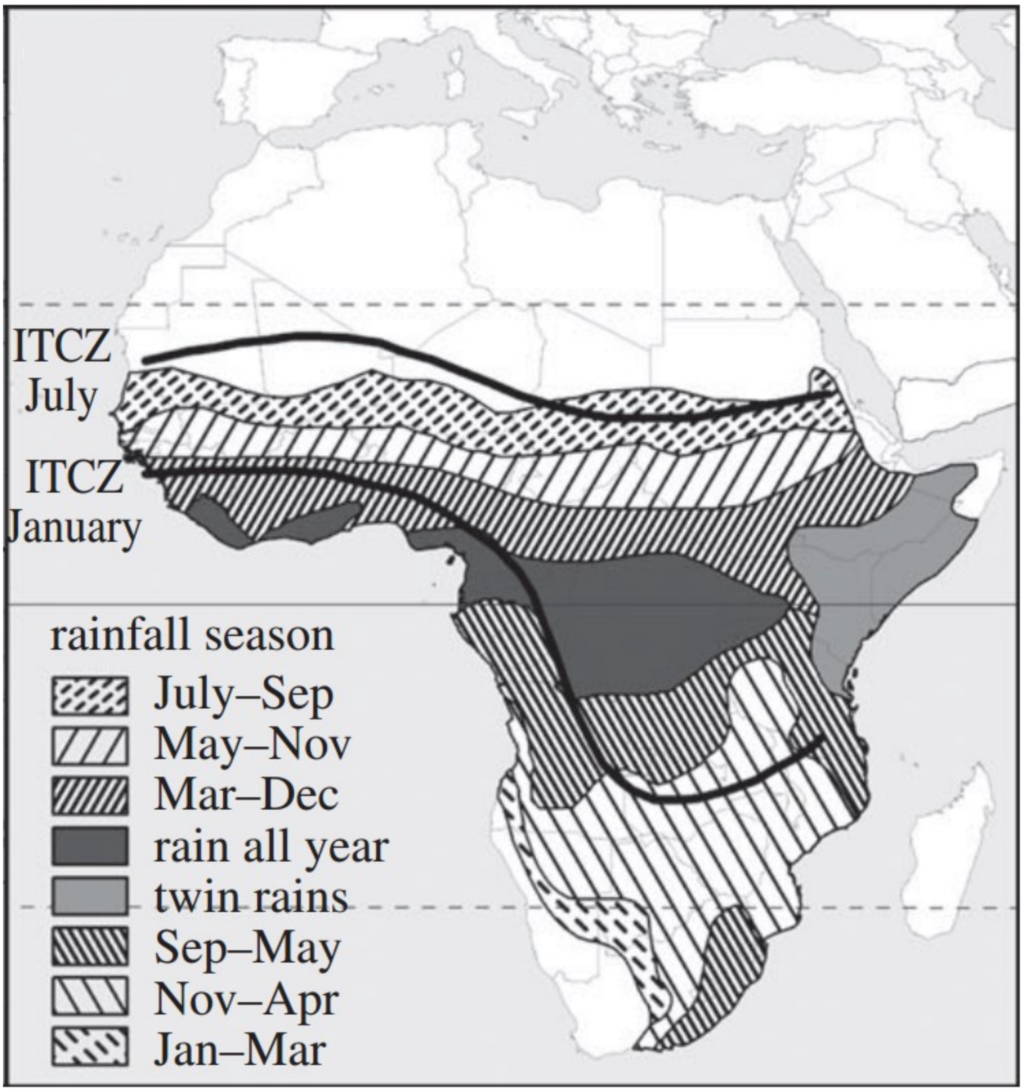


Figure 2.6 - Timing of the wet season and seasonal positon of the ITCZ (Gaidet et al. 2012).

2.4.2 El Niño Southern Oscillation

The El Niño Southern Oscillation (ENSO) is the most dominant inter-annual climate phenomenon in the tropical ocean-atmosphere system (Lau and Waliser, 2005). The El Niño anomaly represents the oceanic driver of climate, referring to the episodes of anomalously warm sea surface temperatures in the Niño 3 region, coupled with abnormally heavy rainfall in the equatorial Pacific (Niño 3.4 region) (Quinn et al., 1978). The Southern Oscillation component is a fluctuating bimodal wave of atmospheric mass between the eastern and western Pacific, and thus alters sea level pressure which is often represented by the normalised Southern Oscillation Index (Cane, 2005). Anomalous events are characterised by unusually warm (reduced air pressure) or cold sea surface temperatures in the Niño 3.4 region and are referred to as El Niño or La Niña respectively (Kogan, 2000; Detsch et al., 2016). Due to the tele-connective nature of the ENSO phenomena the impacts of changing SSTs and subsequent alteration to the connected air pressure and trade winds are known to significantly impact the global climate (Ropelewski and Halpert, 1987; Cane, 2005).

El Niño causes an overall increase in rainfall amount and temperature over the Tanzanian coastline during the OND season, and to a lesser extent during MAM, whereas La Niña results in a reduced amount of rainfall, with both impacting the rainfall seasonality (Nicholson and Selato, 2000; Kijazi and Reason, 2005). It must be noted that this influence does diminish towards the southern coastline as a result of approaching a transition zone between eastern equatorial and southern Africa (Kijazi and Reason, 2005). ENSO events are highly associated with Tanzania's OND season, more so than MAM, the drivers of which remain poorly understood, but have been loosely linked to ENSO through the Madden-Julian Oscillation which is discussed further in section 2.4.3 (Kabanda and Jury, 1999; Pohl and Camberlin, 2006b).

ENSO events are becoming increasingly predictable on seasonal scales with lead times of up to a year, the impacts of these events are increasing in uncertainty due to increasingly observed changes in the understanding of precipitation-ENSO connections and breakdowns in occurrence relationships (Anyamba et al., 2002; Thomson et al., 2006a). There has been increased reporting of breakdowns in the inverse relationship between ENSO and the Indian summer monsoon, leading to speculations that changes in global temperatures could influence Walker circulations and the land-ocean thermal gradient (Kumar et al., 1999; Ashrit et al., 2001). This is noted to be inconsistent as this relationship was present in the 2001-02 ENSO event (Cane, 2005). Overall, this reduces certainty in predictions based on ENSO impacts as it remains unclear how climate change will impact future ENSO events and subsequently the behaviour of Tanzanian rainfall (Ashrit et al., 2001; Thomson et al., 2006a).

2.4.3 Madden-Julian Oscillation

The Madden-Julian Oscillation (MJO) is characterised by a seasonally peaking, eastward-propagating tropical convective wave system and associated circulation anomalies with a time period between 30 and 60 days (Madden and Julian, 1994; Slingo et al., 2004). Regeneration of MJO convective anomalies begins over the Indian Ocean and propagates eastward evolving through a systematic cycle of amplification and decay (Hendon and Salby, 1994; Matthews, 2000). Where El Niño is considered the main mode of inter-annual variability, the MJO is recognised as a dominant driver of intra-seasonal variability in the tropics, with greatest activity occurring in boreal winter (Madden and Julian, 1994; Jones et al., 2004). The mechanisms driving its eastward movement and regeneration in the Indian ocean remain poorly understood and thus difficult to simulate in global climate models, though improvements continue to be made (Matthews, 2000; Slingo et al., 2004).

Studies conducted on the MJO to examine its global influence on climate, have observed seasonal responses from precipitation patterns to the peaks and troughs associated with the amplification and decay cycle of the MJO (Hendon and Salby, 1994). Results demonstrate that enhanced MJO activity in the Indian Ocean increases the likelihood of increased extreme precipitation over Tanzania when compared to quiescent episodes (Jones et al., 2004; Zhang, 2005). This impacts both the MAM and OND rainfall seasons, however responses are spatially different between each season which can be attributed to the influence of local topography and further differences in large scale zonal gradients which play differing roles in each season (Pohl and Camberlin, 2006a, 2006b). Further to this, there is mounting evidence of links with the onset of El Niño and further evidence suggesting that the MJO may be a coupled ocean-atmosphere phenomenon (Madden and Julian, 1994; Mutai et al., 2000; Hendon et al., 2007).

Strong MJO events have been frequently observed during the onset and growth stages of recent major El Niño events which has encouraged increased research into potential links (Kessler and Kleeman, 2000; Jones et al., 2004; Zhang, 2005; Hendon et al., 2007) . Results so far remain inconclusive, with differing and in some cases controversial conclusions reached. It is speculated that the MJO could influence ENSO events through the following; net cooling of SST's, alterations in zonal currents and suppression of the thermocline via oceanic Kelvin waves for which discussion of each can be found in the relevant papers (McPhaden, 1999; Zhang, 2005; Hendon et al., 2007; Zavala-Garay et al., 2008). It is important in the scope of this research to acknowledge the potential impacting links between the MJO and ENSO phenomena for which understanding is still limited. Interpretation of results will be treated based on understanding of the impact of individual phenomena with the consideration that this could change with further examination.

2.4.4 Topography and orography

Variations in topography (and land cover) can act as a strong regional scale forcing mechanism which is able to modify surface heating abilities and rainfall distribution patterns through mechanisms such as the adiabatic lapse rate, foehn effect, and influencing low lying jet streams (figure 2.7) (Sumner, 1982; Wang et al., 2004; Barry, 2012). The adiabatic lapse rate relationship is observed where increases in elevation result in reductions in atmospheric pressure which in turn changes local atmospheric characteristics, resulting in lower temperatures at higher altitudes (table 2.3) (Met Office, 2011; Maeda and Hurskainen, 2014). Lapse rates for Mt. Kilimanjaro have been documented in the literature, in particular by an extensive study carried out by Duane et al. (2008). Within the tropics, a typical lapse rate of 0.55°C/100m was observed by Lauer in 1976 (Hemp, 2006). However, Duane et al. (2008) report high variability in lapse rates recorded at different elevations (table 2.3).

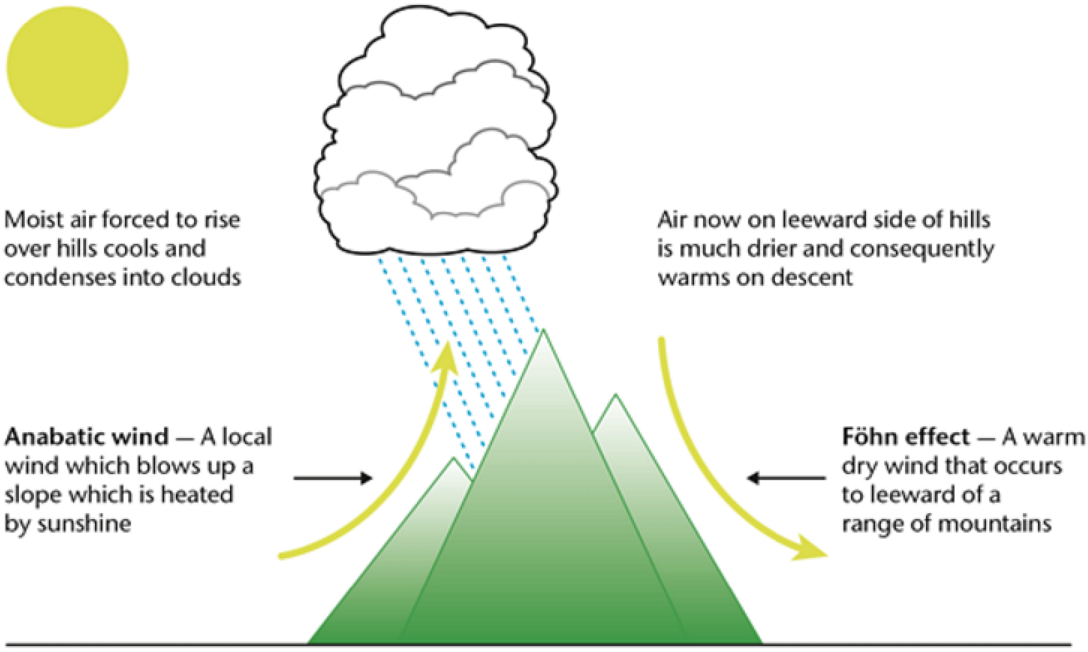


Figure 2.7 - Influences on mountain weather, including adiabatic lapse rate and the Föhn (Foehn) effect. *(Met Office, 2016b).*

Table 2.3 - Day and night-time recorded temperatures and accompanying descriptive data (including altitude) obtained at 10 logger sites, cross referenced with observed changes in mean, min and max temperatures associated with lapse rates for Mt. Kilimanjaro. Data obtained from Duane et al. (2008) and Maeda and Hurskainen. (2014). – means no data. M.a.s.l equals meters above sea level. Lapse rates are derived based on comparison with the immediate station below.

<table>
<tr><td></td><td colspan="2">Annual mean LST (°C)</td><td></td><td></td><td></td><td colspan="6">Recorded Air Temperature (°C)</td><td>Relative Humidity (%)</td></tr>
<tr><td>Altitude range (m.a.s.l)</td><td>Daytime (10:30 am)</td><td>Night-time (22:30 pm)</td><td>Logger No.</td><td>Elevation (m)</td><td>Site description</td><td>Mean</td><td>Lapse Rate (°C/km)</td><td>Min</td><td>Lapse Rate (°C/km)</td><td>Max</td><td>Lapse Rate (°C/km)</td><td>Mean</td></tr>
<tr><td>1,500-2,000</td><td>26.6</td><td>13.7</td><td>1</td><td>1890</td><td rowspan="2">Dense montane rainforest</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td rowspan="3">2,000-3,000</td><td rowspan="3">16.6</td><td>8.5</td><td>2</td><td>2340</td><td>11.5</td><td>-</td><td>8.4</td><td>-</td><td>14.8</td><td>-</td><td>97.7</td></tr>
<tr><td></td><td>3</td><td>2760</td><td>Sparse montane rainforest</td><td>9.2</td><td>5.6</td><td>4.9</td><td>8.3</td><td>14.4</td><td>0.9</td><td>96</td></tr>
<tr><td></td><td>4</td><td>3170</td><td>Transitional zone between rainforest and subalpine heathland</td><td>7.8</td><td>3.5</td><td>1.9</td><td>7.3</td><td>15.5</td><td>2.7</td><td>88.9</td></tr>
</table>

			5	3630	Subalpine heathland	7.1	1.4	3.3	3	13.3	4.8	77.3
Above 4,000	19.3	-2.3	6	4050	Alpine with limited vegetation	-	-	-	-	-	-	-
			7	4570		-	-	-	-	-	-	-
			8	4970	Bare rock	-0.9	6	-3.9	5.4	3.4	7.4	65.5
			9	5470		-2.8	3.8	-6	4.2	2.4	2	56
			10	5800	Ice field	-6.2	10.3	-9.4	10.3	-2	13.3	54.4

Furthermore, the northern orography of East Africa is observed to influence and be influenced by the East African Low Level Jet (EALLJ) also referred to as the Somali Jet. The jet is most prominent during the June-September season and thus does not directly impact the major monsoon seasons for Tanzania, although orographic influences do impact local climatology at altitude (Duane et al., 2008; Chakraborty et al., 2009). The jet is observed to originate in the Indian Ocean easterlies, travelling westward before traveling northward up the East African coast, following a narrow longitudinal line before crossing Somalia and turning eastward across the Arabian Sea as a westerly trade wind (figure 2.8) (Findlater, 1969; Krishnamurti et al., 1976). The East African highlands are noted to play a crucial role in providing a western boundary to the flow and reduces the overall speed of the jet, including Tanzania's Mt. Kilimanjaro which lies within the jets influential zone of the East African highlands (Krishnamurti et al., 1976; Findlater, 1977; Chakraborty et al., 2002).

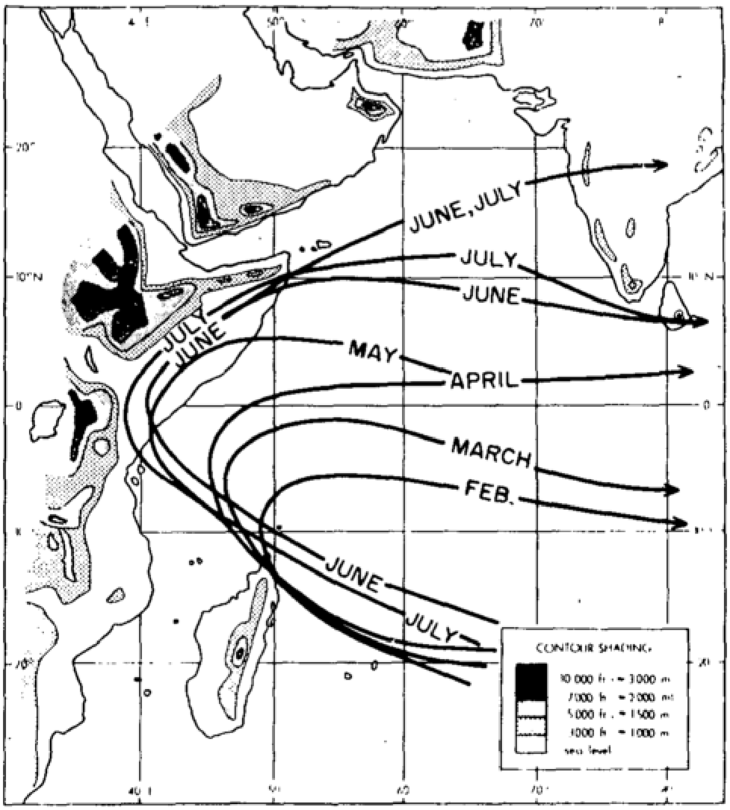


Figure 2.8 - Month by month progression of the pathway taken by the EALLJ *(Krishnamurti et al., 1976)*

The close proximity of the EALLJ, particularly during the months of June and July, to Mt. Kilimanjaro play a key role in further altering local climatologies in the area. The jet is a fundamental part of the rainfall transportation mechanism within the Indian Ocean monsoon system (Findlater, 1969, 1977; Cadet and Desbois, 1981; Vizy, 2003). As such, when moisture-laden clouds reach Mt. Kilimanjaro and by extension the East African Highlands, some of these clouds produce precipitation due to air being forced to rise, cool and condense into clouds (Barry, 2012). This is supported by the recording of rainfall and local rainfall patterns in the Mt. Kilimanjaro region during the non-monsoon months of JJAS (figure 2.9 and 2.10) (Nicholson, 1996; Hemp, 2006). Furthermore, the EALLJ has been suggested to play a role in the temperature and humidity trends observed by Duane et al., (2008) in the Mt. Kilimanjaro region. Although, it is important to consider the logger location, elevation and month when observations were collected during their study due to variations in mountain climate depending on upslope or leeside location in comparison to the jets varying wind directions by month (figures 2.7, 2.8 and 2.9).

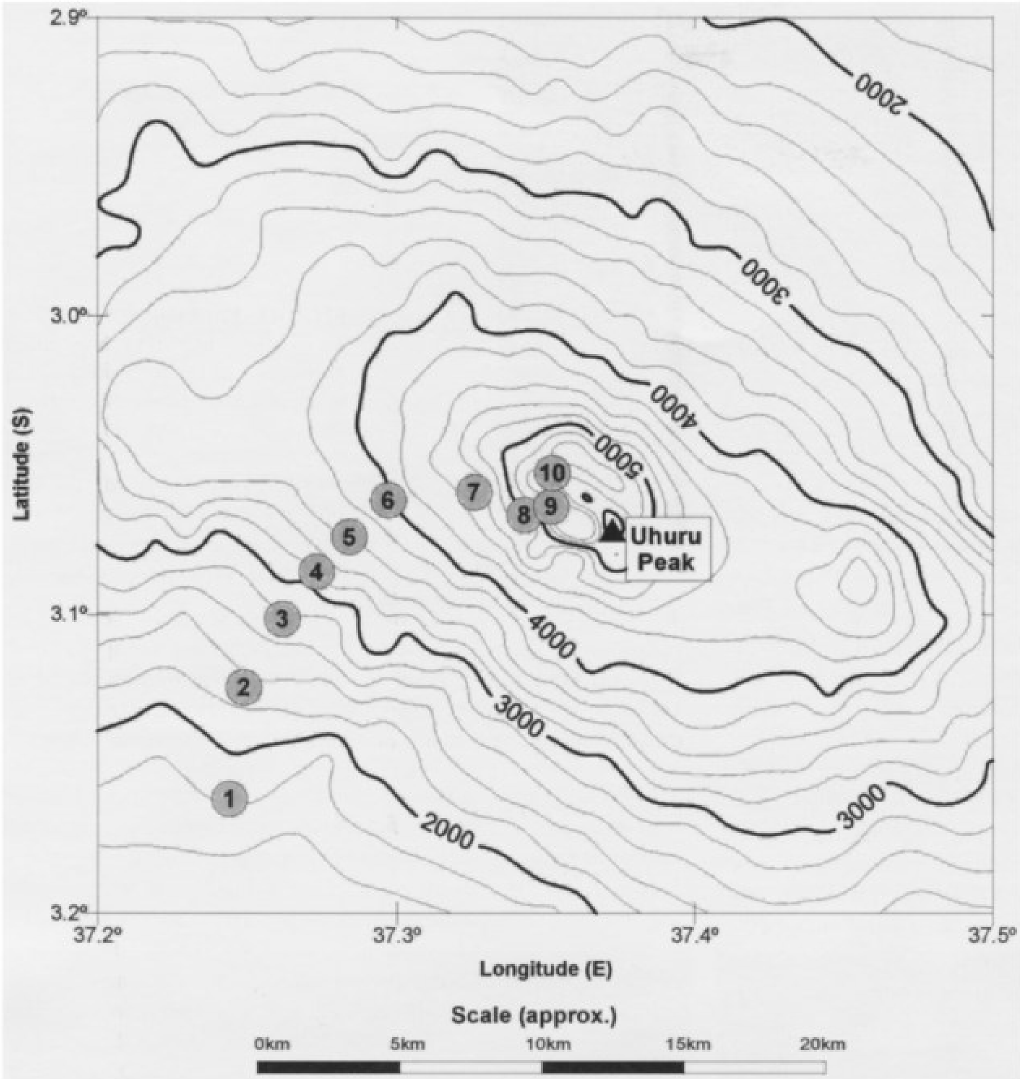


Figure 2.9 - Locations of loggers used in Duane et al., (2008) study.

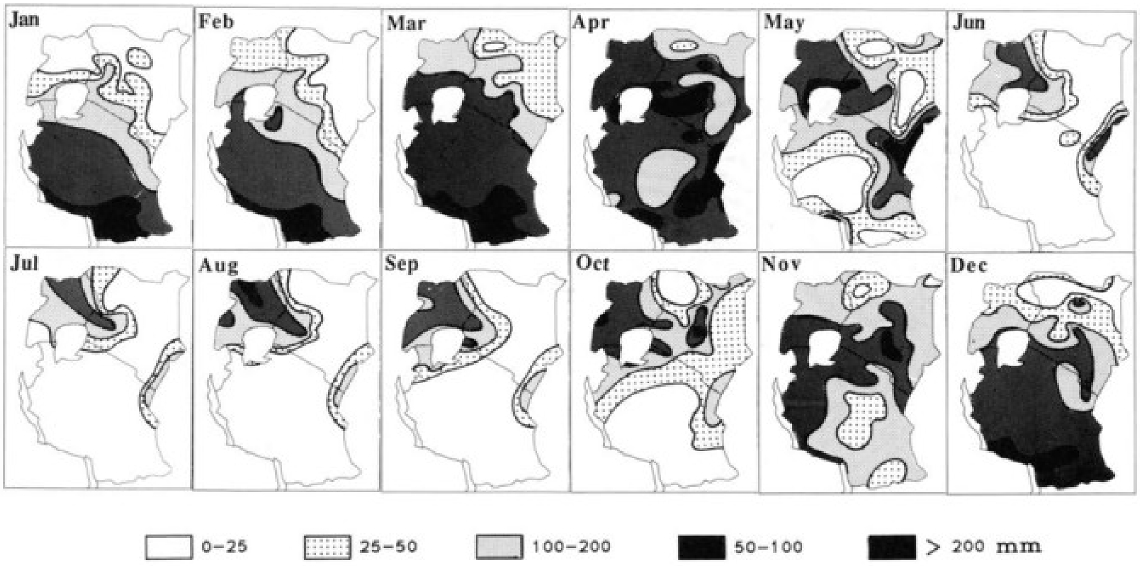


Figure 2.10 - Mean monthly rainfall in mm during the period 1931-1985. (Nicholson, 1996).

2.5 Malaria

Malaria has evolved to become the most prevalent vector borne disease globally, where Tanzania is one of the greatest contributors to both the global number of malaria cases and malaria burden in 2015 (WHO, 2015c). Malaria accounts for over 30% of the national disease burden in Tanzania, with approximately 14-18million new cases reported, resulting in 120,000 deaths (Makundi et al., 2007; Winskill et al., 2011). Understanding malaria and its development in Tanzania remains difficult to quantify as a result of inconsistent data provided between 2000 – 2015 (MoHSW, 2013b; WHO, 2015c). Although, available data suggests Tanzania is undergoing an epidemiological transition, with 60% of the population living in hypo-endemic areas (up from 30% in 2000), and 100% of the population at risk of contracting malaria (MoHSW, 2013b; WHO, 2015c).

Malaria is caused by the parasite *Plasmodium* of which multiple species are globally present (Lyke, 2017). *P. falciparum* is the most virulent and carries the highest incidences of mortality, accounting for 96% of infection in Tanzania, with the remaining 4% being attributed to *P. malariae and P. ovale* (Silué et al., 2008; Mboera et al., 2013; USAID, 2015). The parasite *P. falciparum* has been problematic to treat, fast developing resistance to medical treatments raising concerns for future treatments for malaria as options are reduced (Mueller et al., 2005; Whitty et al., 2008; Lyke, 2017). *P. falciparum* (figure 2.11) is introduced to humans (the host) via the bite of a female mosquito taking a blood meal to support its reproductive cycle, a cycle which is repeated with each blood meal (figure 2.12) (Tolle, 2009; Smith et al., 2014).

The major vectors of malaria in most areas of Tanzania are members of the *Anopheles gambiae complex* found in table 2.4 (Githeko et al., 1996; MoHSW, 2013b). *An. gambiae s.s* was historically the most significant transmission vector, of which pregnant women attracted twice as many *An. gambiae s.s* mosquitoes over a range of 15m than their non-pregnant counterparts (Mnzava and Kilama, 1986; Ansell et al., 2002). The introduction of multiple prevention methods has had a significant impact on the distribution of *An. gambiae s.s,* leading to a change in epidemiology, where *An. arabiensis* is becoming the major transmission vector (MoHSW, 2013b; USAID, 2015).

Figure 2.11 - Malaria parasites amid red blood cells *(Bonniers Forlag, 2017)*.

Figure 2.12 - Anopheles mosquito after a blood meal *(Sturrock, 2017)*.

Table 2.4 - Major malaria transmitting vectors in Tanzania. *(Githeko et al., 1996; MoHSW, 2013b).*

Malaria Vector	**Biting behaviour**	**Resting behaviour**	**Emerging treatment resistance**
Anopheles gambiae sensu stricto (s.s)	anthropophagic	endophilic	Treatment is effective. Becoming resistant to pyrethroids in some districts.
Anopheles arabiensis	zoophilic	exophilic	Becoming resistant to IRS and LLINs, and becoming the dominant vector.
Anopheles funestus	anthropophagic	endophilic	Resistance to pyrethroids in some districts.

Table 2.5 - Comparing temperature ranges of mechanistic malaria transmission models. Adapted from *(Mordecai et al., 2013).*

Model	Min (°C)	Max (°C)	Opt (°C)	Transmission metric	Temperature-dependent parameters and functional forms
Mordecai *et al.* (2013)	17	34	25	R_0	**Quadratic:** Vector competence, proportion of eggs that produce adults, daily adult survival, eggs per female per day
					Briere: parasite development rate, mosquito development rate, biting rate
Parham and Michael (2010)	20	39	32-33	R_0	**Linear (or combination of linear functions):** total number of mosquitoes, biting rate, proportion of infected mosquitoes that become infectious
					Unimodal: adult mortality rate
Craig *et al.* (1999)	18	40	30	p^{EIP} (fraction of vectors surviving sporogeny)	**Linear:** parasite development time within the mosquito, larval duration.
					Nonlinear monotonic: adult daily survival probability
Martens *et al.* (1997)	18	38	31	Epidemic potential (reciprocal of the critical mosquito density necessary to maintain parasite transmission)	**Linear:** parasite development time wtithin the mosquito, biting rate.
					Unimodal: adult daily survival probability

2.5.1 Environmental determinants of malaria distribution in Tanzania

In order for malaria to successfully thrive, suitable environmental temperatures and water conditions must be present (Drakeley et al., 2005; Lardeux et al., 2008; Weiss et al., 2014). Warmer temperatures enhance the rate of malaria transmission through increasing the development rate of both the parasite and larvae (sporogonic cycle) and mosquito survival and feeding (gonotrophic cycle) (Teklehaimanot et al., 2004; Bennet et al., 2016). Suitable temperatures are present throughout the tropics, however definitive optimal temperature conditions are still debated within the literature as shown in table 2.5 (Mordecai et al., 2013; Ryan et al., 2015). Overall, Tanzania's year-round tropical temperatures provide a habitat suitable for malaria to thrive (Caldas de Castro et al., 2004; Hagenlocher and Castro, 2015).

As introduced in section 2.4, rainfall is a key driving mechanism of changing environments in Tanzania. This contributes significantly to the seasonality and spatial distribution of malaria transmission (Reiner et al., 2015). Rainfall provides habitats which support vegetation growth for mosquito shelter as well as shallow pools of water for breeding (Parham and Michael, 2010; Gwitira et al., 2015). Vegetation plays an integral role in providing shelter for both larval habitats and mosquitoes, particularly during the hottest times of the day where overheating would lead to desiccation of larvae and mosquitoes (Bayoh and Lindsay, 2004). Changes in rainfall and vegetation coverage under El Niño conditions have been linked to increases in malaria incidence due to increasingly favourable conditions, further indicating the impact of both on malaria (Propastin et al., 2010).

Links between malaria and relative humidity are poorly understood, despite increasingly compelling arguments to consider relative humidity in risk assessments due to recent results. It has been established that increases in relative humidity impact on the flight and subsequent host-seeking behaviour of mosquitoes and influence in larvae development (Yé et al., 2007; Khormi and Kumar, 2015). Whilst further research is required, a clear link exists which prompts the inclusion of relative humidity in epidemiological modelling of malaria, which is discussed further in chapter four.

2.5.2 Re-emergence of malaria

Current literature focuses on the resurgence of malaria incidences as a result of environmental changes introduced in section 2.5.1 (Cohen et al., 2008; Smith et al., 2014; Bhatt et al., 2015). A key consideration raised in the expansion of malaria despite significant reduction and increased efforts in containment is that of changing spatial limits. Historically, highland areas (> 1500m) were considered malaria free zones. However, observations during the 1990's saw increasing occurrences of highland malaria epidemics suggesting considerable changes in conditions were occurring (Lindblade et al., 2000). Several hypotheses have been explored to increase understanding of alterations in highland malaria including the following; climate change (Hoshen and Morse, 2004; Parham and Michael, 2010; Mabaso and Ndlovu, 2012; Beck-Johnson et al., 2013), land use change (Lindblade et al., 2000; Kulkarni et al., 2010; Hardy et al., 2015), drug resistance (Gubler, 1998; Kweka et al., 2013; Killeen and Chitnis, 2014), subsidence of malaria control activities (Lindblade et al., 2000; Kristan et al., 2008) and demographic changes (Martens and Hall, 2000; Mlozi et al., 2015; Shayo et al., 2015). Each of these aspects highlight the complexity of malaria in relation to climatic and socio-economic factors that drive disease dynamics.

Despite its importance, current knowledge on the nature and drivers of changing endemicity in sub-Saharan Africa remains weak by comparison, supporting the case for further investigation into the key drivers of change (Bhatt et al., 2015; Mlozi et al., 2015; Shayo et al., 2015).

2.6 Bacterial meningitis

Meningococcal meningitis (sometimes referred to as cerebrospinal fever or cerebrospinal meningitis) is a bacterial infection of the thin lining (meninges) that surrounds the brain and spinal cord (WHO, 2015a). The bacterium responsible was identified as *Neisseria meningitidis* (the meningiococcus) initially reported as cited in Marchiafava & Celli (1884) (Moore, 1992; Greenwood, 1999; EOCHA, 2014). The bacterium itself can be classified into 13 distinct groups, and whilst a variety of these groups are responsible for cases of meningitis major epidemic outbreaks are caused predominantly by group A and to a lesser extent group C meningococci (Moore, 1992; Rosenstein et al., 2001). Humans are the only documented natural reservoir of *N meningitidis,* of which 2%-10% of healthy people were believed to be carriers, although recent WHO publications suggest that a much higher 10%-20% of humans are carriers of potentially pathogenic meningococci at any given time (Moore 1992; Rosenstein et al. 2001; WHO, 2015a). Transmission occurs via person-to-person contact through aerosol or throat secretions before colonising on the nasopharynx region. If the bacteria becomes pathogenic, the average incubation period is approximately four days however has been documented to range anywhere between 2 to 10 days (WHO, 2015a). Meningococcal meningitis has a case-fatality rate of 5% - 25% and neurological damage is common among survivors (Moore, 1992).

Originally defined by Lapeyssonnie (1963), the meningitis belt was depicted as an area with high incidence and recurring epidemics of meningitis, which coincided with the 300 - 1100-mm mean annual rainfall isohyets south of the Sahara, comprising much of semi-arid and sub-Saharan Africa, including the Sahel (Lapeyssonnie, 1963; Molesworth et al., 2003). This region in particular is uniquely susceptible to intense group A meningococcal epidemics, occurring in 8 to 14 year cycles (Moore, 1992). However, the boundaries of epidemic limits are not clearly defined. Numerous and regular reports from countries located outside the originally defined boundaries have appeared within examinations, including Kenya, Tanzania, Mozambique and South Africa (Greenwood, 1999). Whilst the original belt in the Sahel region experiences greater regularity in occurrence, it stands that a significant shift in distribution is highly possible given the high number of reports elsewhere in the African continent. Cheesbrough et al. (1995) re-mapped the distribution based on outbreak reports, retaining Lapeyssonnies (1963) original isohyet limit but including reports where outbreaks occurred from time to time (figure 2.13), illustrating the expansion of the original meningitis belt based upon reported epidemics.

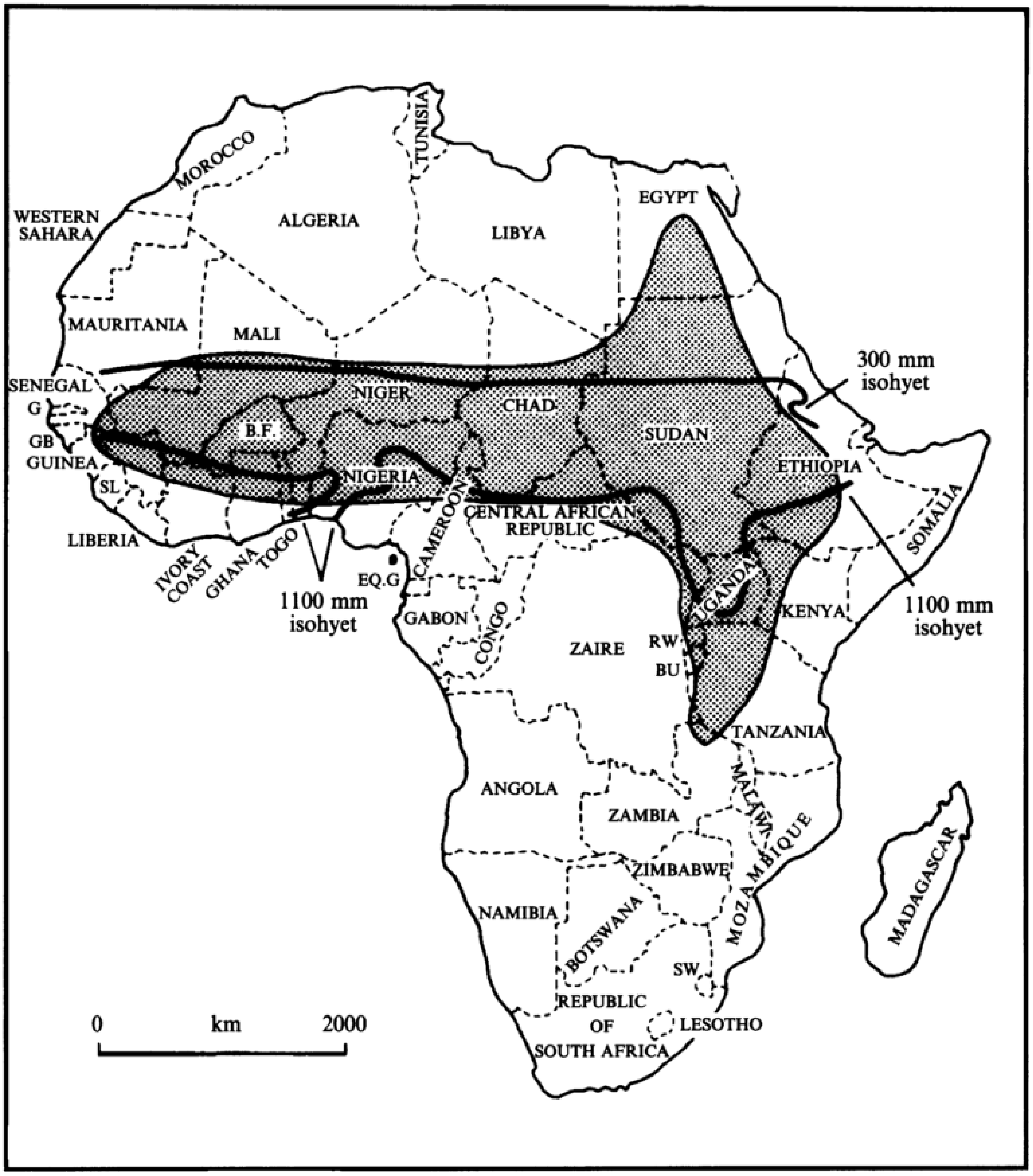


Figure 2.13 - The original meningitis belt as described by Lapeyssonnie (1963). Including expansion of areas with infrequently reported epidemics of meningitis (Cheesbrough et al. 1995).

2.6.1 Environmental contribution to bacterial meningitis distribution in Tanzania

A significant theory in the geographical distribution and occurrence of meningitis outbreaks is that of environmental influence. Multiple studies report an explicit pattern of seasonality surrounding outbreaks whereby epidemics start during the dry season and subside with the onset of the rains. Notable ecological patterns have been reported by each study with the consensus being that factors such as low absolute humidity, land-cover and dusty atmospheric conditions may play an important role, particularly in allowing epidemic forecasting (Lapeyssonnie, 1963; Moore, 1992; Cheesbrough et al., 1995; Patz et al., 2001; Molesworth et al., 2002, 2003; Thomson et al., 2006a). Whilst the relationship between climate is clear, the exact occurrence remains poorly understood and unpredictable (Thomson et al., 2006a; Abdussalam et al., 2014). Furthermore, factors predisposing populations to meningitis epidemics are poorly understood with population susceptibility, introduction of new strains, poor living conditions and concurrent infections all being suggested as further potential catalysts behind driving epidemic outbreaks, the impact of which remains unquantified (Molesworth et al., 2003). It is of concern that these areas of climate interest could be disproportionately affected due to added vulnerability of the populations however further study is needed (Abdussalam et al., 2014).

The exact role of climate moderation on meningococcal disease remains unclear, particularly when considered in a wider context with population movement and living conditions. However, with recent advancements in records of both climatic and increased accuracy assessment of meningococcal disease within developing countries, all that remains is a comprehensive re-analysis of available datasets in order to establish a clearer relationship and in turn allow for more accurate prediction (Greenwood, 1999; Molesworth et al., 2003). However, projecting the future risk involves a considerable number of uncertainties due to many factors in addition to climate including vaccination changes, cultural and behavioural practices and prevalence of other related diseases (Abdussalam et al., 2014).

2.7 Chikungunya

Chikungunya virus (CHIKV) is an arthropod-borne virus, which was first isolated in southern Tanzania in 1952. Initially documented as being transmitted by *Aedes (Ae.)* mosquitoes, the virus itself was initially constrained to the tropical and subtropical regions of Africa and around the Indian Ocean islands, including south and southeast Asia due to *Aedes'* habitual limits (Burt et al., 2012; Zhang et al., 2013). Recipients of CHIKV demonstrate acute febrile characteristics, skin rashes and incapacitating arthralgia following an incubation period ranging from 1 day to 12 days with an average of 2-4 days (Pardigon, 2009; Burt et al., 2012). Although the incubation period has not been thoroughly examined, evidence provided from the re-emergence outbreaks support the short incubation period of approximately 2 to 10 days (Renault et al., 2012; Thiberville et al., 2013). The virion itself is particularly sensitive to desiccation and air temperatures greater than 58°C (Thiberville et al., 2013). Whilst the majority of symptoms resolve, some patients continue to experience arthralgia for several years following infection, resulting in a bent or stooping posture and ultimately severely reducing quality of life (Burt et al., 2012; Renault et al., 2012). Furthermore, there is no vaccine available for CHIKV. Cases are treated symptomatically with bed rest, fluids and medicines such as paracetamol, aimed more at relieving symptoms rather than treating the virus itself (Burt et al., 2012; Zhang et al., 2013).

Lack of initial interest in chikungunya within the scientific community appears to have led to a significant knowledge shortage up until the recent outbreaks of the disease in previously rarely documented areas, demonstrated by the publication records on chikungunya published by Thiberville et al. (2013) (figure 2.14).

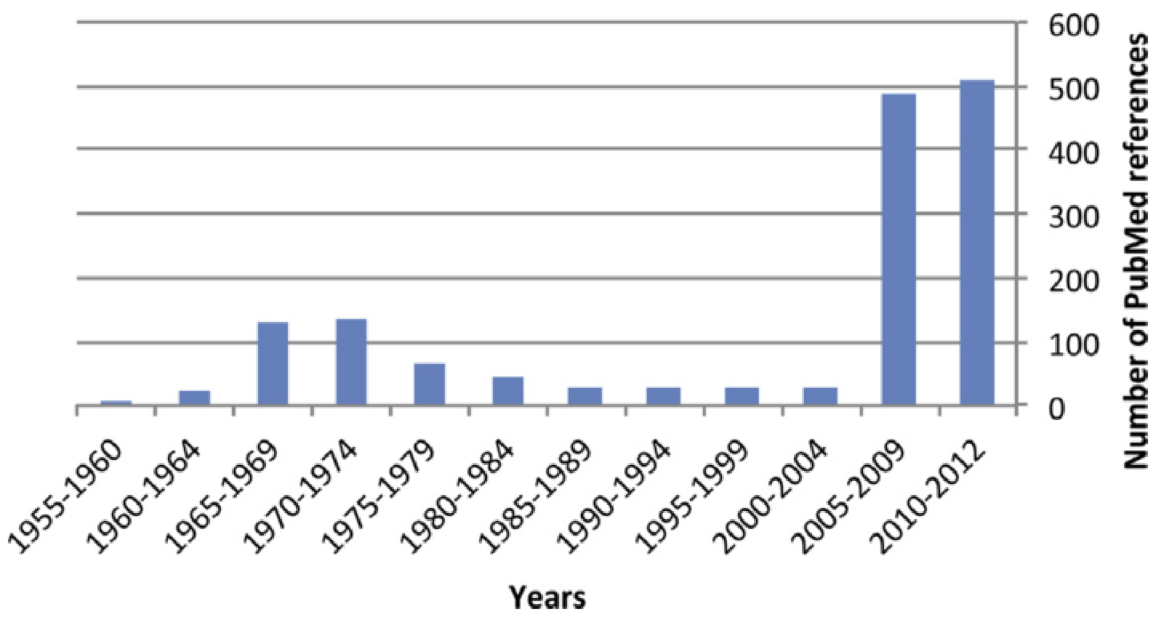


Figure 2.14 - Publications related to outbreaks of chikungunya fever in the PubMed database. Articles published between 1950 and September 2012 were identified using the MeSH term "chikungunya", and are reported by five year periods *(Thiberville et al., 2013)*.

Several sources speculate that the understudied nature of chikungunya (in comparison to diseases such as malaria) stemmed from the endemic behaviour of the virus and years of quiescence (Burt et al., 2012; Thiberville et al., 2013; Higgs and Vanlandingham, 2015). However, it is important here to note the similarity in the symptoms associated with chikungunya to that of those with malaria (see section 2.5). Each of these diseases demonstrate similar febrile symptoms, contributing to the leading causes of morbidity and mortality in developing countries (Higgs and Vanlandingham, 2015). When considering the growing concern surrounding malaria during the time-period of CHIKV quiescence, it is theoretically possible to see considerable potential in misdiagnosis of chikungunya cases being mistaken for malaria or dengue. Particularly during a time period where access to health facilities, let alone accurate diagnosis, was low. Whilst this will remain undetermined due to the gaps in chikungunya studies, one key development supporting the plausibility of undetected chikungunya cases leading to spread during the “quiescent” period is the remaining dominance of febrile illnesses in developing countries, despite significant reductions in malaria transmission, morbidity and mortality (Chipwaza et al., 2014). This malarial decline coincides with recent resurgences in chikungunya cases, although present day diagnosis allows for increased accuracy, there are still significant limitations particularly in developing countries such as Tanzania (Zhang et al., 2013; Chipwaza et al., 2014).

2.7.1 Re-emergence of chikungunya

Current literature focuses heavily on the re-emerging nature of chikungunya, particularly documenting changes in its spatial location, distribution vectors and gene mutation (Pardigon, 2009; Ng and Hapuarachchi, 2010). The long-term impact of the gap in examination becomes clear when examining the scenario surrounding the re-emerging outbreaks. Where the virus was initially constrained to Africa and the Indian Ocean region, alterations in its vector transmission appears to have significantly expanded its sphere of influence, reaching as far as the United Kingdom, observed in 2014 (Burt et al., 2012; Zhang et al., 2013; Higgs and Vanlandingham, 2015). This is believed to be due to gene mutation within the virus to alter vector specificity, allowing the virus to adapt to allow replication in alternative vectors (Ng and Hapuarachchi, 2010; Thiberville et al., 2013). Evidence from the Reunion outbreak strongly supports the evidence placed forward disputing gene mutation, given the predominant vector on the island is *Aedes albopticus*, not *aegypti,* the vector identified as the original transmitter in its initial discovery (Burt et al., 2012; Renault et al., 2012)

A key aspect of chikungunya transmission is the vector itself. *Ae. aegypti* is found mostly across the tropics and sub-tropics, displaying major variations in morphology, ecology, behaviour and vector competence. Two subspecies have been described in the literature. One form described as the “light” form, named *Ae. aegypti aegypti (Aae)* possesses a highly domestic and anthropophillic behaviour often found distributed through urban landscapes. The second subspecies termed the “dark” form is referred to as *Ae. aegypti formosus (Aaf)* is endemic to Africa and thrives in wooded environments. Both forms are described to occur in sympatry in East Africa (Picker et al., 2004; Paupy et al., 2009).

Thus, chikungunya remains a growing concern amongst multiple academic and social communities due to the comparatively understudied nature of the disease and its adaptive capacity coupled with a clear change vector dynamics as their epidemiological role remains unknown alongside a heightened potential of transmission from the urban distributor (Picker et al., 2004; Kucharz and Cebula-Byrska, 2012). This results in a high amount of uncertainty when examining the development of the disease in relation to the climatic impacts on distribution via transmission vectors.

2.8 Climate and disease prediction

Climate can be defined as the average state of the atmosphere observed as the weather over a finite time period (e.g. a season) for a number of different years (Lorenz, 1963; Schneider, 1992). The conditions of which vary significantly across the surface of the Earth, allowing suitable (or otherwise) conditions for climatically related diseases (combined with other factors) to be present across a wide swath of the Earths surface (Thomson et al. 2006b). Early climate studies formed the basis of climate modelling using empirical mathematical equations to predict short term weather changes based on observed parameters (Phillips, 1956; Schneider and Dickinson, 1974; Schneider, 1992). However, the physical laws which govern the climatic state do not allow for accurate representation or predictability of such a large scale system where minor changes can subsequently have significant impacts (Lorenz, 1963; Schneider, 1992). As numerical modelling progressed to utilise the computer power available at the time this allowed for development of more sophisticated coupled dynamical circulation models (Lynch, 2008).

2.8.1 The science of forecasting

The work of Lorenz (1963) on chaos theory proved fundamental in developing climate prediction. Lorenz outlined how climate may be defined as an ensemble of all states during a long, yet finite timespan (Lorenz, 1963; Schneider and Dickinson, 1974). However, whilst this provided the basis for allowing the mathematical development of representative climate models examining change, issues were simultaneously highlighted in that accurate long term forecasting was highly uncertain given varied and incomplete representations of starting conditions (Lorenz, 1963; Schneider and Dickinson, 1974; Palmer, 1993). Early numerical weather prediction models based upon empirical analysis of observed values of periodic elements proved to be promising in representing more abstract and onedimensional aspects of the climate system. Although, even at this stage uncertainties were fast encroaching as forecasts attempted to cover longer periods. Lorenz and others in the field noticed that the inherent instability within atmospheric motion rendered predictions increasingly inaccurate after approximately ten days or more using empirical based calculations (Phillips 1956; North & Cahalan 1981).

This issue of inconsistency persisted as modelling developed into the first principles approach whereby models were created which examined circulation levels on a three-dimensional basis. Global Circulation Models (GCM) included multidimensional representation of parameters examining time evolution of temperature, humidity, wind, soil moisture, sea ice, and other variables through three dimensions in space (Phillips, 1956; Schneider, 1992). Whilst their capabilities extended beyond those of empirical methods, Lorenz (1963) noted that GCMs would still not solve the accuracy issues given that the advection/ convection processes, which initiate variances in climate behaviour, are sub-model-grid scale. Even as GCMs and computing power advances (despite limitations through costs and available technology) it remained that instabilities within atmospheric processes rendered predictions increasingly inaccurate after approximately ten days or more as a result of these smaller processes (Schneider and Dickinson, 1974; North and Cahalan, 1981; Schneider, 1992). Thus, it is crucial that models strive to represent the smaller processes as accurately as possible to increase accuracy in understanding larger processes. Several GCMs built upon this hierarchical foundation, where accurately representing the smaller process through mathematics were conglomerated into increasingly complex and dynamic models. These included the Kashara-Washington model at the National Centre for Atmospheric Research (NCAR), The Community Atmosphere Model (CAM) and by Extension the Community Climate System Model (CCSM) (Lynch, 2008).

Advancements in computational technology and dynamical formulas have allowed fully-coupled, global climate models to be created with the ability to simulate past, present and future climate states of the earth (Lynch, 2008). A key development and widely applied technique in addressing simulation accuracy is the method of ensemble forecasting. Palmer (1993) took the conventional Lorenz model and initiated an investigation into ensemble forecasting (Palmer, 1993; Branković and Palmer, 1997). The success of this technique in increasing output accuracy has since been widely applied as ensembles allow for an estimation of the probability of atmospheric states through a finite sample of deterministic integrations. The mean of the ensemble acts as a filter to average out the unpredictable processes, providing more uniform representations (Schneider, 1992; Palmer, 1993; Branković and Palmer, 1997).

Current models have advanced significantly, with one of the most sophisticated being developed by the European Centre for Medium-range Weather Forecasts (ECMWF). The aim of this model is to deliver weather forecasts of increasingly high quality and scope from a few days to a few seasons ahead. This has been successfully achieved through using a spectral primitive equation model, with a semi-lagrangian integration to allow longer time steps, a semi-implicit time scheme. Furthermore the model is fully coupled to an ocean wave model and treats physical processes comprehensively (Wang et al., 2004; Lynch, 2008). ECMWF sought to advance the concept of seasonal climate forecasting via multi-model ensembles (MMEs) through the DEMETER project (Hoshen and Morse, 2004; James et al., 2014). A central aspect to the DEMETER project is the evaluation of the potential behind seasonal climate forecasts for end-user communities, such as those concerned with agricultural output and malaria epidemic control (Hoshen and Morse 2004; Thomson et al. 2006a; Thomson et al. 2006b).

2.8.2 Seasonal forecasting

Over the past 30 years the science of predicting seasonal-timescale variations has improved significantly through the use of probabilistic forecasting, increasingly powerful technology and advancements in climate system knowledge (Palmer et al., 2004; Weisheimer and Palmer, 2014). As a result climate prediction has become a routine which is now carried out daily for a number of global uses (Weisheimer and Palmer, 2014). Despite advancements, it remains difficult to accurately predict weather events beyond two weeks maximum using traditional numerical forecasting and remains impossible using climate models due to the spin-up time required (Troccoli, 2010; Doblas-Reyes et al., 2013). However, due to seasonal weather events being linked to larger scale and slower developing climatic components (e.g. oceanic-land), it is possible to use these factors to assess how climate and thus seasonal weather events will develop (Chen et al., 2004; Doblas-Reyes et al., 2013).

Seasonal forecasting operates between short range numerical weather forecasting (NWP) and decadal to medium and long range climate projections, thus inherits shortcomings associated with each (Soares and Dessai, 2014). Due to the relatively short timescales involved, it is difficult to realistically simulate the atmosphere in such a short space of time using GCMs leading to initial condition uncertainty (Palmer et al., 2005). Furthermore, they inherit the uncertainties in climatic relationships and feedbacks which are a constraint in long range climate prediction models (figure 2.15) (Slingo and Palmer, 2011; Doblas-Reyes et al., 2013). Uncertainty in these models is reduced through the increased use of seasonal ensemble integrations (Palmer et al., 2000; Slingo and Palmer, 2011). A probabilistic method of modelling, which has been utilised in developing seasonal forecasting models from early models such as PROVOST and DEMETER (Palmer et al., 2000). Improvements in computational capabilities and knowledge have allowed expansion in scope with newly implemented models such as the Met Offices GloSEA5.

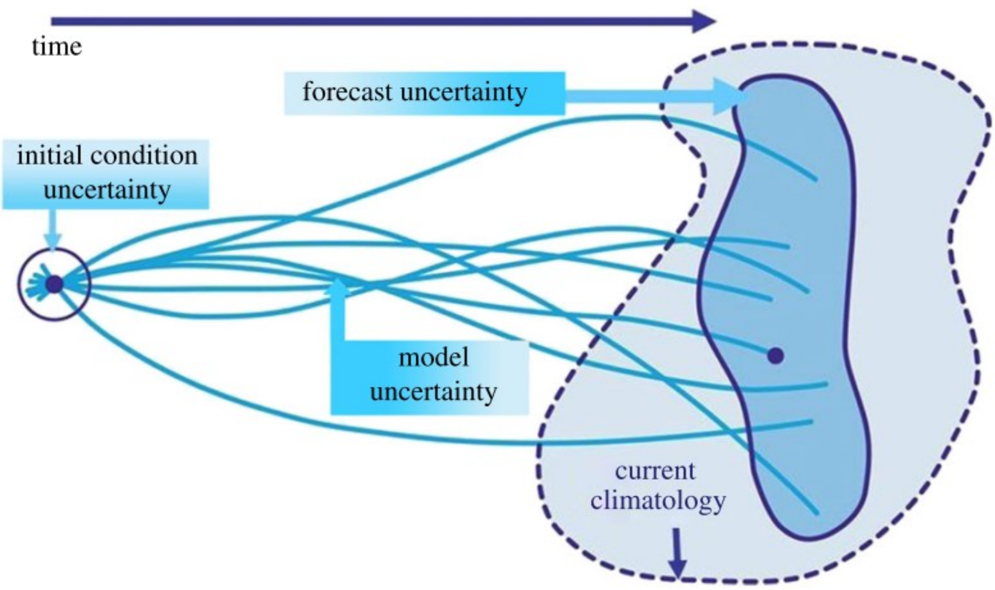


Figure 2.15 - Uncertainty in climate and weather prediction. *(Slingo and Palmer, 2011).*

Translating seasonal-to-decadal forecasts is at present difficult, due to the complex mechanisms involved at the various stages of dynamical climate modelling. This consists of three major dynamical model types which have already been broadly introduced, specifically NWP (5-10 days), Seasonal (months), and decadal/medium to long-range projections (Schwierz et al., 2006; Soares and Dessai, 2014). For the latter, emphasis is placed on high spatial resolution and simulation of the ocean driven by emissions scenarios, each of which forces respective coupled climatic models to simulate atmospheric physics and chemistry. Synoptic-scale weather processes are not included (Schwierz et al., 2006). This differs somewhat from the seasonal model drivers where both NWP and coarser resolution coupled Atmospheric-Oceanic-Global-Climate-Models are used, without climate scenarios/pathways, focusing on processes most relevant to the corresponding time and spatial scales involved (Goddard et al., 2012; Weisheimer and Palmer, 2014). As a result, it is difficult to link seasonal and decadal forecasts.

The importance of seasonal climate modelling has become more widely appreciated throughout a number of sectors, particularly with respect to its usefulness in malaria modelling (Githeko et al., 2014; Meehl et al., 2014; MacLeod et al., 2015). Malaria epidemics occur when increasingly suitable parasite and vector conditions develop, particularly in association with unusual meteorological conditions (Jones and Morse, 2012). As a result, seasonal forecast models are highly useful in providing information on the evolution of a disease months in advance in order to support decision makers in putting appropriate measures into place should the conditions for an epidemic outbreak be observed (Palmer et al., 2004; Githeko et al., 2014). Due to the anticipated use of these models in decision making it is therefore of utmost importance that models are as accurate as possible in order to yield the best results for decision makers, governments and ultimately clinical patients (Jones et al., 2007; Meehl et al., 2014; Soares and Dessai, 2014).

2.8.3 Taking climate modelling forward

Climate modelling has developed substantially since its earlier conceptions; however, development is still needed in order to increase model precision, reliability and accuracy. The best approach to take with regards to advancing climate modelling is a current topic of interest within the literature in terms of both scenarios considered by the models and the modelling approach (Katzav et al., 2012; Ebi et al., 2014; Katzav and Parker, 2015). Katsav and Parker (2015) highlight the numerous issues apparent when choosing between the Unified, Hierarchy and Pluralist approaches, which are key to the challenges faced by current climatologists. There is still a considerable way to go in terms of providing end users with reliable forecasts, in particular for precipitation, which is of particular importance for Africa. Whilst the ECMWF model does perform significantly well in comparison to other models and should be seen as an aspirational achievement, there are still regions of the globe which require improvement in simulation accuracy (Meehl et al., 2014; Weisheimer and Palmer, 2014).

Overall, there are still improvements required, the models consensually perform well enough to allow progression to be made in terms of examining climate impacts on health in Tanzania since the models currently perform best in the African region. Debates continue on how best to improve model performances which may involve: changing scenario format (as seen in the recent IPCC report) (IPCC, 2013, 2014); changing models (Weisheimer et al., 2014); and importantly, better understanding and representation of the physical drivers behind the global climate (Weisheimer & Palmer 2014; Meehl et al. 2014). The latter would be best achieved through international research collaborations within structured frameworks such as the regional forums outlined in section 2.3.2 (Katzav et al., 2012; Katzav and Parker, 2015).

2.8.4 Climate and environment roles in epidemiological modelling

Diseases such as malaria and bacterial meningitis are associated with specific environments, dictated by a number of climate and environmental factors as presented in section 2.5 (Kalluri et al., 2007; Khormi and Kumar, 2015). These relationships, although complex, can be approached and represented through various modelling methods, including mathematically driven biological models, statistically based geographical analysis and seasonal climate models (Ermert et al., 2011; Mandal et al., 2011; Khormi and Kumar, 2015). Mathematical models have been used in predicting malaria outbreaks for over 100 years, where understanding of interactions between the host, parasite and environment has improved considerably (Mandal et al., 2011; Chabot-Couture et al., 2014). Supporting mathematical developments, spatially explicit geographic distribution models have further developed, allowing disease rates and transmission to be addressed more thoroughly (Chaput et al., 2002). Whilst many approaches are now present in disease modelling, almost all rely on environmental and climate information, provided by historic climate records or climate models, the details of which have been discussed for Tanzania earlier in this section.

Controlling and monitoring vector-borne diseases in particular, such as malaria, presents a major ongoing challenge to health officials and policy makers (Mutero et al., 2014; WHO, 2015c). The overall benefits of disease modelling are abundantly clear, despite outstanding improvements to be made, environmental disease models using a range of methods have been proven to be successful in providing crucial information to decision makers (WHO et al., 2013). This has allowed for the successful surveillance and prediction of outbreaks though decision support tools which have not yet been thoroughly examined or implemented for Tanzania (Racloz et al., 2012; MoHSW, 2013b; Pathirana, 2013). Whilst malaria is predominantly, controlled by environmental conditions, the role of socioeconomic, cultural and population dynamics has been recognised to play a role in malaria distribution and is discussed in section 2.7 (Khormi and Kumar, 2015; Mlozi et al., 2015; Shayo et al., 2015).

2.9 Socio-economic, cultural and policy implementations impacting malaria in Tanzania

2.9.1 Population dynamics and distribution

Population dynamics within Tanzania have been significantly shaped by ecological suitability (water provision and land fertility) alongside specifically designed political policies aimed to influence population distribution (Maro, 1990). The population of Tanzania (as of 2012) was recorded to be 44.9 million people, almost four times that recorded in 1967, projected to further increase to 50.1 million people as of 2016 (MoHSW, 2015; NBS, 2016). Population growth to this degree can be attributed to increased longevity, from 42 years (1967) to 61.8 years (2015) and declining infant mortality from 155 (1967) to 46.2 (2015) per 1000 live births. Despite its large population, Tanzania remains sparsely populated with an overall population density of 51 persons per square kilometre, varying by region with Dar es Salaam and Mjini Magharbi (on the island of Zanzibar) being 3,133 and 2,581 respectively (figure 2.16) (NBS, 2013a). High risk demographic categories for malaria include children under five, which make up 15.2% of the population, and women, whom slightly outnumber men in Tanzania at a ratio of 100 to 95 according to the 2012 census (figure 2.17 and table 2.6) (NBS, 2013a).

Whilst all age groups are at risk of developing severe malaria, women and children under the age of five are biologically most vulnerable and account for the highest malaria morbidity and mortality rates (Deressa and Ali, 2009; Bousema et al., 2012). In addition, women and children in poverty, often living in rural areas and urban slums, are at higher risk than those in comparatively well off urban areas (Reuben, 1993). Women are at increased risk, especially during pregnancy, due to alterations in immunity status, leading to an increased susceptibility to *P. falciparum* malaria. In cases of no natural immunity, malaria parasites can result in still-birth or low birth-weight babies (Schwarz et al., 2008; Dellicour et al., 2010). Additional consequences of malaria exposure during pregnancy, is increased risk of malaria contraction, morbidity and mortality in early life for the child, alongside natural lack of immune system defence due to under-exposure in children under the age of five (Schantz-Dunn and Nour, 2009). These demographic groups are important to consider throughout policy discussion, and is further expanded upon in section 2.9.4.

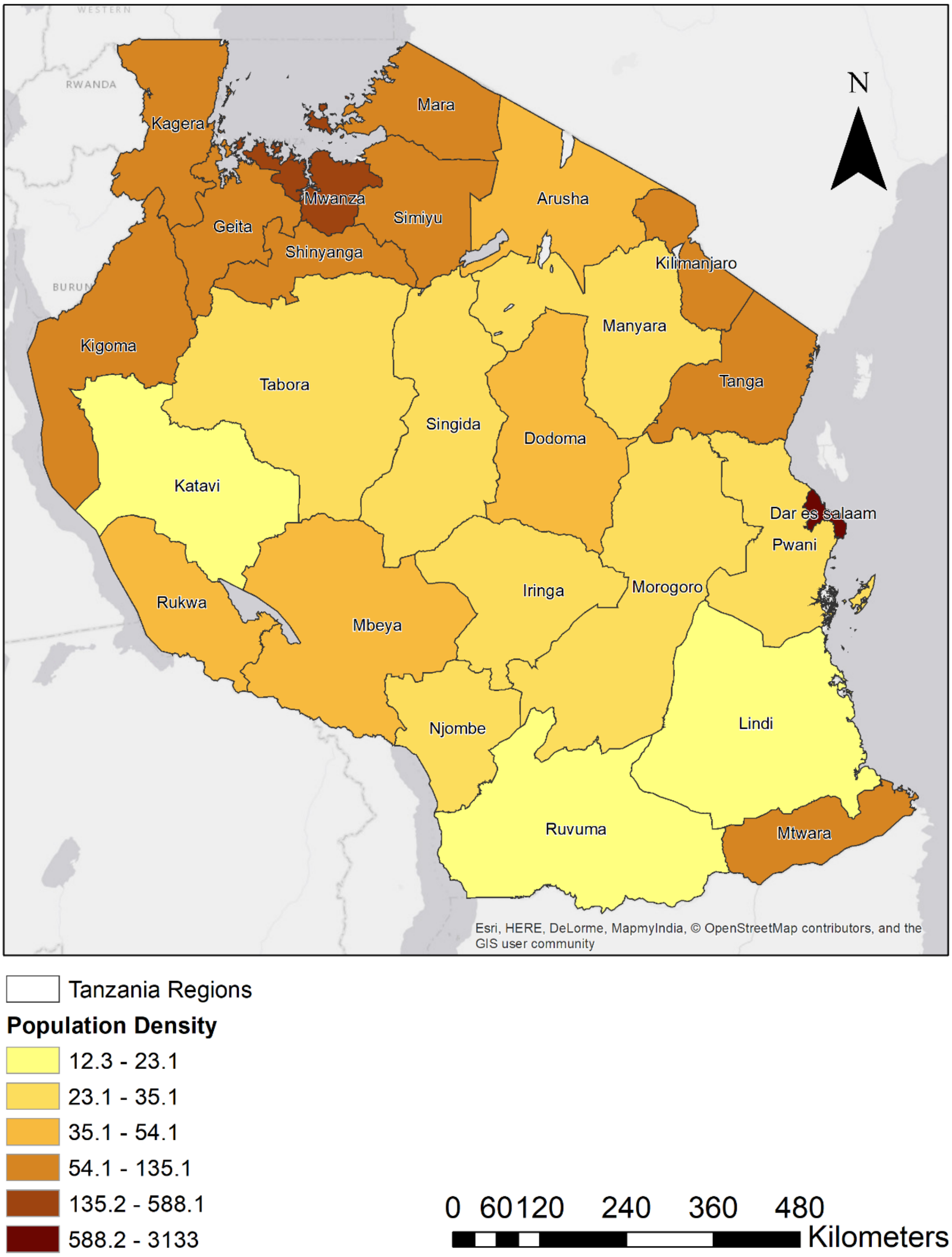


Figure 2.16 - Population density per region (people per km^2). Data from the 2012 Tanzanian census *(NBS, 2013b)*.

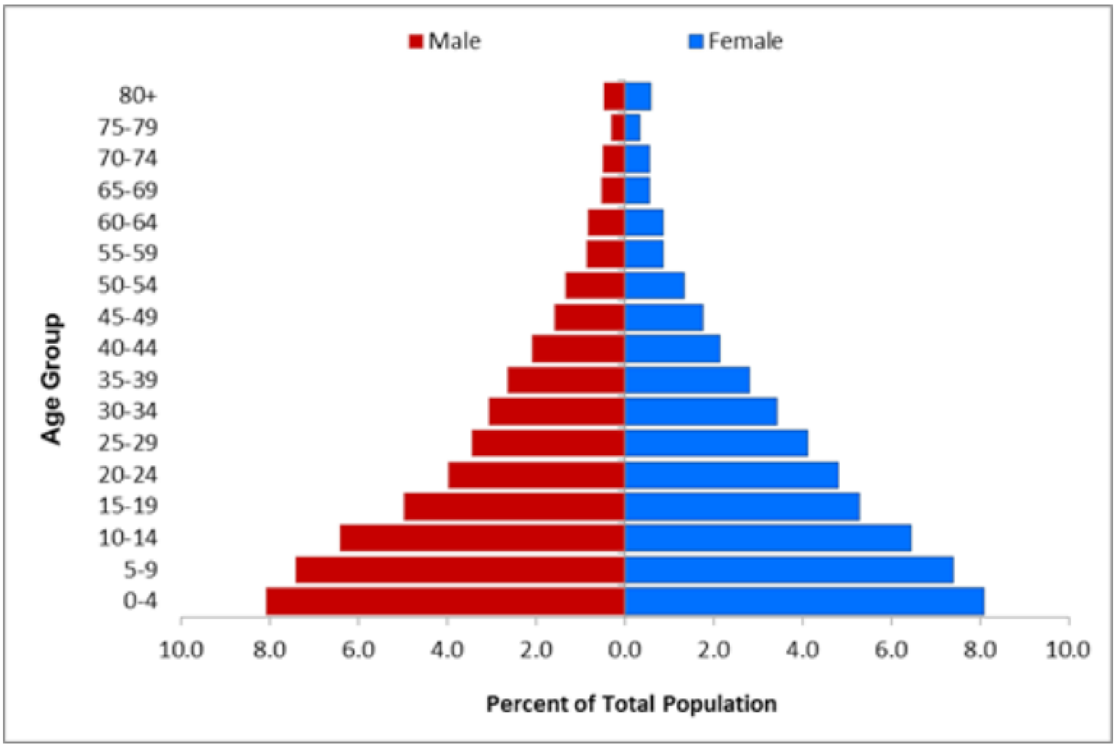


Figure 2.17 - Percentage distribution of population by age group and sex in Tanzania, 2012. *(NBS, 2013b, 2016).*

Table 2.6 - Key indicators from 2002 and 2012 population housing censuses, Tanzania *(NBS, 2013a, 2016)*.

Indicators	**2002**	**2012**
Total population (million)	34.5	44.9
Children population < 5 years (%)	16.4	15.2
Young population < 15 years (%)	44.2	43.9
Youth population 15 – 35 years (%)	-	35.1
Working age population 15 – 64 years (%)	51.8	52.2
Elderly population 60+ years (%)	5.7	5.5
Elderly population 65+ years (%)	3.9	3.8
Sex ratio (males per 100 females)	96	95
Life expectancy at birth	51	61.8
Life expectancy at birth (male)	47	59.8
Life expectancy at birth (female)	50	63.8
Percent of urban population	23.1	29.6
Percent of rural population	76.9	70.4
Persons with Disability (%)	2	9.3
Child orphan hood (%)	1.1	7.7
Annual growth rate	2.9	2.7
Households without toilets (%)	9.2	7.8
Floor materials (Mud) (%)	73	60

2.9.2 Current malaria prevention and treatment policies

Various approaches to malaria prevention and treatment have been implemented during the period 2000 to 2014, predominantly since 2001 and funded by various bodies throughout this period (figure 2.18). With some governmental policies predating this period, discussed further in section 2.9.2.1. As shown in figure 2.18 a), funding for implementation of malaria policies has varied throughout 2000 to 2014, with a five-year period where no extra funding at all was provided (or recorded) from 2004 to 2008. This observation could be considered unusual when multiple flagship malaria policies for Tanzania were launched in 2004, this is further discussed in sections 2.9.2.1 to 2.9.2.3. Funding has predominantly come from external sources, with the greatest contributions coming from the global fund, followed by USAID and the world bank / others according to WHO records (USAID, 2015; WHO, 2015c). Sources of funding is an important factor to consider when examining the effectiveness of prevention and treatment policy as donors have been observed to disproportionately impact malaria policy based on their own agendas (Mutero et al., 2014).

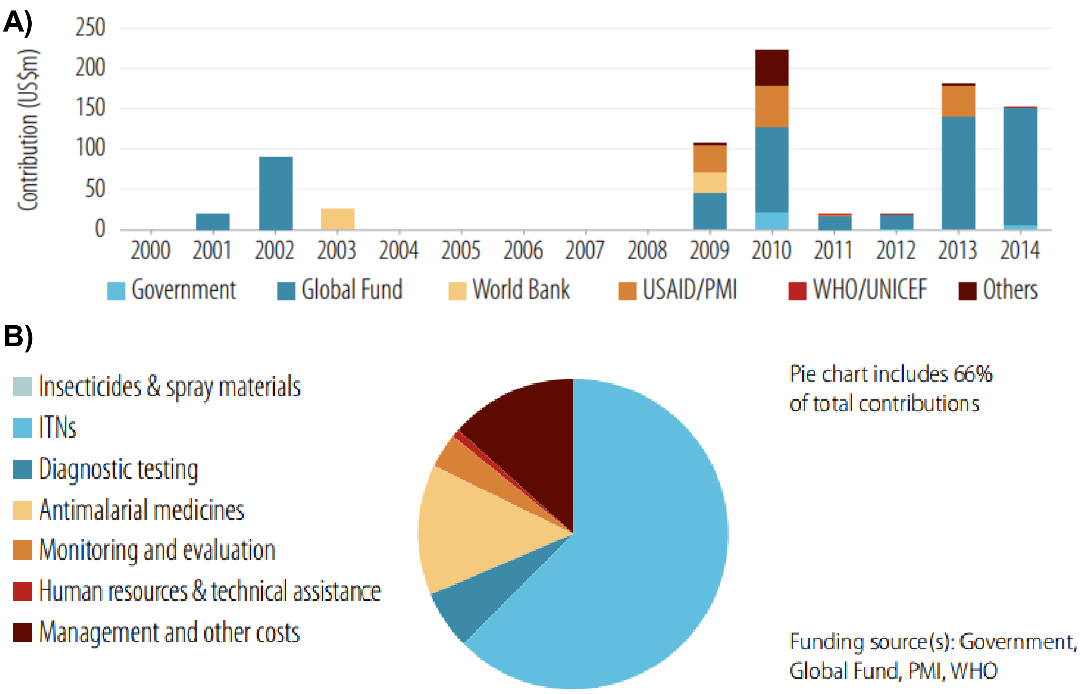


Figure 2.18 - a) Sources of financing for malaria policies in Tanzania b) Distribution of funding by intervention method in 2014 *(WHO, 2015c)*.

2.9.2.1 Insecticide Treated Nets (ITNs)

As shown in figure 2.18 b) ITNs currently form the majority of malaria intervention in Tanzania, and are widely identified as one of the most effective malaria prevention methods (Alliance for Case Studies for Global Health, 2009; West et al., 2012). Investment in ITNs in Tanzania can be attributed to extensive research and investment prior to 2000 in the development and implementation of bed nets in Tanzania (table 2.7) (Magesa et al., 2005). This research led to the development of the National Insecticide Treated Nets programme (NATNETS), a large public private partnership (PPP), which aims to make ITNs accessible and affordable to all those at risk of malaria, alongside a countrywide target of protecting 60% of the population at high risk by 2005 (Hanson et al., 2005; Magesa et al., 2005). The programme was further developed through the introduction of the Tanzanian National Voucher Scheme (TNVS) in 2004 and implemented countrywide in 2006, which targeted pregnant women and children, distributing discount vouchers at their first antenatal visit (Marchant et al., 2010; Bonner et al., 2011; Kramer et al., 2017).

Table 2.7 - The critical path of insecticide-treated nets (ITN) research and implementation in Tanzania, 1982 to 2004 *(Magesa et al., 2005)*.

Efficacy studies	**Effectiveness studies**	**Policy developments**	**Going to scale**	
Reducing malaria vector exposure (including net and insecticide developments)	Reducing malaria morbidity and mortality	Impact (morbidity and mortality) and cost assessment in pilot programmes.	National strategies and partnerships for an enabling environment	National ITN strategy and policy NATNETS
1983 - 1995	1985 - 1995	1992 - 2000	1997 - 2000	>2000

The impact of the implemented PPP, ITNs and TNVs combined within Tanzania on malaria has been closely examined with regards to its success and continued development. A key upgrade phase was the universal coverage campaign (UCC) starting in 2009, aiming to distribute 17.6 million Long Lasting Insecticide Nets (LLINs) to replace current ITNs, offering longer lasting protection, particularly for households in rural locations with poor access to dispensaries and clinics (Magesa et al., 2005; Bonner et al., 2011; Kramer et al., 2017). Overall the combined ITN/LLIN and TNV is an argued success, with average national bed net ownership increasing from 45.7% (2008) to 63.4% by 2011 with regional variations. ITN/LLIN use for under-fives was reported to increase from 28.8% to 64.1% (Bonner et al., 2011; Eze et al., 2014; Kramer et al., 2017). A summary of voucher redemptions and ITN/LLIN distributions can be found in table 2.8.

Despite overall successes, this is not unanimously achieved countrywide. Affordability amongst the poorest residents, and often the ones at highest risk, who cannot afford the $0.80USD (1000 TZS) top up remains an issue to which no feasible solution has yet been found (figure 2.19) (Heierli and Lengeler, 2008; Marchant et al., 2010). In addition, whilst distribution of nets has been an overall success, education on their use and effectiveness appears lacking in some districts. In order for the TNV system to be effective, a five step process must be adhered too. Steps include: women attending an antenatal clinic, obtaining a voucher, retrieving and subsidising the remaining cost of a net, treating the net themselves with insecticide and then using the bed net properly (Marchant et al., 2010). Information on how to use nets properly varies by district, for example only 74.5% of households in the Muleba district (Kagera region) were provided with guidance on how to hang or use nets, with hang-up campaigns being identified as an important step to ensure conversion of ownership into usage (West et al., 2012).

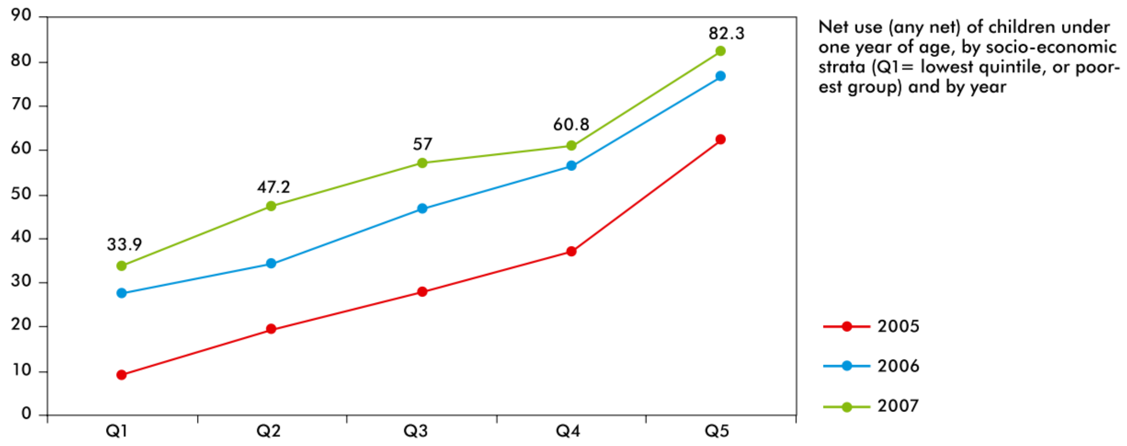


Figure 2.19 - Net use (any net) of children under one year of age by socio-economic strata (Q1 = lowest quintile, or poorest group) and by year *(Heierli and Lengeler, 2008)*.

Table 2.8 - Malaria prevention outputs, 2007 – 2012 *(MoHSW, 2013b).*

	2007/08	**2008/09**	**2009/10**	**2010/11**	**2011/12**	**2012/13**	**Total**
TNVs Infant vouchers redeemed	332,055	516,102	394,690	768,338	548,924	750,783	3,310,892
TNVs Pregnant women vouchers redeemed	931,193	827,805	527,163	722,439	675,278	785,084	4,468,962
Under five years catch up campaign LLIN distributed	0	0	5,498,322	3,264,116	0	0	8,753,438
Universal coverage campaign LLIN distributed	0	0	0	4,641,192	12,976,699	0	17,617,891
Total ITN/LLIN distributed	1,263,248	1,343,907	6,420,175	9,363,085	14,200,901	1,535,867	34,151,183
Number of house structures sprayed with insecticides	34,745	95,548	425,118	425,118	1,144,621	1,167,998	3,053,247
Number of districts implementing IRS	1	2	2	7	18	18	18

2.9.2.2 Antimalarial medicines

Chloroquine (CQ), a mono-therapeutic antimalarial, was used as the antimalarial drug of choice globally for 45 years in most malaria endemic sub-Saharan African countries due to an effective cost to performance ratio and its availability (Nsimba et al., 1999; Mubyazi and Gonzalez-Block, 2005). However, as malaria resistance to the drug rose, the clinical usefulness eroded (Baird, 2005). Extensive research was presented to the Tanzanian government and policy makers supporting the case for changing the first line malaria drug treatment from chloroquine to sulfadoxine pyrimethamine (SP), with the second line drug of choice as Amodiaquine (AQ) (Mubyazi and Gonzalez-Block, 2005). Following drug use policy changes, the performance of SP was assessed in 2004, with treatment failure increasing for SP at 25.5% and 12% for AQ prompting further policy change in 2006 (MoHSW, 2006; Mboera et al., 2007). Some studies conducted during this time period further indicated that misuse of antimalarials was likely to be a further contributory factor, with only 8% of mothers stocking antimalarials and widespread negative perceptions of SP (Eriksen et al., 2005).

The observed steady decline in clinical success of mono-therapeutic antimalarials (such as CQ, SP and AQ) in malaria-endemic countries, including Tanzania, has led to the recommendation and adoption of artemisinin combination therapy (ACT) for the treatment of uncomplicated malaria (table 2.9) (MoHSW, 2006; Whitty et al., 2008; Masanja et al., 2010). Whilst ACT is recommended by the WHO, the implementation of ACT in Tanzania has proved problematic and has stagnated between 2009 and 2013 with SP still being overall favourable in 2016 (Eriksen et al., 2005; Mboera et al., 2013; ACTwatch Group et al., 2017). Challenges include overcoming high cost and distribution to the poorest communities which need them most (MoHSW, 2006; Whitty et al., 2008). These challenges are aiming to be addressed by policies such as the Affordable Medicines Facility for malaria (AMFm), aiming to reduce cost and increase accessibility in rural Tanzania, although early results suggest that this scheme has not yet proved effective (Yadav et al., 2012). A crucial step in the success of ACT is that the treatment is only accessible with a positive malaria diagnosis test, due to high cost and the need to slow the rate of parasite resistance, which is discussed further in section 2.9.2.3 (Masanja et al., 2010; Hutchinson et al., 2017).

Table 2.9 - Malaria diagnosis, treatment and preventive therapies, 2007 – 2012 *(MoHSW, 2013b).*

	2007/08	**2008/09**	**2009/10**	**2010/11**	**2011/12**	**2012/13**	**Total**
ACT procured and distributed through public healthcare facilities	16,227,818	15,387,302	18,091,532	16,156,620	16,159,890	11,835,260	93,858,422
QAACT procured and distributed through private facilities	0	0	0	1,865,050	9,747,340	14,060,200	25,672,590
mRDTs procured and distributed through public healthcare facilities	0	0	1,937,300	5,003,000	9,247,600	13,335,850	29,523,750
Number of regions (n=21) implementing mRDTs	0	0	3	8	16	21	21

2.9.2.3 Diagnostics, monitoring and management

As indicated in section 2.9.2.2, the accessibility and effectiveness of new malaria treatments such at ACT is increasingly dependent on accurate malaria diagnosis (Hutchinson et al., 2017). Historically, malaria was treated presumptively although research found that in many cases this led to over-diagnosis, the over prescription of malaria drugs and under-diagnosis of other illness inducing ailments (Reyburn et al., 2007; Aung et al., 2015). The development of malaria rapid diagnostic testing (mRDT) (figure 2.20) was seen as a crucial step forward in solving issues surrounding over-diagnosis and over-treatment of malaria, allowing for appropriate management of newly introduced ACT treatments (MoHSW, 2013b; WHO, 2015b; Hutchinson et al., 2017). Despite this, early evidence has indicated widespread misuse whereby mRDT were either not used at all or in cases where a negative result was received, malaria treatment was prescribed despite the negative indication by the test (Reyburn et al., 2007; Hutchinson et al., 2017).

Figure 2.20 - Example of a malaria rapid diagnostic test *(USAID, 2013).*

In Tanzania, on-site malaria diagnosis was highlighted as an important step forward under the national malaria strategic plan (2008 to 2013) which led to the introduction of mRDT in 2009 with national treatment guidelines updated to further support the use of mRDT in 2011 (MoHSW, 2008, 2013b; WHO, 2015b). The initiative can widely be viewed as successful in Tanzania in terms of mRDT capacity increase which has improved from 30% coverage when mRDT were first introduced (2009) to 75% as of 2012 (table 2.10) (Mboera et al., 2013). Despite mRDT presence in Tanzania improving considerably since 2009, and widespread availability since 2012, mRDT does not yet dominate as a means of decision making around malaria, highlighting the need for further work (Mboera et al., 2013; Bruxvoort et al., 2015; Hutchinson et al., 2017).

Table 2.10 - Malaria service readiness of health facilities in Tanzania, 2009 and 2012. *Rapid diagnostic test of microscopy *(Mboera et al., 2013).*

Variable	2008/2009	2012
Offering diagnosis (%)	81	86
Offering treatment (%)	97	86
Facilities with malaria treatment services (n)	603	1209
Trained staff (diagnosis and treatment) (%)	66	59
Guidelines available (%)	64	60
Trained in Intermittent Preventive Treatment (%)	-	37
Guidelines on Intermittent Preventive Treatment (%)	-	45
Diagnostic capacity on site* (%)	30	75
Artemisinin Combination Therapy in stock (%)	80	77
Sulfadoxine-pyrimethamine (%)	80	78
Insecticide treated mosquito nets (%)	-	61
Total health facilities (n)	635	1297

2.9.3 Healthcare accessibility

As shown in section 2.9.2, availability of malaria treatment in various forms including mRDTs, ACT, ITN's / LLINs, has improved significantly throughout Tanzania over the past 15 years as a result of increased investment and management (Mboera et al., 2013). Whilst many policies have led to increased availability in malaria prevention, diagnosis and treatment, overall accessibility remains a concern. These concerns are particularly applicable to the most vulnerable demographics and populations, the disparities of which will be highlighted in this section.

The Tanzanian health system is based on a central-district government structure with a hierarchical system and referral structure from primary to tertiary district, regional, consultant and specialised hospitals outlined in figure 2.21 (MoHSW, 2013a, 2013b). Dispensaries serve populations ranging from 6000 to 10,000 people, health centres serve 50,000 – 80,000 people and a district hospital serves more than 250,000 people. Regional hospitals serve as a referral centre to four to eight district hospitals, with four consultant hospitals serving as referral centres to several regional hospitals. Examination of Tanzania's service availability and readiness using a sample of the total health facilities (table 2.11) concluded that as of 2013, 65% of all types of facilities are located in rural areas, with 35% in urban areas (MoHSW, 2013a). Facility ownership varies between urban and rural areas, with more than half of facilities in urban areas being private-not-for-profit or private-for-profit owned facilities in comparison to only 12% ownership in rural areas (table 2.12) (MoHSW, 2013a).

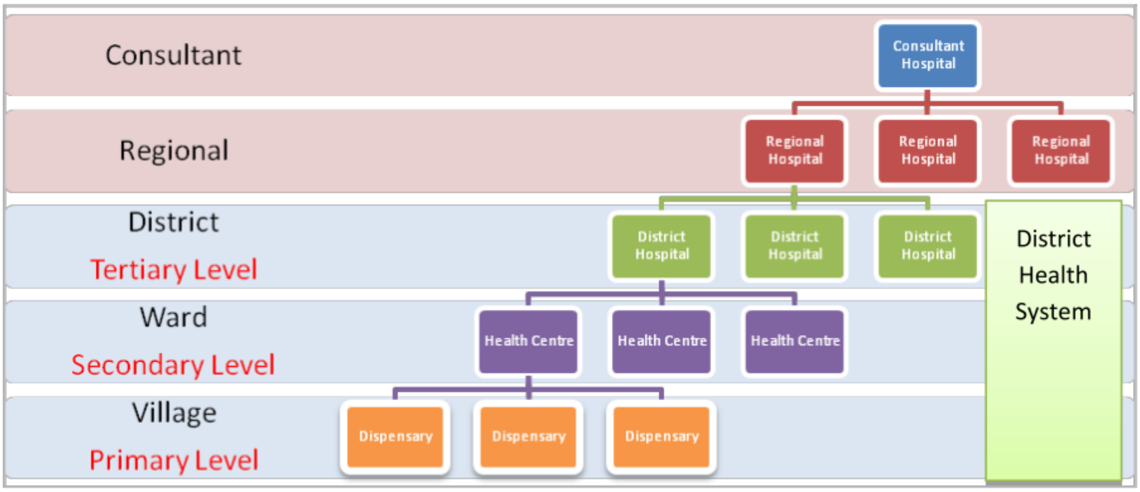


Figure 2.21 - Administrative and functional level type of facilities *(MoHSW, 2013b).*

Table 2.11 - Number of health facilities in Tanzania Mainland, 2010-2015 (*including 89 clinics) *(NBS, 2016).*

Health Facilities by Type	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Hospitals	240	236	241	254	254	252
Health Centers	687	684	742	711	713	718
Dispensaries	5,394	5,132	5,680	5,680	6,002*	6,549*
Total	**6,321**	**6,052**	**6,663**	**6,645**	**6,969**	**7,519**

Table 2.12 - Percent distribution of health facilities by residence, according to level of service, managing authority and owner. Based on sample study for the SARA report. *(MoHSW, 2013a).*

Background Characteristic	**Percent Rural**	**Percent Urban**	**Number of Facilities**
Level of service			
Dispensary	77	24	1100
Health Centre	60	40	137
MCH Clinic	46	54	8
Hospital	47	54	52
Managing authority			
Government / public	84	16	923
Mission / faith based	64	36	132
NGO/Not-for-profit	56	44	9
Private-for-profit	18	83	233
Ownership			
Public/Govt	84	16	923
Private	39	61	372
Total	73	27	1297

2.9.4 Current access and immunity to malaria treatment

Human population dynamics greatly influence malaria vector, transmission and its control in urban and rural settings (De Silva and Marshall, 2012). In Tanzania, malaria prevalence in urban areas is one third of that found in rural areas (3% and 10% respectively), resulting from a number of influential factors (Mboera et al., 2007; MoHSW, 2013b). Densely populated and built-up areas limit the breeding capacity of mosquitoes due to reduced vegetation and suitable breeding habitats, where potential habitats are easily identified and accessed for vector control (figure 2.22) (Caldas de Castro et al., 2004; Kabaria et al., 2016). Access to facilities is also comparatively high in urban areas with 96% of the population living within a 5km radius of a health facility in urban areas compared to 54% in rural (MoHSW, 2013a, 2013b). Despite good access in terms of proximity, the urban public health sector is severely overburdened, particularly for the densely populated Dar es Salaam, and the private sector unaffordable for a large part of the population, of which dominates urban environments in Tanzania (section 7.3) (MoHSW, 2013b). This is an important factor to consider within the context of wider initiatives and urban environment changes.

2.9.4.1 Urban malaria

Although malaria prevalence is considerably lower in urban areas when compared to rural areas, the prevalence of fever is similar between the two settings, highlighting concerns of over-diagnosis in urban settings where the newly implemented diagnosis techniques are still not used routinely and clinical diagnosis is applied instead (Mboera et al., 2007; Rumisha et al., 2007; MoHSW, 2013b). These concerns of over-diagnosis are warranted, considering urban malaria is overall predicted to be low and reducing with increasing populations due to generally better quality “mosquito-proof” housing, higher human to mosquito ratios, polluted water deterring mosquitoes, and lack of habitat suitability in urban environments (De Silva and Marshall, 2012; Kabaria et al., 2016). Over-diagnosis leads to increased resistance which would be have a greater impact on rural communities in comparison to the urban communities, where patients are often misdiagnosed due to symptom similarity to other febrile illnesses, as proven in numerous studies where parasite presence was examined, demonstrating misdiagnosis of malaria (Mboera et al., 2007; Reyburn et al., 2007; Chandler et al., 2008). Thus, despite access to malaria treatment being overall acceptable, diagnosis shortfalls and private clinic costs are problematic in urban settings.

Transmission risk remains high, particularly in peri-urban areas, often where low socioeconomic migrants from rural communities have settled looking for work, overall contributing to increased likelihood of malaria contraction (De Silva and Marshall, 2012). Despite overall environmental difficulties for mosquitos in urban areas, peri-urban areas offer a foothold through a combination of the less dense building layout, increased vegetation, and water pooling in domestic containers (Kabaria et al., 2016). *Anopheles gambiae s.l / s.s* have been discovered in both organic and polluted urban aquatic habitats, such as urban rivers and rain filled domestic containers (Awolola et al., 2007; Kabaria et al., 2016). This emphasises the need to continue preventing, treating and monitoring the development of urban malaria.

Figure 2.22 - Example of the urban environment in Dar es Salaam. (Reynolds, 2015).

2.9.4.2 Rural malaria

Section 2.9.3 highlights the disparity between healthcare access and availability between urban and rural environments, with only 54% of the rural community within 5km of a hospital, often experiencing much poorer transport links (MoHSW, 2013a). This is somewhat offset by increased focus of policy implementations introduced in section 2.9.2 which has contributed to rural communities overtaking urban populations in terms of percentage ownership of LLINs as a result of vulnerable group focus programmes, however urban ownership does remain high (86.8% urban, 92.7% rural) (Mboera et al., 2013). This indicates that the increased efforts are beginning to improve overall accessibility to healthcare in rural locations, although improvement in other facilities such as roads, electricity and public transport could further contribute to accessing healthcare facilities (MoHSW, 2015; Shayo et al., 2015).

Rural communities are increasingly likely to experience intense malaria transmission, commonly as a result of low human population density in proximity to a large number of potential mosquito breeding sites due to suitable environmental conditions (figure 2.23 and 2.24) (Caldas de Castro et al., 2004). Mosquitoes prefer cleaner, organic water for breeding and vegetation for shelter making pastoral and crop fields surrounding rural villages increasingly suitable and surrounding villages and workers at higher risk (Bødker et al., 2003; Mboera et al., 2010; Mlozi et al., 2015). This is further exacerbated by considerably different livelihoods of the rural community, including farming and pastoral practices, housing and education which is further discussed in section 2.9.5.

Figure 2.23 - Many Tanzanian villages are surrounding by highly suitable environments as depicted here, with provision of water and vegetation with close proximity to human hosts. (Reynolds, 2015).

Figure 2.24 - Example of farming conditions in Africa, where irrigation is required to grow staple grains such as maize *(Farm Africa, 2017)*.

Unlike urban communities, rural communities are observed to possess increased natural immunity through generations of exposure to malaria infection, although this is further influenced by malnutrition and prevalence of immunodeficiencies, alongside the presence of non-immune residents who are increasingly likely to contract malaria such as young children (Kovats et al., 1999; Kuhn et al., 2005). Herd immunity offers a natural collective protection against malaria, often in historically high transmission areas, creating endemic stability (Sutherst, 2004). Herd immunity is observed to naturally fluctuate with exposure, where periods of low malaria transmission disrupted by environmental factors can reduce immunity (Reiter, 2001). The introduction of prolonged mass drug administration during epidemic outbreaks can reduce natural herd immunity, causing a rebound effect in infection cases (Brady et al., 2017). Thus the impact of drug administration should be carefully considered in rural communities (WHO, 2015b).

2.9.5 Socioeconomic and sociocultural impacts on malaria

As indicated throughout this chapter socioeconomic and sociocultural conditions play a vital role in an individuals (and wider communities) exposure to malaria and subsequent health seeking behaviour (Tanner and Vlassoff, 1998; Mlozi et al., 2015). Despite facilities and programmes being in place, the success of these schemes relies on public engagement with these policies to have a significant impact upon malaria control. A number of factors, both economic and cultural have been identified to impact malaria exposure and treatment which are further discussed in the following sub-sections, with potential changes to the existing dynamic discussed in section 2.10 and chapter seven.

2.9.5.1 The impact of working and housing conditions on malaria transmission

Malaria is prominent amongst low socioeconomic status families and often referred to as a disease of those in poverty (Reuben, 1993). The dominant source of income for rural residing and in most cases low-socioeconomic status families is pastoral and farming work which forms the backbone of the Tanzanian economy, and in cases results in a migratory lifestyle (Mboera et al., 2010; Shayo et al., 2015; Swai et al., 2016). Besides the importance of crop farming as a source of food for many families in poverty, crop irrigation systems such as rice farming provide increasingly suitable habitats for breeding adult mosquitoes (Mboera et al., 2010; Mazigo et al., 2017). This is reflected in studies examining these communities, where higher disease burden is observed in comparison to other communities, particularly wealthier urban communities (Kitula, 2006; Mazigo et al., 2017).

Higher disease burden is observed as a result of increased exposure and farming practices, however the exact interactions and roles of each are not yet fully understood (Mayala et al., 2015; Moshi et al., 2017). Community based studies conducted so far report that housing type and lack of outdoor biting prevention methods could be considerable contributors to high malaria burden amongst these communities (Shayo et al., 2015; Swai et al., 2016; Mazigo et al., 2017). Housing often consists of mud walls, palm leaf roofs and a gap between to allow for air circulation (figure 2.25) (Oberlander and Elverdan, 2000). Despite increases in use of bed nets within mud-huts due to distribution programmes, rural communities often consist of large communities leaving family members sleeping under non-treated bed nets or improperly fitted bed nets if a bed is on the ground, leaving little to no protection (Kweka et al., 2013; Swai et al., 2016; Mazigo et al., 2017). Alternatives are currently being researched in the form of protected portable housing for pastoral workers (Swai et al., 2016).

Figure 2.25 - Example of Tanzanian mud huts *(National Geographic, 2009)*.

Malaria prevalence generally peaks at harvest time, as a result of increased outdoor biting and exposure in rural communities due to working during hours which are suitable for outdoor malaria transmission (Mboera et al., 2007). Harvest time is crucial for securing food and income for low-socioeconomic families. However, it is estimated that a single bout of malaria can result in an individual losing an average of one to five working days, or up to 10 working days for severe malaria, leading to a cycle of increased poverty due to lost working days (Chima et al., 2003; Mboera et al., 2007). Until the poorest populations are able to modify farming and housing practices (figure 2.26), as well as exploring solutions to reduce outdoor biting in rural areas, malaria will continue to be a severe economic burden to many rural communities as well as impacting overall Tanzanian economic development.

Figure 2.26 - Conditions in rice paddy farming *(Guardian, 2013)*.

2.9.5.2 Social beliefs, education and malaria presence

Household responses to illness are known to be further influenced by cultural factors, including beliefs about causes of disease and effective cures, as well as patriarchal society structure, and issues surrounding age and gender discrimination (MoHSW, 2007; Shayo et al., 2015). The extent of this impact remains uncertain, particularly surrounding gender studies where evidence shows cases where gender has not been an influencing factor in malaria acquisition (Ghebreyesus et al., 2000; Brooker et al., 2004). Tanzania is making improvements in education, gender and age discrimination with regards to equality in malaria treatment access issues discussed in this section. Although it is recognised that further inclusion of social science studies across urban and rural communities is required to begin to truly assess the impact cultural roles have on health seeking behaviour and malaria treatment as multiple studies report varying results (Brooker et al., 2004; Pool et al., 2012).

2.9.5.3 Factors relating to age and gender

Women are biologically, increasingly susceptible to malaria when pregnant, attracting twice the number of disease carrying vectors within Tanzania from both long and short ranges (Lindsay et al., 2000; Himeidan et al., 2004; Kourtis et al., 2014). This is a result of immune system changes, making women increasingly susceptible to malaria with recent studies showing women with blood type O and carrying a female child are even more at risk (Ansell et al., 2002; Adam et al., 2017). Pregnancy causes further exposure through the necessity for women to leave the safety of ITNs/LLINs more frequently during mosquito peak biting times, a factor which is unavoidable (Ansell et al., 2002).

Studies have shown the difficulties in women accessing healthcare once malaria has been contracted, due a traditionally run patriarchal household hierarchy which is responsible for providing and controlling household finances (Mlozi et al., 2015). This includes the approval of funding healthcare, which could be declined for women due to many factors including financial hardship, potential perceptions of disloyalty if healthcare was provided by a male healthcare worker and in some cases social pressure constraining women from overtly expressing illness for fear of being perceived as “weak” (Oberlander and Elverdan, 2000; Williams and Jones, 2004). In addition, males often seek to sleep under the protection of the bed-net (figure 2.27), leaving women and children vulnerable, due to them being the main financial provider for the household, where their sickness could result in lost finances leading to further financial difficulties (see section 2.9.5.1) (MoHSW, 2007).

Figure 2.27 - Bed nets hung in dorms, many have holes and are not fitted properly *(Stanmeyer, 2017)*.

Age plays a further role in exacerbating conditions described above, more so for women. Many pregnancies still occur at young ages in rural communities, contributing further to health vulnerabilities. The recommended age for maternity is from 20 years old onwards. However, in Tanzania 23% of young girls aged 15-19 begin to have children with a total of 46% within this age bracket being currently or formerly pregnant (MoHSW, 2007; Makulilo, 2014). In addition, 7.6% of young women aged 15-19 are in a relationship with a man 10 years their senior. Traditionalist values remain dominant particularly with regards to a womans age and subsequent vulnerability, contributing an element of gender-based violence in some cases. This is present in all socio-economic and cultural groups in Tanzania where women are socialised to accept, tolerate and even rationalise domestic violence, contributing to withdrawal and difficulties accessing healthcare (NBS, 2011; Makulilo, 2014).

Tanzania is working towards improving equality between men and women through the national strategy for gender development, overseen by the Tanzanian ministry of community development, gender and children which was implemented in 2003 (Ministry of Community Development Gender and Children, 2003). There has been no official report thus far documenting policy impacts, however it is recognised under the social institutions and gender index that Tanzania has further adopted a program successfully implemented in Brazil, partnering with men to reduce violence, promote shared parental duties and gender equality (OECD, 2014). This is somewhat reflected in increasing use of bed nets by women in remote rural communities, although it remains unclear how much the bed net initiatives have contributed to this by making more bed nets available to families (Mboera et al., 2013; Mazigo et al., 2017). Overall, inequality remains categorically high, particularly within education and work (Pacchiotti, 2012; OECD, 2014).

2.9.5.4 Education

Lower education levels have also been significantly associated with lower levels of malaria knowledge, fewer antenatal visits and hospital deliveries, and lower frequencies of clinic visits (Williams and Jones, 2004; Hagenlocher and Castro, 2015). Women tend to have lower levels of education than men in Africa, which is reflected in the percentage of women in unskilled manual labour (17% vs 13% for men) and lack of women in management roles in Tanzania (3% vs 5% for men) (Williams and Jones, 2004; NBS, 2011). This is even greater in the high-risk agricultural sector where the majority of women who work are not paid (72%) and 42% are employed by a family member (NBS, 2011; Pacchiotti, 2012). Malaria transmission is typically high in rural communities, where education is low and funding for health provisions and schools are limited. In these communities, malaria awareness is spread through community knowledge.

Studies have shown that in low education and rural communities there is an awareness surrounding malaria exposure. Many communities report increased incidences of outdoor biting, particularly as many rural residents stay outdoors in the evening due to poor housing structure and ventilation (Mayala et al., 2015; Moshi et al., 2017). Whilst education on indoor prevention is growing due to large public projects and investment (section 2.9.2), education surrounding outdoor prevention is poor in Tanzania, resulting in persistent malaria transmission due to lack of outdoor biting awareness and lack of investment in outside prevention methods, such as residual spraying (Shayo et al., 2015; WHO, 2015c; Moshi et al., 2017). This indicates outdoor malaria transmission awareness and prevention methods should be implemented in order to effectively tackle malaria transmission, particularly in rural communities (Mayala et al., 2015; Swai et al., 2016).

2.10 Translating scientific evidence into policy

Policy development and decision making utilises both quantitative (e.g. epidemiological) and qualitative data (e.g. narrative accounts) upon which to base final implementations and decisions (Brownson et al., 2009; Peters et al., 2013). Scientific evidence is highlighted as an important factor in guiding public health policy development (Samet, 2000; Murtaugh et al., 2017). However, there is concern that the gap between what scientific evidence demonstrates as an effective approach, and what public health policies are being implemented and enforced is growing (Brownson et al., 2009).

This could be due to several factors. Research is considered most likely to influence policy development through an extended process of communication and interaction, as outlined in the interface of science and health policy in chapter one (Samet, 2000; Brownson et al., 2009). There is increasing evidence that scientific findings and results are inaccessible due to poor communication of findings in a way which is useful to policy makers (Samet, 2000; Wardekker et al., 2008). Bodies such as the WHO and IPCC are able to guide public policies and policies with direct involvement, however further influential force is exerted by private funding bodies. Projects which are stakeholder driven and thus have an invested interest, have been discovered to be biasedly influenced by stakeholder demands over scientific evidence (Tonnang et al., 2010; Mutero et al., 2014)

Despite the challenges faced in science informed policy the importance of data communication cannot be overlooked. This thesis will attempt to summarise recommendations and conclusions drawn from the following experimental chapters in a way which is clear and direct for the benefit of policy consideration.

Chapter 3 : Examining baseline climatology and the effect of El Niño events on climate conditions in Tanzania.

3.1 Introduction

As outlined in chapter two, a variety of environmental variables underpin the epidemiological processes for a range of tropical diseases found throughout the African continent and Tanzania. Climatic conditions play a key role in the formation of suitable habitats and conditions and thus form a basis upon which disease transmission occurs (Tonnang et al., 2014; Pandya et al., 2015). This premise forms the motivation for this chapter, which builds upon the points outlined within chapter two in relation to climate conditions and intra-annual patterns throughout Tanzania, further examining how these patterns are altered through the impact of large climatic changes such as El Niño events. This is important to the overall aims and objectives of this thesis as in order to understand the processes at work, the foundation, in this case climat, must be thoroughly understood and examined (Bhatt et al., 2015; Mlozi et al., 2015; Shayo et al., 2015).

The meteorological stations and parameters chosen for examination provide an original insight into the climates experienced within these locations. The results will guide future chapters and contributions and therefore relevance to later work is commented upon.

3.1.1 Aims and objectives

Objective one is to provide an analysis of the climatological mean, minimum and maximum conditions and seasonality for temperature, rainfall and humidity across five identified locations within varying environments in Tanzania for a set time period. These variables were specifically chosen due to their importance in influencing the distribution patterns of a number of diseases (Kulkarni et al., 2010; Rohr et al., 2011; Altizer et al., 2013). Objective two aims to statistically assess the impact of categorically strong El Niño events on the baseline climatology. El Niño was chosen to be representative over La Niña due to the global scale on which disasters of varying types and capacities area seen during El Niño events, alongside the general global temperature rise of 0.5˚C (Kovats et al., 2003). This value is more indicative of potential future climate conditions than those seen under La Niña episodes, where epidemics are predominantly seen to follow periods of increased temperature and rainfall (Kovats et al., 2003; Kulkarni et al., 2010).

The overall aim of this chapter is to address research objective one, identifying key climatic characteristics and features of Tanzania including assessing sensitivity to El Niño events. This research will contribute to understanding how various environments and locations within Tanzania react to changes in the local climate and to identify areas and environments that suggest heightened sensitivity and quick response to climatic alterations within each area. This highlights areas which may be increasingly sensitive to changes in climate dynamics, using the impact of El Niño as a proxy, overall outlining areas which may experience epidemiological shifts under anticipated future scenarios.

3.2 An overview of climate and environments of Tanzania

Tanzania is broadly identified as having two major rainfall zones or regimes. North Tanzania experiences a bi-modal regime where southern Tanzania generally experiences a unimodal regime within which conditions and time of onset can vary considerably (Zorita and Tilya, 2002; Rowhani et al., 2011; Timiza, 2011). The controlling factor of this annual seasonality is the movement of the Inter-Tropical Convergence Zone (ITCZ), a large scale synoptic process which affects a number of countries across the African continent (figure 3.1). Prior analysis upon Tanzania's regimes have resulted in area classifications which vary between 7-12 separate climatic “zones” within the country which are based solely upon rainfall values (Ogallo and Chillambo, 1982; Basalirwa et al., 1999; TMA, 2014).

Rainfall amounts are generally reported as mean annual values. These appear to vary within the literature with some examinations concluding between 200mm up to 1000mm of rainfall is distributed across various locations within Tanzania, with higher amounts seen within the highland areas (Basalirwa et al., 1999; Timiza, 2011; Griffiths et al., 2013). However, more recent reports provided by the Tanzania Meteorological Agency (TMA) conclude that higher altitudes do not necessarily equate to higher rainfall amounts. For example, Dar es Salaam lies at 55m above sea level and is reported to receive a mean annual rainfall total of 1268mm whereas Mbeya, the highest station included in this study at 1704 masl receives only 776mm of rainfall per year which by comparison is considerably less (TMA, 2014).

Annual mean temperature range is reported to vary from 25˚C up to 32˚C, where cooler temperatures persist in the highland areas averaging between 10˚C and 20˚C (McSweeney et al., 2013). Although this contradicts other literature reporting average temperatures reaching as low as 5˚C in the Mbeya (south western highlands region) (TMA, 2014). Low elevation areas experience more tropical humid conditions with temperatures generally remaining above 20˚C with the warmest temperatures experienced along the coastal belt. Minimum temperatures are generally experienced in July, where maximum temperatures are reported to peak in February (Timiza, 2011; McSweeney et al., 2013; TMA, 2014).

In comparison to temperature and rainfall, humidity is less well studied and reported for Tanzania. Studies conducted by the TMA (2014) on selected stations for relative humidity demonstrate no discernible annual trend for Dar es Salaam, Iringa, Kigoma and Zanzibar meteorological stations between 1971-2001. Duane et al. (2008)

examined variations in relative humidity following an up-slope transect for Mt. Kilimanjaro covering a range of environments beginning at 1890m and covering environments from dense rainforest, through alpine conditions up to the summit ice field zone. Results from this particular analysis reported mean relative humidity conditions of approximately 97.7% at a station situated at 2340m, reducing to a mean of 54.4% at 5800m (Elliott and Kipfmueller, 2010). Whilst humidity records are not widely documented it is important to note in order to provide a comparison for the results in this chapter.

Each of the parameters described above vary considerably from location to location across Tanzania. This provides a range of environments which are further shaped by local topographical variations, soil properties and the resulting local vegetation as a result of a combination of these factors. The five meteorological stations chosen for inclusion in this analysis aimed to represent a range of environments including different climates, topography, landscapes and population densities as summarised in table 3.1. This is in order to ensure that impacts of El Niño conditions on a range of local conditions are adequately assessed. Figure 3.2 demonstrates the location of each of the chosen stations within Tanzania. The station selection process is further expanded upon in section 3.2.1.

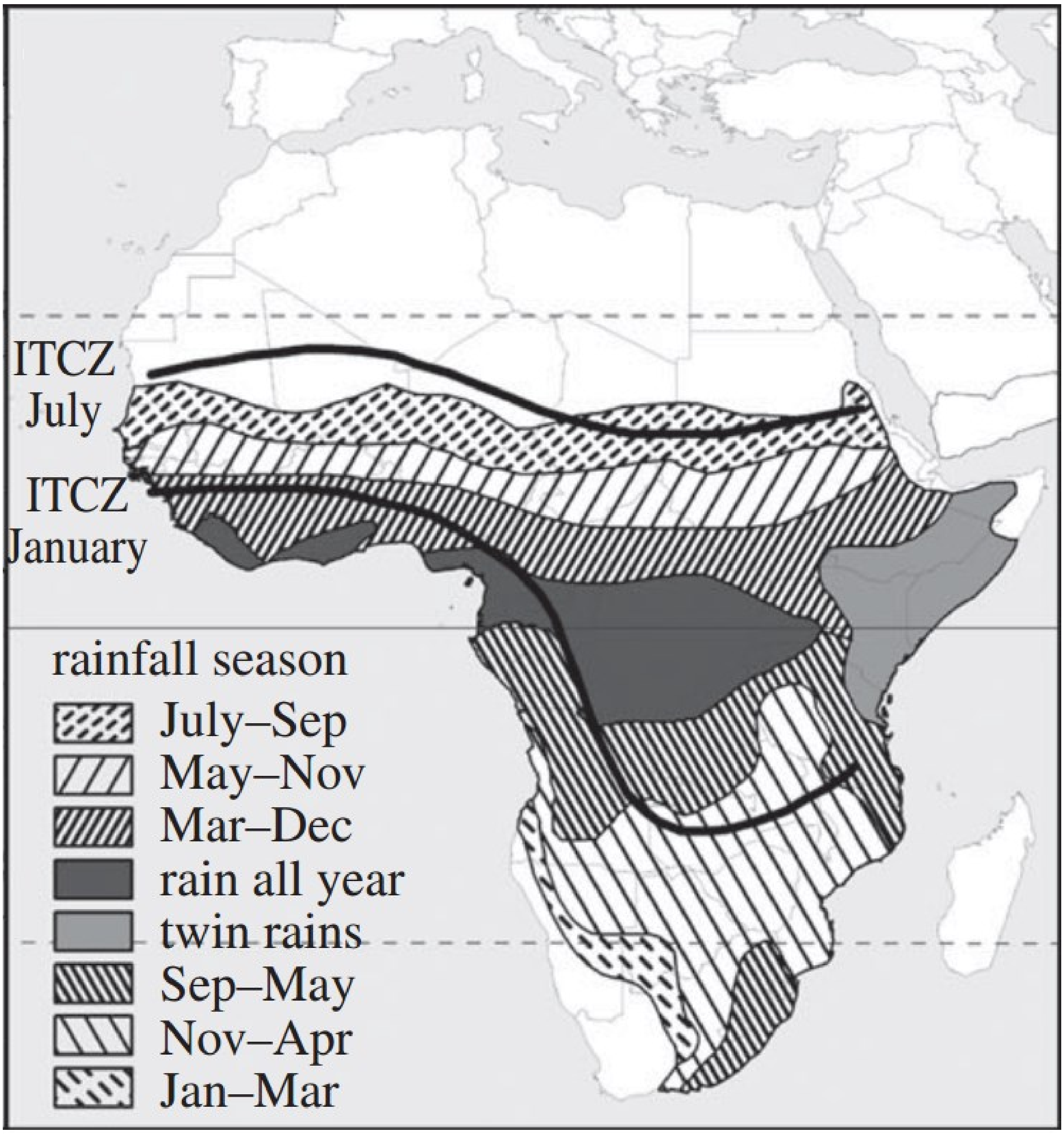


Figure 3.1 - Movement of the ITCZ across the African continent and associated timing of wet seasons *(Gaidet et al., 2012)*.

Table 3.1 - Meteorological station information for chosen stations in Tanzania. Climate Zones and summary values taken from TMA (2014). A timescale over which this data was collected is not reported in TMA (2014). Population density figures obtained from NBS *(NBS, 2013b)*.

Station	**Elevation (m)**	**Latitude**	**Longitude**	**Climate Zone**	**Mean Monthly Min Temp (˚C)**	**Mean Monthly Max Temp (˚C)**	**Mean Annual Rainfall (mm)**	**Population density (2012) (Pop/km ^{2})**
Dar es Salaam Airport	55	-6.867	39.2	North Coastal	18.2	32.4	1268	3113
Dodoma	1120	-6.17	35.767	Central	13.7	31.1	630	50
Kilimanjaro Airport	896	-3.417	37.067	North Eastern Highlands	8.3	33.1	786	124
Mbeya	1704	-8.933	33.467	South Western Highlands	5.3	26.6	776	45
Mwanza	1140	-2.476	32.917	Lake Victoria Basin	15.4	29.0	1128	293

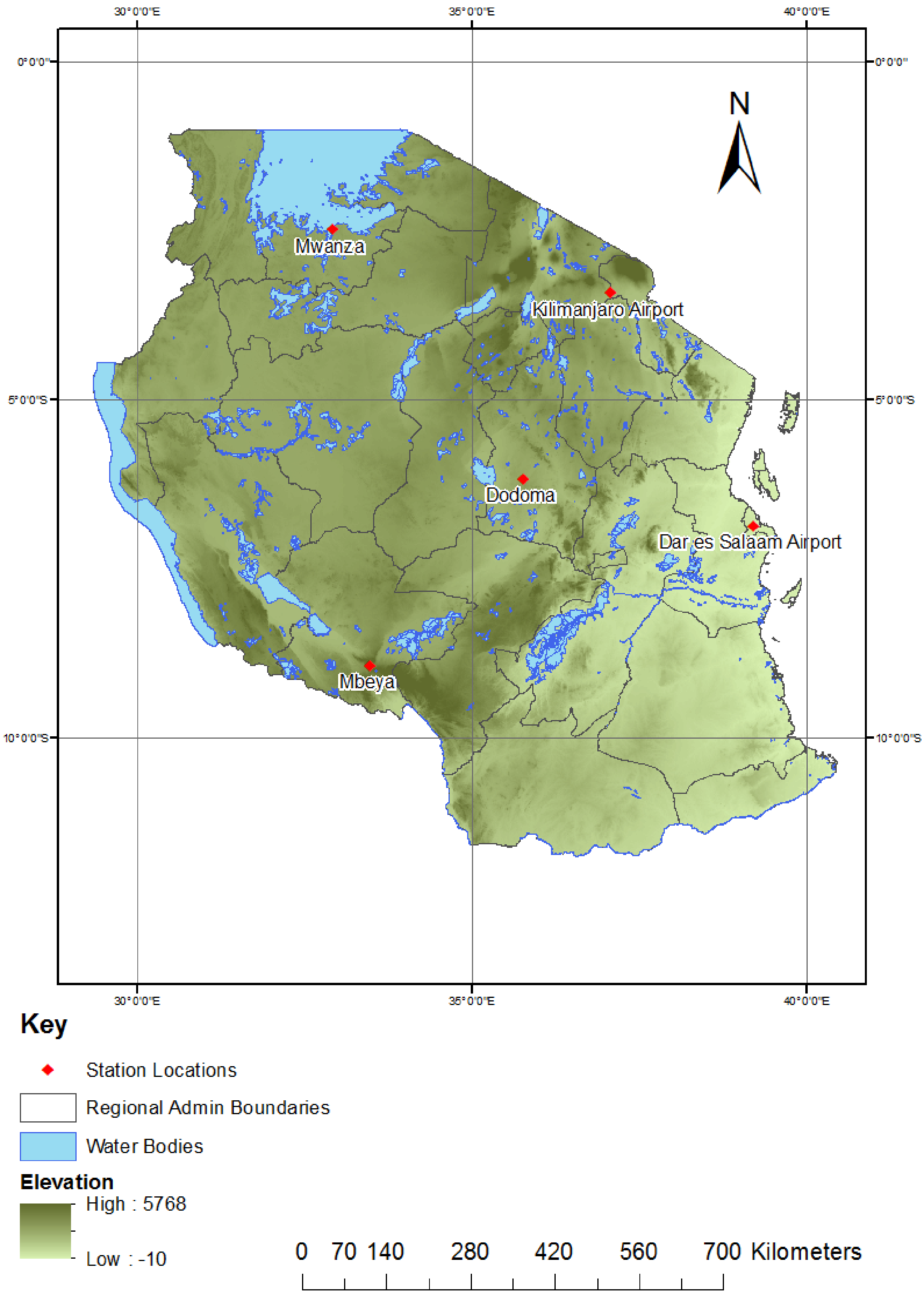


Figure 3.2 - Meteorological station locations and elevation for Tanzania. Grid units: Decimal Degree Seconds.

3.2.1 Meteorological stations analysed in this study

Station location choice was guided through climatological rainfall zones reported by Basalirwa (1999), Timiza (2011) and TMA (2014). Further to this topographic variation was taken into account in conjunction with varying bedrock and soil composition found across Tanzania which further contributes to local environmental conditions and influences local microclimates (Government of Tanganyika, 1955; Natural Resources and Tourism, 1974). Demographic factors were also considered given the premise of the overall thesis in relation to disease transmission and to aid in decision making for future chapter assessments as outlined in the aims and objectives of this chapter (Section 3.1.1).

3.2.1.1 Dar es Salaam Airport

Dar es Salaam is geologically underlain by fluvial sand, gravel, silt and limestone (Government of Tanganyika, 1955). Soils are predominantly red laterite (locally known as murram) soils overlaying grey and black non-calcareous soils, with areas including friable clay (Government of Tanganyika, 1955). This combination of bedrock and soil conditions support bushland of various plant species, with some areas possessing friable clay (imperfect drainage conditions) supporting the growth of open woodland (Natural Resources and Tourism, 1974). The area immediately surrounding the meteorological station is urban in nature, with a minor patch of open woodland being present immediately adjacent to the airport in the Kitunda district. Overall, the station is surrounded by a dense urban environment as a result of Dar es Salaam's growth since the station began operation in 1974. The airport lies 4km from the city centre and coastline, which similarly will influence the station via urban heat impacts and coastal conditions.

3.2.1.2 Dodoma

Dodoma is located on the Tanzanian plateau, 1120 masl. The meteorological station began operation in 1983 and is located in the centre of an urban settlement north-east of the Dodoma city airport. A mixture of plutonic rocks such as granite compounds and terrestrial sediments such as sand and gravel underlies the area. Patches of marine limestone, clay, mudstone and sand are also present surrounding Dodoma. This forms the basis for predominantly red laterite soil with grey and calcareous black soil with areas containing friable clay sediments nearby (Government of Tanganyika, 1955). Vegetation is sparse with the area being covered predominantly by open bushland of various species with patches of dry open grassland where drainage varies from imperfect to good (Natural Resources and Tourism, 1974).

3.2.1.3 Kilimanjaro Airport

Kilimanjaro airport is located at the foot of Mount Kilimanjaro at 896 masl. The airport meteorological station began operation in 1974. The region is underlain by typically alkaline volcanic rocks including basalt and pyroclastics. The Airport itself lies at a boundary between the volcanic bedrock and Archaean sediment with rocks including marble, graphite and a variety of others (Government of Tanganyika, 1955; Fishwick and Bastow, 2011). Surrounding soils are of a brown clay type. Vegetation is dry open grassland generally characterised by imperfect to good draining depending on the soils. In this case a clay underlay would make for poorer drainage. The airport is surrounded by open grassland with no urban settlements in the immediate vicinity, reducing the impact of urban heat effects (Natural Resources and Tourism, 1974). The nearest urban settlement is a small village 2.8km from the site.

3.2.1.4 Mbeya

Mbeya station began operation in 1983 and is located on the outskirts of Mbeya city at 1704 masl. Mbeya is located in the south west highlands in a valley within the mountain range's varied topography. The local geology varies between Mesozoic Era continental and marine sandstone and Archaean marble, granite and other varieties of sediments and rock. Soils in the area are predominantly pumice layered which generally allows for good drainage, interspersed with brownish red soils containing friable clay (Government of Tanganyika, 1955; Fishwick and Bastow, 2011). The dominant vegetation type ranges from woodland to grassland north of Mbeya, where woodland density increases upslope accompanied by sandy/loamy soils and drainage ranging from imperfect to excessive. To the south (where the station is located) vegetation changes to more dry, open grassland with varied drainage (Natural Resources and Tourism, 1974). The general bedrock suggests drainage should overall be adequate in the area. Its proximity to a substantially sized urban area and dense urban sprawl may allow some urban signal in records.

3.2.1.5 Mwanza

Located at 1140 masl on the shores of Lake Victoria, Mwanza's meteorological station began operation in 1983. Mwanza has a similar total population to Mbeya but is more densely populated (NBS, 2013b). The area is characterised by a plutonic bedrock consisting mostly of orogenic granite varieties. Local top-soils are mostly red/grey mixed with calcareous black soils (Government of Tanganyika, 1955). Bushland vegetation of a mixture of variations dominates the immediate area surrounding Mwanza before transitioning into dry open grassland further afield (Natural Resources and Tourism, 1974).

3.3 Methodology

3.3.1 Data

Meteorological station data was collected from the Met Office Integrated Data Archive System (MIDAS), which is supplied via the British Atmospheric Data Centre (BADC) (Met Office, 2012). Whilst there are now a number of publicly available datasets which allow access to global meteorological records, the MIDAS dataset was chosen for this study due to its implementation of a network wide guided data collection system. Further to providing guidance for data recorders, the Met Office (MO) also runs quality checks on data before being released with the aim to provide high quality data (Met Office, 2016a). Despite this, some anomalous data was found during analysis and treatment of this, for example the removal of outliers, is further explained in section 3.3.2.

Years 1985 through to 1995 were chosen to represent the baseline climatology for Tanzania. This was due to many stations within Tanzania only officially beginning operation from 1983 onwards with initial issues with irregular data entries hence starting the data period two years after the start of the majority of the stations themselves. Furthermore, an El Niño year of particular interest and included in this study (1997) occurred relatively shortly after data recording began hence restricting the dataset to 11 years. The 11 year period chosen is reflective of the wider 30 year climatology (1985 - 2014) with examples taken from Kilimanjaro Airport for temperature, precipitation and absolute humidity as shown in figures 3.3, 3.4 and 3.5 respectively. This highlights the suitability for the use of the chosen 11 year period for this analysis.

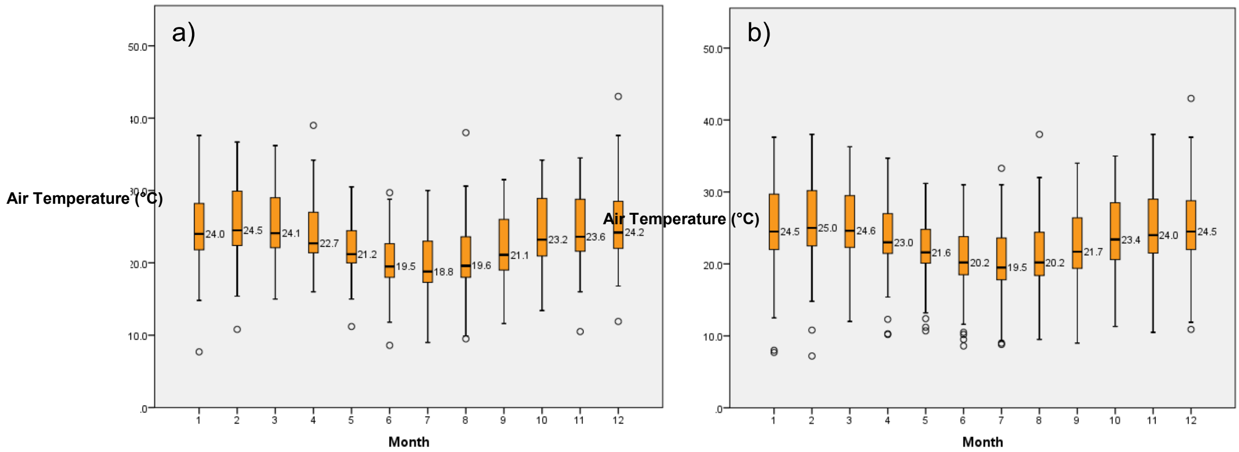


Figure 3.3 - a) Distribution of monthly temperature data over a 30year climatological period (1985 – 2014) b) Distribution of monthly temperature data over the 11 year baseline period (1985 – 1995). Outliers are represented as a circle, and are deemed plausible genuine results and thus have been retained. Units: °C.

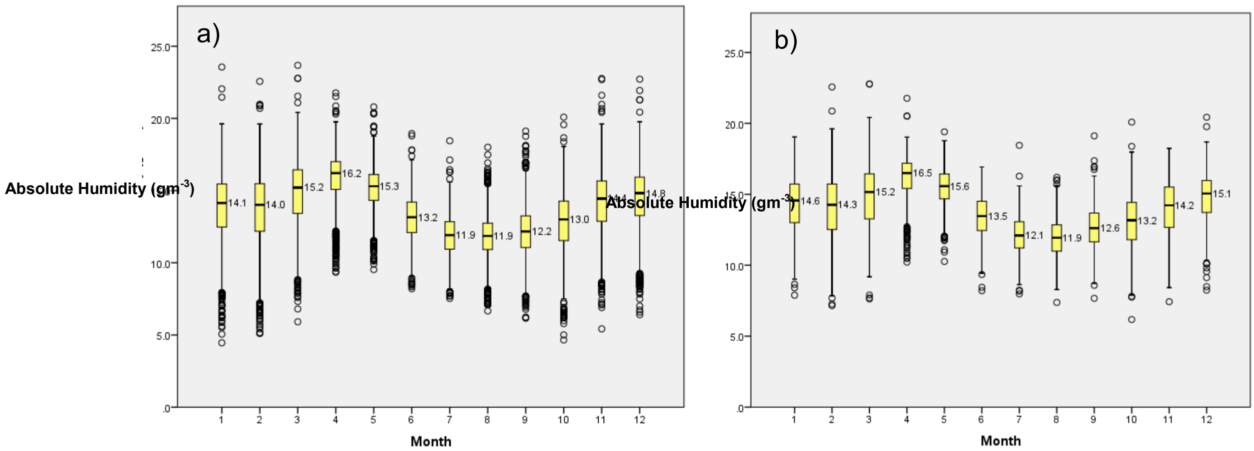


Figure 3.4 – a) Distribution of monthly absolute humidity data over a 30 year climatological period (1985 – 2014) b) Distribution of monthly absolute humidity data over the 11 year baseline period (1985 – 1995). Outliers are represented as a circle, and are deemed plausible genuine results and thus have been retained. Units: gm^{-3}.

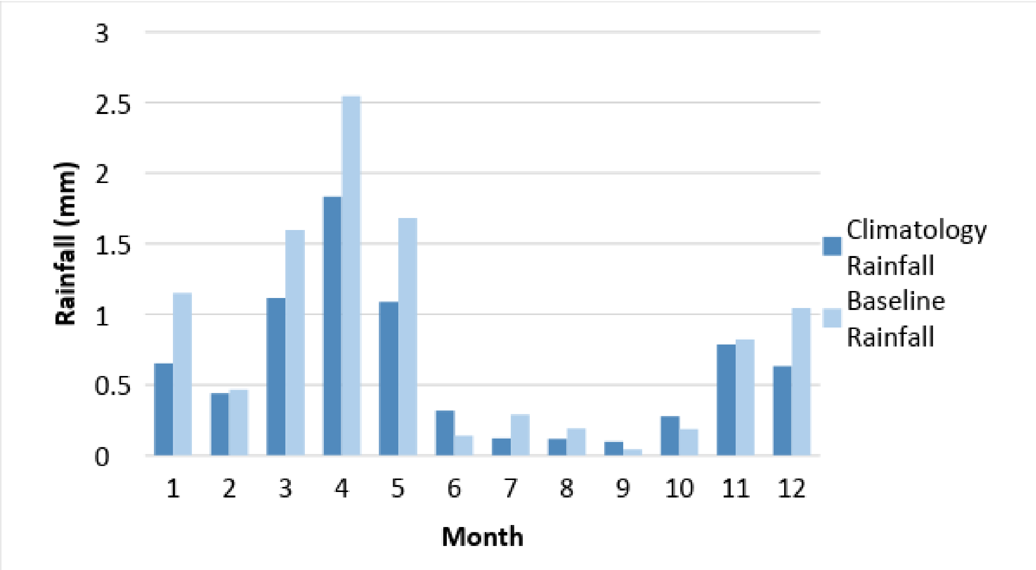


Figure 3.5 - Distribution of mean monthly rainfall data for a 30 year climatological period (1985 – 2014) and for the 11 year baseline period (1985 – 1995). The baseline period data is within one standard deviation of the 30 year climatological period. Units: mm.

El Niño years 1997 and 2015 were chosen to assess the impact of changing global conditions on the Tanzanian climate due to their categorically strong Southern Oscillation Index (SOI) values and relatively recent occurrence with the overall impacts of the 2015 event yet to be fully assessed and quantified (NOAA, 2015).

3.3.2 Analytical process

The workflow diagram presented in figure 3.6 demonstrates the process to assess each dataset for each station. Baseline climatology (1985-1995), 1997 and 2015, were each individually assessed using descriptive statistics before being combined and compared using ANOVA analysis. ANOVA tests were applied to determine whether there was any statistically significant difference between the climatological baseline (1985-1995) and the two El Niño years (1997, 2015). If a P value above 0.05 was returned, then further tests were not carried out.

Post-hoc tukey and bonferroni tests were undertaken if ANOVA returned statistically significant results in order to highlight within which months the statistically significant differences lie. The Tukey test performs to a reasonable accuracy despite theoretically requiring equal sample sizes and is outlined the stronger of the two tests for this type of analysis hence the presentation of the Tukey results in tables 3.7-3.11. Equal sample sizes have been maintained as far as achievable through the use of reducing the dataset to use synoptic hours only (Wallenstein et al., 1980). Bonferroni tests were performed to provide further evidence to support the statistical outcome as whilst every measure has been taken to ensure equal sample sizes this does vary (see section 3.6) (Ekstrøm and Sørensen, 2015).

The removal of outliers was required despite the quality assurance checks performed by the MO upon the MIDAS dataset (Met Office, 2016a). Some records still indicated errors of abnormally high temperatures when the dataset was manually scanned, for example some entries included recorded temperatures of 99˚C and in some cases lower dew point values than the recorded temperature resulting in relative humidity values above 100%.

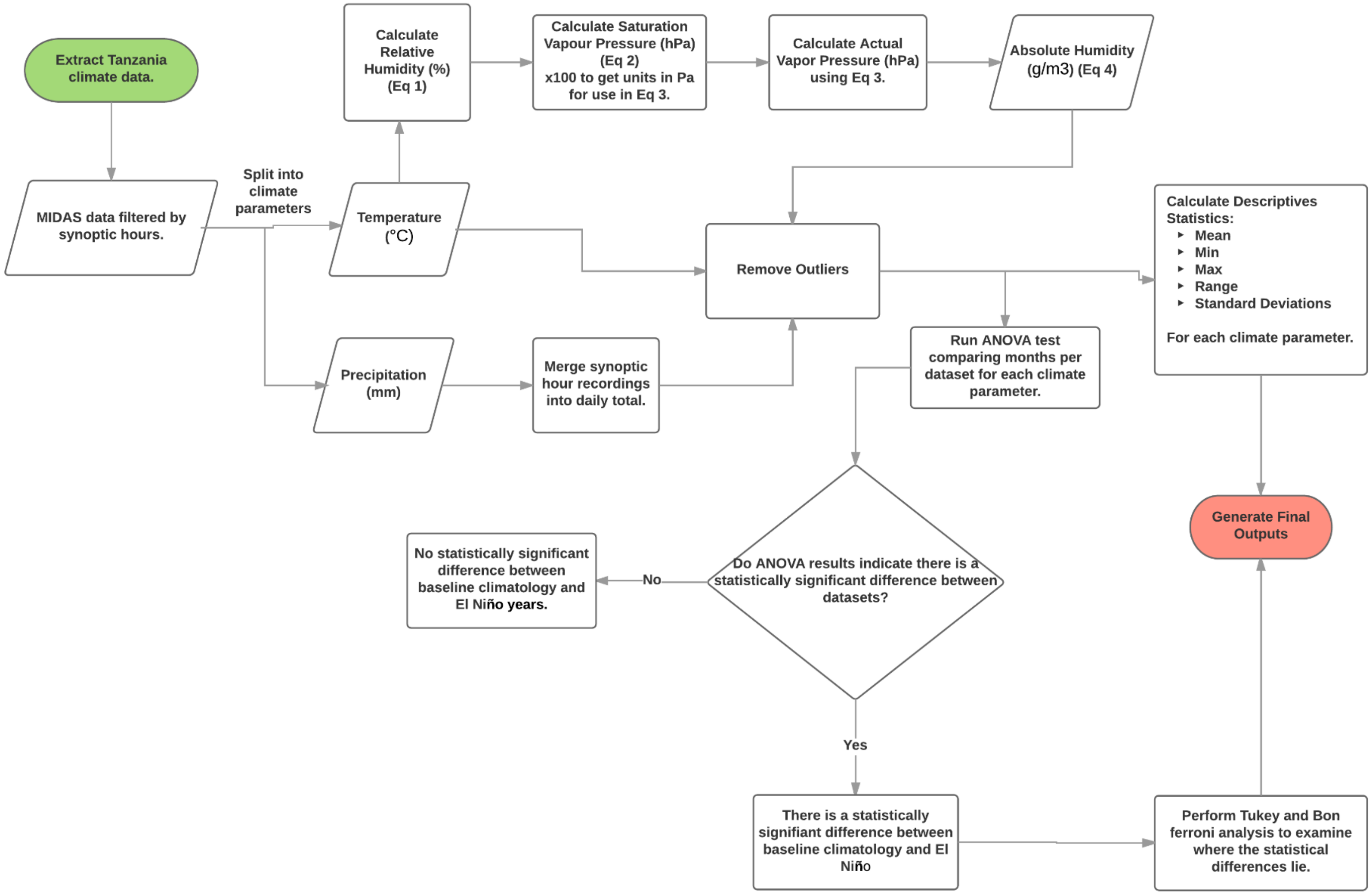


Figure 3.6 - Workflow of analytical process. Equations referred to can be found at equations 3.1 to 3.4.

Data was obtained in synoptic hours (00:00, 06:00, 12:00, 18:00 GMT) in order to have an equal number of data observations per year due to earlier records only recording parameters at synoptic hour intervals (Met Office, 2016a). Relative humidity was calculated initially using temperature and dew point provided in the station data and calculated using equation 1 (Equation 3.1) and the constant values provided in table 3.2. Whilst relative humidity is commonly reported, absolute humidity provides more comparable results when examining diseases such as bacterial meningitis and hence relative humidity was converted using equations 3.2, 3.3 and 3.4 (Cheesbrough et al., 1995; Vaisala, 2013; Pandya et al., 2015). All conversion equations and constants used have been taken from Vaisala (2013). Synoptic hourly recordings for rainfall were aggregated into daily totals to allow for easier interpretation. Temperature and humidity values were assessed in synoptic hourly format in order to retain minimum and maximum daily variations with a view to further use this data to calculate degree day cycles in a later chapter and thus daily range, minimum and maximum values were necessary to retain.

Table 3.2 - Constants used in humidity conversion *(Vaisala, 2013)*

	A	**m**	**Tn**	**Max error (%)**	**Temperature Range (˚C)**
Water	6.116441	7.591386	240.7263	0.083%	-20…+50 ˚C

Equation 3.1 - Calculating relative humidity using dew point, temperature and constant values (Vaisala, 2013).

$$RH = 100\% \cdot 10^{m[\frac{Td}{Td+Tn} + \frac{Tambient}{Tambient+Tn}]}$$

Equation 3.2 - A, m, Tn = constants found in table 3.2. Units are in hPa (Vaisala, 2013).

$$P_{ws} = A \cdot 10^{(\frac{m \cdot T}{T+Tn})}$$

Equation 3.3 - Calculation of water vapour pressure (Pw) (Vaisala, 2013).

$$P_w = P_{ws} \cdot RH/100$$

Equation 3.4 - Calculation of A (absolute humidity) using constants and values outlined in table 3.3 (including units) (Vaisala, 2013).

$$A = C \cdot \frac{P_w}{T}$$

Table 3.3 - Constants used in equation 3.4.

C	Constant 2.16679 gK/J
Pw	Vapour pressure in Pa
T	Temperature in K
Units	g/m^{-3}

When identifying outliers (figure 3.7), any values outside of four times the standard deviation were removed. This method is common practice at NOAA (Peterson et al., 2013; Weisent et al., 2014). It is important to note that this method was only applied to temperature and humidity due to these parameters being normally distributed. Rainfall outliers were removed manually and discretion applied. For example, values depicting 601mm of rainfall in one synoptic hour period (6 hours) seemed unreasonable when compared to other values. The non-normal distribution of the data made this unsuitable to apply a four times standard deviation rule as potential natural variability would have been otherwise removed.

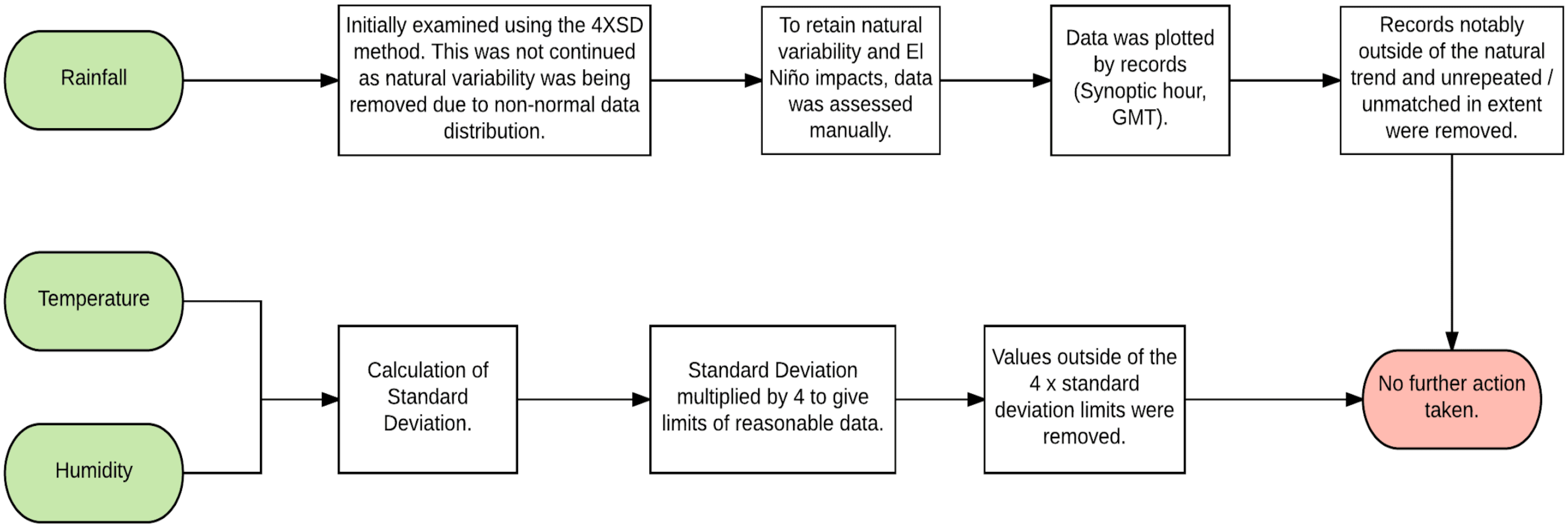


Figure 3.7 - Process for removal of outliers using four times standard deviation method *(Weisent et al., 2014; Reynolds et al., 2017).*

3.4 Results

3.4.1 Climatology (1985-1995)

Mean monthly conditions for each parameter assessed are presented in figures 3.8-3.10 and accompanied by standard deviation results in tables 3.4-3.7. Highest monthly mean temperatures are observed in the coastal region of Dar es Salaam all year round, with all temperature profiles exhibiting a reduction in temperature between the months of May and September (figure 3.8). Mwanza demonstrates the most consistent profile, with minor annual fluctuations in temperature (table 3.4). Mbeya, the highest station altitudinally, demonstrates the lowest temperatures.

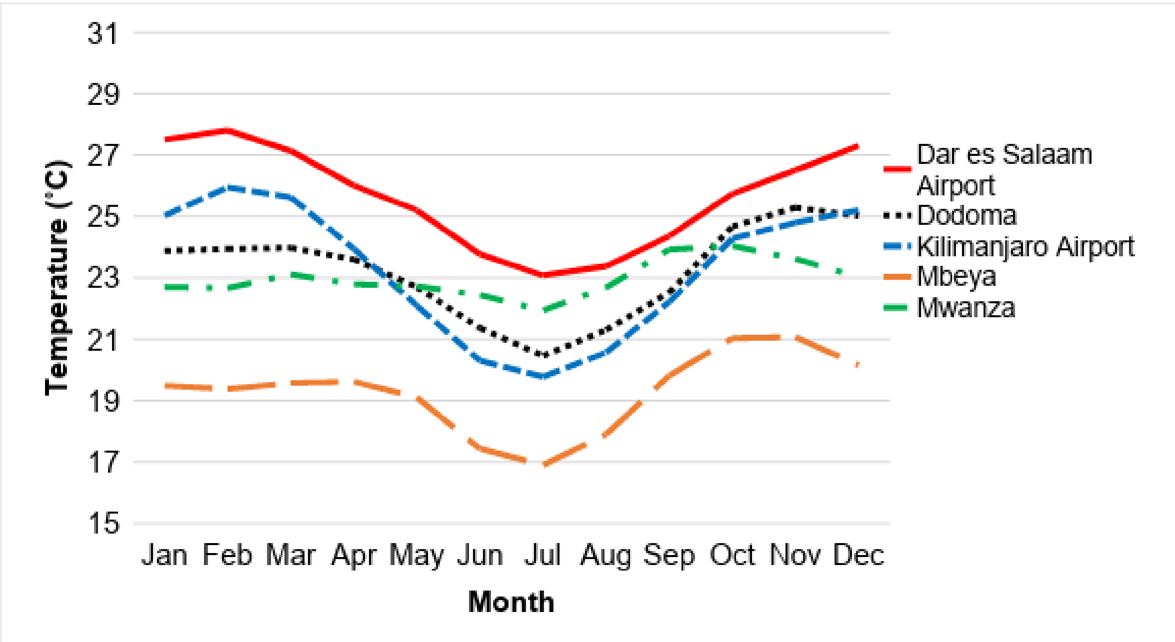


Figure 3.8 - Mean monthly temperature (˚C) for Tanzania's baseline climatology at each chosen meteorological station (1985-1995).

Monthly standard deviation was calculated to provide an indication of monthly temperature variability (table 3.4). Kilimanjaro airport demonstrates the highest degree of standard deviation peaking at 4.80°C temperature deviation from the mean, followed by Dodoma and Mbeya. Dar es Salaam and Mwanza demonstrate less variation from the mean monthly temperature, indicating more consistent temperature conditions.

Table 3.4 - Standard Deviation values for mean monthly temperature (˚C) at each station (1985-1995).

Month	Dar es Salaam Airport	Dodoma	Kilimanjaro Airport	Mbeya	Mwanza
Jan	2.57	3.80	4.56	2.72	2.95
Feb	2.76	3.73	4.80	3.06	3.11
Mar	2.99	3.76	4.52	3.01	3.11
Apr	2.67	3.52	3.47	2.63	2.83
May	2.81	3.80	3.02	2.86	2.92
Jun	3.36	4.26	3.44	3.99	3.45
Jul	3.54	4.27	3.79	4.40	3.66
Aug	3.58	4.18	3.84	4.29	3.39
Sep	3.80	4.43	4.37	4.41	3.02
Oct	3.61	4.50	4.61	4.05	2.76
Nov	3.24	4.27	4.31	3.53	2.81
Dec	2.78	4.12	4.27	3.03	2.89

Mean total monthly rainfall is observed to reach the highest peak in the coastal region of Dar es Salaam during the MAM rainfall season, reducing between May to September before increasing again during the OND season. Kilimanjaro and Mwanza follow a similar profile, with overall less total rainfall recorded. Mbeya and Dodoma are in the unimodal rainfall regime which is clearly profiled in figure 3.9 with both reaching their maximum total monthly rainfall in January.

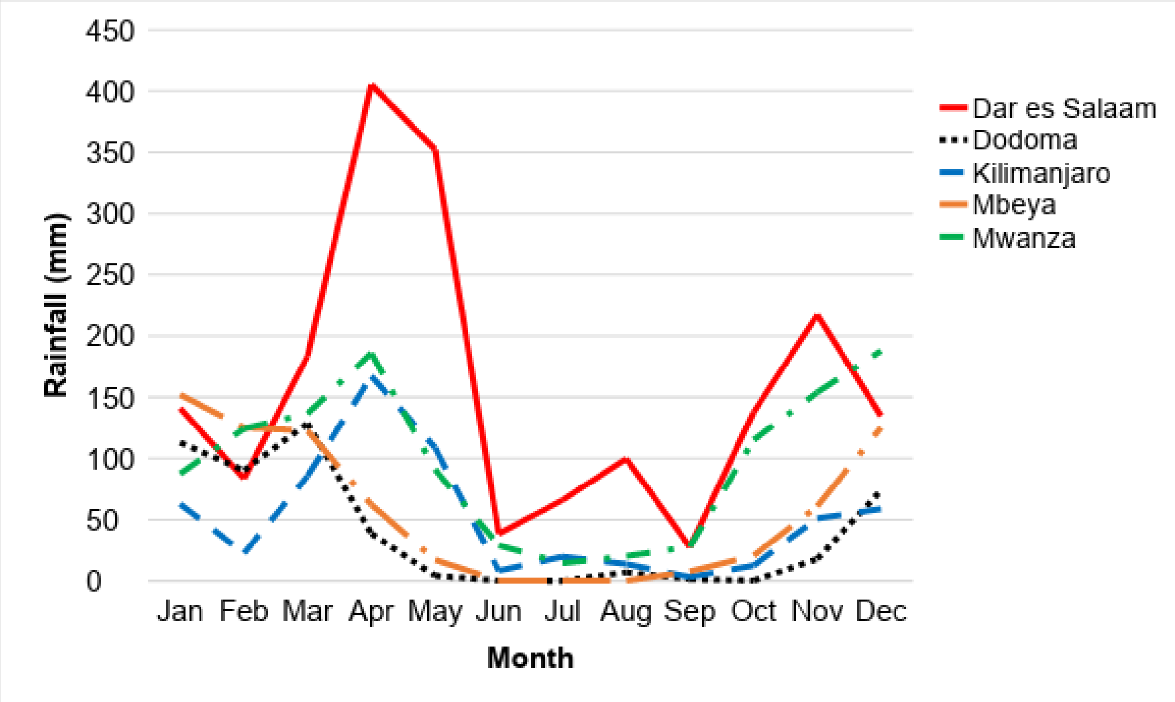


Figure 3.9 – Mean monthly total rainfall (mm) representing Tanzania's baseline climatology at each chosen meteorological station (1985 – 1995). Monthly totals were summed to include each contributing year then the total divided by the number of years included to provide mean monthly totals.

Monthly standard deviation was calculated to provide an indication of monthly total rainfall variability (table 3.5). Dar es Salaam demonstrates the highest degree of standard deviation peaking at 23.01 in May, followed by Mwanza. Dodoma, Kilimanjaro and Mbeya demonstrate less variation from the mean within a month, indicating more consistent rainfall totals.

Table 3.5 - Standard deviation values for mean total monthly rainfall (mm) at each meteorological station (1985-1995).

Month	**Dar es Salaam Airport**	**Dodoma**	**Kilimanjaro Airport**	**Mbeya**	**Mwanza**
Jan	18.52	12.40	8.82	10.95	9.39
Feb	11.66	10.31	4.13	9.18	15.38
Mar	18.90	13.57	10.49	10.38	13.16
Apr	21.58	5.77	13.47	5.48	13.31
May	23.01	0.86	8.52	2.77	9.89
Jun	10.71	0.07	1.37	0.14	7.21
Jul	9.35	0.00	6.10	0.13	4.90
Aug	11.79	3.92	2.62	0.02	4.06
Sep	5.47	0.85	0.95	4.32	4.86
Oct	16.73	0.11	3.75	3.35	11.41
Nov	16.72	6.09	8.10	8.98	15.50
Dec	13.84	10.96	8.13	9.27	14.79

Mean monthly absolute humidity is highest in the coastal region of Dar es Salaam, peaking during March, reducing between May to September before increasing again, in line with the bi-modal rainfall seasons (figure 3.10). All stations follow a similar profile, with similar values observed between Dodoma, Kilimanjaro and Mwanza. Mbeya demonstrates the lowest overall absolute humidity, reaching below nine gm^{-3} during July and August.

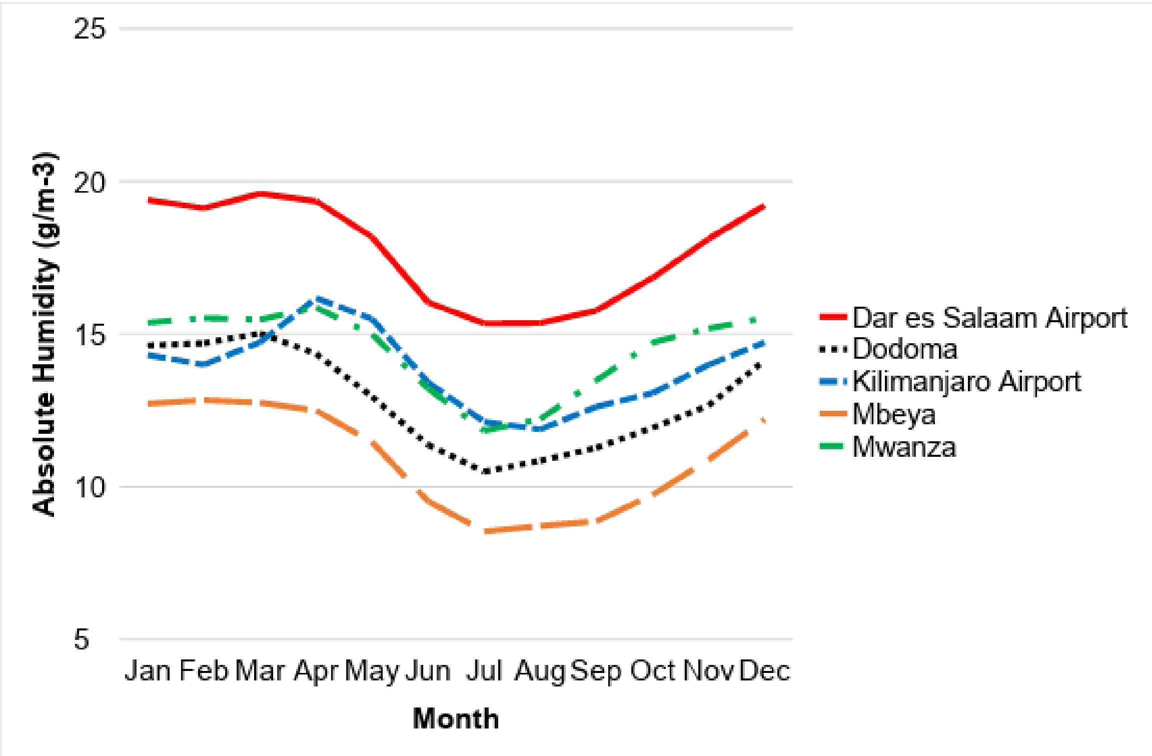


Figure 3.10 - Mean monthly absolute humidity (gm^{-3}) for Tanzania's baseline climatology at each meteorological station (1985-1995).

Monthly standard deviation was calculated to provide an indication of monthly absolute humidity variability, demonstrated in table 3.6. Mwanza demonstrates the highest degree of standard deviation in absolute humidity peaking at 2.6 gm^{-3} in August, followed by Kilimanjaro Airport, and Dodoma. Mbeya and Dar es Salaam demonstrate less variation from the mean within a month, indicating more consistent absolute humidity values.

Table 3.6 - Standard Deviation values for mean monthly humidity (gm^{-3}) at each chosen meteorological station (1985-1995).

Month	**Dar es Salaam Airport**	**Dodoma**	**Kilimanjaro Airport**	**Mbeya**	**Mwanza**
Jan	1.25	1.47	1.8	1.09	1.4
Feb	1.28	1.46	2.2	1.03	1.4
Mar	1.21	1.37	2.2	1.04	1.7
Apr	1.18	1.22	1.5	1.09	1.2
May	1.45	1.29	1.3	1.22	1.6
Jun	1.68	1.36	1.4	1.29	2.2
Jul	1.73	1.41	1.3	1.21	2.3
Aug	1.64	1.48	1.4	1.21	2.6
Sep	1.48	1.69	1.5	1.33	2.5
Oct	1.59	1.88	1.9	1.56	2.1
Nov	1.38	1.85	1.9	1.60	1.5
Dec	1.21	1.95	1.7	1.29	1.4

3.4.2 Comparing El Niño and baseline climatological conditions

Monthly minimum and maximum values for temperature have been plotted and compared for the baseline time period, 1997, and 2015 (figure 3.11a-e). Statistical comparisons are presented in section 3.4.3.

All stations demonstrate changes across baseline minimum and maximum temperatures during El Niño years. Minimum temperatures increase on average across all stations under El Niño conditions, further depicting clear variations in seasonality across the majority of stations (figure 3.11a-e). Increased annual fluctuations in minimum temperature are observed during El Niño conditions for some stations. This is most prominent for Mwanza and Mbeya (figure 3.11d, 3.11e). In contrast, decreases in minimum temperature fluctuations are observed at some locations, specifically Dodoma and Kilimanjaro Airport (figure 3.11b, 3.11c). Despite variations in minimum temperature fluctuations between El Niño year profiles, both demonstrate an average increase in minimum temperature.

Maximum temperatures demonstrate overall little change to both seasonality and fluctuation in extremities, with average decreases in maximum temperature observed at Dodoma, Mbeya and Mwanza (figure 3.11b, 3.11d and 3.11e). Fluctuations are less extreme than those observed for minimum temperatures, suggesting maximum temperatures are less impacted than minimum temperatures under El Niño conditions. Stations such as Dar es Salaam Airport and Kilimanjaro Airport demonstrate reductions in fluctuation and an overall similar seasonality to the baseline during El Niño years (figure 3.11a, 3.11c).

Average temperature profiles under El Niño conditions indicate overall increases across all stations due to minimal changes to maximum temperatures and widespread increases for minimum temperatures.

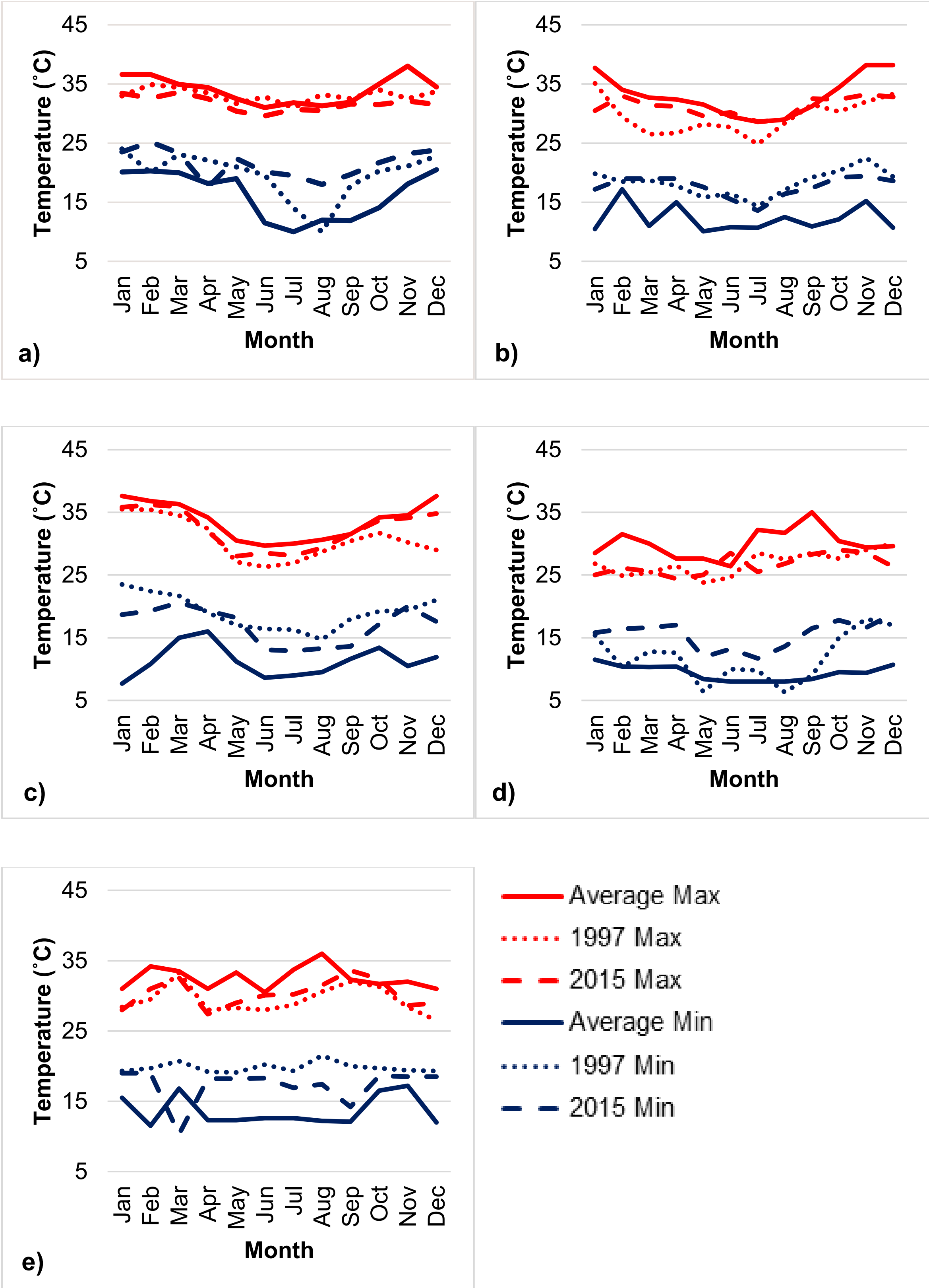


Figure 3.11 - Minimum and maximum temperature values for baseline climatology, 1997 and 2015 for a) Dar es Salaam Airport b) Dodoma c) Kilimanjaro Airport d) Mbeya and e) Mwanza.

Total monthly rainfall values have been plotted for the baseline climate, 1997 and 2015 (figure 3.12a-e). Statistical comparisons are presented in section 3.4.3.

Results show clear changes in rainfall seasonality for both the MAM and OND seasons under El Niño conditions. This is accompanied by increased variation in rainfall fluctuation. Dodoma demonstrates the largest increase in rainfall volume at the start of the OND season for both 1997 and 2015, with total rainfall amount increasing by over 300% in comparison to baseline conditions (figure 3.12b). Dodoma also demonstrates the biggest decrease at the start of the 1997 MAM season with 100% decrease in rainfall.

Changes in seasonality are most prominent at Dar es Salaam Airport, Dodoma and Mwanza (figures 3.12a, 3.12b and 3.12e). Seasons do not change unanimously under El Niño conditions, although at Dodoma similar changes to seasonality are observed for both El Niño years during the MAM season (figure 3.12b). Dar es Salaam shows the greatest seasonal change with a sudden increase in rainfall amount at the start and end of the 2015 MAM season. During 1997 at this time, rainfall is observed to start early, decline mid-season and peak again in June, post season. In addition, during 1997 the OND season starts early, peaking in September (figure 3.12a). A similar occurrence is observed in Mwanza where seasons extend beyond current boundaries.

Overall, rainfall volume is observed to increase under El Niño conditions due to increases in extreme volumes of rainfall both in and out of season.

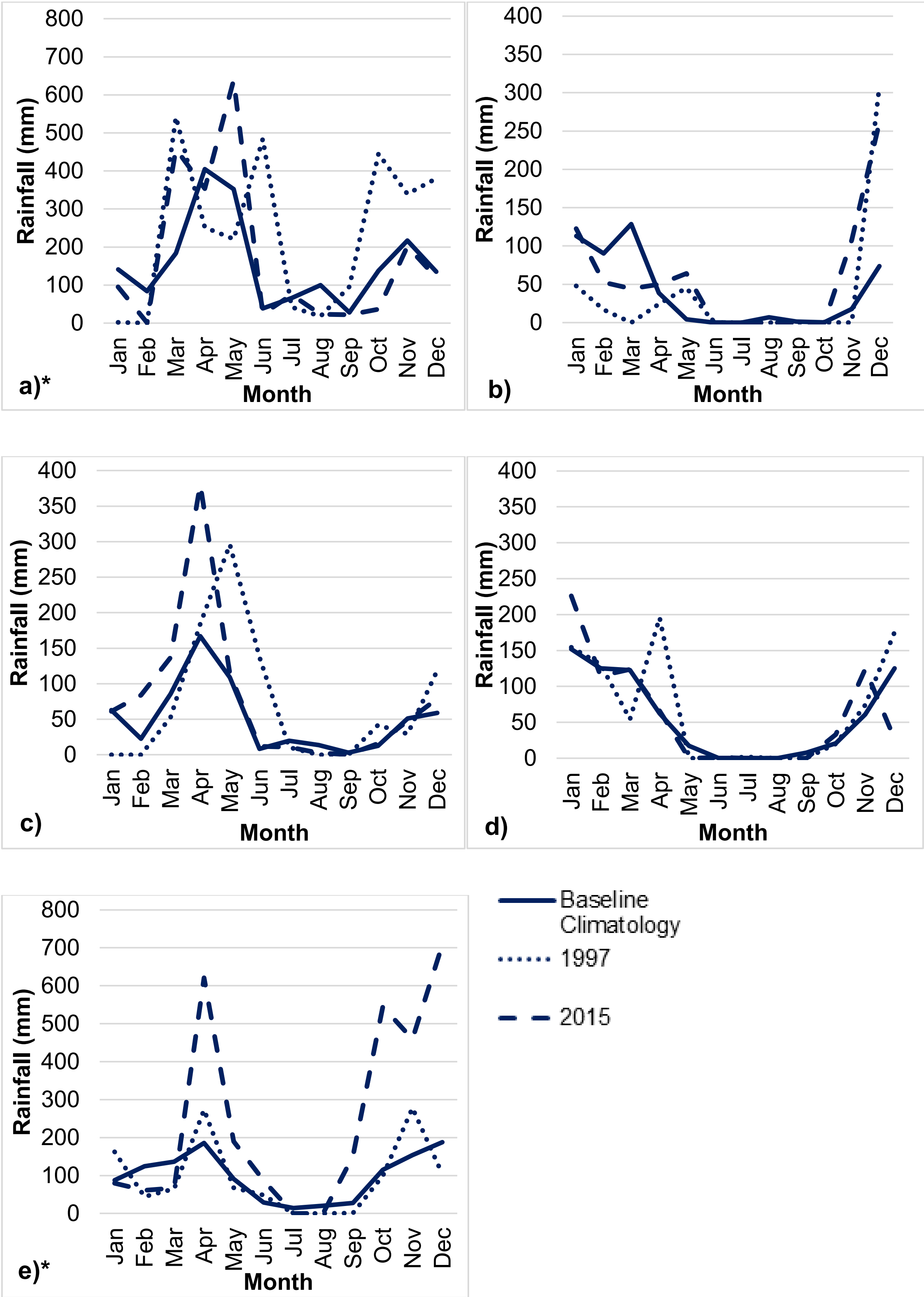


*Figure 3.12 - Total monthly rainfall (mm) values for baseline climatology, 1997 and 2015 for a) Dar es Salaam Airport b) Dodoma c) Kilimanjaro Airport d) Mbeya and e) Mwanza. *Differing scales for Dar es Salaam Airport and Mwanza.*

Monthly minimum and maximum absolute humidity values have been plotted for the baseline climate, 1997 and 2015 (figure 3.13a-e). Statistical comparisons are presented in section 3.4.3.

Minimum absolute humidity values are observed to increase for all stations under El Niño conditions. This is predominantly in accordance with changes in temperature and water vapour as explained by the equations presented in section 3.3.2. Increases in fluctuations of minimum absolute humidity are observed in comparison to baseline conditions. This can be attributed to increased variation in atmospheric water vapour due to increased variation in rainfall for both El Niño years assessed. Dar es Salaam demonstrates the greatest increase in comparison to the baseline conditions, with Mbeya demonstrating the least amount of change respectively.

Maximum absolute humidity values show little to no change across all stations with the exception of Dodoma, which demonstrates a unanimous reduction in maximum absolute humidity (figure 3.13a-e). Maximum humidity profiles demonstrate overall increased fluctuation in values under El Niño conditions in comparison to the baseline. Changes do not occur equally between El Niño years. The greatest fluctuations are observed at Dar es Salaam and Mbeya (figures 3.13a, 3.13d). Reduced fluctuation in maximum humidity values are also observed at Kilimanjaro airport, Mbeya and Mwanza for 2015 (figure 3.13c, 3.13d and 3.13e).

Overall, average absolute humidity values are observed to increase under El Niño conditions due to increases in minimum absolute humidity values and little to no change observed for maximum humidity values.

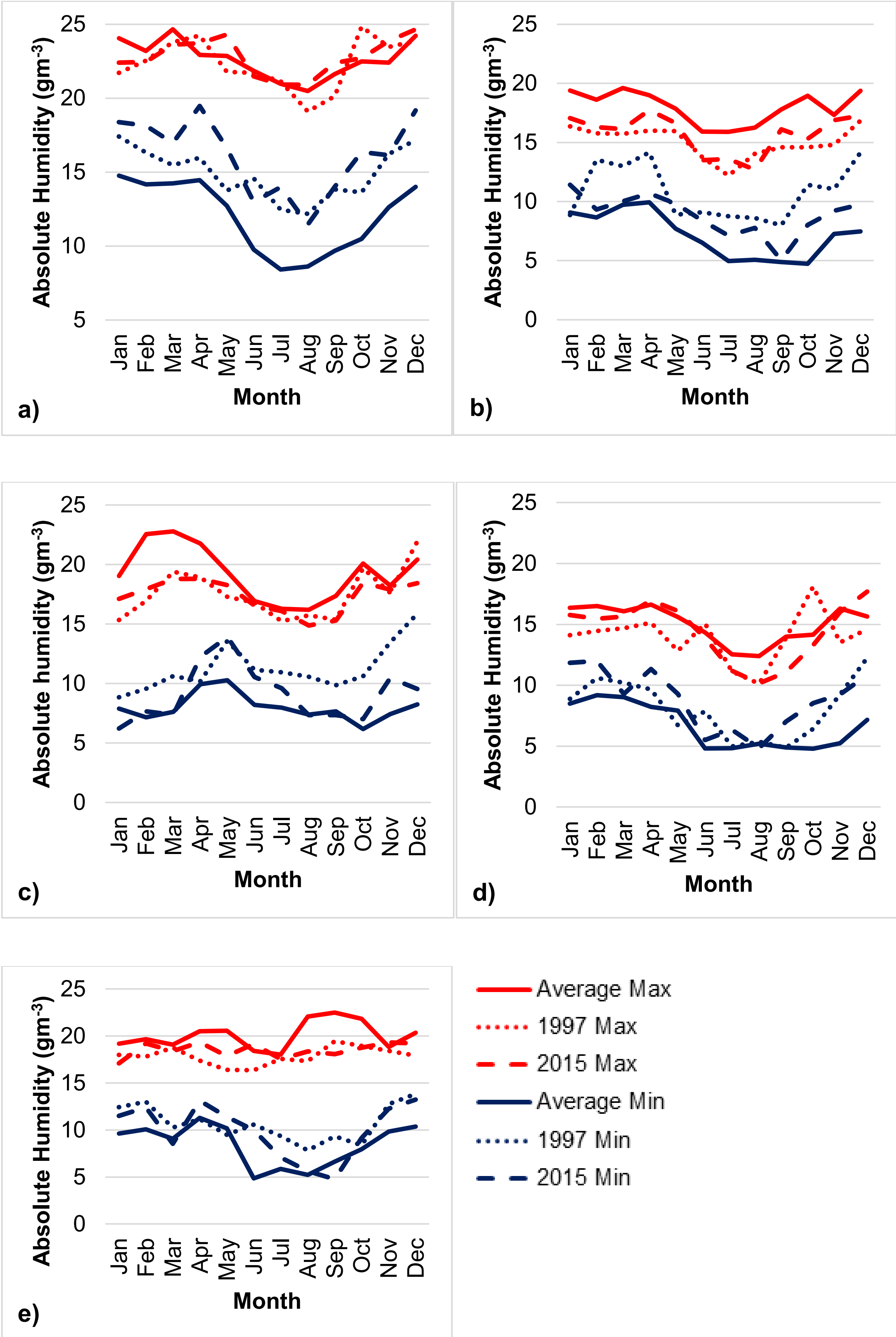


Figure 3.13 - Minimum and maximum absolute humidity (gm^{-3}) values for baseline climatology, 1997 and 2015 for a) Dar es Salaam Airport b) Dodoma c) Kilimanjaro Airport d) Mbeya and e) Mwanza.

3.4.3 Statistical difference between the baseline climatology and El Niño conditions

Tukey test results are presented in tables 3.7-3.11. Statistically significant figures are presented in bold. If the conclusion of a statistically significant result is not supported by Bonferroni tests a "*" is present. If ANOVA returned a result depicting no statistically significant difference ($P > 0.05$) a "–" symbol is used.

3.4.5.1 Dar es Salaam Airport

Statistical significance test results for Dar es Salaam are shown in table 3.7. Temperatures demonstrate significant differences were observed in January and December during the 1997 El Niño event in comparison to baseline climatology. Conversely for the 2015 El Niño event, all months experience a significant difference in temperature compared to baseline conditions (except for May). Comparing 1997 and 2015 temperatures, results indicate statistically significant differences between the two events, indicating differing climatic reactions between El Niño events in Dar es Salaam.

Rainfall results show that five months throughout the year have statistically significant differences in total rainfall amounts where 2015 experienced four months of significantly differing rainfall amounts. These significant changes can be attributed to increases in rainfall (figure 3.12a). Comparing 1997 and 2015 El Niño events, four months demonstrate statistical significance between the events, further confirming differing reactions in climate to El Niño events.

Absolute humidity shows the most significant difference between baseline conditions and both 1997 and 2015 El Niño events. 2015 shows statistically significant changes in absolute humidity throughout the entire year, whilst 1997 shows 11 months of significant change except for February. When compared to each other, 2015 and 1997 demonstrate less statistically significant difference to each other than baseline conditions, indicating potential similarities in absolute humidity reaction between El Niño events. This is supported by the Dar es Salaam absolute humidity profiles shown in figure 3.13a where similar values are observed in 1997 and 2015.

Table 3.7 - Dar es Salaam Airport statistical significance test results. Results highlighted in bold demonstrate months of statistically significant difference between the associated years. Results not in bold or marked "–" are not statistically significant. Results with a "*" indicate results are not supported by Bonferroni correction tests.

	Climatology and 1997			***Climatology and 2015***			***1997 and 2015***		
Month	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity
January	**0.005**	**-**	**0.000**	**0.020**	**-**	**0.000**	0.952	**-**	**0.011**
February	0.302	**-**	0.851	**0.000**	**-**	**0.000**	**0.000**	**-**	**0.000**
March	0.536	**0.000**	**0.000**	**0.003**	**0.007**	**0.000**	**0.005**	0.762	0.879
April	0.765	**-**	**0.000**	**0.000**	**-**	**0.000**	**0.017**	**-**	0.581
May	1.000	0.682	**0.000**	0.500	**0.008**	**0.000**	0.219	**0.010**	**0.000**
June	0.291	**0.000**	**0.000**	**0.000**	0.969	**0.000**	0.085	**0.000**	**0.001**
July	0.561	**-**	**0.000**	**0.000**	**-**	**0.000**	**0.015**	**-**	**0.003**
August	0.155	**-**	**0.000**	**0.000**	**-**	**0.000**	0.266	**-**	0.104
September	0.936	**0.032**	**0.000**	**0.013**	0.991	**0.000**	0.157	0.104	**0.010**
October	0.644	**0.000**	**0.000**	**0.001**	0.500	**0.000**	**0.000**	**0.000**	0.862
November	0.818	**-**	**0.000**	**0.001**	**-**	**0.000**	0.075	**-**	0.413
December	**0.007**	**0.000**	**0.000**	**0.000**	0.823	**0.000**	**0.000**	**0.000**	**0.000**

3.4.2.2 Dodoma

Statistical significance test results for Dodoma are shown in table 3.8. Temperatures overall demonstrate very little statistically significant changes between baseline conditions and both El Niño years. 1997 results indicate only May and June experience a statistically significant change in temperatures, with only February indicating the same in 2015. The same three months demonstrate statistically significant differences from each other when 1997 and 2015 were compared. Overall, results indicate mostly non-statistically significant changes in temperature under both El Niño years examined here.

Rainfall analysis results for both 1997 and 2015 exhibit statistically significant differences in both May and December for Dodoma. When compared to each other, no statistical difference between rainfall in El Niño years was found. This indicates both El Niño events resulted in similar impacts to each other, and overall little impact on baseline conditions.

Absolute humidity values demonstrated more significant changes under 2015 El Niño conditions than 1997 conditions. Results comparing 1997 and baseline conditions indicate absolute humidity values only differed significantly during December. 2015 results indicate six months of statistically significant change in absolute humidity. When compared to each other, El Niño events demonstrated five months of significant difference between the two years.

Table 3.8 - Dodoma statistical significance test results. Results highlighted in bold demonstrate months of statistically significant difference between the associated years. Results not in bold or marked "–" are not statistically significant. Results with a ""*

	Climatology and 1997			***Climatology and 2015***			***1997 and 2015***		
Month	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity
January	**-**	**-**	0.082	**-**	**-**	0.082	**-**	**-**	**0.009**
February	0.457	**-**	0.977	**0.001**	**-**	**0.000**	**0.037**	**-**	**0.047***
March	**-**	**-**	0.288	**-**	**-**	**0.000**	**-**	**-**	0.942
April	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**
May	**0.002**	**0.000**	**-**	0.765	**0.000**	**-**	**0.023**	0.777	**-**
June	**0.016**	**-**	0.091	0.816	**-**	**0.000**	**0.015**	**-**	**0.000**
July	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**
August	**-**	**-**	0.242	**-**	**-**	**0.001**	**-**	**-**	**0.015**
September	**-**	**-**	0.580*	**-**	**-**	**0.000**	**-**	**-**	0.655
October	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**
November	**-**	**-**	0.738	**-**	**-**	**0.000**	**-**	**-**	0.471
December	**-**	**0.000**	**0.000**	**-**	**0.050***	0.457	**-**	0.226	**0.006**

3.4.2.3 Kilimanjaro Airport

Statistical significance test results for Kilimanjaro airport are shown in table 3.9. Temperature results for 1997 compared to baseline climatology indicate statistically significant temperatures for four months of the year. 2015 El Niño conditions show 2 months (January and August) of significant difference, correlating with two of the months demonstrating significant change under 1997 conditions. There is no significant difference observed between 1997 and 2015, suggesting similar impacts of El Niño conditions on temperatures at Kilimanjaro.

Rainfall results for 1997 compared to baseline climatology indicate two months of significantly differing rainfall amounts (May and June) which can be observed in the rainfall profiles (figure 3.12c). 2015 results indicate no significant difference between 2015 El Niño rainfall and baseline rainfall amounts. 1997 and 2015 indicate significant differences in rainfall in May only.

Absolute humidity results demonstrate a significant change throughout eight months of the year during 1997 El Niño conditions when compared to baseline conditions. February to May demonstrated no change in absolute humidity. 2015 shows significant changes during seven months of the year compared to baseline conditions. This indicates that the greatest impact from both El Niño years occurs in absolute humidity values. When compared, 1997 and 2015 results demonstrate five months of statistically significant difference from each other, further indicating differing local reactions to El Niño events.

Table 3.9 - Kilimanjaro statistical significance test results. Results highlighted in bold demonstrate months of statistically significant difference between the associated years. Results not in bold or marked "–" are not statistically significant. Results with a "*" indicate results are not supported by Bonferroni correction tests.

	Climatology and 1997			***Climatology and 2015***			***1997 and 2015***		
Month	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity
January	**0.000**	**-**	**0.000**	**0.017**	**-**	**0.000**	0.051	**-**	0.810
February	**0.024**	**-**	**-**	0.727	**-**	**-**	0.121	**-**	**-**
March	**0.031**	**-**	0.580	0.787	**-**	**0.000**	0.157	**-**	0.370
April	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**
May	**-**	**0.000**	0.662	**-**	0.990	**0.001**	**-**	**0.003**	0.483
June	**-**	**0.000**	**0.000**	**-**	0.992	0.425	**-**	0.005	**0.000**
July	**-**	**-**	**0.000**	**-**	**-**	**0.000**	**-**	**-**	0.077
August	**0.001**	**-**	**0.000**	**0.015**	**-**	0.931	0.277	**-**	**0.000**
September	**-**	**-**	**0.000**	**-**	**-**	**0.000**	**-**	**-**	**0.000**
October	**-**	**-**	**0.000**	**-**	**-**	**0.017**	**-**	**-**	**0.016**
November	**-**	**-**	**0.000**	**-**	**-**	**0.000**	**-**	**-**	0.198
December	**-**	**-**	**0.000**	**-**	**-**	0.887	**-**	**-**	**0.000**

3.4.2.4 Mbeya

Statistical significance test results for Mbeya are shown in table 3.10. Temperature results comparing baseline climatology and 1997 El Niño conditions demonstrate three months of significant temperature changes under El Niño conditions. 2015 El Niño results indicate six months of significant temperature change, indicating 2015 El Niño conditions had a greater impact on baseline temperature in comparison to 1997. Comparisons between 1997 and 2015 show six months where significant differences occur between each year, further indicating differing local climatological reactions to El Niño conditions.

Rainfall results demonstrate less change than temperature conditions. 1997 exhibits statistical change from baseline conditions for two months (April and December) where 2015 demonstrates no significant impact on rainfall conditions in comparison to baseline climatology. Statistically significant differences between each El Niño year is observed in April only, and is clearly observed in the rainfall profiles in figure 3.12d.

Absolute humidity results indicate that during 1997 El Niño conditions, three months experienced significantly different absolute humidity values (January, May and December). For the 2015 El Niño event, a greater impact was observed. Nine months demonstrate a significant change in absolute humidity during 2015 which is supported by the absolute humidity profiles shown in figure 3.13d. Comparison results between 1997 and 2015 demonstrate significant differences in absolute humidity during five months.

Table 3.10 - Mbeya statistical significance test results. Results highlighted in bold demonstrate months of statistically significant difference between the associated years. Results not in bold or marked "–" are not statistically significant. Results with a "" i*

	Climatology and 1997			***Climatology and 2015***			***1997 and 2015***		
Month	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity
January	**0.012**	**-**	**0.000**	0.721	**-**	**0.000**	0.287	**-**	**0.000**
February	**0.004**	**-**	0.132	**0.009**	**-**	**0.010**	**0.000**	**-**	**0.001**
March	0.448	**-**	**-**	**0.029**	**-**	**-**	**0.014**	**-**	**-**
April	0.068	**0.000**	0.817	0.136	0.975	**0.000**	**0.006**	**0.015**	**0.000**
May	**0.000**	**-**	**0.000**	0.233	**-**	**0.000**	**0.000**	**-**	**0.000**
June	0.647	**-**	**-**	**0.000**	**-**	**-**	0.082	**-**	**-**
July	0.743	**-**	0.284	**0.015**	**-**	**0.034**	**0.035**	**-**	0.865
August	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**
September	0.902	**-**	0.109	**0.000**	**-**	**0.050***	**0.026**	**-**	**0.004**
October	0.983	**-**	0.276	**0.008**	**-**	**0.000**	0.224	**-**	0.188
November	**-**	**-**	0.254	**-**	**-**	**0.000**	**-**	**-**	0.234
December	**-**	**0.029**	**0.000**	**-**	0.630	**0.000**	**-**	0.063	0.936

3.4.2.5 Mwanza

Statistical significance test results for Mwanza are shown in table 3.11. Temperature results indicate significant differences during the 1997 El Niño event occurred during four months of the year. During 2015, significant differences in temperature were observed during six months of the year. Comparing each El Niño event, significant differences were seen from August through to November, which can be observed in the temperature profiles presented in figure 3.11e, where 2015 minimum temperatures are lower than that observed during the 1997 event.

Rainfall results indicate that during 1997 only April experienced significantly different rainfall values. In contrast, during 2015 five months exhibit significantly different rainfall amounts, which can be clearly seen within the rainfall profiles presented in figure 3.12e. Significant differences between rainfall during El Niño years are observed during three months, September, October and December.

Absolute humidity values demonstrate four months of significant difference under 1997 El Niño conditions when compared to baseline conditions, occurring around both rainfall seasons in March, May, September and November. 2015 results demonstrate five months of significant difference in absolute humidity compared to baseline conditions. Comparisons between both El Niño events demonstrate four months of significant difference between events, further indicating differing circumstances which can occur during El Niño conditions.

Table 3.11 - Mwanza statistical significance test results. Results highlighted in bold demonstrate months of statistically significant difference between the associated years. Results not in bold or marked "–" are not statistically significant. Results with a "*" indicate results are supported by Bonferroni correction tests.

	Climatology and 1997			***Climatology and 2015***			***1997 and 2015***		
Month	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity	Temperature	Rainfall	Humidity
January	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**
February	0.282	**-**	**-**	**0.000**	**-**	**-**	0.869	**-**	**-**
March	**0.000**	**-**	**0.001**	**0.000**	**-**	**0.000**	0.134	**-**	0.394
April	0.787	**0.039**	**-**	**0.025**	**0.000**	**-**	0.760	0.434	**-**
May	**-**	**-**	**0.012**	**-**	**-**	0.971	**-**	**-**	**0.039**
June	**-**	**-**	0.599	**-**	**-**	**0.000**	**-**	**-**	**0.003**
July	0.098	**-**	**-**	**0.042**	**-**	**-**	0.822	**-**	**-**
August	**0.000**	**-**	**-**	**0.011**	**-**	**-**	**0.030**	**-**	**-**
September	**0.000**	0.813	**0.000**	0.703	**0.006**	0.183	**0.000**	**0.020**	**0.000**
October	**0.001**	0.943	0.679	0.367	**0.000**	**0.000**	**0.000**	**0.013**	**0.007**
November	0.993	0.259	**0.002**	**0.000**	**0.026**	**0.000**	**0.044***	0.789	0.934
December	**-**	0.961	0.399	**-**	**0.000**	**0.000**	**-**	**0.014**	0.343

3.5 Discussion

3.5.1 Baseline climatology

An examination of the baseline climatology clearly demonstrates that varied climatic conditions occur in each of the stations included in this study. The majority of meteorological stations adhere to a similar temperature regime with most peaking between December and February. Mwanza however appears to be an exception whereby peak temperatures are observed in September, and decrease over what is generally classified as the warmer months. This is likely to be due to the addition of complex mesoscale circulation patterns known to operate in the Lake Victoria basin (Anyah and Semazzi, 2004), an influence that would not be present in the other four stations. Overall, the greatest daily range in temperatures per month as demonstrated by standard deviation (table 3.4) show both Kilimanjaro and Dodoma as having the greatest varying daily temperatures. Annually, Kilimanjaro temperatures vary the most (figure 3.8) peaking at 26˚C and reaching as low as 20˚C.

Mean monthly total rainfall trends (figure 3.10) clearly outline areas which experience a unimodal regime, such as Dodoma and Mbeya, where differing monthly totals can be seen, but a similar trend followed with slightly different onset periods, related to the movement of the ITCZ. Both of these stations are confirmed to lie within the unimodal zone (Zorita & Tilya., 2000; Gaidet et al., 2012). Dar es Salaam experiences the greatest variation in rainfall (table 3.5), peaking in April at approximately 12mm per day. Given the proximity of Dar es Salaam to the coast, it can be interpreted that the movement of clouds over the ocean deposit significant rainfall amounts upon reaching the Tanzanian landmass which is further dictated by the movement of the ITCZ. Clear seasonal trends exist at all stations in association with the ITCZ movement and associated rainfall regimes for the individual station locations. Overall, there is a clear reduction in rainfall between June and September for all stations where some experience zero to very minimal rainfall for this period, particularly Dodoma and Mbeya which are dominated by the unimodal regime.

Mean monthly absolute humidity depict very similar seasonal trends across all stations with the exception of Kilimanjaro airport of which the intra-annual trend varies somewhat more than the other four stations (figure 3.11, table 3.6). However, there is a very clear and similar seasonality present across Tanzania where absolute humidity begins to decline at all locations from April through to minimum values in July. Absolute humidity then begins to rise from August reaching a peak in December. An exception is Mwanza which peaks in October, and can be linked to proximity to Lake Victoria and local mesoscale processes due to the relevance of water vapour in influencing humidity. As with temperature, a clear altitudinal relationship can be seen, reported previously by Duane et al. (2008), and Mbeya (1704 masl) experienced the overall lowest mean monthly absolute humidity where values drop below 10gm^{-3} during June to September, a key value associated with the onset of bacterial meningitis (Cheesbrough et al., 1995; Pandya et al., 2015). Dar es Salaam (55 masl) experiences the highest.

In comparison to previous studies, baseline temperatures fit well with those reported previously by various studies (Timiza, 2011; McSweeney et al., 2013; TMA, 2014). This confirms that the data used here to simulate baseline conditions is an accurate representation of these areas and thus a good foundation to base future analysis upon. Due to humidity generally being reported in relative humidity (%), the presentation of absolute humidity values cannot be specifically compared.

3.5.2 Statistical significance and impact of El Niño

Overall, temperature demonstrates a varied reaction to El Niño conditions. Dar es Salaam demonstrates this reaction particularly well. 1997 results show overall no difference between the baseline climatology with the exception of January and December. Alternatively, 2015 experienced significantly different temperatures across the whole year with the exception of May where temperatures remained similar to the baseline. This suggests that Dar es Salaam could potentially be at risk of experiencing significant temperature changes. Dodoma experienced very little statistically significant change. Kilimanjaro, Mwanza and Mbeya all demonstrated between 2-6 months where statistically significant differing temperatures occurred though no discernible pattern either between stations or between years could be seen.

Total monthly rainfall values demonstrate predominantly increased variation in monthly totals with some shifts in seasonality observed. Where statistical significance is observed between the baseline climatology and both El Niño years they are often seen in association with general rainfall periods for that area, whether unimodal or bi-modal. A particularly stark example is Dar es Salaam where total rainfall amounts vary quite considerably in the earlier rainfall period, where seasonality and rainfall pattern varies considerably (MAM). Similarly, Dar es Salaam depicts clear seasonal change in 1997 where total rainfall demonstrates a clear lull in the earlier rainfall period and appears to have 3 significant periods of rainfall within the year with a shorter break period. This is supported in both statistical significance and descriptive statistics (figure 3.12a and table 3.7).

Humidity values demonstrated the most prominent differences when assessed for statistical significance. Dar es Salaam demonstrates the greatest change in absolute humidity for both 1997 and 2015 when compared to the baseline. All months demonstrated significant change with the exception of February, 1997. The reason for this difference can clearly be seen in the descriptive analysis (figure 3.13a) where minimum absolute humidity values can be seen to remain between 1-

4 gm^{-3} higher throughout an El Niño year. Maximum humidity values remain comparatively unchanged with the exception of slight changes in seasonality suggesting that mean absolute temperatures will slightly increase under warmer conditions. Dar es Salaam is the closest station to the coastline, the most densely populated and thus the most developed, both of which could be contributing factors to the results observed.

Less significant changes were experienced at other locations including, Kilimanjaro Airport demonstrates statistically significant changes, and thus sensitivity, to absolute humidity from June through to December in 1997 (table 3.9). This may be attributed to local environment conditions and proximity to forestry which covers the slopes of Mt. Kilimanjaro (Natural Resources and Tourism, 1974). In Mbeya, 2015 conditions also demonstrate significant differences in humidity with the exception of three months, although there is no clear distribution pattern. Overall humidity demonstrates no consistent pattern of change by location, with a number of instances where the conditions experienced in both 1997 and 2015 are different to each other as well as to the baseline climatology. However, it can be concluded that humidity changes experienced under El Niño conditions occur more rapidly by month (figures 3.13a-e). It is notable that the location with the least amount of change is Dodoma which is located inland, away from any water bodies and not influenced by mountain ranges.

3.6 Conclusion

Overall, baseline conditions analysed using the MIDAS dataset for Tanzania are comparable to those reported by the TMA (2014) and McSweeney et al., (2013). Due to absolute humidity (gm^{-3}) commonly being reported as relative humidity (%) no direct comparison was able to be made. However, absolute humidity values were crucial for the consideration of bacterial meningitis and were therefore investigated.

Results demonstrate clear increases in minimum, and reductions in maximum values for temperature and humidity under El Niño conditions. Maximum temperatures do not reduce as much as minimum temperatures increase, resulting in an overall increase in mean temperature and humidity.

Statistically significant differences were observed for temperature, rainfall and humidity between baseline, 1997 and 2015 El Niño conditions. Changes observed are not consistent across Tanzania and no discernible pattern has been identified. Dar es Salaam experienced the most significant differences between baseline climatology and El Niño years. This in part could be attributed to local factors, particularly proximity to the ocean and increased urbanisation. Mbeya, Kilimanjaro and Mwanza each experience a similar degree of statistical change throughout the year, which manifests differently in each area. These variations are likely as a result of varying topography, location and local ground conditions which were not specifically assessed in this chapter.

These results demonstrate a definitive sensitivity and difference in reaction to climate in certain areas, highlighting some locations that appear to be more robust to changes, i.e. Dodoma, brought on through events such as El Niño. Dar es Salaam warrants further investigation into the impacts of potential future climate change given the evidence provided here. Kilimanjaro, Mbeya and Mwanza all pose compelling cases for further investigation, given their elevation and demonstrated sensitivity to El Niño events. Evidence from the literature would support the examination of an area such as Mbeya where vector borne diseases in particular have been shown to be overall increasing in altitude. At present Mbeya would be classified as being on the ecological boundary of mosquito survival (Lindblade et al., 2000; Parham and Michael, 2010; Beck-Johnson et al., 2013). Further to this Mbeya's current absolute humidity suitability for bacterial meningitis during the dry months, shown in figure 3.14, also provides a compelling reason to further examine this area (Cheesbrough et al., 1995; Pandya et al., 2015).

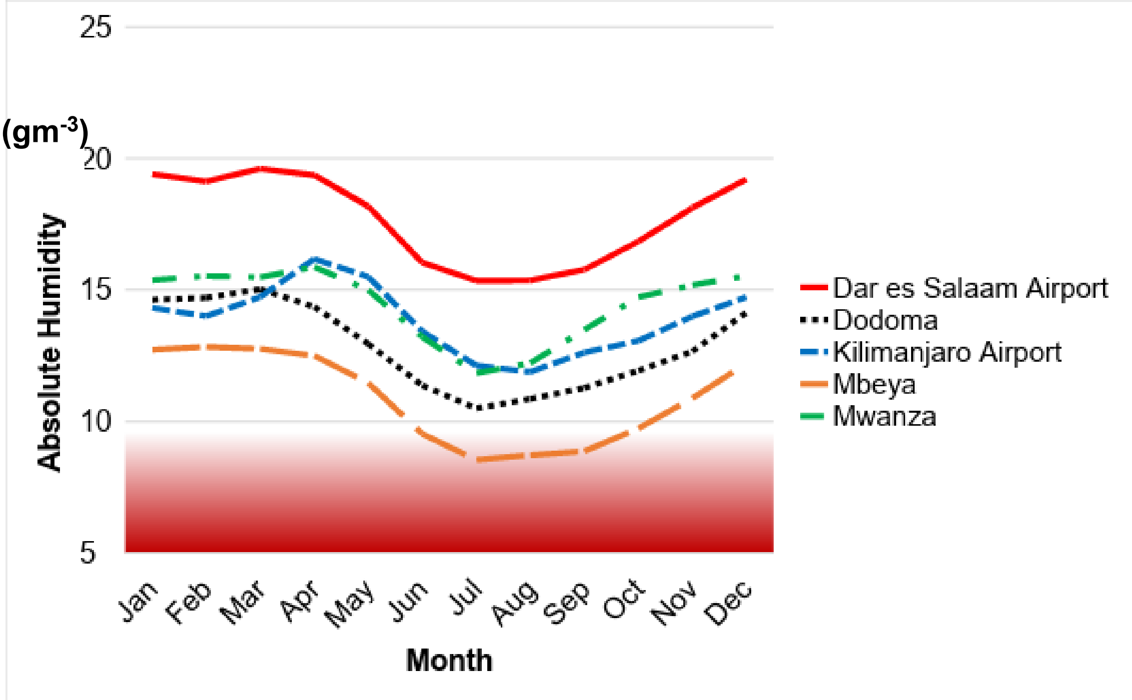


Figure 3.14 - Current absolute humidity (gm^{-3}) suitability threshold for bacterial meningitis (highlighted in red).

It is important to note that there are inherent errors within meteorological data (Biswas and Rao, 2001; Katz and Group, 2002). This has been mitigated where possible through use of a reliable data source (MIDAS dataset) with further checks implemented to ensure a good quality dataset (Met Office, 2012). A further aspect to note is limitations posed by data availability and number of observations. Every step was taken to ensure an even spread of data, although some variation in observation numbers is still present (using synoptic hours). This is something to consider when using and interpreting these results. Furthermore, a future recommendation stemming from this would be an aim to improve the collection, storage and analytical processes amongst the climate data community. This data has been assessed in accordance with methods present in the literature and interpreted to bring out the key conclusions. Whilst more can be drawn from the conclusions and results presented the most relevant and impacting have been discussed in order to direct the following chapters accordingly.

Chapter 4 : Current and projected environmental risk mapping of malaria.

4.1 Introduction

As climate modelling and disease simulation develops, epidemiological assessments and environmental risk mapping are able to be carried out in ever greater detail. This in particular comes with changes in the IPCC's approach to climate modelling, offering increasingly sophisticated future climate simulations, termed Representative Concentration Pathways (RCPs) replacing the older SRES scenarios (Moss et al., 2010; Rogelj et al., 2012; IPCC, 2013). Consensus within epidemiological studies is that the relationships between climate, environment and disease remain poorly understood, particularly when examining the importance and contribution of each aspect (Parham and Michael, 2010; Christiansen-Jucht et al., 2014; Gwitira et al., 2015; Hardy et al., 2015). Thus, a key element underpinning the criticality and uniqueness of this particular research is the highlighted necessity for further research to better understand the nature and drivers of changing endemicity in sub-Saharan Africa (Githeko et al., 2014; Bhatt et al., 2015; Mlozi et al., 2015; Shayo et al., 2015).

4.1.1 Aims and objectives

The aim of this chapter is to develop and apply a predictive environmental risk model to produce a risk map for malaria. This will be achieved through the development of a weighted environmental model consisting of environmental variables relevant to malaria distribution. The model will be built in objective based stages. The initial weighted sums will be ranked and assigned through careful examination of relevant factors identified within the literature before being applied to current environmental data. In order to validate the model, outputs will be compared for accuracy against the observed disease distribution within Tanzania. Once representative of current malaria prevalence distribution, the model will be applied to simulations from the Hadley HADGEM2-ES model for the four RCPs. This will provide a future modelled output for environmental risk for years 2050 and 2070 over four separate scenarios. The final stage will be to compare the future simulation distributions of potential change for the four pathways to that of current distribution.

4.1.2 Associations between diseases and environmental factors

In order to develop an environmentally weighted risk map for disease distribution, the known relationships between malaria and environmental factors, of which climatic factors are considered to be a key dimension, need to be carefully considered (Githeko et al., 2000; Khormi and Kumar, 2015). The impacts of climate and environment on mosquito-borne diseases such as malaria have been closely examined within the literature; being identified as playing important roles in defining population density, reproduction, and transmission of disease (Khormi and Kumar, 2015). To date, no importance ranking of climatic and environmental variables with regards to disease has been published or agreed upon (Mordecai et al., 2013; Ferraguti et al., 2016). Regardless, a number of environmental variables (introduced in section 4.3) have been identified as critically linked to varying stages within the mosquito lifecycle as well as parasite development and thus, integral to examining disease distribution.

Mosquitoes are known to be critically dependent on temperature for a number of aspects on their lifecycle and reproduction cycle, alongside key temperatures in pathogen development within them (Bayoh and Lindsay, 2004; Blanford et al., 2013). Generally, higher temperatures allow for more optimum development into adulthood and thus into a disease transmitting vector within a shorter time period. A number of studies have been conducted to establish the optimum development and transmission temperatures reaching differing conclusions (Martens et al., 1997;

Craig et al., 1999; Hoshen and Morse, 2004; Parham and Michael, 2010). A recent study conducted by Mordecai et al. (2013) used a combined approach, using laboratory data, observed data and historical records in a quadratic model approach and provided a comparison of results from previous studies. Their overall conclusions demonstrated that temperature is a key driver, with optimum conditions at 25°C, which is on average 5°C lower than previously considered by other studies (for example, Martens et al., 1997; Craig et al., 1999; Parham and Michael, 2010).

Rainfall and water bodies are also strongly associated with enhancing transmission and vector distribution (Lindsay et al., 1998; Parham and Michael, 2010). Spatial and temporal distribution of precipitation alongside volume have been found to impact on disease vector habitats and breeding cycles in both the short and long term disease distribution, where increased rainfall is generally associated with an increase in breeding sites and site duration (Githeko et al., 2000; Gwitira et al., 2015). Whilst it is understood that temperature and rainfall both play crucial roles in affecting vector-borne disease transmission, the significance of each individual factor and the cumulative effect of both climatic parameters is still highly debated within the literature, with findings supporting both temperature and rainfall as being most influential in differing locations (Hay et al., 2002; Blanford et al., 2013; Mordecai et al., 2013; Gwitira et al., 2015). It is clear that both parameters do play an important role, particularly through influencing key bioclimatic variables and that this relationship requires further investigation.

Alongside rainfall, substantial permanent and perennial water bodies such as permanent lakes, temporary lakes, or rivers, can play a vital role in supporting and sustaining malaria transmission although varying analyses conclude differing results. Houngbedji et al. (2016) concluded that distance to water bodies was not considered a risk by their particular model framework when conducting a localised study despite strong evidence of the impacts of both temporary and permanent water bodies elsewhere (Ernst et al., 2006; Brown et al., 2008; Thomas et al., 2013). However, Houngbedji et al. (2016), study site was not local to any significant water bodies and thus is considered an anomaly when compared to the wider body of literature. The consensus is however, that distance to water bodies is important, with recent studies suggesting that a distance of 1500m or closer can have a higher than 0.5 impact on incidence rate-ratio (Silué et al., 2008; Raso et al., 2009).

Soil drainage properties have become an area of growing interest, particularly when examining water pooling for mosquito habitats. Patz et al. (1998) demonstrated that for a location in Kenya, modelling soil moisture substantially improved prediction of mosquito biting rates when compared to precipitation alone (Patz et al., 1998; Githeko et al., 2000). Alternatively, Hardy et al., (2015) demonstrated with their boosted regression model that slope angle had a greater influence on malaria infection rates in Zanzibar than soil moisture capacity for both wet and dry seasons, although soil moisture was demonstrated to have a minor influence overall. Both models include varying supporting parameters, where Patz et al., (1998) uses the normalised difference vegetation index (NDVI), Hardy et al., (2015) adopts land cover type over the vegetation index. Similarly to temperature and rainfall, soil conditions and slope remains an area requiring further study in a disease association context (Patz et al., 1998; Githeko et al., 2000; Kelly (Letcher) et al., 2013; Ratmanov et al., 2013; Hardy et al., 2015).

Vegetation coverage is considered an important variable in disease spread due to the increasing body of literature demonstrating a correlation between high NDVI and mosquito larval production (Hay et al., 1997; Thomson et al., 1999). NDVI is a measure of the presence and condition of green vegetation, thus indicating how much vegetation coverage is within an area and can also be related to more common ecological measures (Brown et al., 2008). Vegetation plays an integral role in disease distribution through providing cover for larval habitats and adult mosquitoes, preventing them from overheating and perishing in intense equatorial sunlight (Bayoh and Lindsay, 2004). Furthermore increased incidence of malaria has been linked to areas experiencing an increase in vegetation coverage following El Niño events, conditions which may be potentially representative of future conditions (Githeko et al., 2000; Glass et al., 2000; Propastin et al., 2010).

Relative humidity is often an overlooked factor in the mosquito life-cycle despite recent examinations presenting compelling arguments to consider relative humidity in disease risk assessments. Relative humidity is increased by rainfall, particularly when following a drought period (Takken and Knols, 2009; Khormi and Kumar, 2015). Increases in relative humidity strongly impact on the flight and subsequent host seeking behaviour of mosquitos (Khormi and Kumar, 2015). Furthermore, relative humidity has been noted to be an influencing factor in larvae development (Hopp et al., 2003; Yé et al., 2007). Very few existing models appear to incorporate relative humidity as an influential factor due to a lack of understanding regarding its influence and to some degree due to data resolution and availability. However, as model sophistication and environmental understanding linked to mosquitoes, increases the inclusion of relative humidity is also expected to follow (Chabot-Couture et al., 2014).

Historically malaria transmission in high elevations such as the East African highlands was mainly sporadic and unstable (i.e. epidemic) as a result of increasingly unsuitable conditions as elevation increases (Devi and Jauhari, 2004; Cohen et al., 2008). It has been noted, however, that these patterns are beginning to change, particularly in the latter part of the 20th century (Chaves and Koenraadt, 2010). Increasing instances of epidemic outbreaks have been recorded at higher elevation, an aspect which has been noted to be an important factor for some species of malaria transmitting vectors (Bødker et al., 2003; Shanks et al., 2005; Kulkarni et al., 2010). Typically, as altitude increases, temperature and vegetation cover decreases, resulting in poorer conditions for vector development and transmission. Though recent studies suggest this boundary may be changing as a result of climate change, with malaria conditions observed as high as > 1900m, though no specific elevation has been identified as the new limit (Bødker et al., 2003; Ernst et al., 2006).

Alongside changes in elevation, other topographic features have been identified to potentially contribute to vector habitat suitability and thus malaria distribution (Mushinzimana et al., 2006; Cohen et al., 2008; Chabot-Couture et al., 2014). Terrain attributes such as variation in slope can allow water to collect for a period of time sufficient enough to allow mosquitoes to breed and larvae to develop (Cohen et al., 2008; Githeko et al., 2014). However, whilst the impact of this is briefly mentioned in multiple publications and methods developed to examine runoff direction, research into the angles at with significant runoff and pooling occurs remains somewhat lacking in comparison (Tarboton, 1997; Ragab et al., 2003). Similarly, slope aspect is also mentioned in a number of publications with only a controlled urban study on rooftops directly commenting on slope and aspect impact on evaporation and runoff (Ragab et al., 2003). The conditions described in Ragab et al. (2003), differ markedly from terrain conditions although the basic principles can be applied with looking at the impact on mosquito and disease environments (Balls et al., 2004; Peterson, 2009).

All of the environmental and climatic factors described in this section contribute to malaria seasonality and spatial distribution, some of which are related, and others which counteract each other in terms of effect (Ermert et al., 2012; WHO, 2013b).

Malaria is endemic in Tanzania, and inconsistent or missing data within the climatological record alongside poor station coverage makes it difficult to accurately ascertain seasonal patterns of malaria associated with climate (Githeko et al., 2014). Increases in transmission, leading to epidemics often occur after heavy rainfall and optimum temperatures, which for Tanzania could be a result of the rainfall season occurring or extreme and changing conditions as a result of El Niño (Ernst et al., 2006; Jones et al., 2007).

4.1.3 Representative Concentration Pathways

Representative Concentration Pathways (RCPs) are the set of scenarios from the IPCC, replacing the former sequentially based Special Report on Emissions Scenarios (SRES) (Moss et al., 2010). These new emissions scenarios were developed to adapt to the advancements in data acquisition and knowledge, incorporating the needs of end users whom overall required more flexibility from the scenarios to include globally varying aspects such as socio-economic status as well as moving from a sequential based approach to a parallel approach in modelling (Moss et al., 2010). The final four RCPs (table 4.1) were carefully selected based on criteria tailored to the needs of scenario developers and end users, and span a large range of stabilization, mitigation and non-mitigation pathways, and named according to their peak value in radiative forcing (Wm^{-2}) (Rogelj et al., 2012; IPCC, 2013).

Table 4.1 - The four RCP Pathways (Moss et al., 2010). * MESSAGE: Model for Energy Supply Strategy Alternatives and their General Environmental Impact. International Institute for Applied Systems Analysis, Australia. AIM, Asia-Pacific Integrated Model, National Institute for Environmental Studies, Japan. GCAM, Global Change Assessment Model Pacific Northwest National Laboratory, USA (previously referred to as MiniCAM).IMAGE, Integrated Model to Assess the Global Environment, Netherlands Environmental Assessment Agency, The Netherlands.

Name	**Radiative Forcing**	**Concentration (ppm)**	**Pathway**	**Model providing RCP***
RCP 8.5	>8.5 Wm^{-2} in 2100	>1,370 CO_2-equiv. in 2100	Rising	MESSAGE
RCP 6.0	~6.0 Wm^{-2} at stabilization after 2100	~850 CO_2-equiv. (at stabilisation after 2100)	Stabilization without overshoot	AIM
RCP 4.5	~4.5 Wm^{-2} at stabilization after 2100	~650 CO_2-equiv. (at stabilisation after 2100)	Stabilization without overshoot	GCAM
RCP 2.6	Peak at ~3 Wm^{-2} before 2100 and then declines	Peak at ~490 CO_2-equiv. before 2100 and then declines.	Peak and decline	IMAGE

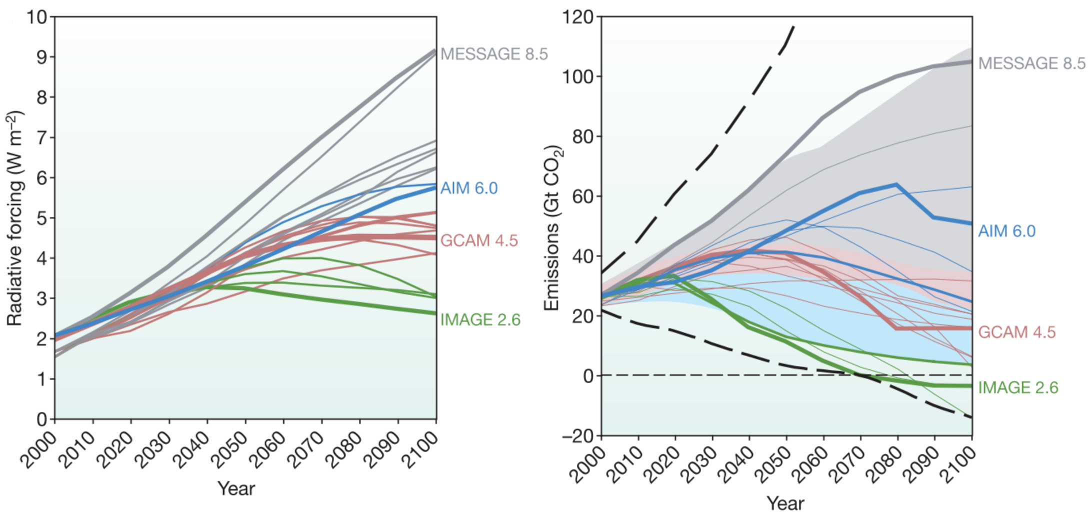


Figure 4.1 - a) Changes in radiative forcing relative to pre-industrial conditions. b) Energy and industry CO_2 emissions for the RCP candidates *(Moss et al., 2010)*.

RCP 2.6 is the lowest, most modest greenhouse gas trajectory, peaking in radiative forcing before 2030 and declining (figure 4.1) (Moss et al., 2010; Rogelj et al., 2012; IPCC, 2013; Abdussalam et al., 2014). Models run using this pathway demonstrate that global temperature change is unlikely to exceed 1.5˚C by the end of the 21st century, comparative to 1850 to 1900 (IPCC, 2013). RCP4.5 and RCP 6.0 are intermediate stabilisation pathways where radiative forcing is stabilised by approximately 2080. RCP 4.5 is not likely to exceed warming of 2˚C by 2100, however RCP 6.0 is likely to exceed a warming of 2˚C (IPCC, 2013). RCP 8.5 represents a high-emission, non-mitigation future, projecting a high range of outcomes by 2100 being likely to exceed 2˚C but unlikely to exceed 4˚C (Rogelj et al., 2012; IPCC, 2013).

4.2 Data methods and processing

The environmental factors highlighted as important which will be included in this study are: temperature, precipitation, relative humidity, elevation, slope, aspect, vegetation coverage, and soil drainage capacity. Datasets for these parameters, both current and CMIP5 simulations, have been collected from a range of sources as outlined in the relevant section below. The datasets described in this section will be referred to as baseline environmental conditions for the month of May, upon which the model will be developed and which future simulations will be compared against. This is due to cumulative peak rainfall for the preceding MAM rainfall season, presented in chapter three, which contributes to heightened malaria risk during this month in conjunction with suitable temperature conditions (Sewe et al., 2016). Some datasets required some pre-processing prior to implementing the main experimental method which are also outlined below.

4.2.1 Temperature

Data for current temperature conditions were freely downloaded from WorldClim, a dataset developed by Hijmans et al. (2005). Baseline conditions are based on observations made from 1960-1990 from a range of sources and were obtained at a resolution of 30 arc-seconds (approximately 1km). For more information on the methods involved development of this particular dataset see Hijmans et al. (2005). Temperature data for four RCP climate model pathways were collected for

HADGEM2-ES, a full earth system model developed by the MO. The pathways included are: RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5.

4.2.2 Precipitation

Data for baseline precipitation conditions were freely downloaded from WorldClim. Current conditions are based on observations made from 1960-1990 from a range of sources and were obtained at a resolution of 30 arc-seconds (approximately 1km). For more information on the methods involved development of this particular dataset see Hijmans et al. (2005). Precipitation data for four RCP climate model simulations produced from 11 global climate models (GCMs) were also obtained via WorldClim at a resolution of 30 arc-seconds. Precipitation data for four RCP climate model pathways were collected for HADGEM2-ES, a full earth system model developed by the MO. The pathways included are: RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5.

4.2.3 Relative humidity

Data for current relative humidity for the month of January was downloaded from Climond, a global climate project for bioclimatic modelling developed by Kriticos et al. (2012). The data representing current conditions is based on 30 years worth of data collected from 1960-1990 and downloaded at a resolution of 10’ (arcminutes). Daily observations were recorded at 09:00 hours and 15:00 hours and the corresponding relative humidity files were split into each observation time in order to provide a daily approximation of relative humidity for easier comparison and inclusion in the model. The files were combined and averaged using ArcGIS.

No future projections of absolute or relative humidity under the RCP scenarios are available and so a proxy dataset has been created as detailed in section 4.3.1.3.

4.2.4 Elevation, slope and aspect

The 30m resolution ASTER Global Digital Elevation Model (DEM) version 2 was freely obtained through the NASA reverb client. The ASTER GDEM is a product of METI and NASA, where there are known inaccuracies and artefacts in the data set. More information on the dataset itself can be collected via NASA Earth Observation (NEO) (NASA, 2016b).

The elevation model was downloaded in a total of 233 tiles, which were stitched together using the raster mosaic tool available in Arc GIS 10.3.1. Following this, the data was clipped to the administrative region of Tanzania only using a shapefile provided by DIVA GIS. Errors were observed in the dataset, which was corrected for using nearest neighbour resampling to re-assign erroneous pixels to a proxy value. Inaccuracies were located mostly at the highest and lowest elevations.

Using the corrected DEM, both the maximum rate of slope change and direction of slope change files were created in ArcGIS using the slope and aspect tools respectively.

4.2.4.1 Slope

Examination of the literature provided no clear threshold regarding the angles at which water will increase the likelihood of runoff and pooling, particularly for clay based soils. The ability for water to pool is a crucial factor in aiding or preventing the formation of appropriate mosquito breeding and residential habitats. Due to the lack of appropriate information available, an experiment was designed and conducted to examine the angles at which runoff could begin to aid pooling and the angles at which runoff is too great and would prevent levels of pooling or potentially wash away mosquito larvae.

Clay soil was chosen as the key representative soil group for this experiment due to this soil type being the most likely to represent pooling opportunities for mosquitoes as a result of low permeability and its presence in areas of Tanzania (Government of Tanganyika, 1955; Mosha, 1983). Due to the difficulty of acquiring a mixed clay soil to use as the base of the experiment an initial step was taken to test two representative soil samples. One was a compost mix found at a local garden centre and the second a pure moulding clay. The soil sample used from a local garden centre proved too absorbent to gain any meaningful results from and thus the pure clay representative was used.

The clay was moulded into a container (figure 4.2a) and an indent the size of a thermos lid made (figure 4.2b). This is to represent potential natural holes in the landscape where mosquitoes may choose to lay eggs if there is a suitable depth of water available. A protractor was attached to the side of the container with a plumb-line and weight (in this instance a needle) attached at the centre of the protractor and set to fall at zero to begin with. Thus, when the container was tilted, the plumb-line would adjust to indicate the angle of the slope. 5ml of water was inserted into the indent via a syringe. Higher volumes of water were tested but this overfilled the indent and would not have provided a good indication of slope runoff.

Figure 4.2 - a) (Left) Indent size in clay base and container. b) (Right) thermos lid used to make indent with size and clay markings.

Six individual tests were conducted overall, including three for assessing the lower angle and three for the upper angle. The lower angle was indicated by the angle at which water will flow over the lip of the indent and run smoothly downslope. The upper angle was assessed as the point at which water flow would be too fast and disruptive for mosquitoes to lay eggs in the indent, and where water may empty from the indent at a quicker rate. The results from both sets of three tests are shown in figure 4.3, tiles a, b and c demonstrate results for the lower angles, with d, e and f demonstrating results from the upper angles. The results were averaged to give one value for lower and upper angles and distributed evenly for the suitability scale discussed in section 4.3.1.1.

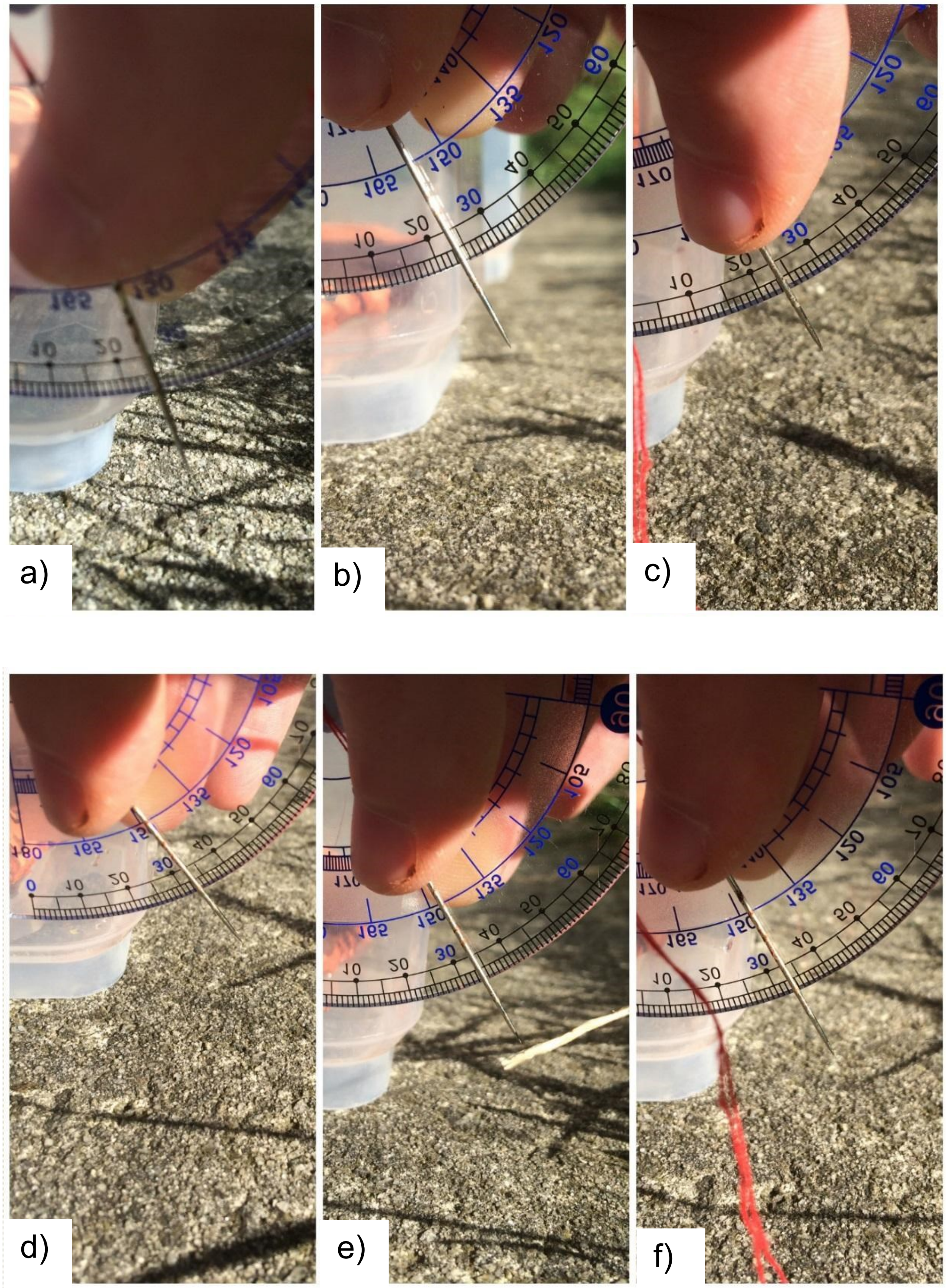


Figure 4.3 - Results from lower angle experiment (a, b, c) and results from upper angle experiment (d, e, f)

4.2.5 Vegetation coverage (NDVI)

Normalised Difference Vegetation Index (NDVI) monthly data was freely obtained for the month of May for years 2003 and 2013. The dataset itself was collected by the MODIS-Terra satellite series and a floating-point raster dataset created by

NASA at a resolution of 0.1 degrees. More information on the development of the vegetation data can be found via the NASA earth observation website (NASA, 2016b).

NDVI for May 2003 is used in development of the baseline predictive model. Whilst future NDVI values are not available for inclusion in the 2050 and 2070 projections, a proxy dataset has been created as detailed in section 4.3.1.7.

4.2.6 Soil drainage capability

Soil drainage data was obtained from the FAO and created as a bi-product of the HWSD (world soil dataset). Soil drainage data was pre-ranked on a scale of one to seven where one represents low drainage rates and seven represents high drainage rates (FAO, 1985; Davidson, 1995).

4.2.7 Water bodies

Vector shape files for lake and river location were obtained from DIVA GIS. These were then combined into one file and rasterized for inclusion in analysis.

4.2.8 Malaria prevalence map

Data for malaria prevalence for the year 2000 was freely obtained in raster format from the Malaria Atlas Project (MAP) (University of Oxford). Data is currently available from 2000 up to 2015 and described in detail by Bhatt et al. (2015). The year 2000 was chosen for this study due to it being most likely to reflect the least amount of disease prevention and control, thus providing clearer evidence in relation to environmental influences. The dataset pixel-size was resampled using the nearest neighbour method in order to compare to the developed model outputs. Prevalence data was used instead of incidence as this accounts for population density and size impact thus removing the impact of population sizes on malaria distribution allowing for clearer environmental relationship results.

4.2.9 Tanzania population density

Data for current population density and distribution (as of 2015) was freely downloaded in raster format from the WorldPop project (The WorldPop Project, 2016). Data provides estimations of population per square grid which have been adjusted to match the UN population division estimates. Data for estimated future population for 2050 and 2070 were downloaded in spreadsheet format provided by the UN population division which was revised in 2015 (UNDP, 2016).

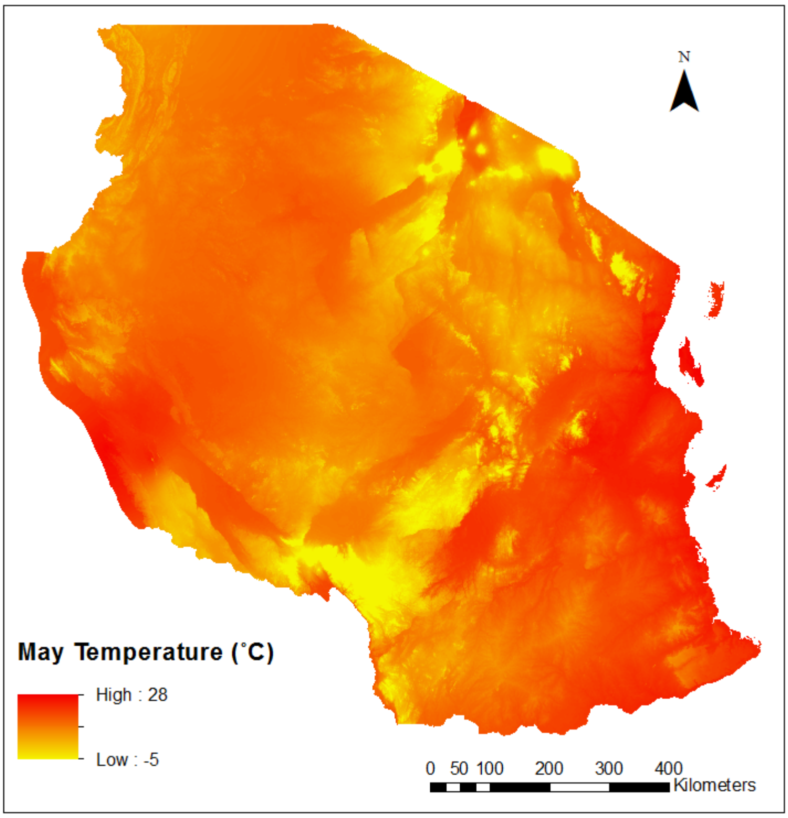
4.3 Methods

4.3.1 Suitability assignment

Prior to running the weighted sum analysis in ArcGIS 10.3.1 each chosen variable (outlined in sections 4.2 and 4.3) required re-classifying to a normalised scale which would be representative and comparable across all variables and thus provide a meaningful environmental risk map.

4.3.1.1 Temperature

Temperature suitability for the transmission of malaria was developed through the examination of papers focusing around the ecological modelling of the transmission of malaria (Martens et al., 1997; Craig et al., 1999; Hoshen and Morse, 2004; Parham and Michael, 2010; Mordecai et al., 2013). Temperature ranges used in this study were collected from analysis conducted by Mordecai et al. (2013). The temperature values used are presented in section 4.3.1.11 with the original and suitability assigned datasets displayed in figure 4.4a and 4.4b. Furthermore, the model weighting of the temperature variable accounted for studies examining the role of temperature in malaria variation, where minimum and maximum temperatures were shown to account for a total of 27.2% of the spatial distribution of malaria in Tanzania (Mboera et al., 2010, 2011).



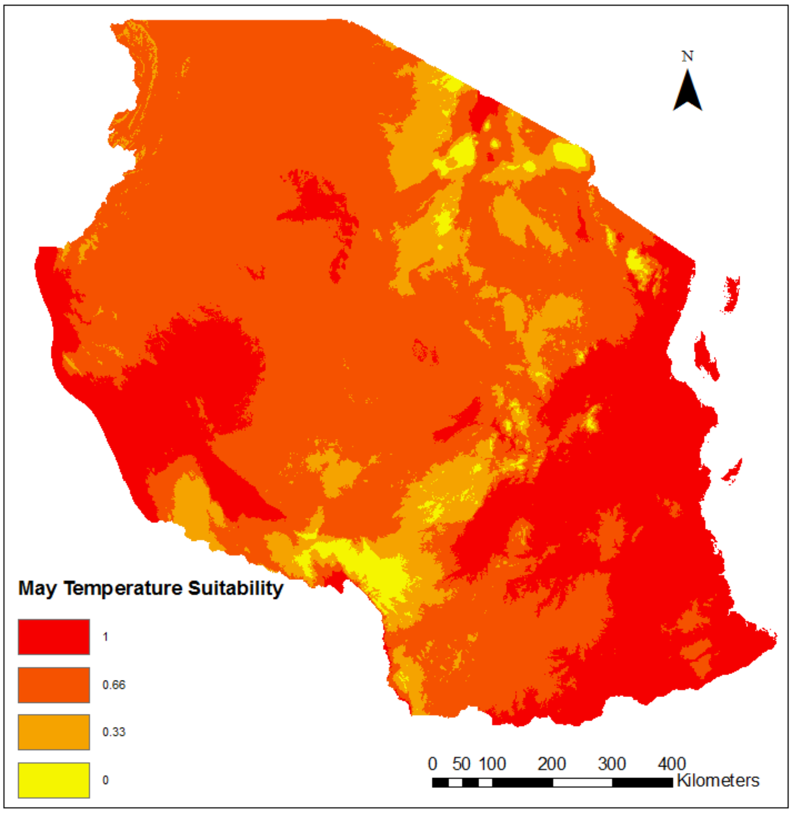
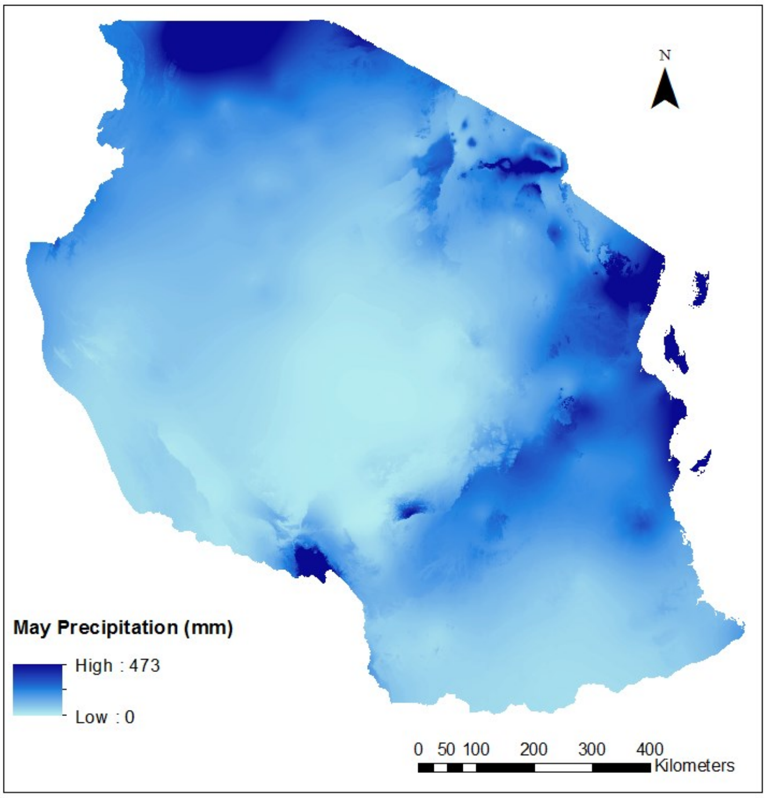


Figure 4.4 - a) Original temperature dataset *(Hijmans et al., 2005)* b) Temperature dataset after being assigned suitability categories.

4.3.1.2 Precipitation

Rainfall thresholds differ by model and, methods used. Precipitation patterns also play a highly influential role. Previous studies have shown that almost the entirety of Tanzania is endemic for malaria, with inherent spatial variation of which mean precipitation accounts for 72.8% of this variation (Mboera et al., 2010, 2011). When examining monthly rainfall quantities required to sustain adequate malarial environments there were notable variations. Usher (2010) reported the lowest monthly rainfall value of 10mm based on agricultural modelling, however this must be sustained for a period of 4 months. Given Tanzania's multi-modal rainfall regime this was not fitting to model the entire country and thus higher values considered.

A number of studies report adequate rainfall values ranging from 50mm up to as much as 80mm per month to sustain transmission ranging from stable: perennial through to epidemic (Craig et al., 1999; Tanser et al., 2003; Parham and Michael, 2010). However, in a number of cases this also varies depending on the associated temperature given that mosquitoes require adequate provision of both for growth and transmission (Craig et al., 1999; Ostfeld et al., 2005; Bomblies, 2012). Tanzania's temperature in most regions is adequate in sustaining potentially epidemic conditions (although this varies spatially). A minimum rainfall value of 50mm per month was chosen as the minimum requirements to aid transmission, with amounts higher than this being more influentially weighted. Temporary pools of water of approximately 50mm are also considered deep enough to sustain reproduction cycles for a given period of time, although pool life time is also dependent on persistence and thus linked to temperature (Ostfeld et al., 2005; Bomblies, 2012). The precipitation dataset prior and post suitability classification are presented in figures 4.5a and 4.5b.



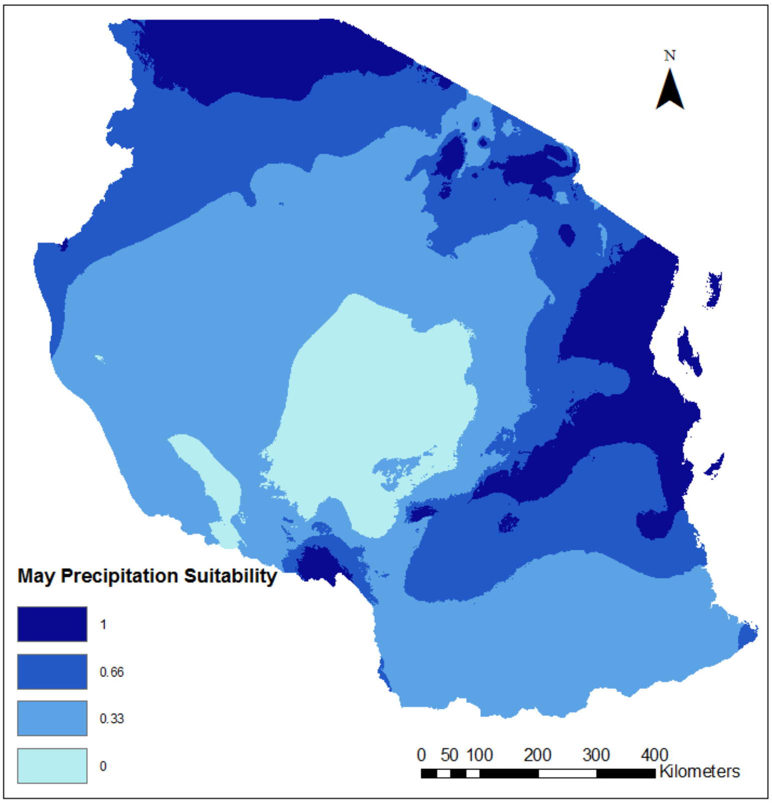
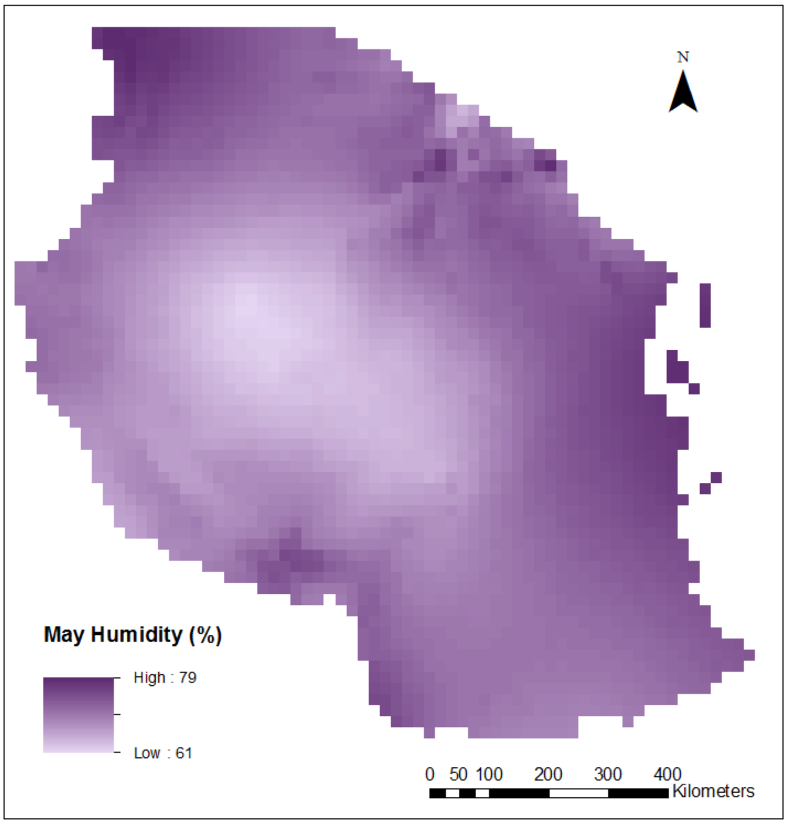


Figure 4.5 - a) Original precipitation dataset *(Hijmans et al., 2005)* b) Precipitation dataset after suitability categorisation.

4.3.1.3 Humidity

As noted, humidity is comparatively under-examined in comparison to temperature and rainfall. Relative humidity impacts adult mosquitoe mortality as well as impacting upon their larval development cycle (Hopp et al., 2003; Yé et al., 2007; Chabot-Couture et al., 2014). Ye et al., (2007) demonstrated how relative humidity values below 60% are linked to a low-risk in contracting malaria, and at 55% humidity the risk of clinical malaria was 25% lower than observed at 60%. Thus 60% relative humidity was allocated as the minimum risk in this model. The original humidity dataset and dataset after suitability classification are presented in figure 4.6a and 4.6b.

Relative humidity projections for the current RCP pathways are not readily available at present. In order to include relative humidity in the future simulations, the baseline average relative humidity has been modified in accordance with the percentage change of ambient air temperature (figure 4.7), given the relationship between relative humidity and temperature (equation 4.1) and assumes no alteration to dew point has occurred.



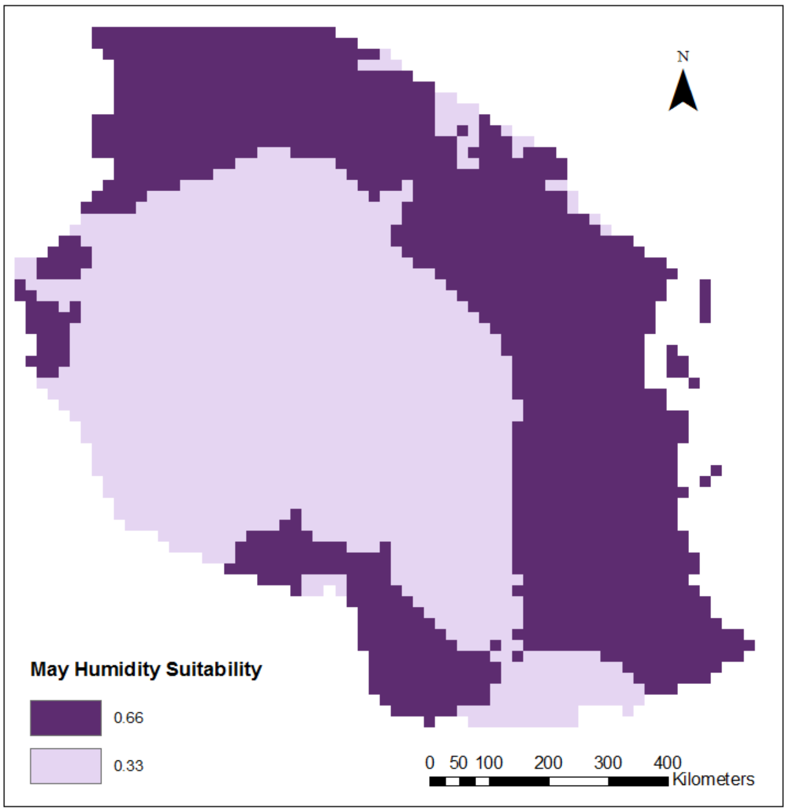


Figure 4.6 - a) Original humidity dataset *(Kriticos et al., 2012)* b) Humidity dataset after suitability categorisation.

Equation 4.1 - Calculating relative humidity using dew point, temperature and constant values. (Vaisala, 2013)

$$RH = 100\% \cdot 10^{m\left[\frac{Td}{Td+Tn} + \frac{Tambient}{Tambient+Tn}\right]}$$

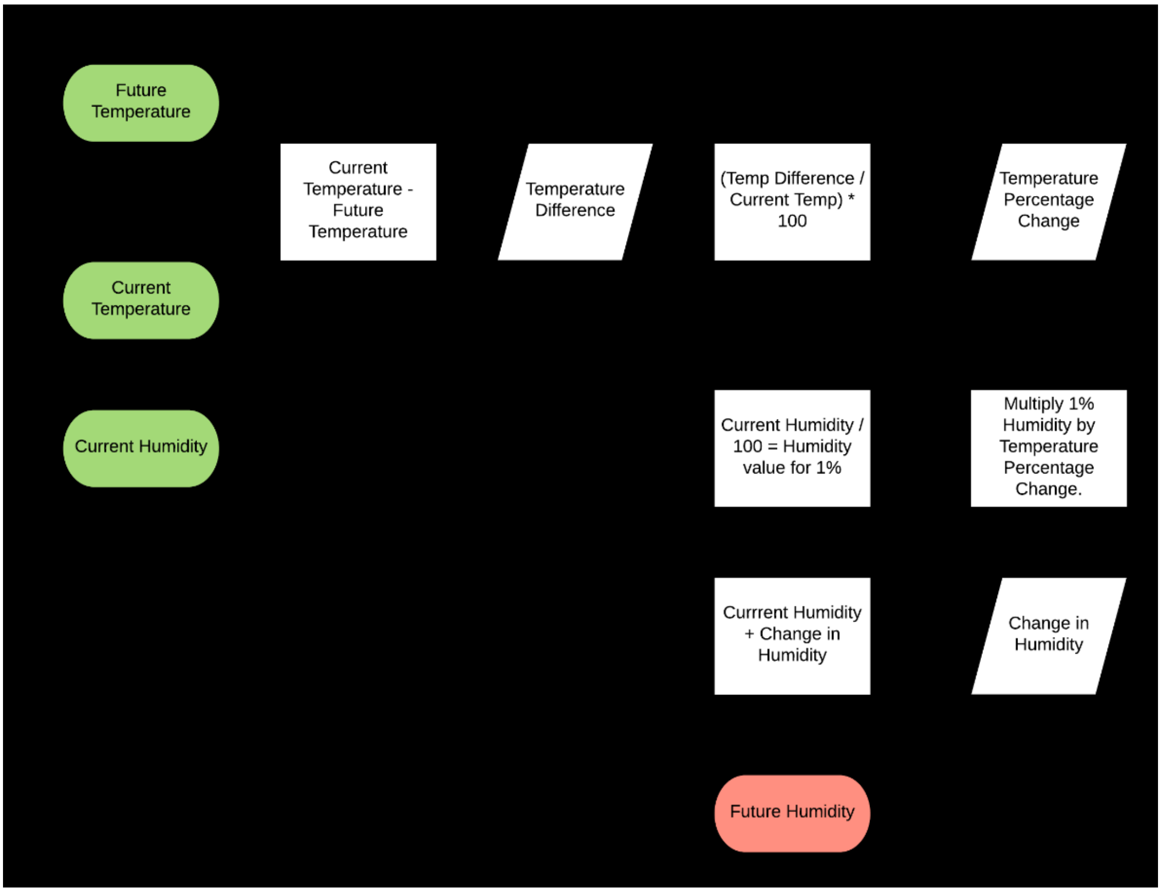


Figure 4.7 - Methodology used to calculate relative humidity in relation to future temperatures.

4.3.1.4 Elevation

Incidences of malaria transmission with relation to elevation have begun to vary in more recent literature than when compared to publications prior to the year 2000. This could be due to increasing awareness of the impact of elevation on disease. The generally accepted height of reduction in transmission is 1500m, and whilst there is evidence of transmission above these altitudes, conditions are overall deemed to be less suitable (Bødker et al., 2003; Ernst et al., 2006). Despite increasing reports of transmission above 1500m, this has been allocated as the cut-off point for this model. Elevations below 1500m have been deemed optimum for transmission on a presence-absence basis (Drakeley et al., 2005; Cohen et al., 2008; Gwitira et al., 2015).

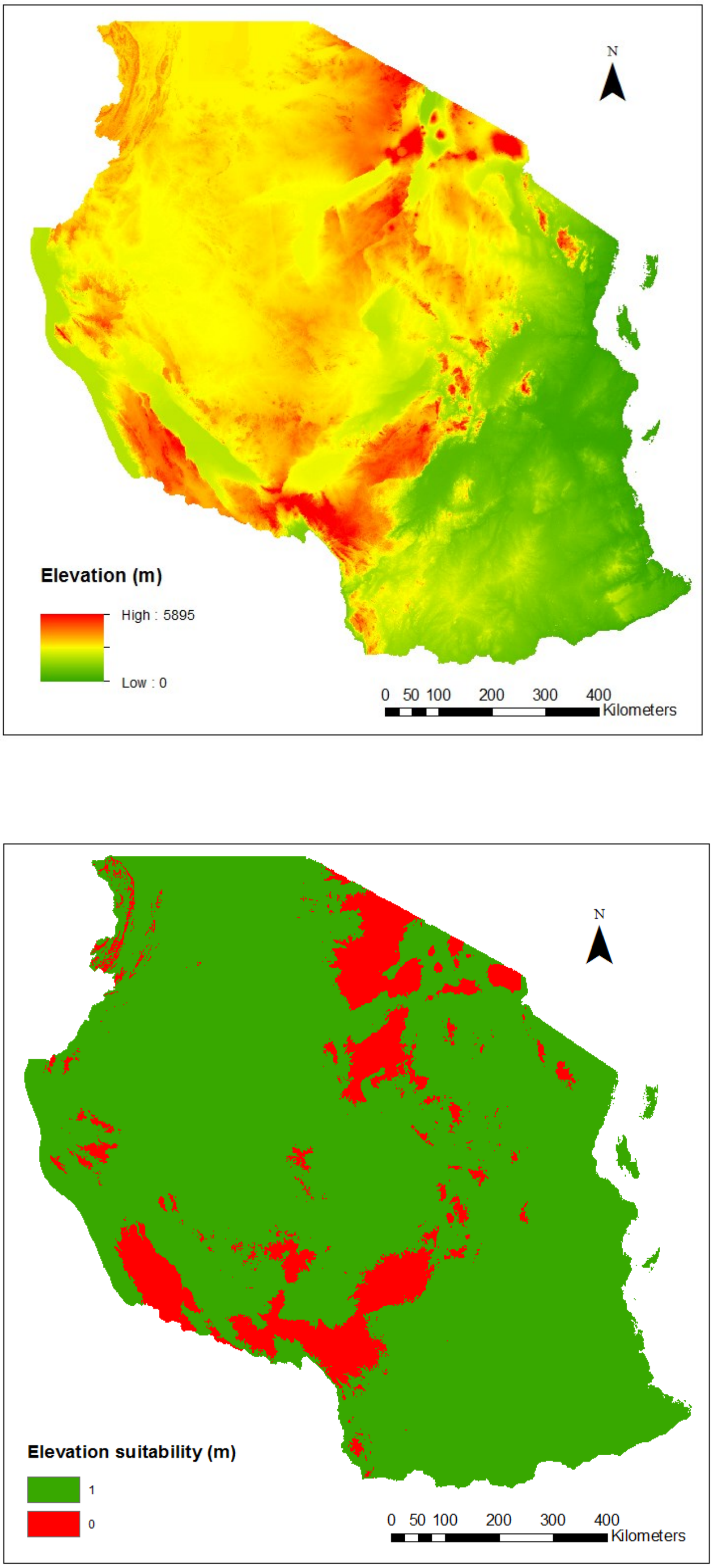


Figure 4.8 - a) Original slope dataset *(NASA, 2016a)* b) Slope dataset after suitability categorisation

4.3.1.5 Slope

Optimum to unsuitable slope values (figure 4.9) were obtained through the experiment conducted specifically for this thesis as outlined in section 4.2.5.1. This is due to no specific slope angles being available for terrain runoff as outlined in section 4.1.2.

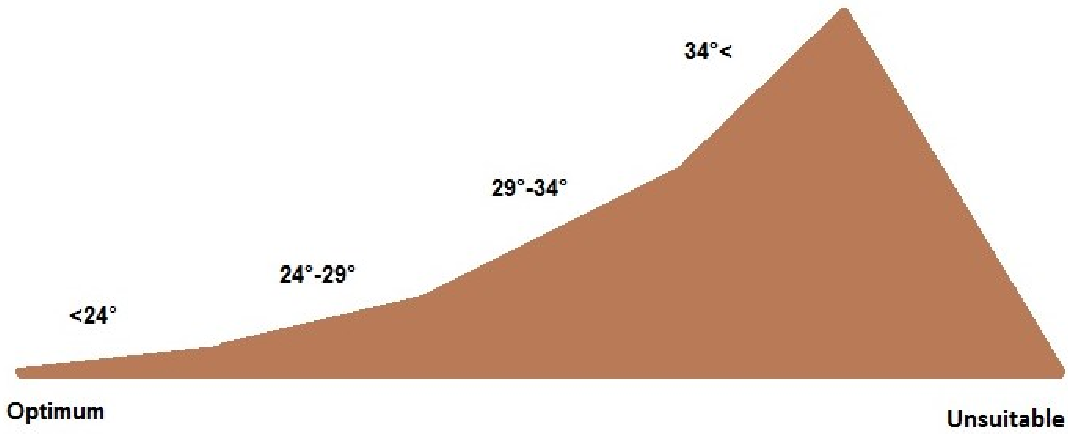


Figure 4.9 - Optimum slope angles for standing water (habitats) through to unsuitable.

4.3.1.6 Aspect

As discussed in section 4.1.1 little is understood about the impact of aspect on mosquito habitats, with no studies to date being conducted that directly examine the impact of aspect on habitats and behaviour. Theoretically, slopes facing away from the sun receive overall less heat, a key variable in mosquito development. Furthermore, slopes facing the sun will experience increased evapotranspiration as a result of being in direct sunlight. For the Northern Hemisphere, Ragab et al. (2003) concluded that northern facing slopes (270° - 90°) receive less sunlight and therefore would be considered less suitable for mosquitoes, whereas southern facing slopes (90° - 270°) face the sun for the majority of the time and thus would be considered more suitable. Evaporation processes and heat are both influential when examining mosquitoes behaviour and habitats (Hoshen and Morse, 2004).

The premise described above was adapted for the Southern Hemisphere where the study is located. Northern facing slopes (270° - 90°) would experience more sunlight in the Southern Hemisphere and thus were assigned a mosquito presence value, where southern facing slopes (90° - 270°) would receive less sunlight and thus were assigned a mosquito absence value (figure 4.10). Due to the lack of investigation surrounding aspect, easterly and westerly facing slopes could not be individually accounted for and as a result were split between both north and south.

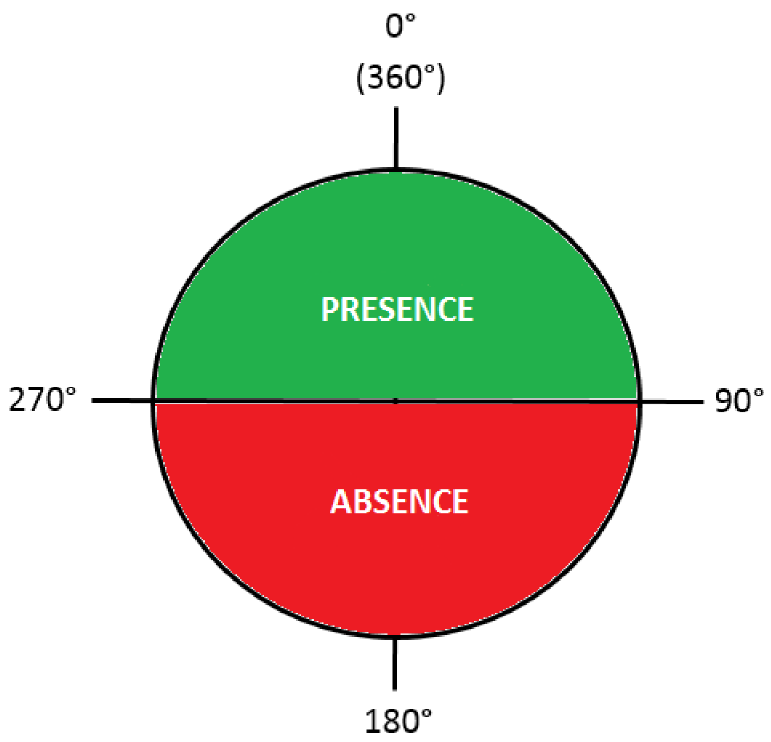


Figure 4.10 - Presence / absence angles used to determine influential slope Aspects.

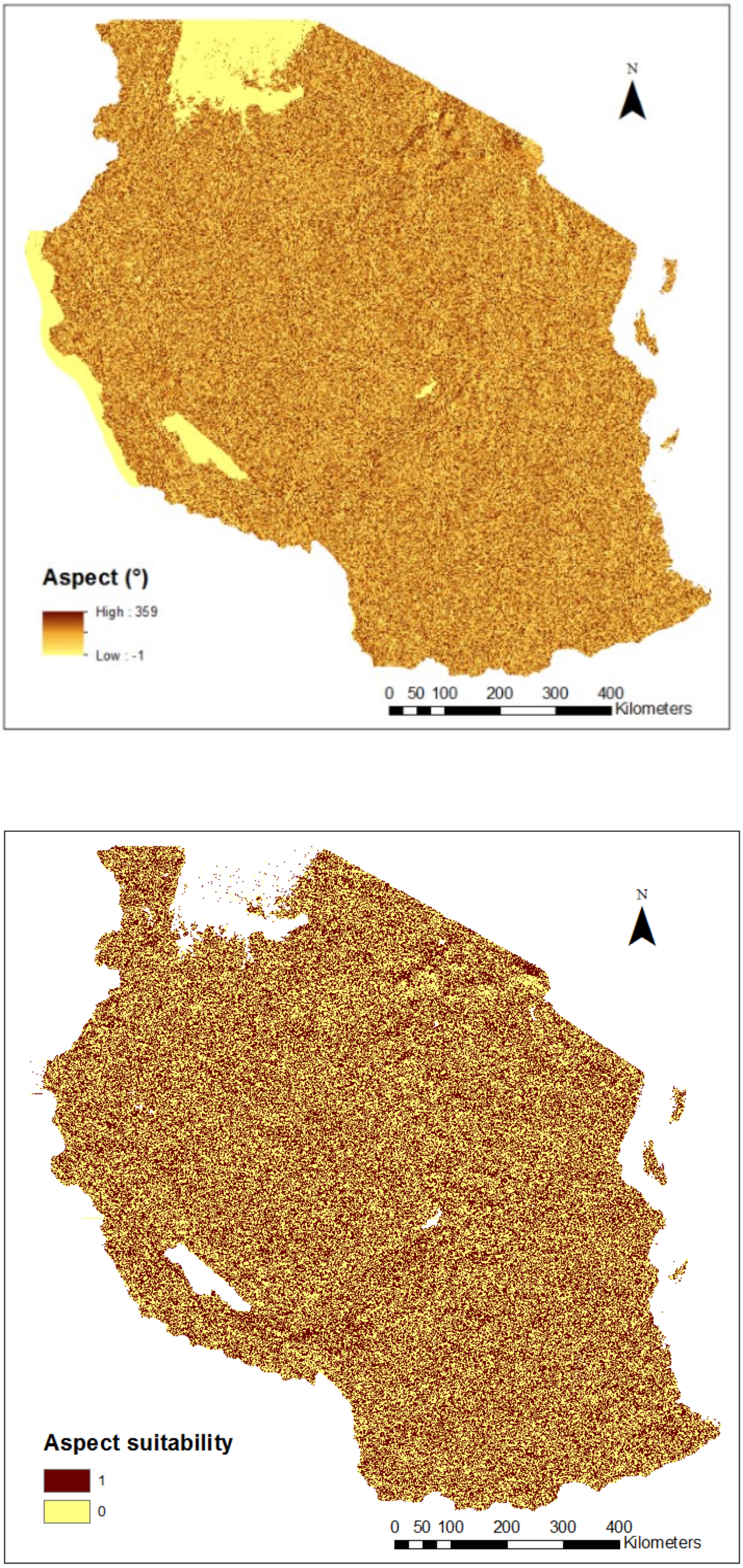


Figure 4.11 - a) Original aspect dataset *(NASA, 2016a)* b) Aspect dataset after suitability categorisation. Where 1 = suitable and 0 = unsuitable.

4.3.1.7 NDVI

The direct statistical relationship between NDVI and incidence of malaria outbreaks or plasmodium falciparum presence in blood does remain limited despite increasing observations of correlation between outbreaks and vegetation coverage (Githeko et al., 2000; Sewe et al., 2016). Studies carried out to assess this direct statistical relationship generally conclude that should NDVI values fall below 0.3 then there is not enough vegetation to support mosquito habitats or disease transmission (Hay et al., 1998; Gaudart et al., 2009; Sewe et al., 2016). Thresholds which have been ascertained through various statistical analysis conclude that NDVI values between 0.3 and 0.4 are strongly associated with increased incidence (Hay et al., 1998; Rogers et al., 2002; Gemperli et al., 2006; Gaudart et al., 2009; Sewe et al., 2016). Thus, based on the available evidence, a threshold of 0.3 was applied in order to cover all potential local biological reactions to NDVI coverage as demonstrated in Sewe et al. (2016). Similarly, vegetation values greater than 0.65-0.7 are shown to have a strong incidence-rate ratio, thus higher suitability (Raso et al., 2009).

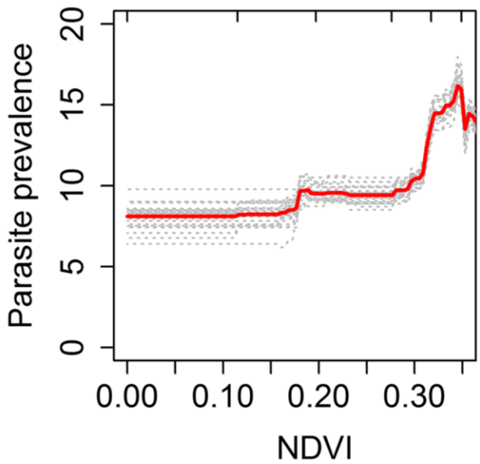
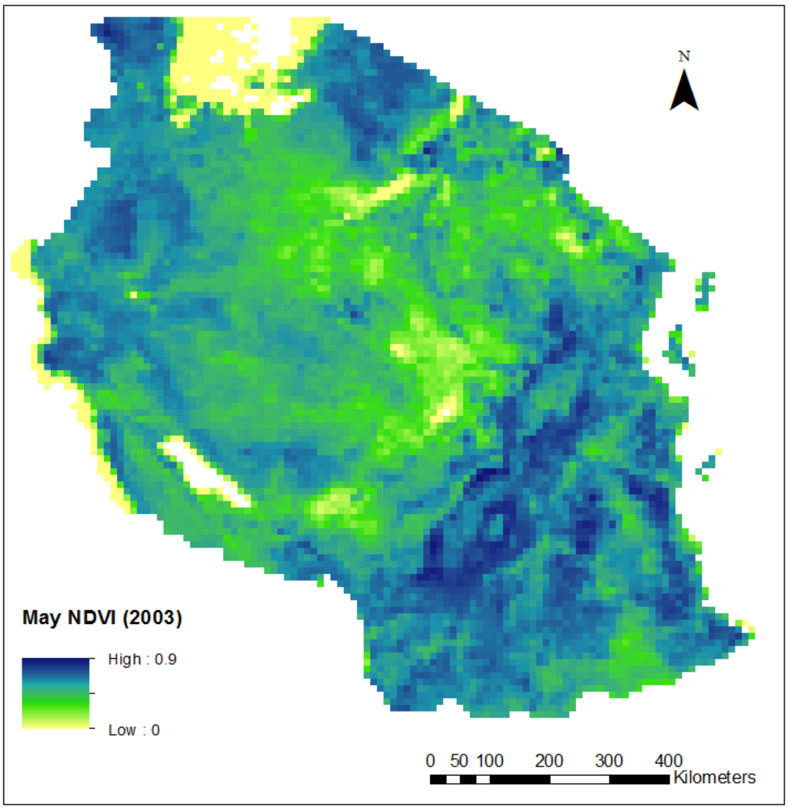


Figure 4.12 - Parasite prevalence in relation to NDVI (Kabaria et al., 2016).



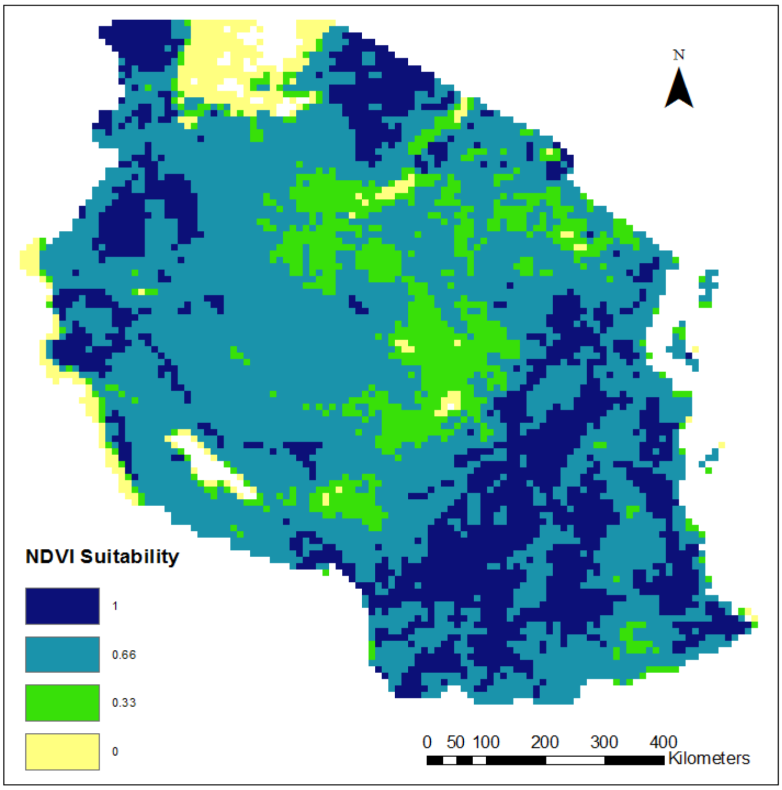


Figure 4.13 - a) Original NDVI dataset *(NASA, 2016b)* b) NDVI dataset after suitability classification.

Unlike other variable factors in this study, future simulated NDVI values are not available or forecast for any climatic scenario. In order to retain inclusion of NDVI in the simulated future RCPs, a proxy dataset has been created. Two proxy datasets in total were created, one to represent NDVI in 2050 and one for 2070. These datasets were created through examining the changing coverage and distribution of vegetation between 2003 and 2013.

Percentage change in NDVI over a ten-year period between 2003 and 2013 was calculated and multiplied by five to represent change to 2050 and multiplied by seven to represent change to 2070. To avoid capturing any impacts from an ENSO year, two years were chosen where the SOI was recorded as neutral for both years at ten years apart (NOAA, 2015). Furthermore, NDVI values for the entire month of May were included to incorporate any lag time, estimated at around 15 days for vegetation to impact on malaria transmission (Gaudart et al., 2009; Sewe et al., 2016).

Whilst this method allows for the projection of potential spatial distribution and values for NDVI in 2050 and 2070, there are several considerations to be noted. Firstly, the method assumes the spatial pattern of change continues along a linear trend of that seen between 2003 and 2013. Secondly, NDVI differences between RCPs cannot be accounted for, there is only one projected scenario for each year. However, performing more complex NDVI and land use projections would require more sophisticated modelling which lies beyond the scope of this project and would introduce further uncertainty into the output. Nevertheless, it is important to consider this factor when interpreting model outputs as there could potentially be considerable differences in vegetation coverage between RCPs which cannot be projected at this time with the data available (Poyil et al., 2016).

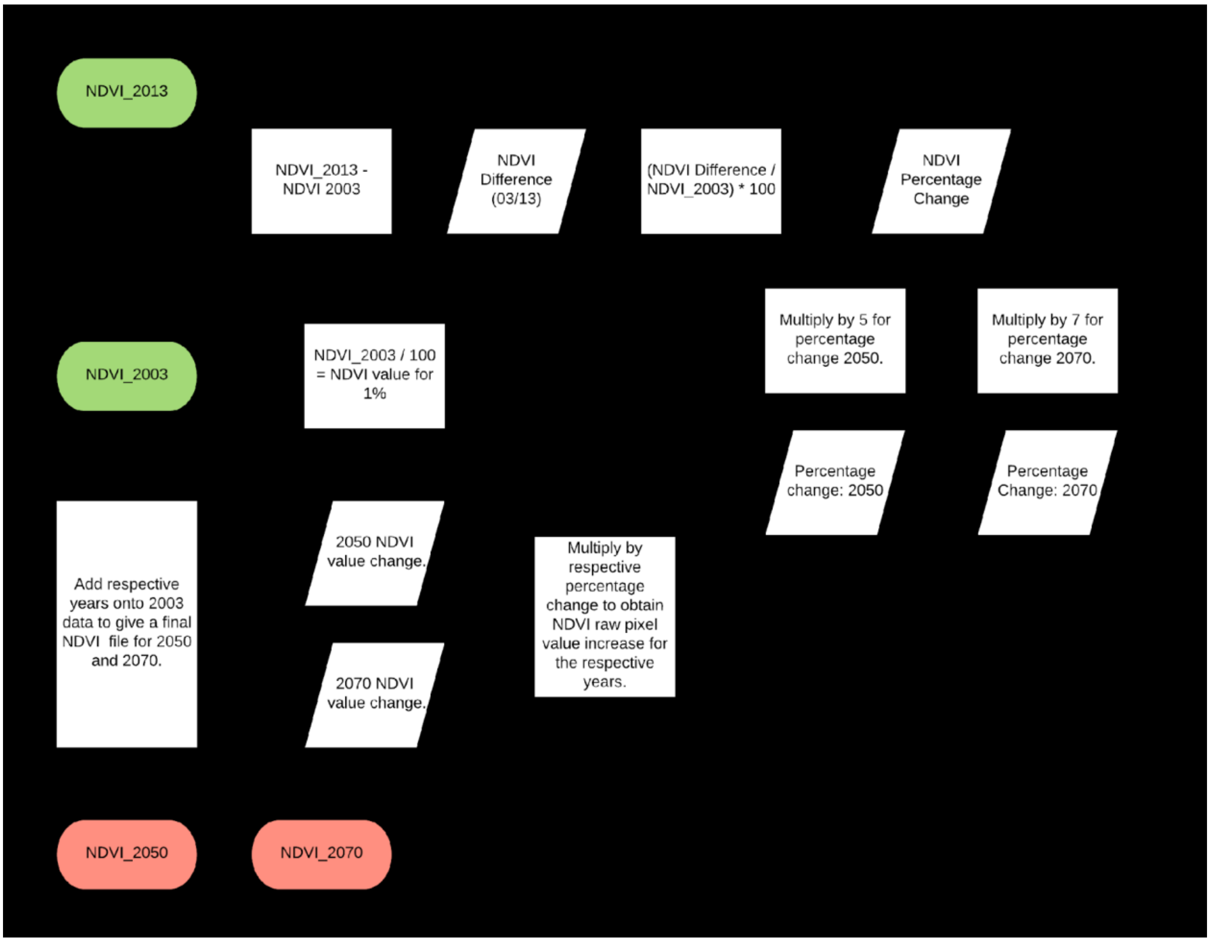


Figure 4.14 - Method to calculate proxy NDVI datasets for 2050 and 2070.

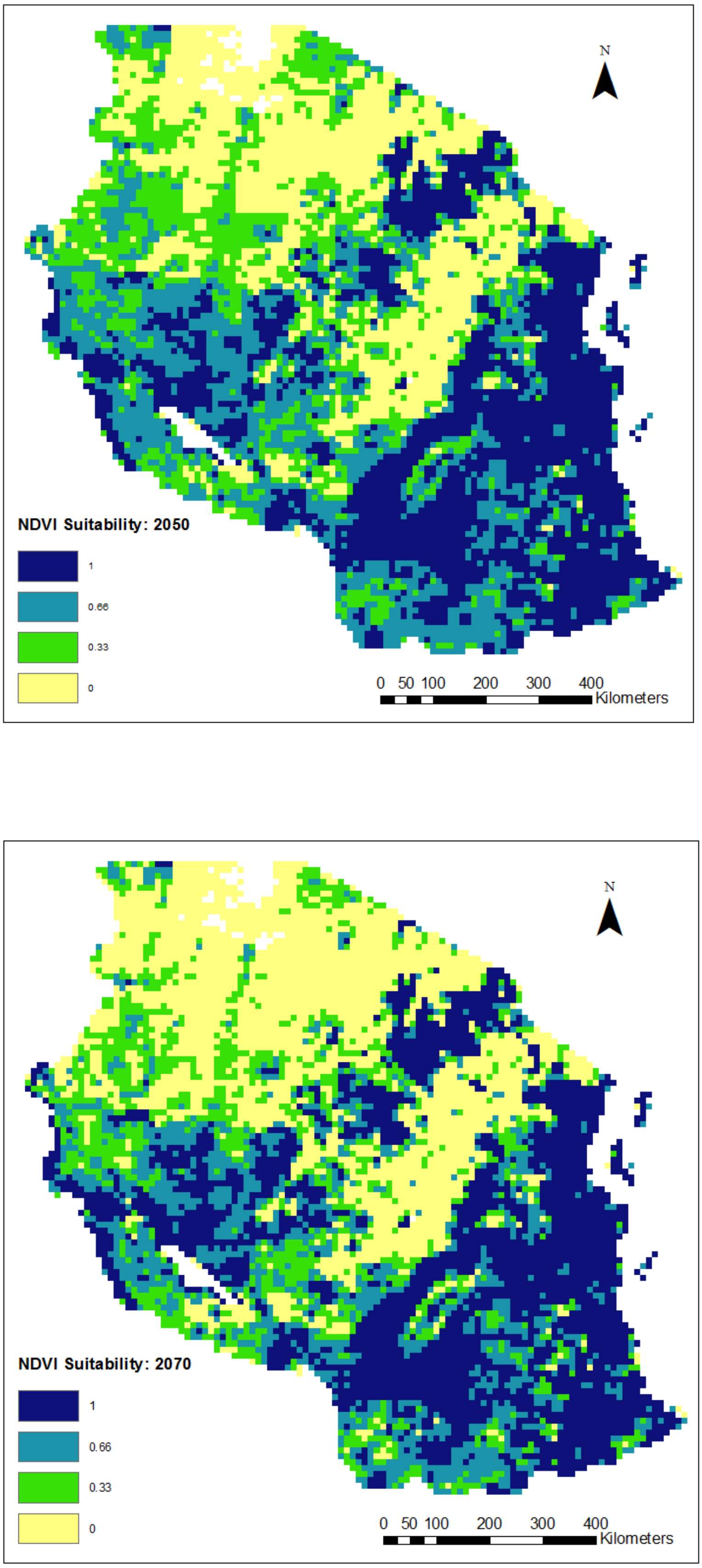


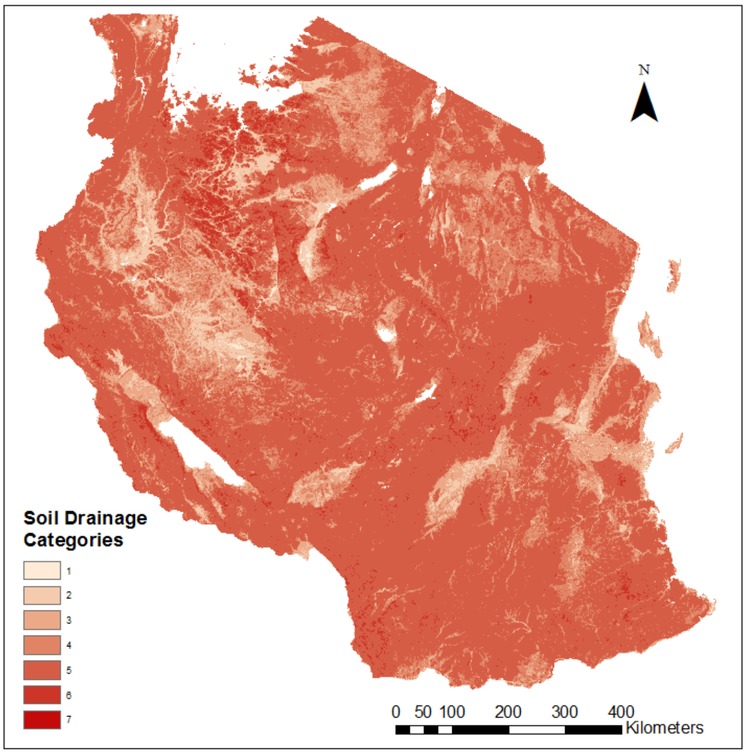
Figure 4.15 - a) Projected NDVI coverage for 2050 b) Projected NDVI coverage for 2070

4.3.1.8 Soil drainage

Soil drainage thresholds were predefined into seven classes by the FAO (FAO, 1985; Davidson, 1995). In order to appropriately fit into the weighting system, they were reduced to four categories based on appropriate judgement ascertained from the FAO and in relation to water requirements for mosquitoes (FAO, 1985).

Table 4.2 - FAO soil drainage classes (FAO, 1985).

Class Code	**Drainage Quality**	**Suitability Code**
1	Very poorly drained	1
2	Poorly drained	
3	Imperfectly drained	0.66
4	Moderately well drained	
5	Well drained	0.33
6	Somewhat excessively drained	
7	Excessively drained	0



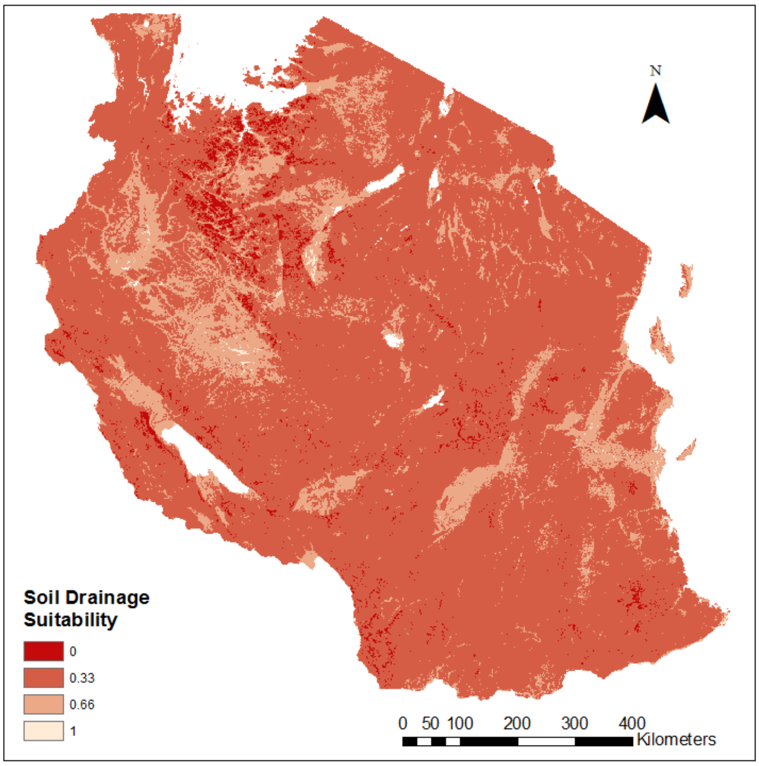


Figure 4.16 - a) Original soil drainage dataset b) Soil drainage set after suitability classification

4.3.1.9 Water bodies

Distance to water bodies are a key environmental factor associated with malaria transmission. Studies including this factor demonstrate populations with notably higher incidence-rate ratios greater than 98% within 1000m of a water body, and greater than 60% within 1500m of a water body (e.g. lake or river) (Raso et al., 2009; Houngbedji et al., 2016). Thus populations within this 1500m range of a water body are increasingly at risk of malaria when compared to populations further than 1500m (Brown et al., 2008; Silué et al., 2008; Raso et al., 2009; Houngbedji et al., 2016). However, the resolution required to capture the changing rate of risk between 500m, 1000m and 1500m was too small for the 1km resolution dataset, thus a presence absence approach was adopted where any area within 1500m would be considered at risk and anywhere outside 1500m distance would be considered no risk in order to include water bodies.

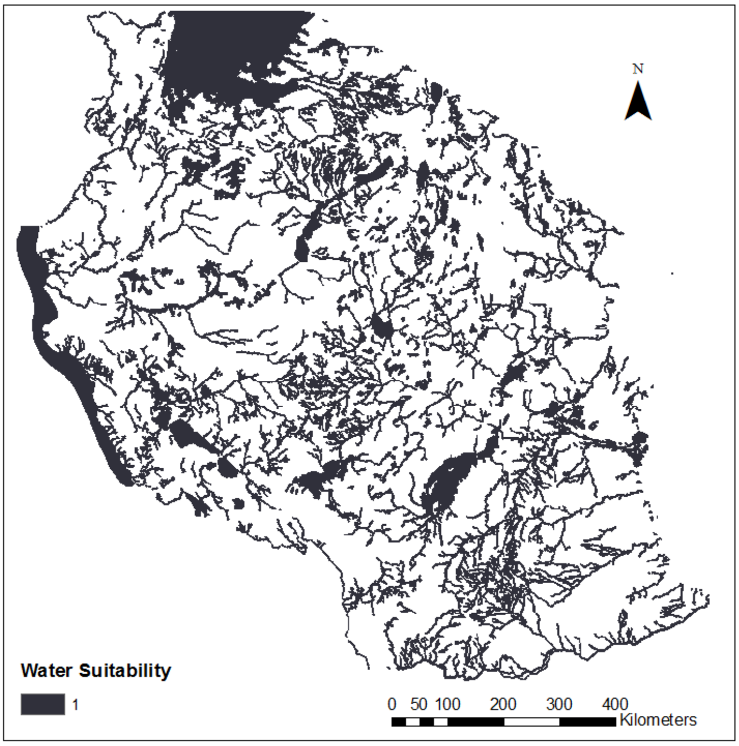


Figure 4.17 - a) Water dataset created from two files (lakes and rivers) where suitability is present or absent (1 or 0).

4.3.1.10 Population density

Changes in population distribution cannot be simulated. However, population figures based on the current distribution have been calculated using percentage change for 2050 and 2070 using figures provided by the United Nations Population Division (UNPD, 2016).

4.3.1.11 Suitability weightings

A suitability weighting assessment was carried out based on the examination of optimum to unsuitable factors presented above and in section 4.3.1. Where appropriate, factors were distributed equally over a normalised scale using equal interval classification. This is in order to reclassify each factor to be on an equivalent scale to produce meaningful and comparable results. An overall summary of the reclassified values and corresponding suitability thresholds can be found in table 4.3.

Table 4.3 - Suitability classification values for each variable included in the model where 0 is unsuitable and 1 is optimum.

Code	**Layer**	**0**	**0.33%**	**0.66%**	**1**
T	Temperature (°C)	0-16	16-19.5	19.5-23	23-28
T	Temperature (°C)	35+	31.5-35	28-31.5	
P	Precipitation (mm)	<50	50 - 100	100 - 150	150+
H	Humidity (%)	<60%	60 - 70	70 - 80	80<
E	Elevation (m)	1500<			<1500
S	Slope (°)	34<	29-34	24-29	<24
A	Aspect (°)	90 - 269			270-89
NDVI	Veg Coverage	< 0.3	0.3/0.5	0.5/0.7	0.7<
D	Soil drainage bands	7 and 6	5 and 4	3and 2	1
WB	Water Bodies (including rivers)	1500			0 -1499

4.3.2 Weighted sum development

4.3.2.1 Sensitivity analysis

A sensitivity analysis using a one factor at a time (OAT) sampling method, where each of the parameters was changed one at a time, was conducted in order to better understand the role of individual factors within the model and to aid in developing the model weightings presented in section 4.3.2.2. Furthermore, it aimed to highlight which variables demonstrated greater sensitivity to varying ranges of percentage change within the context of suitability for malarial mosquitoes. Not all model variables were included as many were nominal datasets which had been pre-categorised and thus did not allow a percentage change to be conducted on the raw observable values. Factors included are: precipitation, temperature, vegetation coverage, relative humidity, elevation and slope.

Each individual factor is adjusted by 10% intervals up to 100% to examine how changes in raw values influence the model suitability category. Results for intervals 20%, 50% and 80% are presented in section 4.4.1. These intervals were chosen to represent an even coverage of the percentage change assessed from comparatively low to high.

4.3.2.2 Exploratory regression analysis

An exploratory regression analysis was carried out on each of the included variables listed in table 4.3 where malaria prevalence is the dependent variable. This type of analysis highlights the most important contributing factors to a dependent variable. Similar to stepwise regression, the exploratory regression is linear and assumes small amounts of co-linearity between variables. However, unlike stepwise regression, exploratory regression tests a range of models and will only pass models which meet all of the criteria required for an ordinary least squares regression, thus providing the best possible model combination. It is important to note that it is recognised that variables included in this analysis will inherently have a degree of collinearity and are further related to other processes, for example aspect is included due to the potential impact of evaporation which is not included here. Thus, the results will be used as a guide but are interpreted and used with discretion.

Data was segmented for the regression using a random points selection tool in ArcGIS for each environmental variable and the prevalence dataset across Tanzania. Total number of points selected to be included was 10% of the total area of Tanzania, which was calculated to be 94508 data points. A buffer was also included for no points to be within 1.45km of each other to avoid diagonal overlap considering the maximum dataset resolution of 1km. The constraints applied resulted in a total of 86140 points being eligible for selection to avoid overlap. The data was further corrected for the removal of “null” or water based data pixels, which reduced the regression dataset to 78381 useable data points. The results are presented in section 4.4.2.

4.3.2.3 Model weightings

Once files were re-classified to match the suitability assignment weighting they were multiplied by the weighting factors displayed in table 4.4 which were created through a combination of examination of the literature and sensitivity analysis presented in section 4.3.2.1.

Table 4.4 - Model weighting factors applied to each included variable.

Variable	**Assigned Weight**	**Percentage Equivalent**
Precipitation	0.22	22%
Temperature	0.18	18%
Vegetation Coverage	0.16	16%
Relative Humidity	0.12	12%
Elevation	0.11	11%
Water Bodies	0.07	7%
Soil Drainage	0.06	6%
Slope	0.05	5%
Aspect	0.03	3%
Total:	**1.00**	**100%**

4.3.3 Model process

A flow diagram of model preparation and development steps can be found in figure 4.18.

4.3.3.1. Pearson product moment correlation coefficient

In order to reaffirm and further develop model quality and performance a Pearson product moment correlation coefficient was run using Whitebox GAT (Lindsay, 2016). Following the results from this analysis, the model was carefully assessed to consider where changes could be made to improve performance. The model that resulted in the strongest correlation between model outputs and observed malaria prevalence was chosen as final model setup. Reults of the Pearson product moment correlation coefficient on the final model are presented in section 4.4.3.

4.3.3.2. Bivariate linear regression

Upon completion of the final version of the model, a bivariate linear regression was run with a view to further assessing the relationship between the model outputs and observed malaria prevalence, as well as extracting a relationship equation for the final model. These results are presented in section 4.4.3.

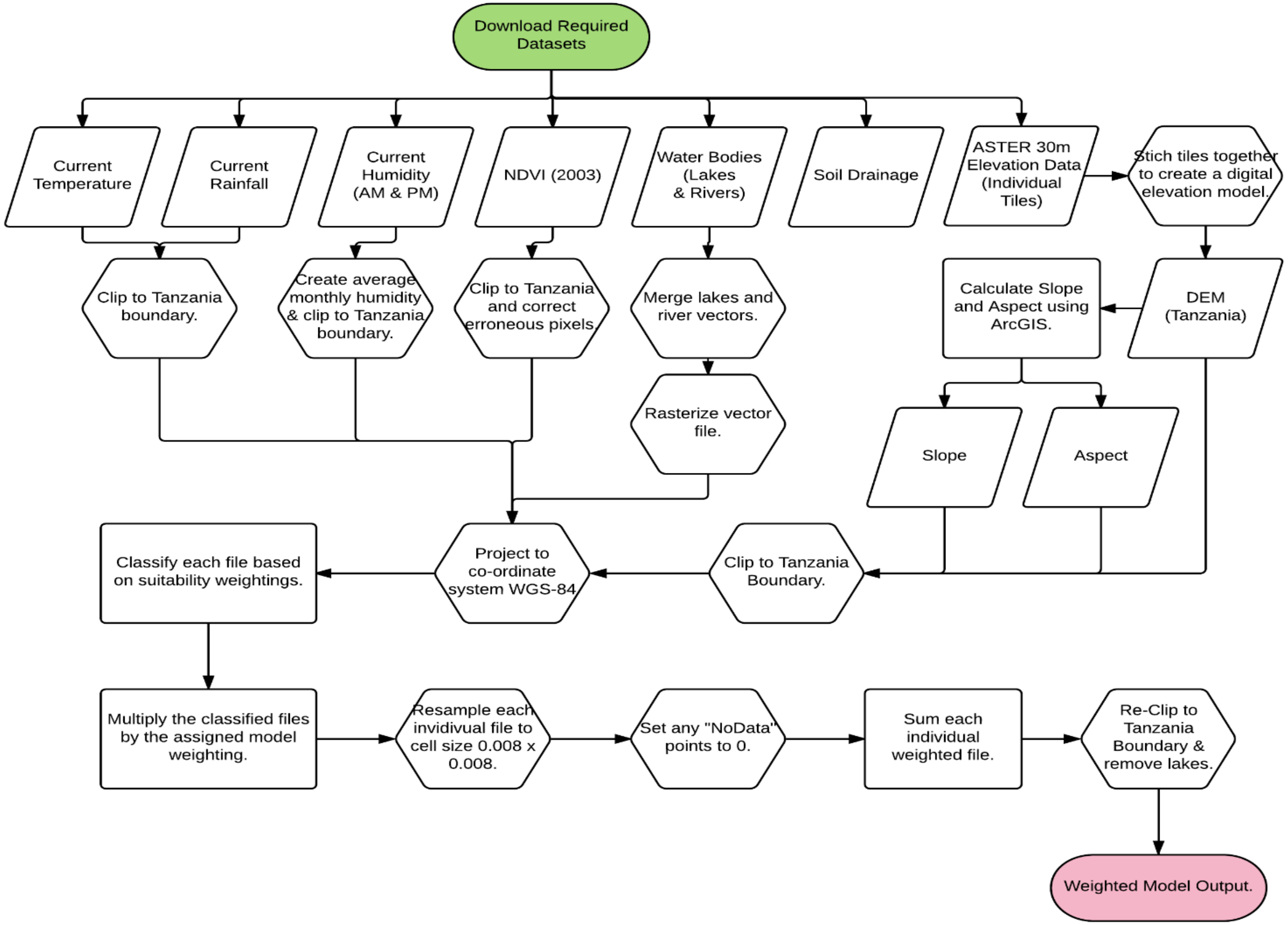


Figure 4.18 - Stages of model development and implementation.

4.3.4 Identifying high risk populations

Tanzania's current population is estimated to be approximately between 48,775,576 as reported by the Tanzanian National Bureau of Statistics (2016) and approximately 53,470,000 as estimated by the UNPD (Melorose et al., 2015). Considering the data used in this analysis, the UNPD estimations were used as the current population figure considering that the WorldPop 2015 dataset is adjusted to their estimates (Linard et al., 2012).

Once all model runs had been completed, the model outputs were used to identify the total population at high risk of catching malaria at present, and for the two most extreme RCP pathways, 2.6 and 8.5 for both 2050 and 2070. The extreme pathways were examined to show the potential variation in population at risk under the best case and worst-case scenarios. Figure 4.7 outlines the method used to calculate future populations at risk through percentage change.

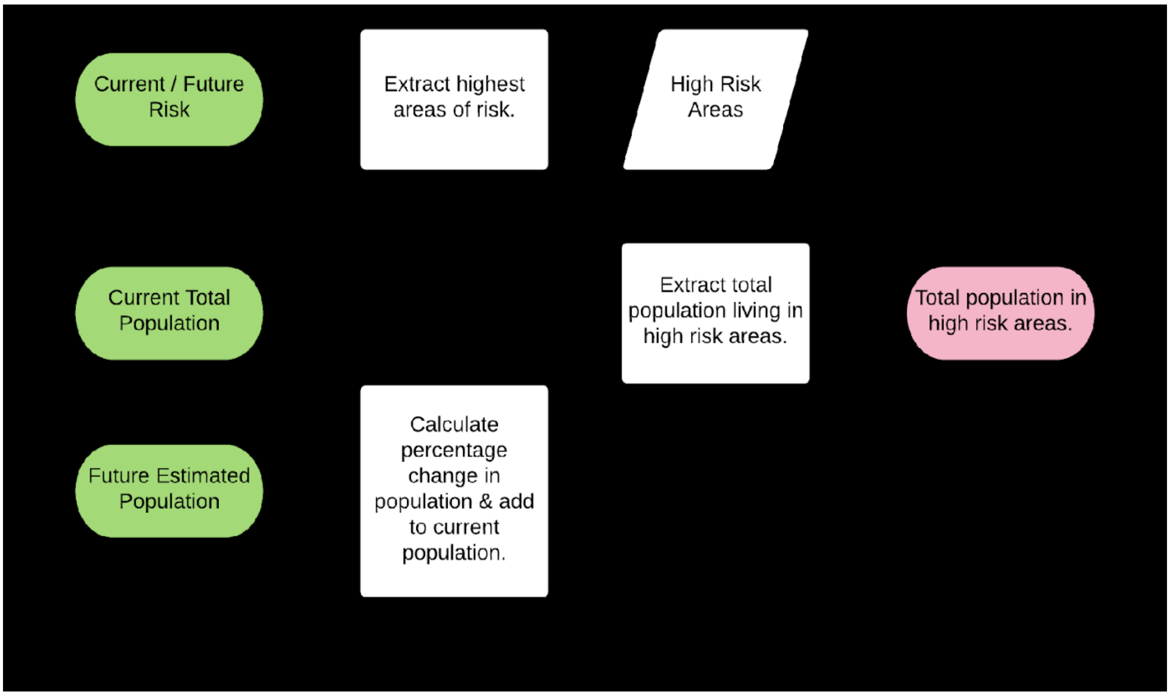


Figure 4.19 - Flow diagram depicting methodology for identifying high risk populations.

4.4 Results

4.4.1 Sensitivity analysis

Starting raw pixel values used in the OAT sensitivity analysis are presented in table 4.5. Percentage changes to raw pixel values are also shown. Table 4.6 demonstrates the baseline model value post-classification for suitability weighting alongside the suitability classes for each sensitivity category where the suitability scale is 0-1 as presented in section 4.3.1.11. Tables 4.7 to 4.9 demonstrate the sensitivity matrix for each variable and compares individual values for each percentage category to that of the baseline model. This analysis concludes that the model is not highly sensitive thus; natural climatic and environmental variation should not affect the model hugely but demonstrate enough sensitivity to reflect changes which will impact upon disease distribution based on the suitability categories.

Table 4.5 - Raw pixel values used in sensitivity test and percentage change values.

Factor	Baseline Values	20%	50%	80%
Precipitation (mm)	44	52.8	66	79.2
Temperature (°C)	19	22.8	28.5	34.2
Vegetation Coverage	0.58	0.696	0.87	1.044
Relative Humidity (%)	72.4	86.88	108.6	130.32
Elevation (m)	1319	1582.8	1978.5	2374.2
Slope (°)	2.6	3.12	3.9	4.68

Table 4.6 - Baseline suitability weightings and resulting weightings due to percentage change in raw values.

Factor	Baseline Values	20%	50%	80%
Precipitation	0	0.33	0.33	0.33
Temperature	0.33	0.66	0.66	0.33
Vegetation Coverage	0.66	0.66	1	1
Relative Humidity	0.66	1	1	1
Elevation	1	0	0	0
Slope	1	1	1	1
Baseline Model Value: 3.65				

Table 4.7 - Sensitivity matrix for 20% change, showing resulting model output and difference from original.

	Precipitation	**Temperature**	**Vegetation Cover**	**Relative Humidity**	**Elevation**	**Slope**
Precipitation	0.33	0	0	0	0	0
Temperature	0.33	0.66	0.33	0.33	0.33	0.33
Vegetation Cover	0.66	0.66	0.66	0.66	0.66	0.66
Relative Humidity	0.66	0.66	0.66	1	0.66	0.66
Elevation	1	1	1	1	0	1
Slope	1	1	1	1	1	1
Model Output	3.98	3.98	3.65	3.99	2.65	3.65
Difference	0.33	0.33	0	0.34	-1	0

Table 4.8 - Sensitivity matrix for 50% change, showing resulting model output and difference from original.

	Precipitation	**Temperature**	**Vegetation Cover**	**Relative Humidity**	**Elevation**	**Slope**
Precipitation	0.33	0	0	0	0	0
Temperature	0.33	0.66	0.33	0.33	0.33	0.33
Vegetation Cover	0.66	0.66	1	0.66	0.66	0.66
Relative Humidity	0.66	0.66	0.66	1	0.66	0.66
Elevation	1	1	1	1	0	1
Slope	1	1	1	1	1	1
Model Output	3.98	3.98	3.99	3.99	2.65	3.65
Difference	0.33	0.33	0.34	0.34	-1	0

Table 4.9 - Sensitivity matrix for 80% change, showing resulting model output and difference from original.

	Precipitation	**Temperature**	**Vegetation Cover**	**Relative Humidity**	**Elevation**	**Slope**
Precipitation	0.33	0	0	0	0	0
Temperature	0.33	0.33	0.33	0.33	0.33	0.33
Vegetation Cover	0.66	0.66	1	0.66	0.66	0.66
Relative Humidity	0.66	0.66	0.66	1	0.66	0.66
Elevation	1	1	1	1	0	1
Slope	1	1	1	1	1	1
Model Output	3.98	3.65	3.99	3.99	2.65	3.65
Difference	0.33	0	0.34	0.34	-1	0

4.4.2 Exploratory regression results

Exploratory regression results for the best resulting model demonstrate R = 0.47 where $p < 0.01$, thus, the null hypothesis is rejected and it is concluded that the factors included in the model are representative of prevalence distribution. A summary of variable significance can be found in table 4.10, where proximity to water bodies, temperature and NDVI are highlighted as the most significantly impacting variables and aspect as the least with less than 1%. Despite aspect being highlighted as having low significance this was kept as a low weighted factor within the model due to its still relatively unexplored relationship to evaporation and sunlight exposure as detailed in section 4.3.1.6. Similarly, the water bodies' results demonstrate a negative effect with malaria prevalence which conflicts with the literature. However, this is likely due to the absence presence nature of the dataset, where absence outweighs presence in the 10% of the randomly selected test data.

Table 4.11 reports the maximum variance inflation factors for each individual variable. All variables demonstrate moderate correlation ($1 < VIF < 5$) with temperature and elevation demonstrating the highest variance values. This is to be expected due to adiabatic cooling processes as temperatures decrease with elevation (Chabot-Couture et al., 2014; Detsch et al., 2016). A spatial autocorrelation was also conducted as part of the analysis returning P value < 0.01 and Z value of 1218.28 indicating that there is significant spatial clustering where there is a less than 1% likelihood that it has occurred by chance

Table 4.10 - Summary of Variable Significance

Variable	**% Significant**	**% Negative**	**% Positive**
Water Bodies	100.00	100.00	0.00
Temperature	100.00	0.00	100.00
NDVI	100.00	0.00	100.00
Humidity	98.44	14.06	85.94
Precipitation	97.66	68.75	31.25
Elevation	95.31	65.62	34.38
Slope	94.53	82.03	17,97
Soil Drainage	93.75	11.72	88.28
Aspect	0.78	98.44	1.56

Table 4.11 - Summary of Multicollinearity

Variable	**VIF**	**Violations**
Water Bodies	1.05	0
Temperature	4.11	0
NDVI	1.19	0
Humidity	2.29	0
Precipitation	1.89	0
Elevation	4.40	0
Slope	1.14	0
Soil Drainage	1.17	0
Aspect	1.00	0

4.4.3 Model comparison to current malaria distribution

The model results shown in figure 4.20 demonstrate a similarity in the spatial distribution of disease when compared to that of malaria prevalence for the year 2000 (figure 4.21). This is validated through use of two methods. Firstly, the Pearson product-moment correlation between the two datasets which demonstrates a strong positive linear correlation ($r = 0.8401$, $p < 0.05$) between the two modelled malaria risk and malaria prevalence. Secondly, a bivariate linear regression which demonstrates $r^2 = 0.706$ where $p < 0.01$, with a relationship equation of: ModelOutput = 1.043 × ModelOutput + 0.100. This supports the conclusion that the model accurately depicts key high risk areas within Tanzania using environmental variables.

Key differences in spatial distribution can be identified and attributed to a number of factors discussed in detail in section 4.5.2.

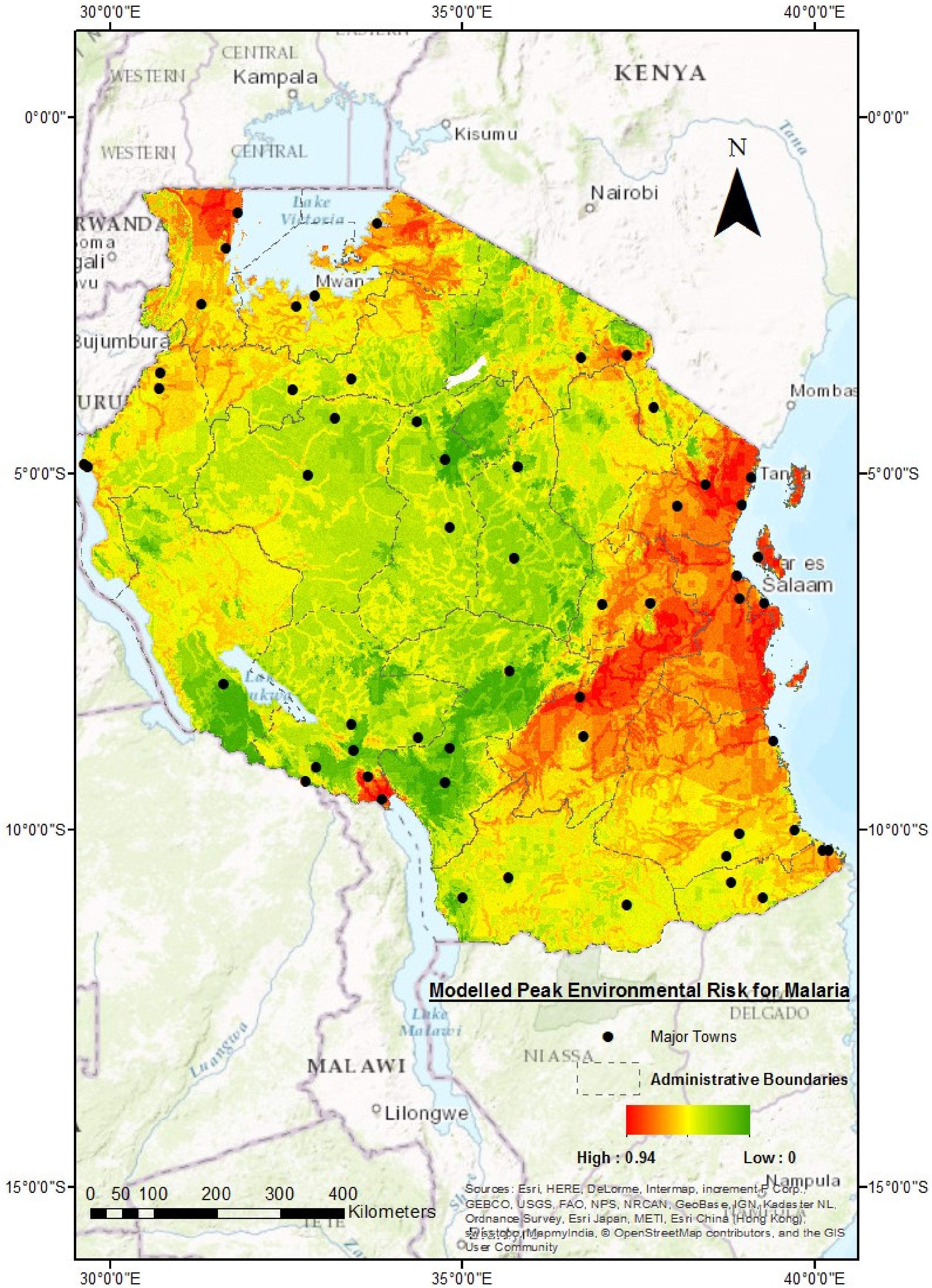


Figure 4.20 - Modelled current peak malaria risk based on values used for the month of May.

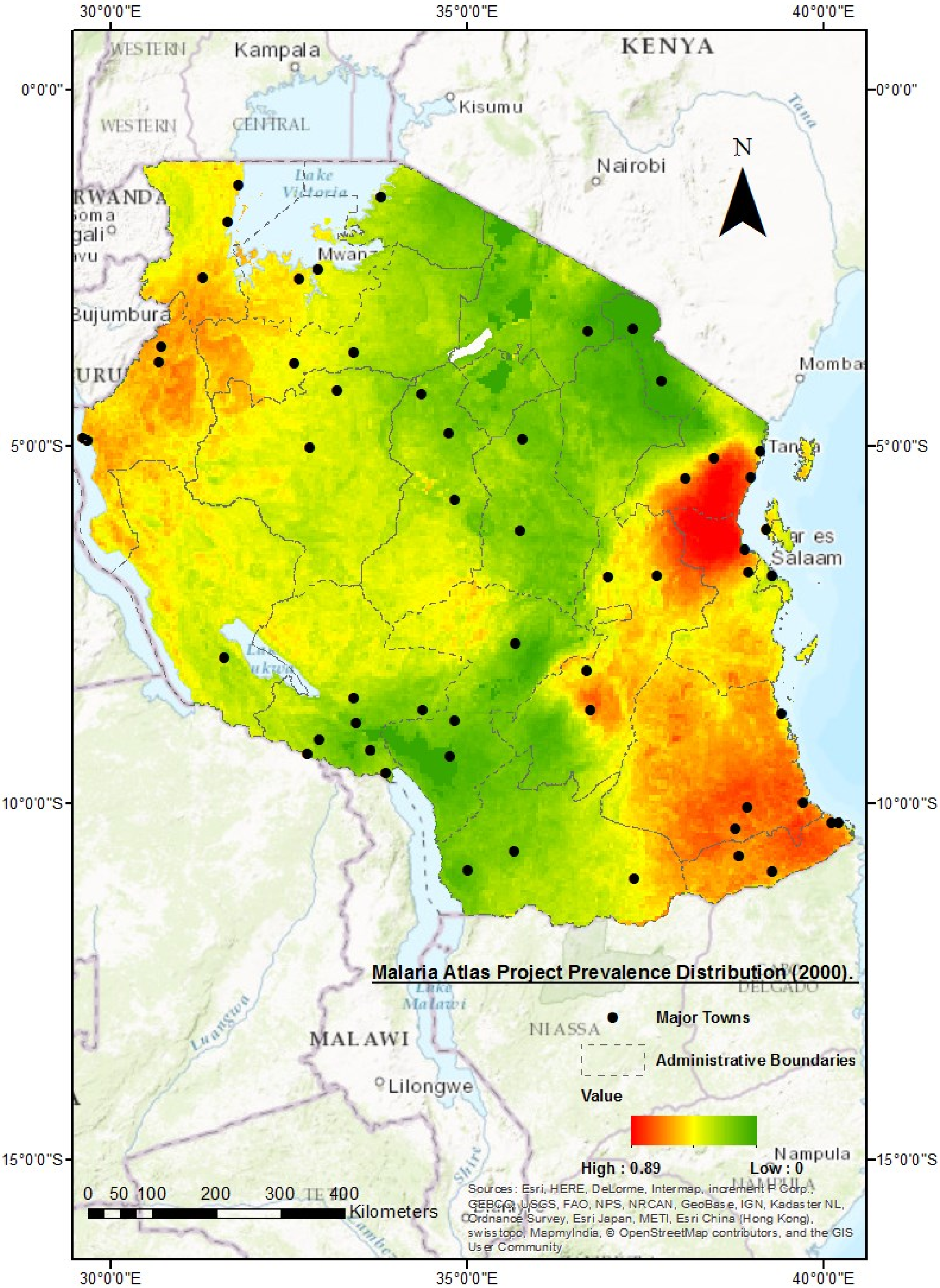


Figure 4.21 - Malaria prevalence for the year 2000. Data provided by MAP *(Bhatt et al., 2015)*.

4.4.4 Malaria risk projections for 2050

Figure 4.22 a) to 4.22 d) shows percentage change in malaria risk model outputs for 2050 and the four assessed RCP pathways when compared to the baseline model outputs (figure 4.20). Spatially, all of the RCP pathways show similar distributions of change, where the largest percentage decreases occur along the coastline. Whereas, the central Tanzanian plateau and mountainous regions demonstrate the highest percentage increases. Areas of no change vary in location across each RCP, as does the intensity of the percentage change (low to high). As expected based on the pathway descriptions, RCP 2.6 shows the overall smallest amount of extreme percentage increase or decrease, with RCP 8.5 demonstrating the most spatial area experiencing very high or very low percentage decrease in risk.

Despite overall large spatial similarities between model outputs, there are key differences in area changes between each model when examined closely. Table 4.12 depicts the overall average percentage change between each RCP when compared to baseline conditions. RCPs 2.6, 4.5 and 6.0 all show an average percentage increase in risk of 3% or more where RCP 8.5 shows a decline of almost 5% in malaria risk. These changes occur in spatially differing locations for each RCP. For example, for RCP 2.6, two cluster areas of no change are situated close to Dar es Salaam and around the town of Tabora in the west. Within the other three model outputs these areas all depict notable percentage change. However, for Dodoma, change is only observed under RCP 2.6 where risk is modelled to increase. For Dodoma under RCPs 4.5, 6.0 and 8.5 no change is depicted. These differences in the change in risk can be predominantly attributed to the changing distribution and values of temperature, rainfall and humidity between each RCP scenario.

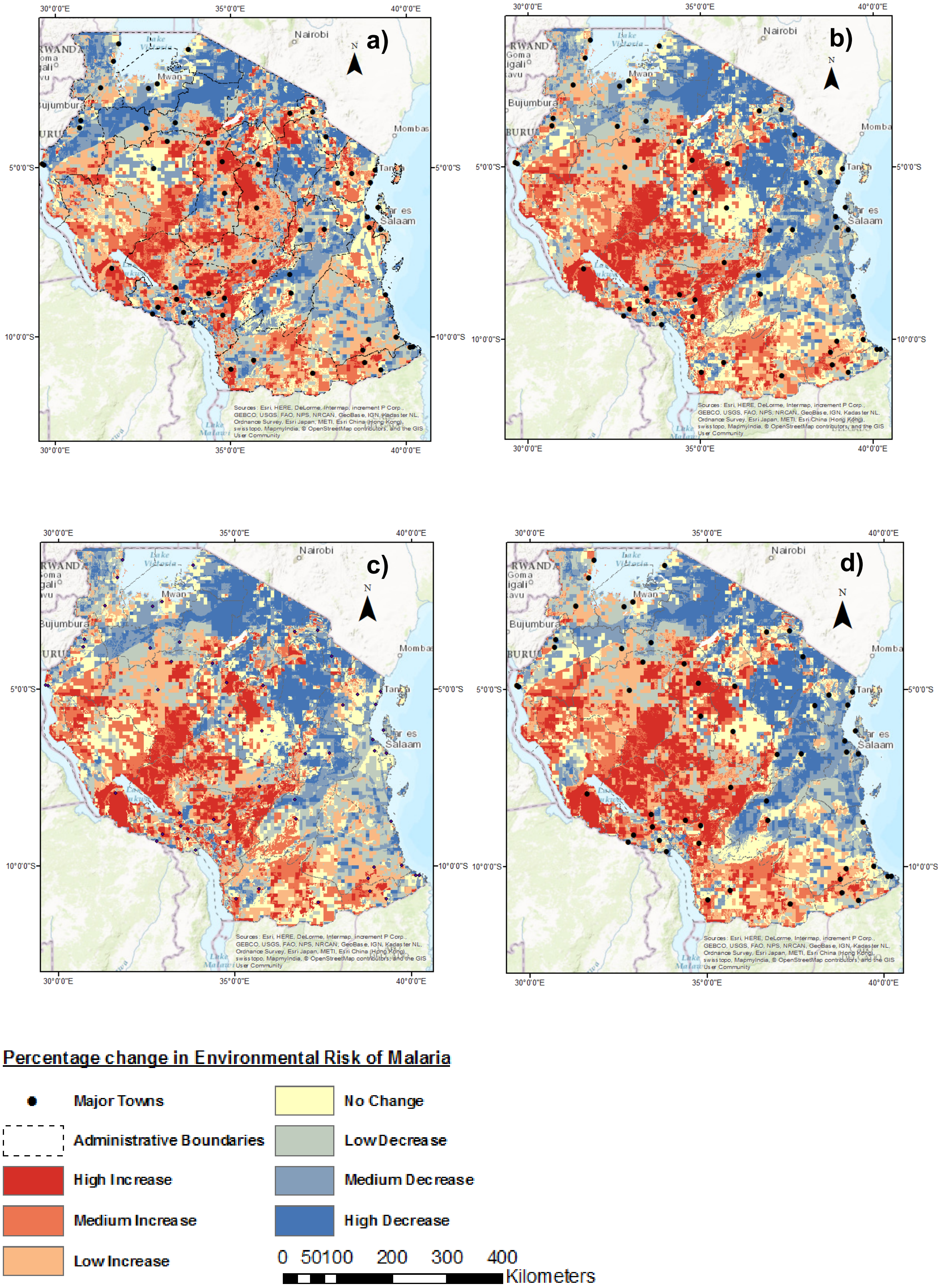
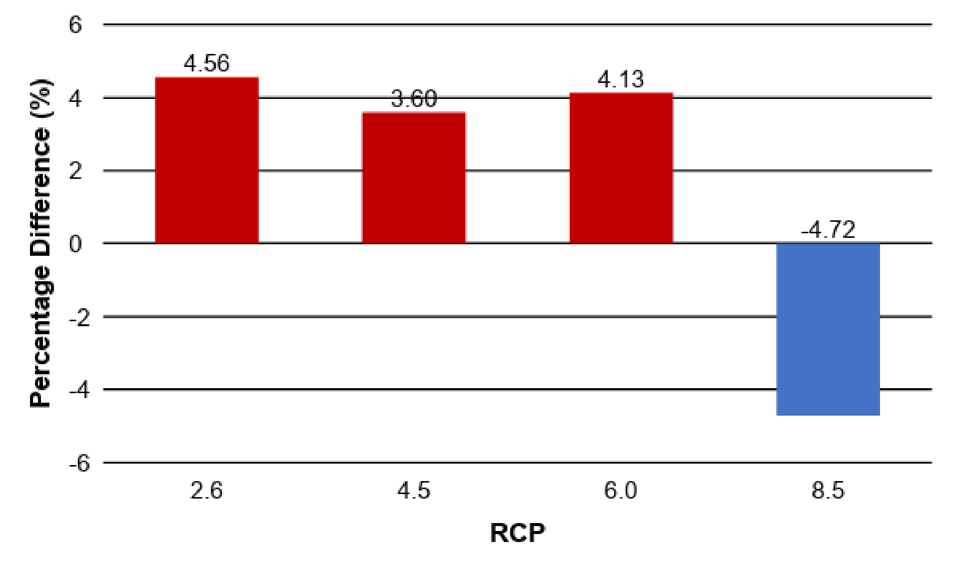


Figure 4.22 - Percentage change in malaria risk for 2050 for a) RCP 2.6 b) RCP 4.5 c) RCP 6.0 d) RCP 8.5.

Table 4.12 - 2050 Mean percentage change per RCP when compared to baseline.



4.4.5 Malaria risk projections for 2070

Figure 4.23 a) to 4.23 d) shows percentage change in malaria risk model outputs for 2070 and the four assessed RCPs when compared to the current model outputs (figure 4.20). These have a similar spatial pattern to the RCP outputs for 2050, where an increase in malaria risk can be seen across the Tanzanian plateau and by 2070, risk extends more notably into the southern and northern mountainous regions of Tanzania. Instances of extreme change, either positive or negative are more prominent throughout 2070 when compared to 2050. Table 4.14 highlights this variance between 2050 and baseline conditions by highlighting mean percentage change from the baseline. RCP 4.5, 6.0 and 8.5 all show an average increase in risk of above 5%, peaking at almost 9% increase in risk under RCP 8.5. A stark contrast to the results seen from 2050. RCP 2.6 demonstrates a decrease in baseline risk of less than 1%, suggesting similar malaria risk conditions to present.

Between all 8 models for 2050 and 2070 some areas can be identified as currently at a threshold of environmental suitability for malaria transmission given the markedly different distributions of change between each model. The area south of

Lake Victoria shows that this area in differing models can experience high percentage decrease in some models and either no change or low to medium increases in others. Similarly, the south-eastern coastline below Dar es Salaam can demonstrate similar variations in percentage change across the model depending on the RCP. Areas defined as experiencing high percentage change appear mostly in the elevated plateau region with every model showing a high percentage increase for the major towns of Sumbawanga near the shores of Lake Rukwa, and Singida in the central plateau region, near the capital Dodoma. Areas of predicted highest decrease are notably in the Ngorongoro region to the north and the coastal areas which are at present, high risk zones.

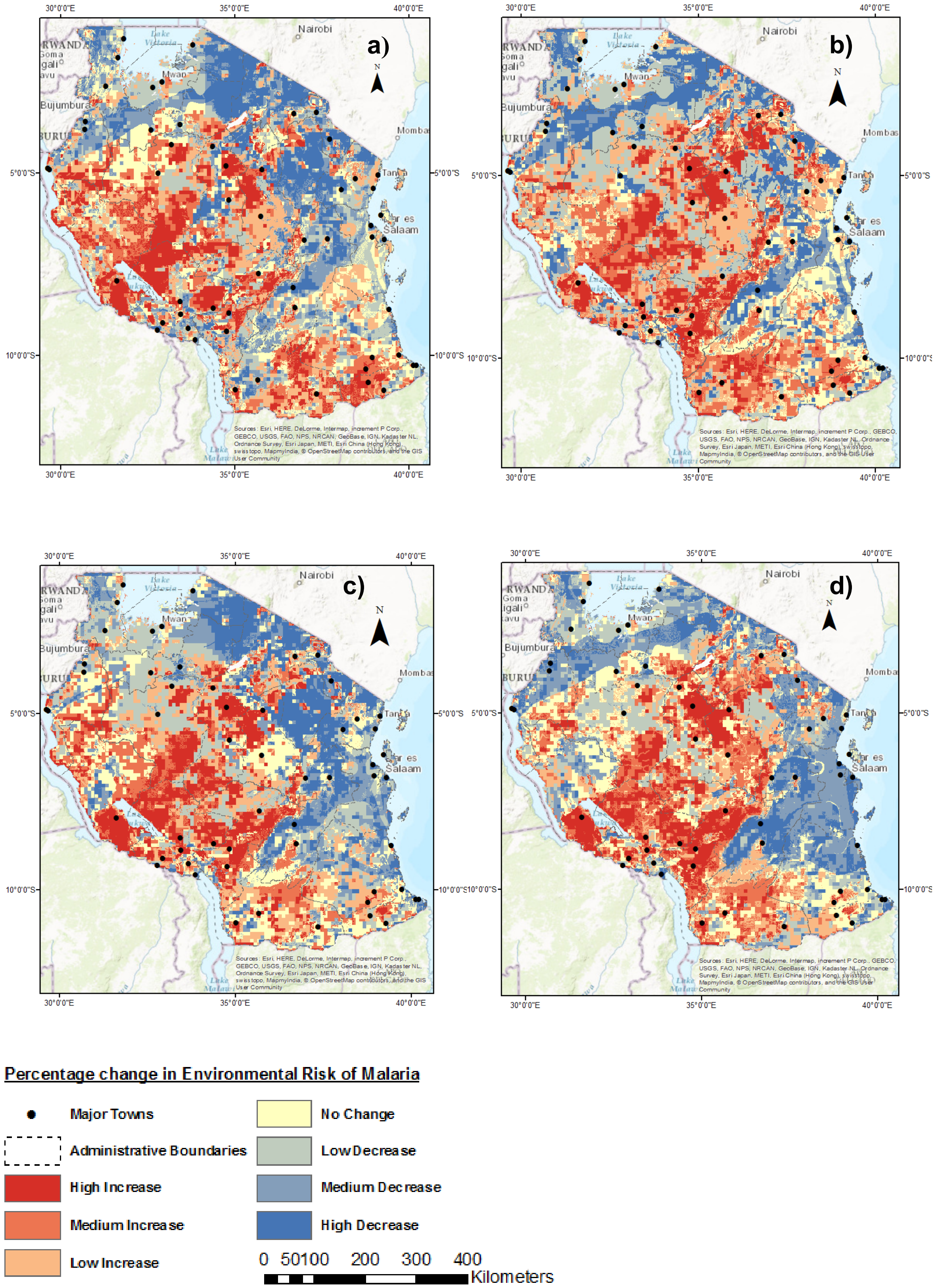
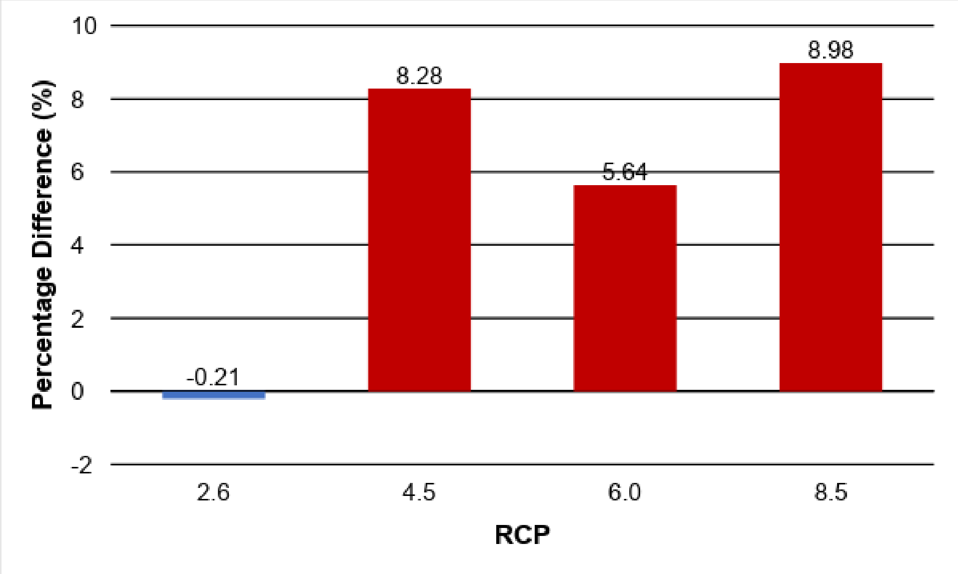


Figure 4.23 - Percentage change in malaria risk for 2070 for a) RCP 2.6 b) RCP 4.5 c) RCP 6.0 d) RCP 8.5.

Table 4.13 - 2070 Mean RCP percentage change from baseline.



4.4.6 Population at risk

Figure 4.24 presents population currently living in high risk malaria areas. Figure 4.25 shows the resulting population at risk for RCP 2.6 and 8.5 for 2050 and 2070. For both 2050 and 2070, RCP 2.6 (figure 4.25a and 4.25c) demonstrates the highest number of the population at risk, figures of 267,723 and 440,490 people respectively. These figures are between 30,000 and 35,000 higher than predicted population at risk for RCP 8.5 for both years. These results indicate that in terms of population risk, RCP 2.6 results in higher populations at risk, despite being the best-case scenario for reducing the impacts of long term climate change.

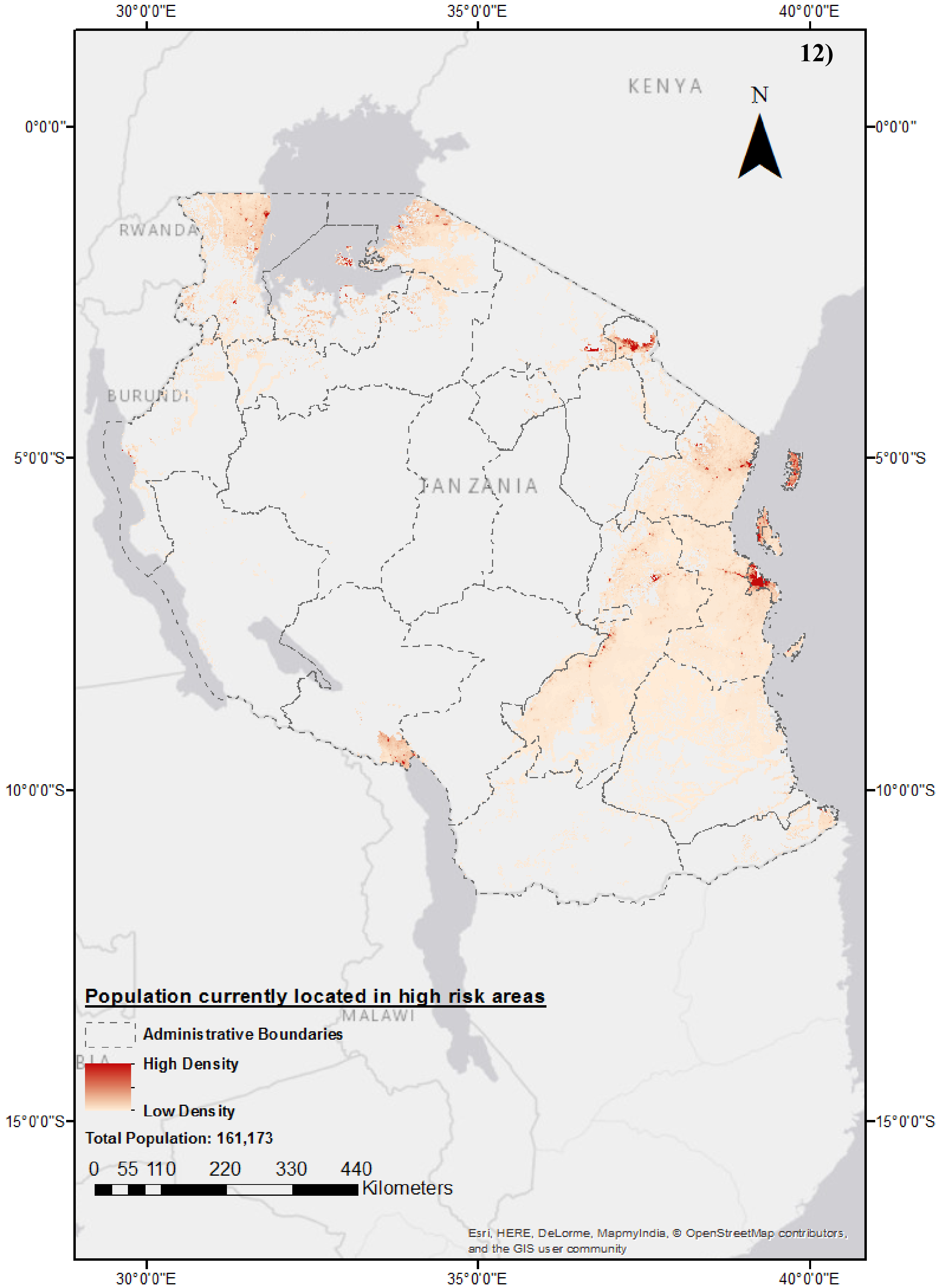


Figure 4.24 - Current population currently living in areas with high risk of malaria

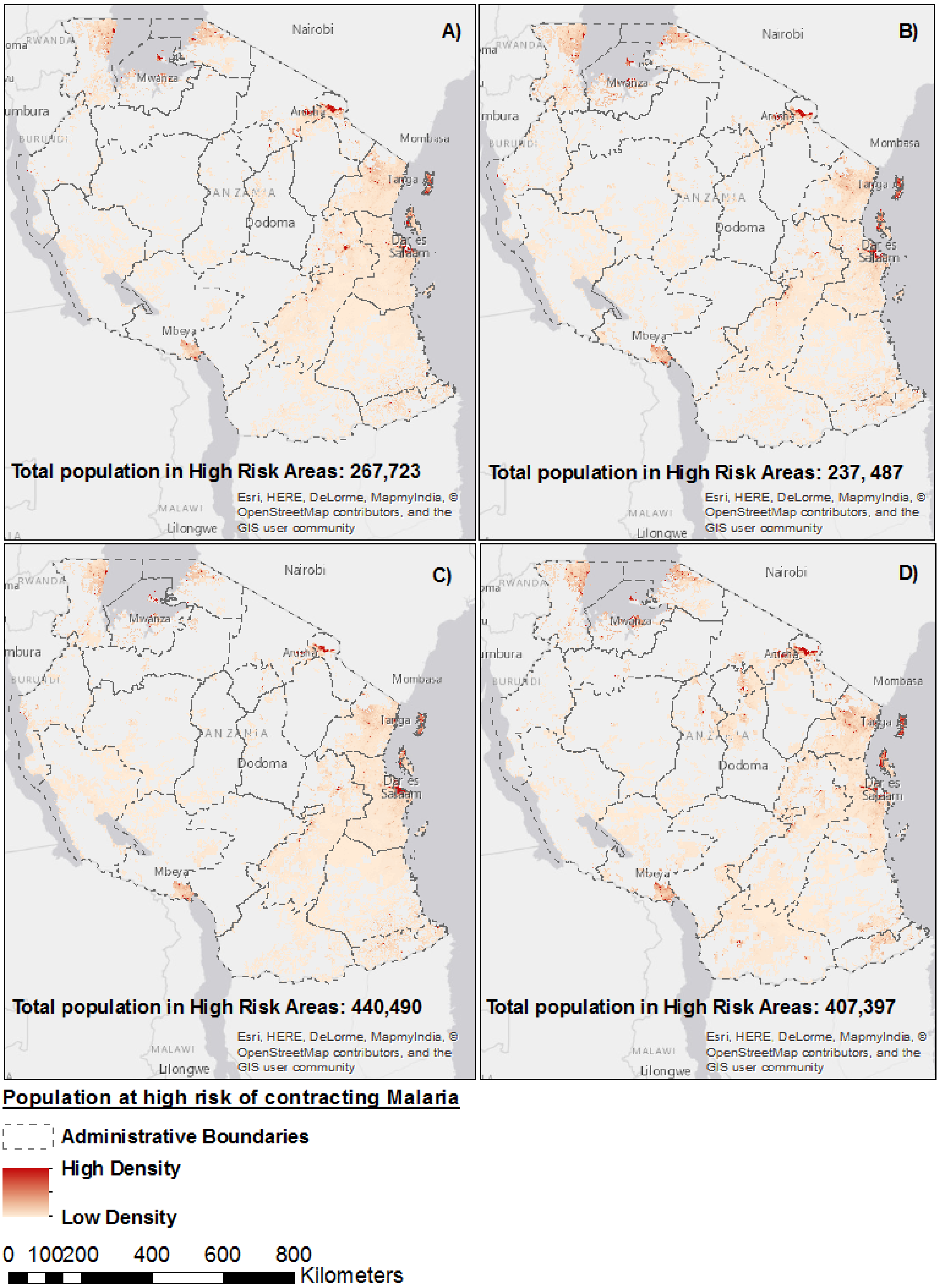


Figure 4.25 - Future populations living in high risk areas a) RCP 2.6, 2050. b) RCP 8.5, 2050. c) RCP 2.5, 2070. d) RCP 8.5, 2070.

4.4.7 Summary of results

The experiments conducted here aimed to develop and apply a predictive environmental risk model to produce a risk map for malaria. A weighted sum model has successfully been developed and validated for the month of May, which has produced an environmental malaria risk map for current conditions, and each of the RCPs for 2050 and 2070. Population distribution within these high risk areas has also been examined and mapped.

Exploratory regression results conclude that the most influential variables on malaria risk distribution are NDVI, temperature and precipitation, with six other variables included in the model which have been identified to be influential or potentially influential and requiring further research (section 4.4.2). Current distribution of high environmental risk is located in predominantly low elevated regions, and areas with increased water presence via rivers or lakes such as Lake Victoria (section 4.4.3). These areas coincide with densely populated regions including Dar es Salaam and Arusha, with a total of 161,173 people residing in the high environmental risk areas (section 4.4.6).

Projection results demonstrate that for both 2050 and 2070 there is a percentage increase in areas of high environmental risk, occurring mostly across the Tanzanian plateau which is predominantly low risk at present. The highest increase of environmental risk is observed for RCP 8.5 under 2070, resulting in a total population of 407,397 living in high risk areas (section 4.4.6). Comparatively, RCP 8.5 for 2050 demonstrates a percentage decrease in risk of 4.72% and increases under all other RCPs. Overall, population growth in high risk areas results in 237,437 living in high risk areas for RCP 8.5 in 2050.

4.5 Discussion

This work has developed a malaria risk model to simulate current and predicted peak risk (during the MAM season), for Tanzania based upon environmental variables. In addition, an examination of populations living in high risk areas has also been conducted to provide an indication of how many people may be living in high risk areas in future. This chapter addresses research objective two.

4.5.1 Variable suitability, sensitivity and weighted sum.

It has been demonstrated that multiple environmental variables influence the spatial distribution and severity of malaria risk. Using the suitability criteria extracted from the existing literature and new experimentation (section 4.3.1), environmental parameters were weighted on a normalised scale based on risk, and a sensitivity analysis was performed. Results from the sensitivity analysis demonstrate that temperature is the most sensitive to change within the suitability model, with differing model results compared to the baseline across all sensitivity thresholds examined. NDVI, precipitation, humidity and elevation also demonstrate consistent change from the baseline model results. It is important to note that this method does not account for strongly correlated variables, so these results are interpreted with caution as some of the included variables are dependent on differing (nominal, ordinal or categorical) scales, an area which is still being developed in statistical analysis (Finch, 2016; Poyil et al., 2016).

Despite sensitivity analysis results suggesting temperature to be the most sensitive variable and whilst it is recognised an important factor, multiple studies conclude NDVI and precipitation to be the most important variables with regards to malaria distribution (Gwitira et al., 2015; Ryan et al., 2015; Kabaria et al., 2016). All of these factors were considered during black box development of the model alongside improvements made after model implementations. NDVI was initially weighted higher than temperature due to an increasing number of studies finding NDVI to be a highly influential factor, particularly in the proximity of water bodies. However, higher weightings for precipitation and temperature were shown to increase the Pearson product-moment correlation coefficient which is likely due to the higher resolution of the temperature and precipitation datasets. This factor was also considered for future forecasts where a proxy NDVI dataset had to be created, thus reducing the reliability of the dataset when compared to temperature and precipitation for future predictions.

4.5.2 Current and future malaria risk

The resulting model depicts peak environmental risk of contracting malaria in Tanzania (figure 4.20). The Pearson product-moment correlation demonstrated that the developed environmental risk model is strongly correlated ($r = 0.8401$, $p < 0.05$) with the observed distribution of malaria prevalence for the year 2000, indicating good model performance. Reductions in model accuracy can be attributed to a number of factors. Firstly, some areas in the malaria prevalence data have recorded a zero-malaria prevalence due to missing data. The majority of these areas correlate with low population, high elevation areas particularly around the Ngoronogoro crater, Lake Manyara, Mt. Kilimanjaro and Mt Rungwe regions (figure 4.21). The absence of data in these areas could potentially be attributed to the absence of local data points upon which the dataset was developed (Bhatt et al., 2015) and could also be due to a number of unsuitable environmental and socio-economic factors. Alternatively, areas demonstrating differences in projected risk and prevalence are most notably located north of Lake Malawi, lower slope regions around Mt. Kilimanjaro and the north-west and north-east of Lake Victoria. Despite being highlighted by the model as environmentally suitable for transmission, the prevalence data depicts low malaria presence. Although efforts have been made to reduce the potential impact of population variation through the use of prevalence data and reducing the impact of malaria control programmes through choosing a dataset prior to the country-wide introduction of prevention schemes in Tanzania (including bed-nets and indoor residual spraying) in order to examine purely environmental risk; it could be argued that socio-economic factors could still be influencing the prevalence data in a number of ways as presented in chapters two and seven.

Variations between modelled outputs and observations may also be a result of inherent accuracies and limitations within the model itself. Firstly, the model could be over-estimating risk in some areas. Whilst the model demonstrates peak risk experienced following the MAM rainfall season based on the most suitable environmental conditions, this will not be able to reflect the impact of reduced environmental suitability on total annual malaria prevalence, which is the only data available for comparison at present as monthly data prevalence was not available. This would be particularly influential in areas which experience a more significant degree of environmental change over an annual period. Whilst efforts have been made to ensure that the model can perform as accurately as possible based on peak environmental risk, expanding the model to operate on monthly timescales and combined to assess annual risk would be of benefit with increased time and resources.

Low data resolution of some influential datasets such as NDVI and water bodies could also be contributing to over and under estimation. It is acknowledged that the spatial resolution of regularly used NDVI sensors is too coarse to capture details about vector habitats, particularly when on average, NDVI datasets are approximately 1km and above (Wayant et al., 2010). For instance, it has been documented that both water bodies and NDVI can impact malaria presence on scales as little as 0-500m, where datasets of 1km resolution and above would not be able to capture this variance and lead to increased homogeneity of pixel values (Sun et al., 2012). This resolution of data is too fine to capture in a national scale model and would be more suited to local fine scale modelling where ground truthing data was also available to ensure accuracy.

Alongside this, the role of environmental parameters in association with disease risk remains poorly understood, hence in part the purpose of this study. Remaining gaps in knowledge contribute to uncertainty in the developed environmental weightings, although good model performance is still observed, it could be improved with further examination of these parameters. As discussed in section 4.5.1, malaria presence is becoming increasingly attributed to vegetation coverage, however data quality at the time of study is not comparable to that of temperature and precipitation and thus less reliable for a high resolution study at present due to reasons commented on previously. This is similar for other datasets included in the study, particularly proximity to water bodies (section 4.3.1.9).

Alternatively it is important to consider other impacting factors. Herd immunity could be playing a role in reducing and preventing instances of malaria despite areas being environmentally suitable. Herd immunity is defined as a natural protection against infectious diseases, occurring when a large percentage of a population has become immune to an infection and are providing protection for members in the community who are not naturally immune (Fine, 1993). Considering malaria has been present in Tanzania for an extended period of time and these communities are highlighted by the environmental model as being high risk, it is plausible that these communities have developed a strong herd immunity, thus reducing the prevalence of malaria in areas of long exposure (Moore, 1992).

Varying socio-economic factors could also be influencing malaria prevalence. It is becoming increasingly documented that socio-economic factors play a key role in determining disease presence and transmission, however it is difficult to quantify and include in predictive studies due to lack of available, good quality data and the range of variants involved, alongside comparatively small study areas at present (Mlozi et al., 2015; Shayo et al., 2015). Despite this, it is important to note that these factors will contribute to variance in spatial distribution and model accuracy to varying extents in different locations, considering that only environmental variables are being examined here.

Percentage change in risk for RCPs 2.6, 4.5, 6.0 and 8.5 for 2050 and 2070 using HadGEM-ES predictions are presented in figures 4.10(a-d) and 4.11(a-d) respectively. The results presented here support conclusions reached through other studies. Whilst in some areas, climate change is anticipated to increase the likelihood of malaria prevalence, it is also expected that in some areas transmission will reduce due to a combination of pathogen and vector thresholds becoming increasingly unsuitable (Altizer et al., 2013). This increase and reduction in environmental suitability for malaria can be seen across all RCPs for each year, to varying degrees. Overall, the Tanzanian plateau demonstrates the greatest increase in disease risk, where low-lying coastal areas exhibit an overall reduction in environmental suitability. This is likely to be due to a combination of increasing temperatures at higher elevations combined with changing rainfall regimes under various climate scenarios (Cioffi et al., 2016). The extent of change can be observed to differ under varying RCPs and also by year.

It is important to consider that the future predictions have been achieved through incorporating proxy datasets created for NDVI and relative humidity. These processes inherently increase uncertainty when compared to the performance of the current and validated simulation model, a factor which at present is unavoidable in predictive modelling of certain environmental factors. However, it is currently a growing subject of interest with an increasing amount of studies attempting to solidify statistical relationships to climate-dependent environmental factors such as land cover, land use and NDVI (Poyil et al., 2016). As techniques and algorithms to better predict NDVI develop it will offer significant improvements to environmental based predictive models, particularly for diseases such as malaria where NDVI has been identified to be a key parameter predicting malaria risk (Ryan et al., 2015; Kabaria et al., 2016).

4.5.3 Future population at risk

Estimated figures for populations living in environmentally high risk areas for RCP 2.6 and RCP 8.5 for 2050 and 2070 are shown in section 4.5.4.2. The results for both 2050 and 2070 demonstrate that what is widely considered the "best case scenario" with regards to long-term climate change is arguably the worst-case scenario with regards to populations at risk of contracting malaria for both 2050 and 2070.

Furthermore, what is notable is that whilst 267,723 and 440,490 people are predicted to be living in environmentally high risk areas for 2050 and 2070. This figure is considerably reduced by the exclusion of the majority of Dar es Salaam, one of the most densely populated areas in Tanzania with 3,133 people per square kilometre, not being considered high risk (figure 4.26) (NBS, 2013a). This model supports the concluded findings of Kabaria et al. (2016) in that densely urban areas with little vegetation reduce the suitability of malaria transmission, thus supporting the results of the predictive outputs of the developed environmental risk model.

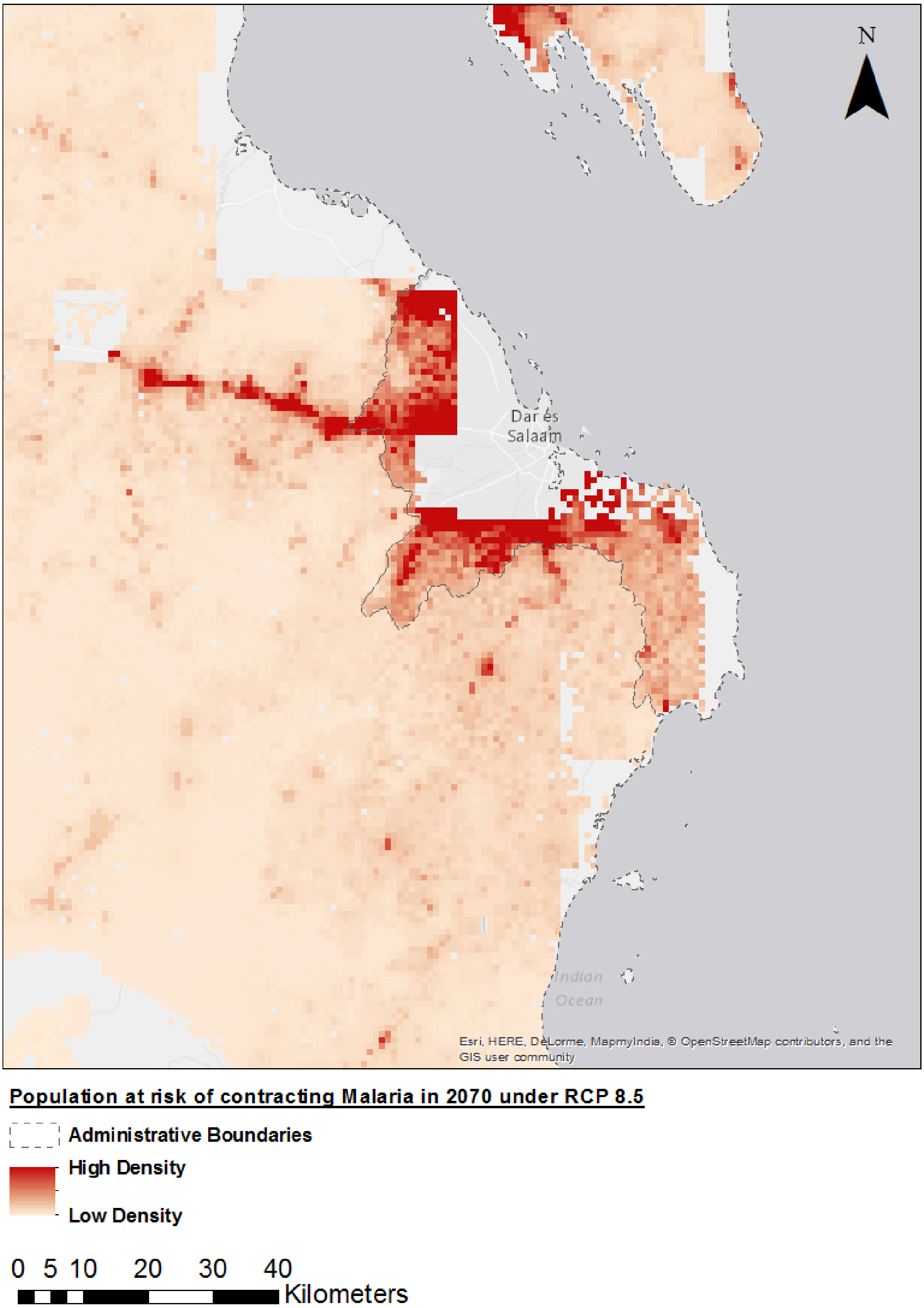


Figure 4.26 - Area of high risk located around Dar es Salaam.

4.6 Conclusion

This study has led to the development of a new weighted high-resolution predictive environmental risk model of peak malaria risk in Tanzania. The model has been validated and is able to accurately simulate present malaria risk based on environmental parameters only and in turn has been applied to four RCPs using CMIP5 HadGEM-ES model outputs to predict future environmental risk under changing climate conditions. Results demonstrate that environmental parameters strongly correlate with current malaria distribution and can be used to predict changes in future distribution. Furthermore, despite RCP 2.6 being the best-case scenario for climate changes in the long term, the short-term impacts on health and malaria risk will be greater than RCP 8.5 as this pathway crosses boundaries into greater environmental unsuitability for malaria.

It has been identified that further work is needed in understanding the role of environmental parameters and the interconnected role they have on disease distribution and risk. Particularly regarding less well considered parameters such as aspect and slope where independent experiments had to be conducted despite the scientific community being aware of the relevance of these factors to disease (Chabot-Couture et al., 2014; Hagenlocher et al., 2014; Ryan et al., 2015). Alongside this, as data availability, resolution and analytical methods continue to improve, this will allow for more detailed and increasingly accurate models where some of these aspects are still not achievable at present, particularly for co-dependent environmental datasets such as NDVI (Poyil et al., 2016). However, this would also require increases in resource availability with regards to computational power, time and storage. With regards to predicting population distribution and settlement growth, finer scale modelling would need to be adopted with an inclusion of ground based examinations to establish potential human movement and interaction. This would be unachievable on a national level.

In future, the environmentally weighted model developed and presented here could be expanded to perform monthly simulations, examining changes in risk over an annual period. This would rely on the availability and suitability of necessary datasets, such as the spatial distribution of malaria prevalence, which is required for model validation. Furthermore, as data resolution becomes increasingly refined, the suitability categories could be re-assessed to be more reflective of ground habitats and impacting conditions, something which is not achievable at present. With regards to assessing populations at risk, this would be dependent on the development of spatial population prediction models. Overall, the model presented contributes to environmental modelling of disease providing scope for improvements in the future.

Chapter 5 : Examining changing malaria epidemiology by 2070s under the worst-case emissions scenario (RCP 8.5) for Tanzania.

5.1 Introduction

Decision makers are increasingly seeking validated malaria epidemic prediction models to aid with planning interventions and prevent known health risks which often accompany epidemic outbreaks (Teklehaimanot et al., 2004; Githeko et al., 2014). A range of methods exist to address this. One of these such methods have been explored in chapter four through geographic distribution modelling. This chapter will examine a second method, the performance of an increasingly complex dynamic mathematical-biological based epidemiology model.

Biological malaria records such as the entomological inoculation rate, are poorly documented and understudied for Tanzania which can be attributed to a number of factors including data availability and local political decisions (Weed, 2002; Hagenlocher et al., 2014). Whilst there is an increase in the implementation and development of these complex models, their use remains sparse, particularly when considering the extensive use of West African countries in comparison to those in East Africa (Ermert et al., 2011). It is cautioned that models run in regions where climate connections to malaria epidemics are not well understood are likely to result in unreliable forecasting (Mabaso and Ndlovu, 2012). However, as knowledge increases it is imperative to begin using these models to examine epidemiological conditions and to further understand and refine models.

5.1.1 Aims and objectives

The aim of this chapter is to establish how and to what extent key epidemic indicators are predicted to change under the worst-case climate scenario (RCP 8.5) for 2070 (representative of a 20-year period, 2061-2080) in Tanzania using a dynamic mathematical-biological model (Hijmans et al., 2005; IPCC, 2014). The focus of this study will be upon the March, April, May (MAM) rainfall season, which accounts for 70% of annual rainfall in Tanzania and will cover key populated districts within the seven uniquely identified climatological zones (Oesterholt et al., 2006; TMA, 2014). Section 5.2 provides an overview of the epidemiological measures to be assessed in this study and their importance in the biology of malaria transmission, before presenting a sensitivity analysis on the malaria model used in this study and resulting percentage changes in values between current conditions (represented by an 11-year period from 2006 to 2016) and 2070 (RCP 8.5).

A comprehensive review of biological epidemic markers has not yet been undertaken for differing climatic zones in Tanzania for both present and future. Thus it is hoped that this study will offer unique insight into the complexities of climate, environment and mosquito relationships, and subsequently contribute to understanding malaria transmission in Tanzania.

5.2 Dynamical epidemiological models for malaria

Mathematically driven models have been used in representing malaria dynamics and predicting malaria outbreaks for over 100 years (Mandal et al., 2011). As understanding of the interactions between the host, parasite and environment has improved, epidemiological models have become increasingly accurate and complex in comparison to the initially simplistic “Ross model” (Chabot-Couture et al., 2014; Finley et al., 2014). Increased understanding of parasite-host-environment interactions has driven the increased complexity and accuracy of these models.

This has resulted in a divergence in prediction approach, with geographic distribution models, seasonal forecast models and dynamic mathematical-biology models all being routinely used and all at least using climate variables (temperature and precipitation) as the underpinnings of their prediction (Kelly Letcher et al., 2013; Chabot-Couture et al., 2014).

Sir Ronald Ross was a pioneer in malarial biological relationships and processes, beginning his work in 1890. Ross determined the life-cycle of the parasite within the mosquito, now commonly referred to as the sporogonic cycle (figure 5.1) and further establishing the underpinning mathematical equations, allowing sophisticated modelling to develop (Mandal et al., 2011; Smith et al., 2014; Finley et al., 2014). This discovery spurred further examination of malaria parasitic and vector behaviour leading to current understanding of biological malaria process represented in figure 5.1. It is understood that climate plays a vital role at varying stages of biological development and transmission allowing for more detailed analysis of climate impacts on malaria transmission than seasonal and geographic distribution models.

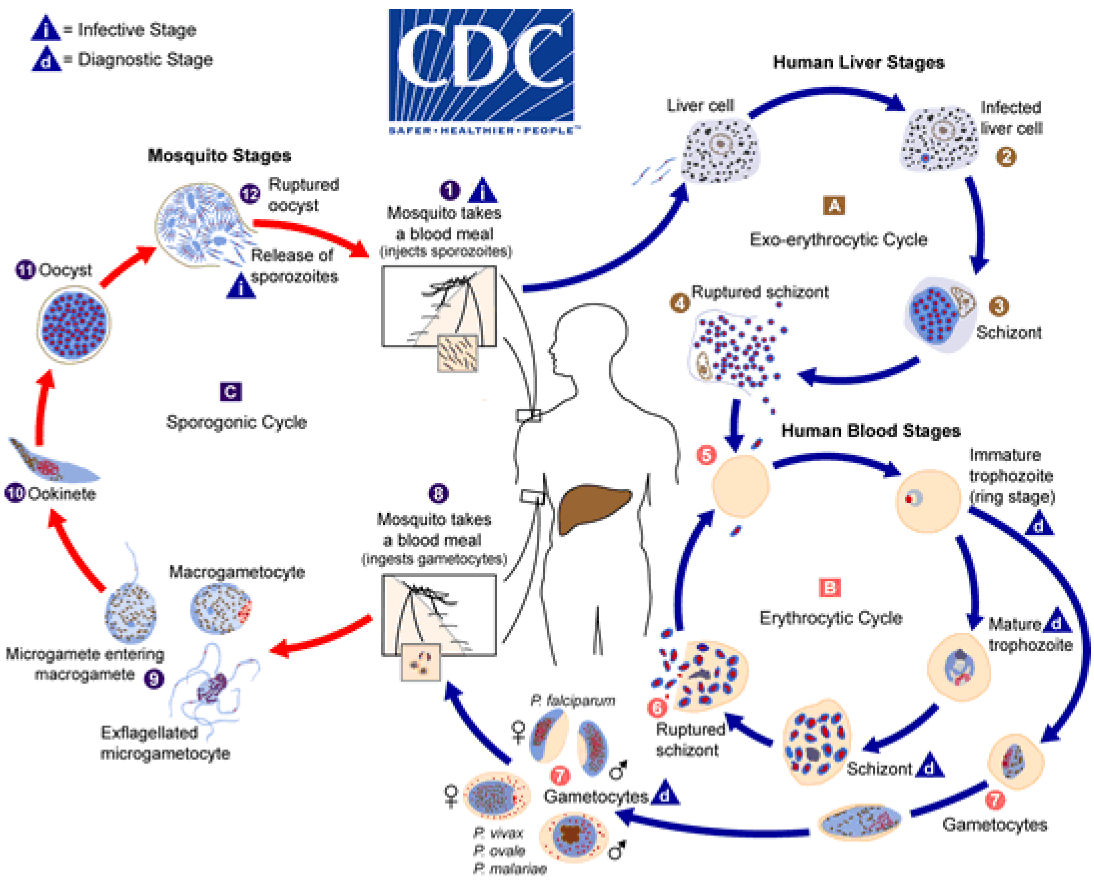


Figure 5.1 - Malaria life cycle diagram *(CDC, 2017b)*

5.2.1 Modelled biological features of malaria

Key mathematically predictable biological features of mosquito and parasite development include the sporogonic and gonotrophic cycle, both of which are quantifiable and often examined in epidemiological studies as potential indicators of future epidemic outbreaks. The sporogonic cycle represented by section C in figure 5.1 is defined as the rate of development of the parasite within the mosquito (Hoshen and Morse, 2004; Jones et al., 2010). This aspect of the malaria cycle is heavily determined by temperature (measured in degree days) and is a critical factor in transmission determination (Teklehaimanot et al., 2004; Emami et al., 2017). The gonotrophic cycle (figure 5.2) is defined as the duration of time between two ovipositions, i.e. site-seeking and egg laying between blood meals (Petrić et al., 2014). The gonotrophic cycle is also heavily controlled by temperature and measured in degree days (Murdock et al., 2016).

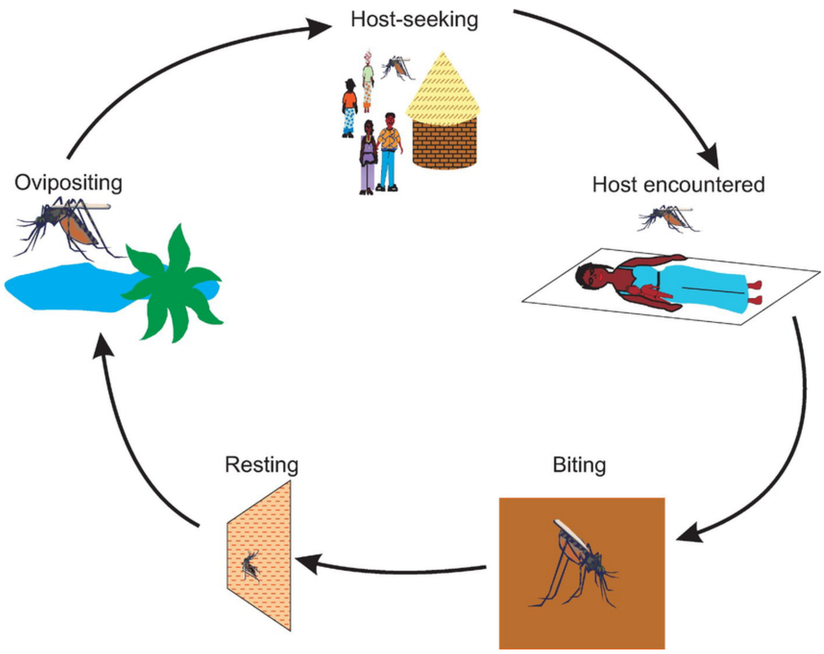


Figure 5.2 - The feeding (gonotrophic) cycle of the female mosquito *(Chitnis et al., 2008)*.

These parasitic and vector life-cycles are key biological factors contributing to determining transmission potential through impacting vector capacity in association with climatic and environmental changes (Lardeux et al., 2008). Whilst rainfall is an important factor in providing habitats for breeding and supporting the gonotrophic cycle, temperature is the main driver allowing for rapid parasitic and larval development provided other conditions are suitable. Teklehaimanot et al., (2004) demonstrated the impact of temperature on the sporogonic cycle presented in table 5.1. Conditions which allow rapid sporogonic development, e.g. higher temperatures, are crucial to monitor and model due to the known significant impact on the occurrence of malaria and subsequent indication malaria epidemics (Teklehaimanot et al., 2004; Githeko et al., 2014).

Table 5.1 - The effect of mean temperature on the duration of a mosquito life cycle and sporogonic cycle and its effect on the amount of lead time from the availability of breeding sites to the occurrence of malaria cases *(Teklehaimanot et al., 2004).*

	Availability of breeding sites ****************> malaria**		
Mean temperature (Rainfall temperature	**Mosquitoes life cycle**	**Sporogony**	**Incubation period in human host**
	*Larva *****> Adult (days)*	Adult first bite *****> Infectious bite (days)	
16 °C	47	111	**(10 to 16 days)**
17°C	37	56	
18 °C	31	28	
20 °C	23	19	
22 °C	18	7.9	
30 °C	10	5.8	
35 °C	7.9	4.8	
39 °C	6.7	4.8	
40 °C	6.5	4.8	

The completion of the sporogonic and gonotrophic cycles, enabling malaria transmission, is particularly vulnerable to the daily survival probability of the vector, due to the necessity for the mosquito to complete both gonotrophic and sporogonic cycles before transmission of the parasite to hosts is available (Smith et al., 2014; Christiansen-Jucht et al., 2015). Mosquito survival probability is calculated as the proportion of mosquitoes which are likely to survive each blood meal and in turn, completes the gonotrophic cycle, the longevity of which is determined by temperature and further influenced by humidity due to the poikilothermic nature of mosquitoes (Martens et al., 1995; Kristan et al., 2008). Consensus on optimal to survivable daily temperatures vary within the literature although is generally accepted to be between 20°C and 25°C, where exceedance of absolute maximum and minimum thresholds result in vector desiccation (Martens et al., 1995; Mordecai et al., 2013).

Where conditions are met to allow the above cycles to take place, transmission of the malaria parasite between vector and host occurs via a blood meal (Jones et al., 2007; Chitnis et al., 2008). Transmission potential, severity and overall presence of malaria spread is often mathematically expressed via the basic reproduction rate, entomological inoculation rate and malaria prevalence. The basic reproduction rate, $R_{0,}$ is defined as the number of new cases of a disease that will arise from one case in a non-immune host population during a single transmission cycle (Dietz, 1993; Patz et al., 2001; Finley et al., 2014). In highland areas, the R_0 of malaria is typically below one during non-endemic periods, and above one signifies potential endemicity. This varies from location to location as vectoral capacity (in the form of survivability and other indicators) play a crucial role, hence it is recommended to assess multiple factors when examining malarial endemicity (Kristan et al., 2008; Finley et al., 2014).

Entomological inoculation rate (EIR) is defined as the number of bites per person per time unit and is empirically derived from the density of human-biting mosquitoes, their sporozoite rate and the human blood index (human biting rate), providing an indication of transmission intensity (Drakeley et al., 2005; Gu and Novak, 2005; Smith et al., 2014). EIR is an increasingly used metric, though comparatively understudied for sub-Saharan Africa, as it is considered to be a more direct measure of transmission than incidence of prevalence, however, questions remain surrounding the validity of EIR due to non-standardisation of methods, datasets and techniques (Kelly-Hope and McKenzie, 2009; Finley et al., 2014). Despite this, studies are encouraged to examine climatological impacts on entomological parameters whilst universal techniques become more defined (Drakeley et al., 2005; Finley et al., 2014).

Prevalence is the proportion of persons in a population who have malaria (or the disease of interest) at a specified point in time or over a specified period of time (CDC, 2017a). Prevalence is commonly used as a measure of morbidity and preferred over the use of incidence because the population who already have the disease are accounted for, which is useful in areas where malaria is endemic and constant background transmission occurs (Kelly-Hope and McKenzie, 2009). Malaria prevalence is highly sensitive not only to climatic changes, but also changes in surveillance, resistance and behavioural changes of both humans and vectors, thus it is important to consider these when interpreting prevalence results (Parham and Michael, 2010). For this reason, it is argued that prevalence is less reliable than EIR which is presented in detail in section 5.6.

5.3 Data and methods

The Liverpool Disease Model Cradle (DMC) was recommended (Caminade *Pers. Comm.*, 2016) and has been downloaded to act as an interface to the Liverpool

Malaria Model version 1.3.1 (LMM_{2004}) developed by Hoshen and Morse in 2004 and further modified by Ermert et al. (2011) to become LMM_{2010}. The LMM_{2010} was initially developed and further updated and validated to perform well in West Africa and has not yet knowingly been executed in detail for East African countries such as Tanzania (Morse, 2013). Due to the nature of epidemiological modelling, daily data is required to input into the model. The latest version LMM_{2010} will be used in this chapter and is referred to as LMM throughout.

ERA Interim daily rainfall and temperature data with a timestamp of 12:00 (mid-day) was downloaded from the ECMWF MARS retriever for the 11-year period between 01-01-2006 to 31-12-2016 at a resolution of 0.75 x 0.75 degrees. Justification for the use of an 11 year period can be found in chapter three. Inputs for the DMC require specific data formatting per 0.75 x 0.75 degree grid which was achieved via tailored R code and a mask was also created for Tanzania. More information on the Liverpool DMC and formatting can be found in the Disease Model Cradle practical document and QWECI documents (Hoshen and Morse, 2004; Ermert et al., 2011; Morse, 2013). Current and 2070 RCP 8.5 temperature and precipitation conditions from HadGEM2-ES were obtained from WorldClim for use in forecasting future conditions, which is further explained in section 5.3.1. RCP 8.5 only was chosen due to the modelled heightened risk of malaria (and population) for this RCP in 2070 from chapter four (figure 5.3). It is suggested that future work could explore the full range of RCPs, as discussed in section 5.6.3.

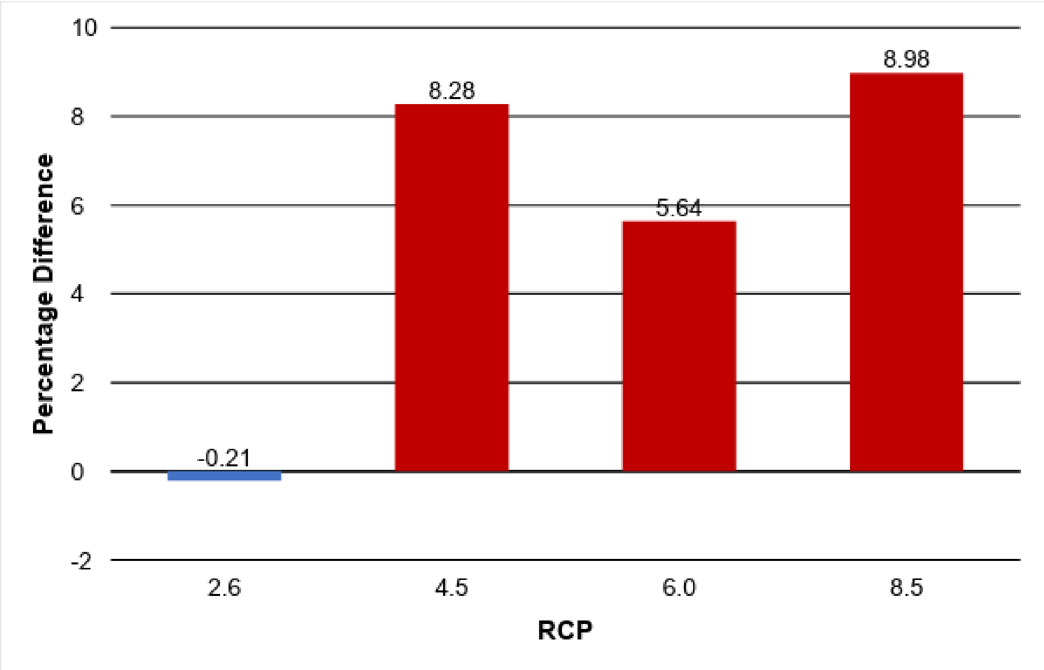


Figure 5.3 - Percentage difference in malaria risk in Tanzania from current conditions by 2070 across RCPs. Results taken from risk model in chapter four.

5.3.1 Methods

Prior to importing data into the LMM, data was formatted to the specific input requirements for the DMC interface using bespoke R script. Temperature and precipitation values were converted to represent the units of degrees Celsius (°C) and mm respectively. Raw ERA Interim data time is represented in hours since 01-01-1900 and as such was re-formatted to represent the Gregorian calendar date-time for use in separating monthly values at a later stage. Following this, temperature and precipitation data for each grid-square was separated by unique longitude and latitude combinations and formatted with a header line containing longitude, latitude, number of records contained in the file followed by daily variable values for the 11-year period. Separate node files were created for temperature and precipitation for import into the DMC.

Functions of the LMM using the DMC interface are limited and data was presented annually per grid-square for the season of interest, where an 11-year mean output was desired. Considering the specific aims and objectives of this chapter, seven districts, contained in seven grid squares were chosen and the annual raw output data from the DMC further modified using bespoke R script to obtain an 11-year mean for the MAM season (table 5.2 and figure 5.4). The seven districts were chosen to represent the most populated settlements within each of the seven climatological zones in Tanzania (NBS, 2013a; TMA, 2014). Raw numerical output data for each of the grid-squares was exported and tailored using R script. An 11-year mean was calculated per factor of interest for the MAM rainfall season only which has previously been highlighted in chapter four.

Table 5.2 - Grid latitudes and longitudes for export from the LMM/DMC for each residential district of interest with district elevation and population density figures *(NBS, 2013a)*.

District	**Elevation (m)**	**ERA Grid-Latitude (°)**	**ERA Grid-Longitude (°)**	**Population density 2012 (Pop/km^2)**
Arusha	1387	-3.00	36.00	45
Dar es Salaam	55	-6.75	39.00	3113
Dodoma	1120	-6.00	35.25	50
Mbeya	1704	-8.25	33.00	45
Mtwara	31	-9.75	39.75	76
Mwanza	1140	-2.25	32.25	293
Songea (Ruvuma Region)	1147	-10.5	35.25	22

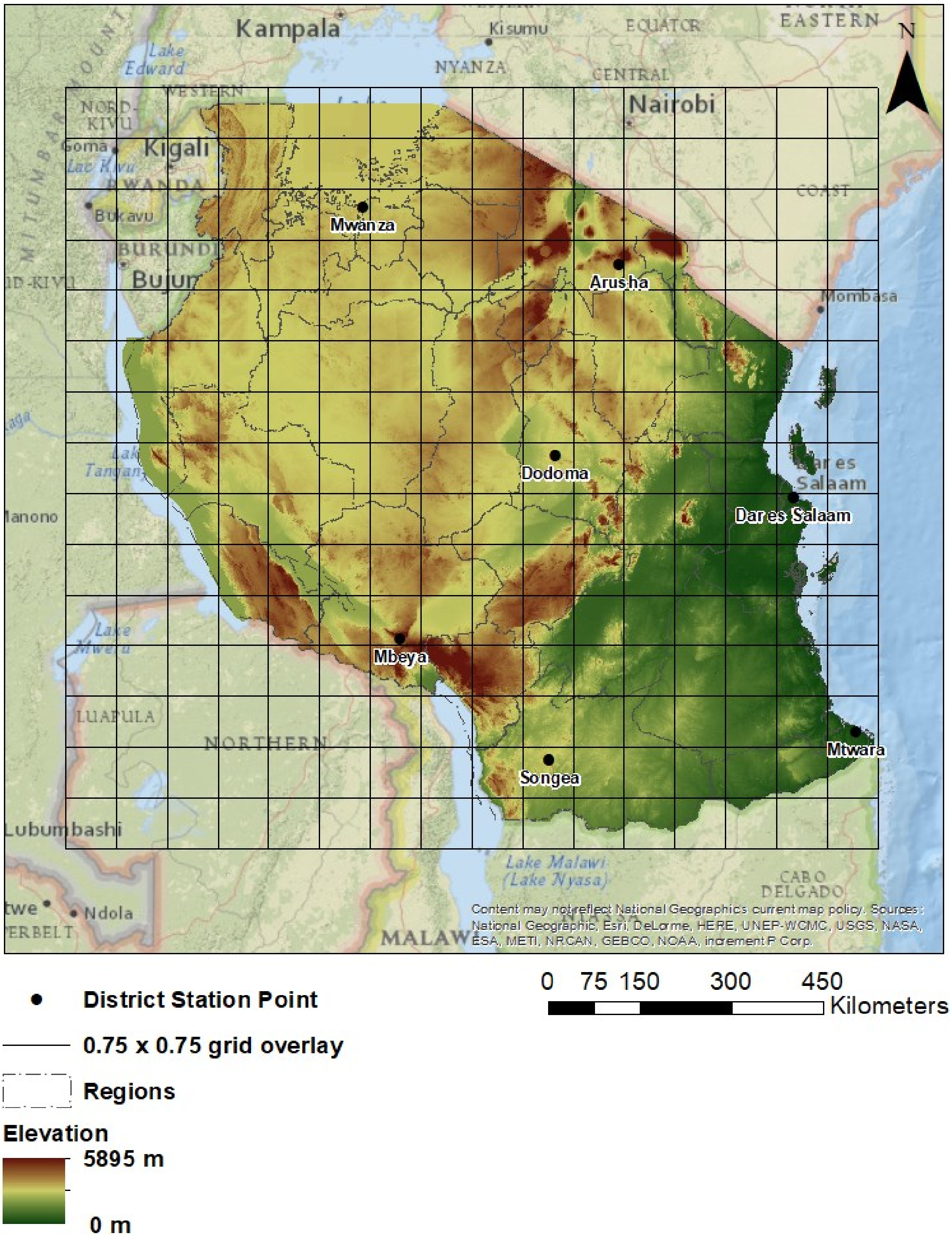


Figure 5.4 - 0.75° x 0.75° grid squares of data downloaded from ERA interim overlaying Tanzania districts included in the study and elevation.

As 2070 RCP 8.5 estimated daily data is not available, mean annual temperatures and precipitation values for RCP 8.5 in 2070 was calculated using current HadGEM2-ES outputs and 2070 RCP 8.5 projections provided via WorldClim version 1.4. The annual mean (rather than seasonal mean) was calculated due to data requiring input into the DMC in annual format. This percentage change in respective variables was then applied to the current data (2006 – 2016), input into the LMM via the DMC and mean values calculated for 2070. The mean of the 11-year representative dataset was calculated to represent the year 2070, and the MAM season values extracted for each grid-square and epidemiological factor being examined in this study. A method flow diagram of this process can be found in figure 5.5.

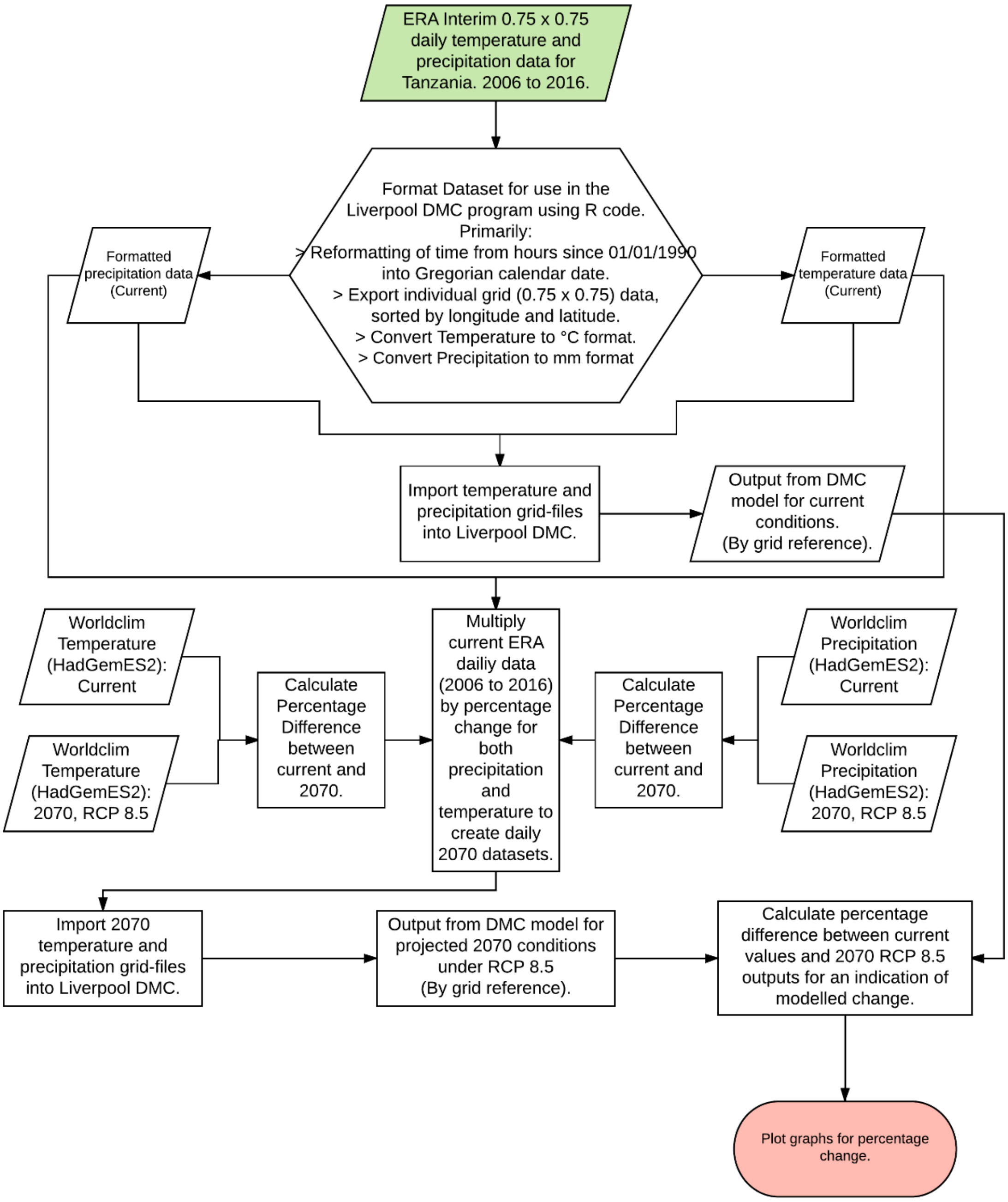


Figure 5.5 - Workflow of methodology for calculating current and future temperature and precipitation and the subsequent epidemiological output factors using the LMM DMC for Tanzania.

5.3.1.1 Sensitivity analysis

A one-factor-at-a-time (OAT) sensitivity analysis was conducted where temperature and precipitation were changed one at a time to assess the impact on malaria prevalence (Saltelli et al., 2010). This was conducted in order to better assess the role of temperature and precipitation within LMM and to further consider whether the model adequately reflects the known impacts of temperature and precipitation on malaria prevalence. This particular approach was recommended in Hoshen and Morse (2004) and has been used in other studies as an effective preliminary approach, providing an insight into model sensitivity (van Griensven et al., 2006).

The data used to assess sensitivity is the mean daily temperature and precipitation value for all seven districts included in the study (table 5.2) for the 11-year period from 2006 to 2016. Seven districts were included to provide a comprehensive sensitivity analysis covering all climate zones in Tanzania. The full 11-year period was assessed to enable assessment of potential impacts seen during El Niño years which are present in the dataset. Each individual factor was adjusted by 25%, 50% and 75% step changes in both positive and negative directions resulting in 6 sensitivity profiles for each temperature and precipitation. These intervals were chosen to represent an even coverage of percentage change ranging from plausible to extreme in order to clearly highlight potential model limitations.

5.3.1.2 Epidemiological output factors

The indicative biological factors introduced in section 5.2 will be modelled by the LMM. Table 5.3 provides a brief summary of each factor with accompanying description and units for reference. Degree days (or growing degree days) are defined as a measurement of heat unit over time which is considered accurate for mosquitoes due to a predictable development pattern based on heat accumulation (Murray, 2008).

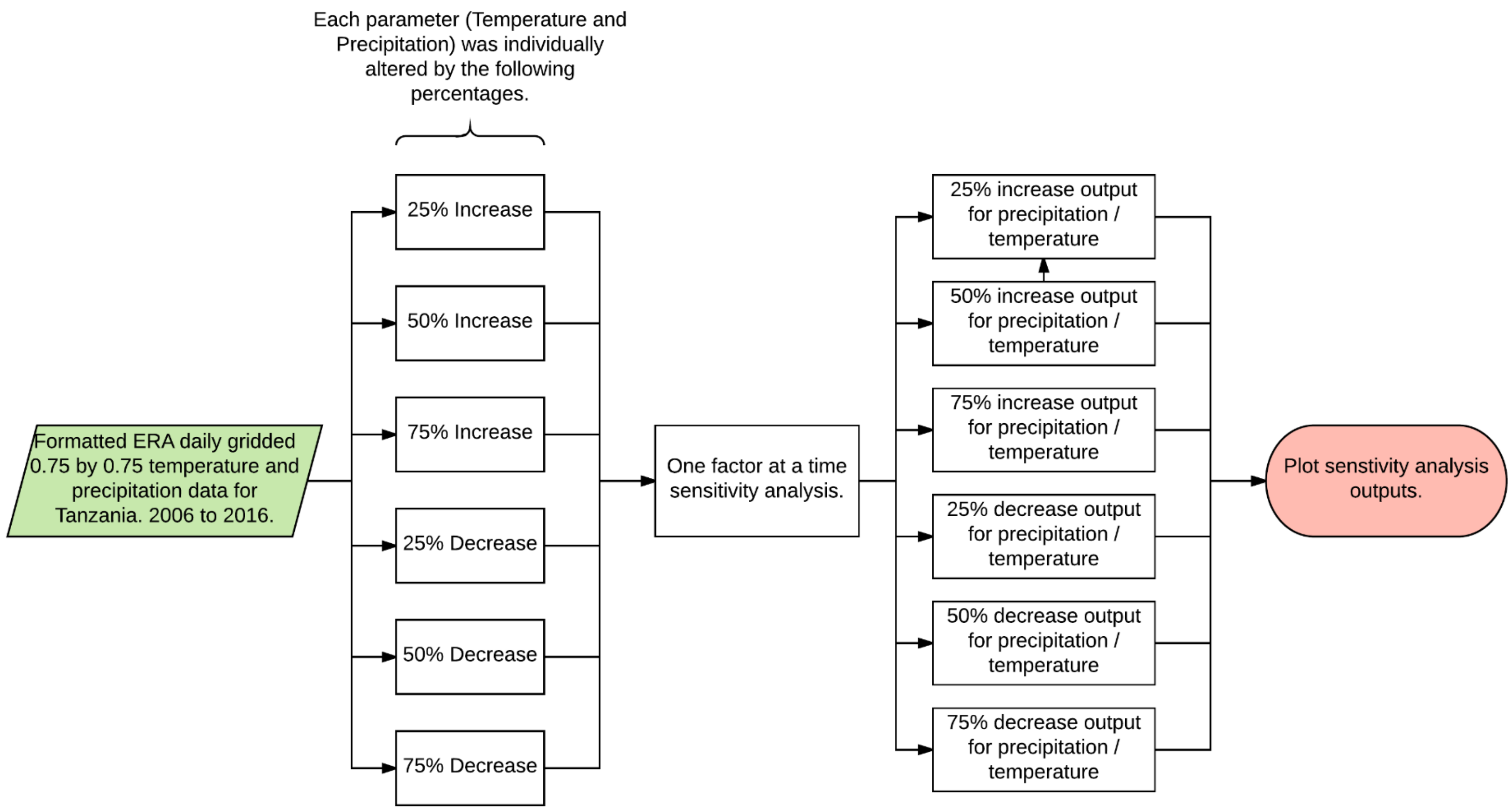


Figure 5.6 - Workflow of methodology for examining LMM sensitivity.

Table 5.3 - Summary of epidemiological output factors examined in this study *(Jones et al., 2010; Finley et al., 2014; CDC, 2017a)*.

Output factor	**Description**	**Units**
Sporogonic cycle	Cycle (and rate) of development of the malaria parasite within the mosquito.	Degree days
Gonotrophic cycle	The biting-laying cycle of the mosquito, which is governed by the rate at which eggs can be produced.	Degree days
Mosquito daily survival probability	Proportion of mosquitoes which survive each blood meal.	Percentage (%)
Basic reproduction rate (R_0)	Number of secondary infections originating from a primary case in the absence of immunity.	See description
Entomological inoculation rate	Number of infective bites per person per time unit	See description
Malaria prevalence	Proportion of persons in a population who have malaria at either: a) a specified point in time b) over a specified period of time.	Number of cases per specified population. E.g. per 10,000 or 100,000 people.

5.4 Results for model sensitivity

This section of work has examined the sensitivity of the LMM in Tanzania through exploring the mean percentage change in prevalence from 2006 to 2016 as a result of changing temperature and precipitation values by pre-defined thresholds. Results are presented in section 5.4.1 and 5.4.2.

5.4.1 Temperature sensitivity results

Sensitivity results for temperature (figure 5.7) demonstrate good model sensitivity for each threshold examined, with both increases and decreases in temperature resulting in reductions in prevalence which arguably highlights the niche temperature range within which malaria transmission operates, and is further discussed in section 5.6. Increasing temperature thresholds (+25%, +50%, +75%) demonstrate the greatest impact on prevalence, and results in decline of in malaria prevalence. Temperature decrease thresholds (-25%, -50%, -75%) demonstrate prevalence decline to a lesser extent than temperature increases. The 25% increase threshold results in (on average) an approximate 20% reduction in prevalence, where alternatively, a 75% temperature increase results in approximately a 95% reduction in prevalence, almost eradicating malaria.

Whilst increased thresholds for temperature appear to reflect expected annual seasonality, decreased temperature thresholds demonstrate a more arbitrary sine curve, with a notable reversed seasonality, as would be expected with decreased temperatures, which is amplified as the threshold increases. It is not clear why this appears to be the case for decreased temperature thresholds. Further analysis would need to be conducted to explain potential model artefacts and climatic response.

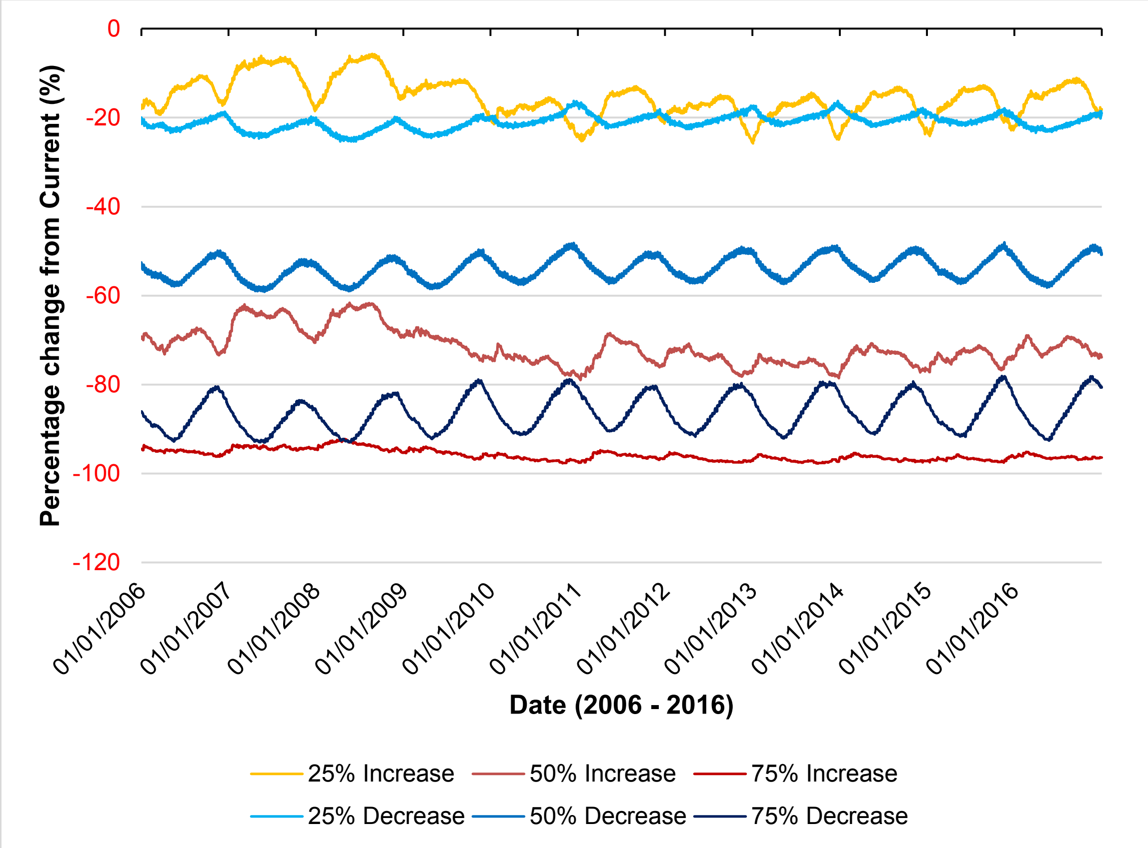


Figure 5.7 - Percentage difference from current prevalence for pre-defined temperature thresholds to assess LMM sensitivity.

5.4.2 Precipitation sensitivity results

Sensitivity results for precipitation demonstrate good model sensitivity, in-keeping with current knowledge with regards to malaria dependence on precipitation, discussed further in section 5.6. Results demonstrate that malaria prevalence is less sensitive to changes in rainfall than changes in temperature. Increases in rainfall between the 25% and 75% threshold show overall, limited increase in prevalence, peaking at a 10% increase between 2015 and 2016, a known El Niño year which explains this exacerbated peak in the data for this year at the 75% threshold. Overall, at present, sensitivity analysis suggests that rainfall in Tanzania is close to the overall optimum amount required for malaria transmission, which is supported by Bayoh and Lindsay (2004), thus suggesting that the model performs well with regards to rainfall.

A decrease in rainfall demonstrates a more dramatic response, however does not completely reduce prevalence in the same way that is observed in the temperature results. Rainfall decreases of up to 75% demonstrates at the lowest point, a 32% reduction in prevalence, further suggesting that with minimal amounts of rainfall malaria transmission is still viable and that temperature is the more dominant factor.

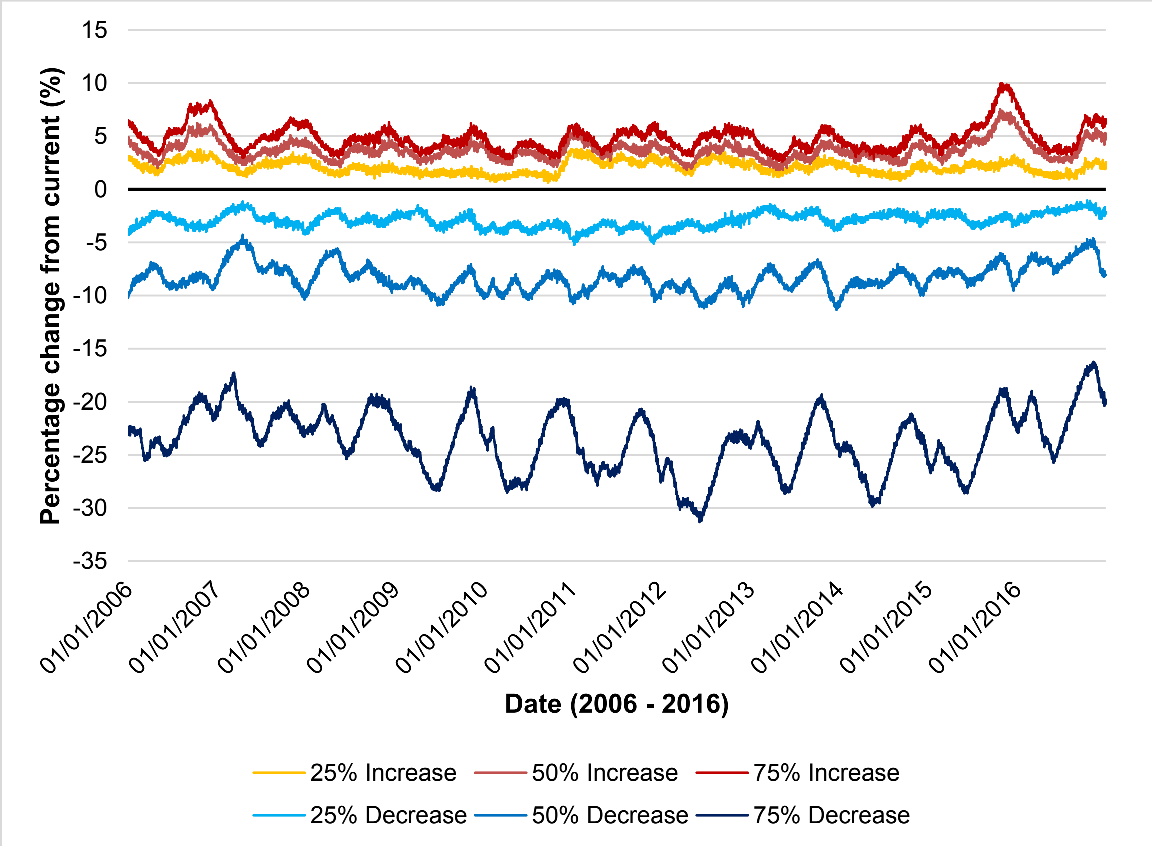


Figure 5.8 - Percentage change from current prevalence for pre-defined precipitation thresholds to assess LMM sensitivity.

5.5 Results for relative percentage change in biological indicators

This section examined the percentage change in six biological indicators (outlined in section 5.3.2.1) for malaria during the MAM rainfall season under RCP 8.5 by 2070 using the LMM. Results are presented for seven distinct climatological zones in Tanzania, each with densely populated regional townships. Results are further split by rainfall regime, either unimodal or bimodal, for context and comparison. Graphs are plotted by five-day running mean throughout the MAM season in order to reduce the impact of any potentially erroneous outputs.

5.5.1 Gonotrophic cycle length

Graphed results for percentage change in gonotrophic cycle length (the duration of time between two ovipositions) between current conditions and 2070 RCP 8.5 for all districts within each rainfall regime for the MAM rainfall season are presented in figures 5.9 and 5.10 with total percentage change over the 3 months presented in tables 5.4 and 5.5.

5.5.1.1 Bimodal

Gonotrophic cycles are overall modelled to reduce by 2070 under the RCP 8.5 pathway for the MAM season (figure 5.9). This equates to shorter time periods between female ovipositions, thus theoretically increasing the amount of eggs a female could lay in their lifetime as well as over a shorter period of time. The greatest decreases are observed in Mwanza and Arusha, two areas of high altitude in the bimodal regime (figure 5.9). Mwanza marginally demonstrates the greatest decrease across the season of -15% (table 5.4) reducing throughout May as the rainfall season nears an end and as temperatures decrease. Arusha demonstrates a differing profile, increasing to reach peak reduction in cycle length during April, before decreasing in cycle length again throughout May, with a seasonal average reduction of -15%. Dar es Salaam also demonstrates a shortening of cycle length, consistently ranging between 13% and 14% with reductions beginning to fluctuate towards the end of May.

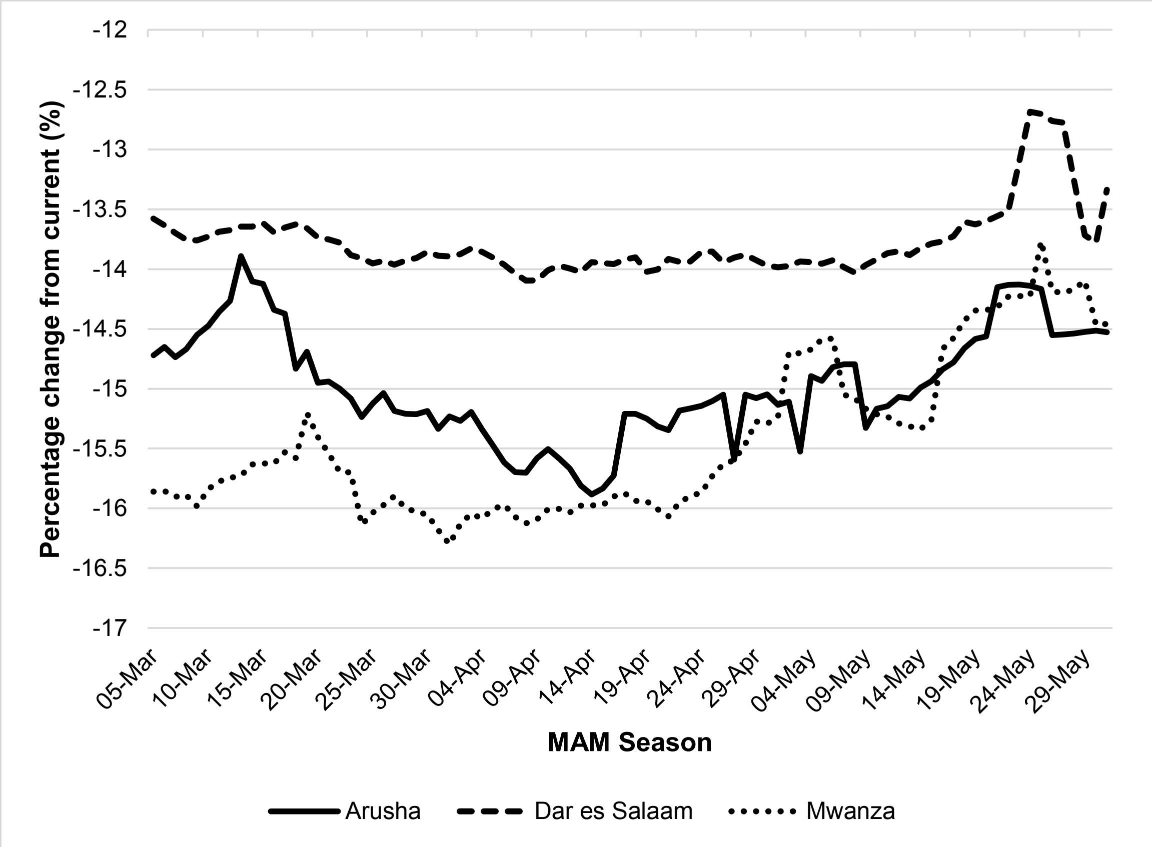


Figure 5.9 - Percentage change in mean (5 day running mean) gonotrophic cycle length from current conditions in bimodal districts (2006-2016) by 2070 under RCP 8.5.

Over the three-month period, the greatest average reduction in gonotrophic cycle length is seen in Mwanza, followed by Arusha and Dar es Salaam (table 5.4). Overall there is 1.67% range in the overall reduction of gonotrophic cycle length. Conditions improve towards optimum gonotrophic suitability, where no thresholds towards unsuitability have been crossed.

Table 5.4 - Mean monthly percentage changes in gonotrophic cycle length over the MAM season for each bimodal regime district.

	Arusha	**Dar es Salaam**	**Mwanza**
Average % Change	-14.95	-13.75	-15.42

5.5.1.2 Unimodal

Similar to trends seen in the bimodal regimes, Songea and Mbeya, the two highest altitudinal locations included in the unimodal regime, demonstrated the highest percentage reduction in gonotrophic cycle length with Songea by -16% in early March, and -14% and -15% towards the end of May. Mbeya follows a similar trend although shows slightly more fluctuations indicating variable conditions (figure 5.10). Dodoma and Mtwara demonstrate slightly smaller reductions in the range of -13% to -15%, with both showing fluctuations of up to 4% from mid-April onwards.

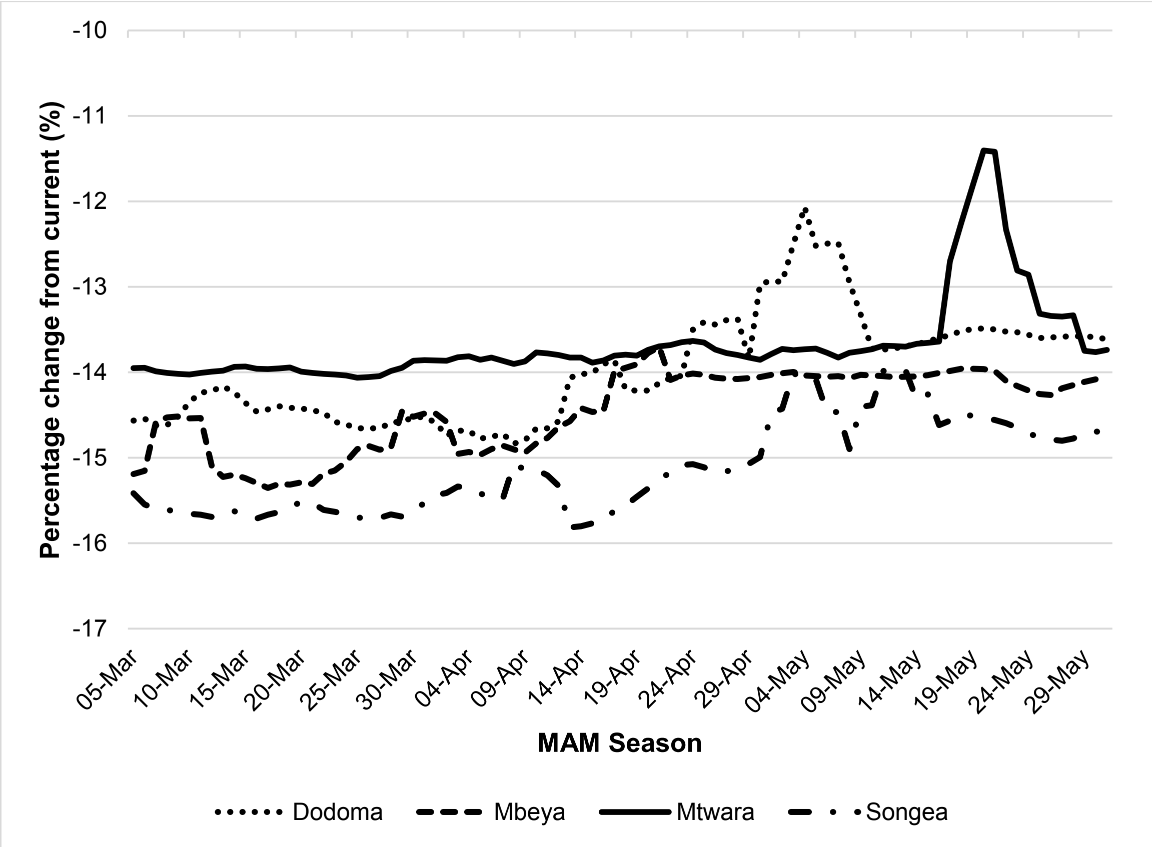


Figure 5.10 - Percentage change in mean gonotrophic cycle length from current conditions in unimodal districts (2006-2016) by 2070 under RCP 8.5.

Over the three month season the greatest average reduction in gonotrophic cycle length is seen in Songea, followed by Mbeya, Mtwara and Dodoma (table 5.5). There is a 1% difference between each reduction in location gonotrophic cycle length suggesting that, similarly to the bimodal regime, conditions are likely to become universally more suitable for the gonotrophic cycle length of the malaria life cycle.

Table 5.5 - Mean monthly percentage changes in gonotrophic cycle length over the MAM season for each unimodal regime district.

	Dodoma	**Mbeya**	**Mtwara**	**Songea**
Average % Change	-13.97	-14.46	-13.68	-15.12

5.5.2 Sporogonic cycle length

5.5.2.1 Bimodal

Sporogonic cycle lengths exhibit a drastic reduction in length throughout the MAM season in 2070 for RCP 8.5, indicating a shortening of the time needed for parasitic reproduction, enabling a mosquito (once the parasite is ingested through a blood meal) to become infectious with malaria quicker. Arusha and Mwanza demonstrate the most varying and overall greatest mean reduction over the season, averaging -37% over the course of the season (figure 5.11, table 5.6). Arusha surpasses -50% in cycle time in the earlier half (March – April) of the season, when temperatures are generally warmer. Dar es Salaam by comparison shows a more modest decrease in cycle length averaging -29% reduction in cycle time over the MAM season.

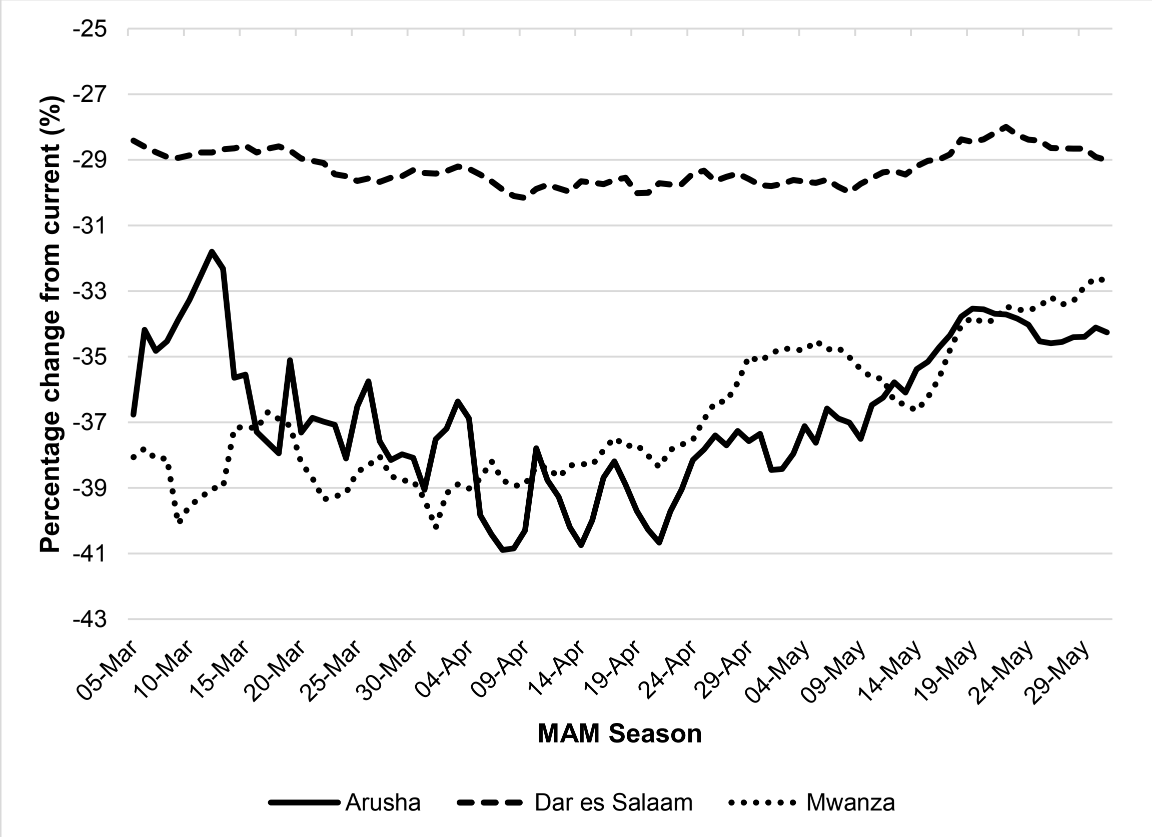


Figure 5.11 - Percentage change in mean sporogonic cycle length from current conditions in bimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.6 - Mean monthly percentage changes in sporogonic cycle length over the MAM season for each bimodal regime district.

	Arusha	Dar es Salaam	Mwanza
Average % Change	-36.77	-29.22	-36.78

5.5.2.2 Unimodal

Unimodal regime districts depict a less varied change in cycle length to those seen in the bimodal regime districts, particularly Mwanza and Arusha. Songea demonstrates the overall greatest mean reduction at -36% throughout the season, showing an overall different pattern of reduction to the other three districts in this regime whereby cycle length only marginally drops in mid-April compared to other districts. Mbeya demonstrates the second highest mean reduction in sporogonic cycle length of -32%, followed by Dodoma at -31% and Mtwara at -29% where

Mbeya and Dodoma show similar patterns of cycles slightly lengthening throughout April. Mtwara displays a profile similar to that of Dar es Salaam, remaining fairly constant in sporogonic cycle length throughout the season (figure 5.12, table 5.7).

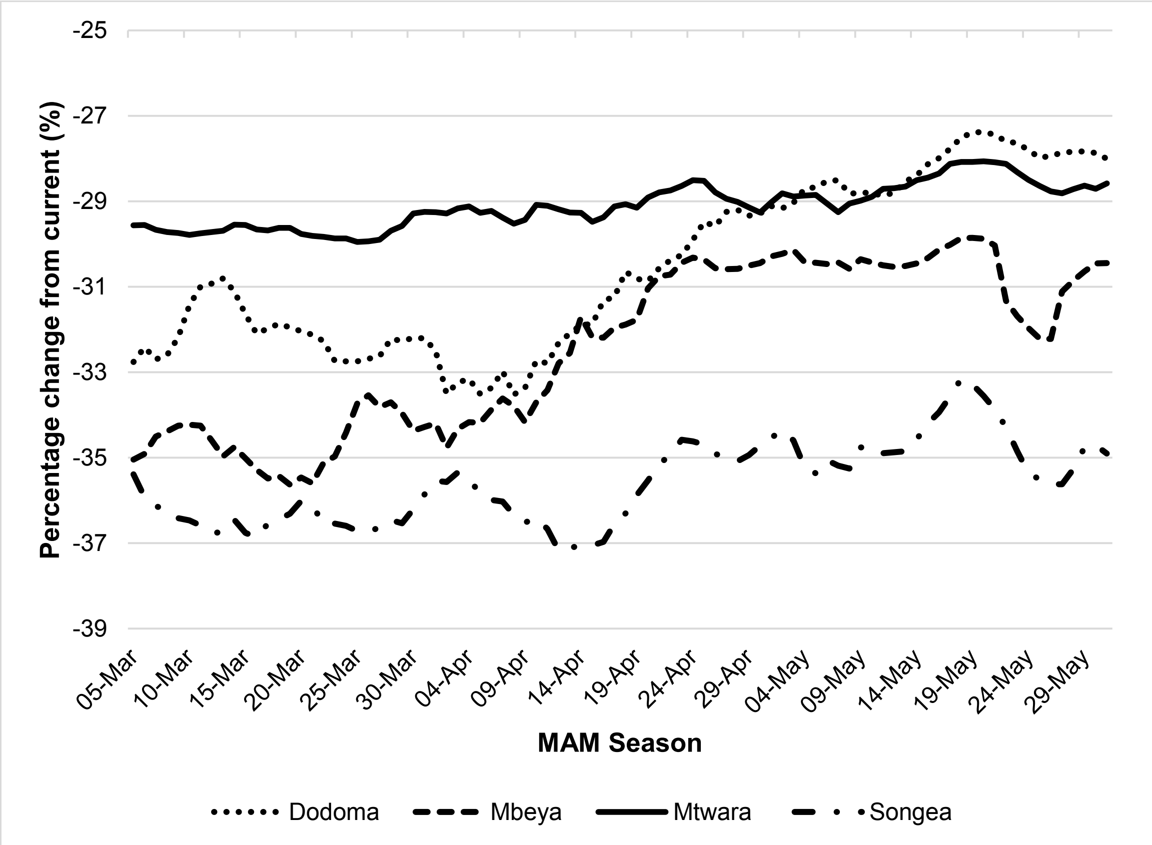


Figure 5.12 - Percentage change in mean sporogonic cycle length from current conditions in unimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.7 - Mean monthly percentage changes in sporogonic cycle length over the MAM season for each unimodal regime district.

	Dodoma	**Mbeya**	**Mtwara**	**Songea**
Average % Change	-30.52	-32.14	-29.11	-35.56

5.5.3 Basic reproduction rate

5.5.3.1 Bimodal

Mwanza demonstrates the highest mean percentage increase in R_0, indicating an increased number of secondary infections in the absence of immunity. Averaging 82% over the MAM season, the majority of this increase is observed in the earlier half of the season in March and April and reducing towards the end of May. Arusha demonstrates an opposing profile, averaging an overall seasonal increase of 61%, the majority of this is accounted for later in the season from mid-April to late May where fluctuations in reproduction rates become greater towards the end of May suggesting highly changeable conditions. Dar es Salaam contrasts the results presented in Mwanza and Arusha, demonstrating an average seasonal reduction in reproduction rate of -32%, suggesting climate conditions have become increasingly unfavourable for reproduction. Fluctuations are less evident in the Dar es Salaam profile suggesting consistent climatological conditions (figure 5.13, table 5.8).

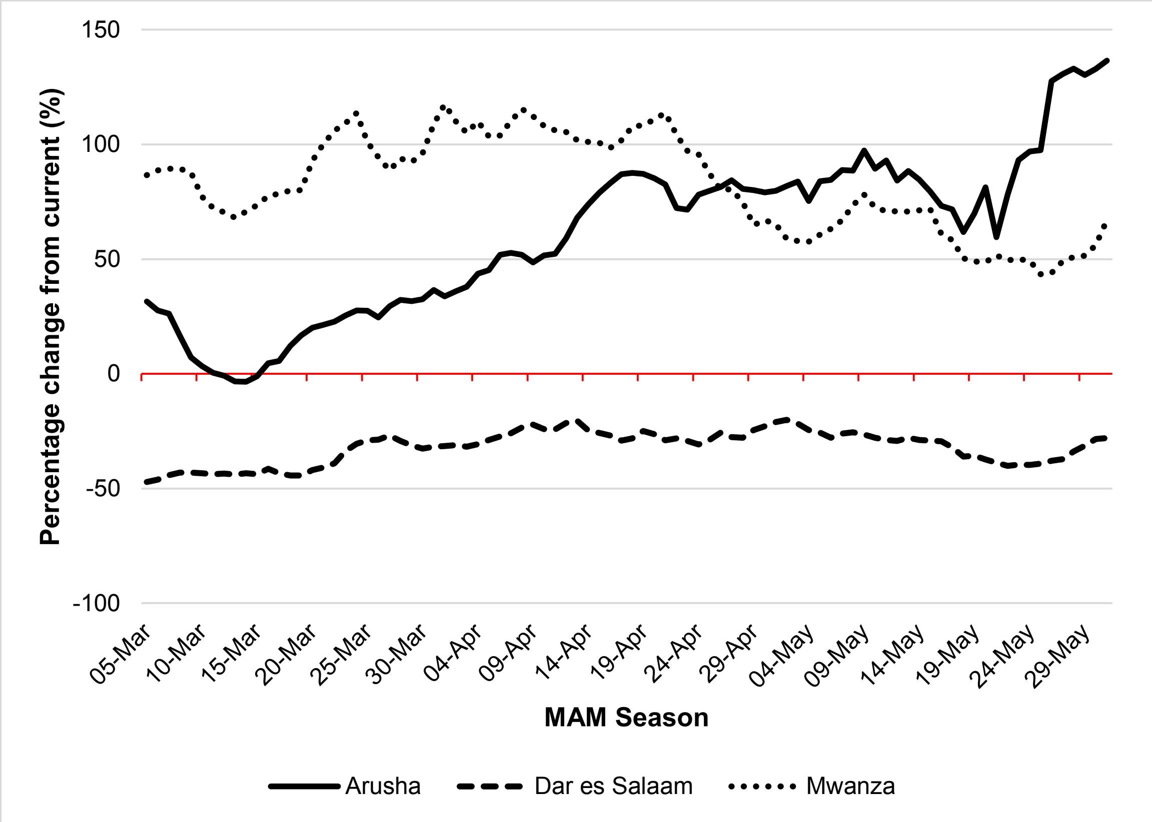


Figure 5.13 - Percentage change in mean reproduction rate from current conditions in bimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.8 - Mean monthly percentage changes in reproduction rate over the MAM season for each bimodal regime district.

	Arusha	**Dar es Salaam**	**Mwanza**
Average % Change	+61.47	-32.30	+81.86

5.5.3.2 Unimodal

Songea demonstrates the highest seasonal average increase of R_0 in the unimodal area of 87% higher than current conditions, occurring mostly towards the end of the season. This is followed by Mbeya, which shows a fairly consistent increase across the MAM season, with an average increase of 50% in R_0. Dodoma presents interesting results, showing in parts, increases and decreases in secondary infectious cases throughout the season, with an average increase of 1%. However, the profile suggests that climatological suitability in Dodoma is approaching a threshold towards unsuitability for infectious disease spread. Mtwara displays a reduction in R_0, averaging -27% throughout the season, showing no major fluctuations in profile suggesting that conditions become consistently less suitable (figure 5.14, table 5.9).

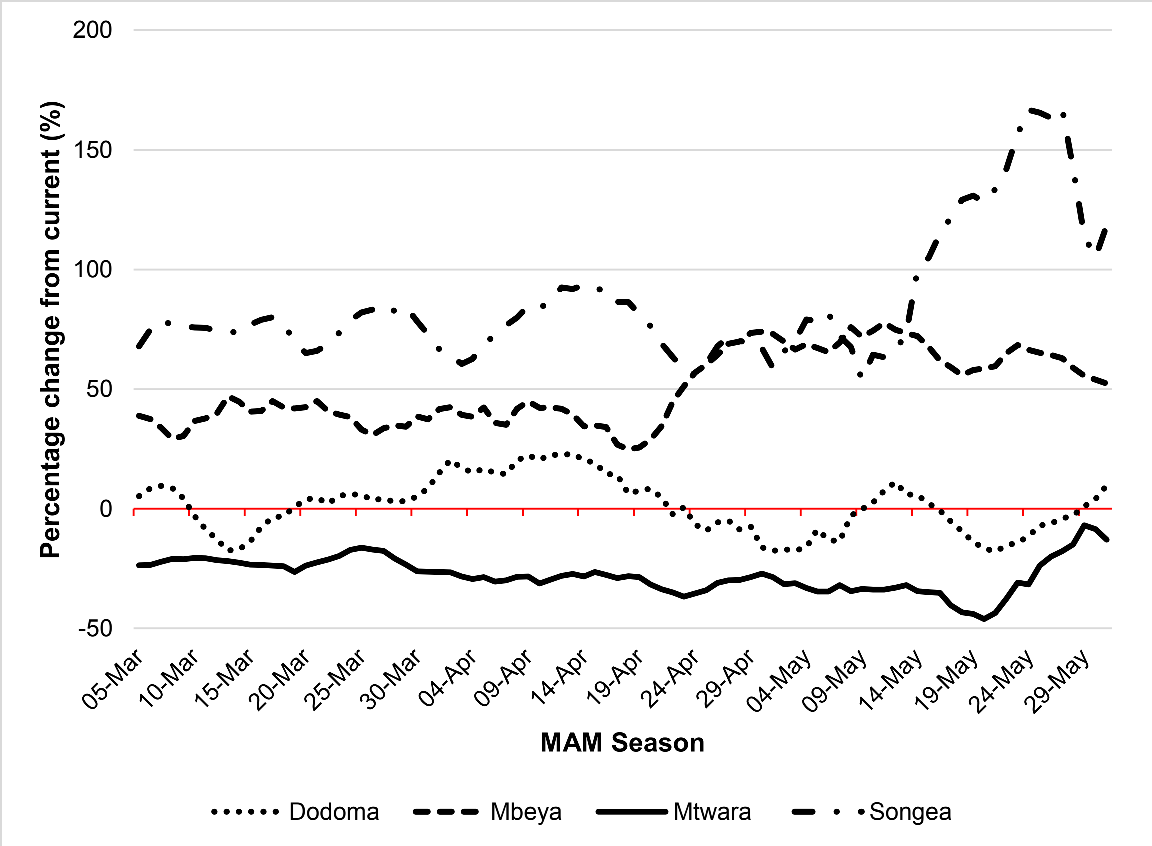


Figure 5.14 - Percentage change in mean reproduction rate from current conditions in unimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.9 - Mean monthly percentage changes in reproduction rate over the MAM season for each unimodal regime district.

	Dodoma	**Mbeya**	**Mtwara**	**Songea**
Average % Change	+1.33	+49.67	-27.43	+86.50

5.5.4 Survival probability

5.5.4.1 Bimodal

Overall survival probability, *i.e.* the likelihood of a mosquito surviving each blood meal and completing the gonotrophic cycle, reduces in all districts under the bimodal regime. This indicates that fewer mosquitoes are likely to survive to contribute to malaria transmission. The greatest reduction in survival probability is seen in Dar es Salaam where up to 14% of mosquitoes may be able to survive in early March. Across the MAM season as a whole, Dar es Salaam experiences an average reduction of -4% in survival probability. Arusha and Mwanza exhibit slight reductions in survival probability, averaging -3% and -1% respectively (figure 5.15, table 5.10).

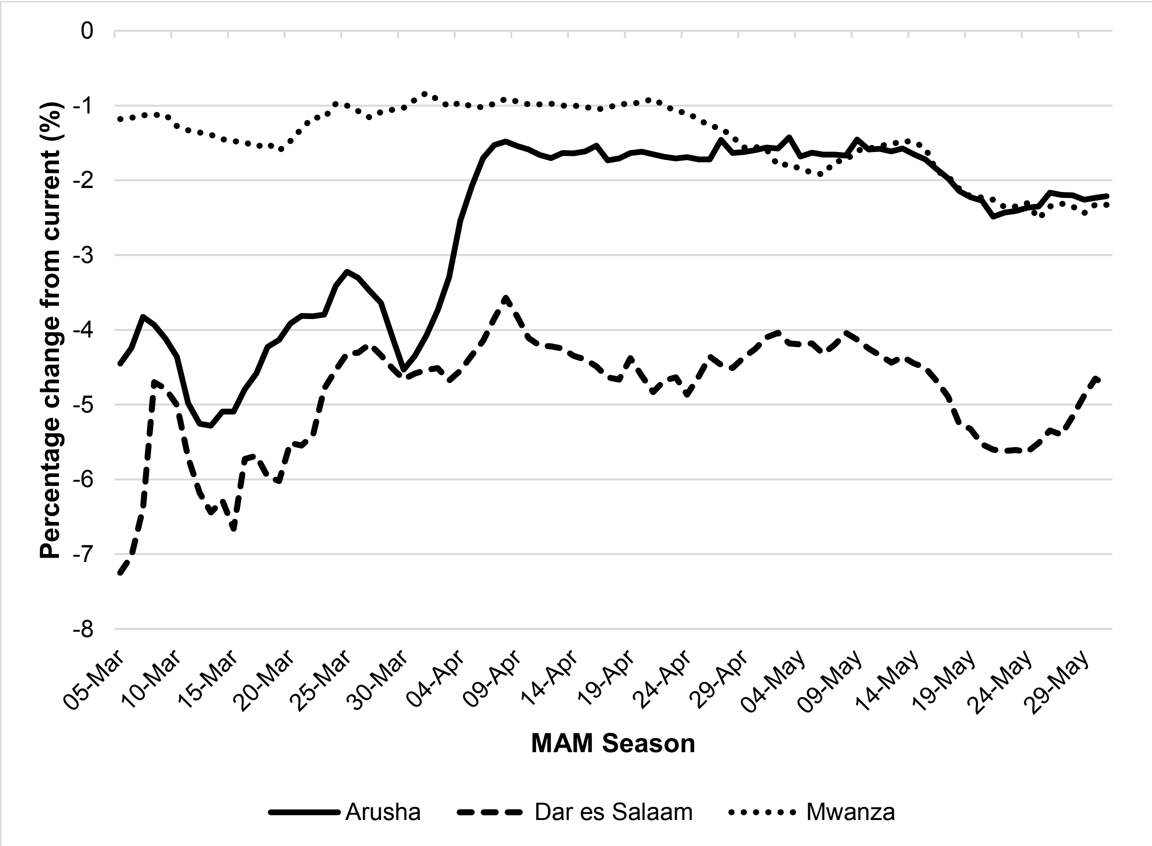


Figure 5.15 - Percentage change in mean survival probability from current conditions in bimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.10 - Mean monthly percentage changes in survival probability over the MAM season for each bimodal regime district.

	Arusha	**Dar es Salaam**	**Mwanza**
Average % Change	-2.65	-4.91	-1.46

5.5.4.2 Unimodal

Survival probability in the unimodal regime reduces overall. Dodoma demonstrates the largest average season reduction totalling -5%, peaking at over -8% in May. Mtwara experiences the second highest average seasonal reduction at -5%, followed by Mbeya and Songea at -3% and -2% respectively. All profiles show similar trends where survival probabilities increasingly reduce from mid-April onwards with the exception of Songea which maintains a steady profile indicating conditions are maintained in relation to survival probability (figure 5.16, table 5.11).

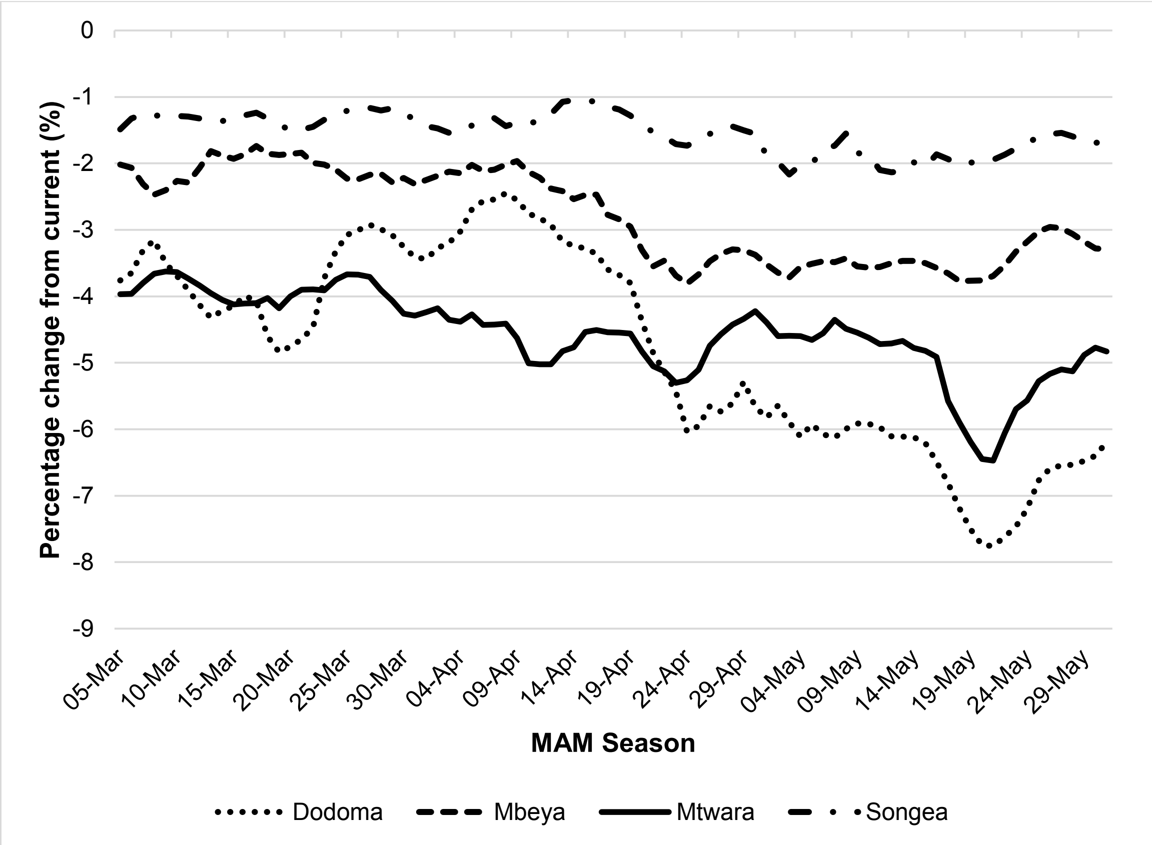


Figure 5.16 - Percentage change in mean survival probability from current conditions in unimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.11 - Mean monthly percentage changes in survival probability over the MAM season for each unimodal regime district.

	Dodoma	Mbeya	Mtwara	Songea
Average % Change	-4.80	-2.79	-4.57	-1.54

5.5.5 Entomological inoculation rates

5.5.5.1 Bimodal

Entomological inoculation rate percentage change profiles fluctuate between increases and decreases in percentage change in the bimodal regime, particularly for Arusha which has notable high peaks of up to +150% increase in infectious bites per person per day (based on mid-day daily data used) towards the end of May. Overall, it is difficult to distinguish patterns of change from the profiles presented in figure 5.17. On average over the season, Arusha is the only area to experience an increase in infective bites per person per day at +10% modelled increase. Mwanza experiences an overall reduction in infective bites of -4% where Dar es Salaam experiences the greatest reduction of -14% (table 5.12).

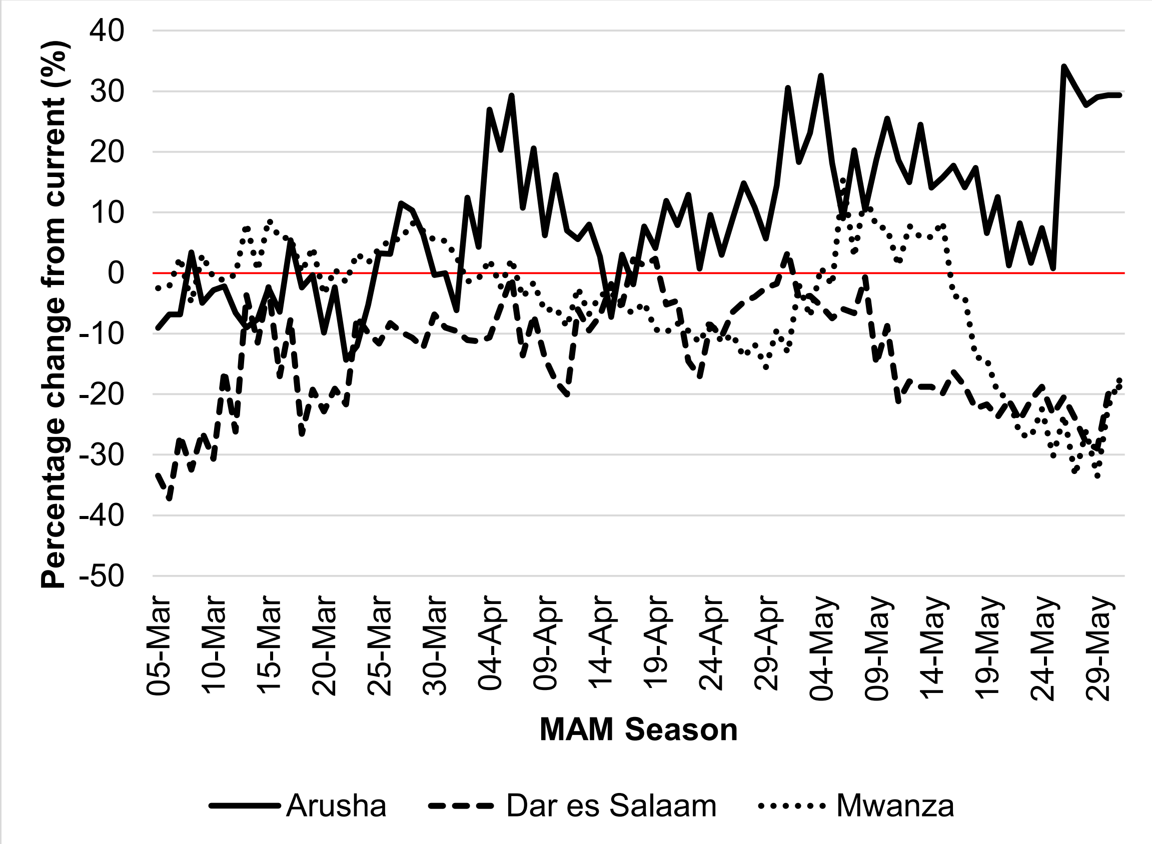


Figure 5.17 - Percentage change in mean entomological inoculation rate (five day rolling average) from current conditions in bimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.12 - Mean monthly percentage changes in entomological inoculation rates over the MAM season for each bimodal regime district.

	Arusha	**Dar es Salaam**	**Mwanza**
Average % Change	+9.56	-13.89	-4.39

5.5.5.2 Unimodal

Similarly to the bimodal regime, EIR values fluctuate in percentage change throughout the MAM season for unimodal regime districts to a degree where no discernible pattern is observed. Songea demonstrates the highest peaks, reaching up to a +340% increase in infectious bites per person per day towards the end of May. Overall more districts in the unimodal regime see an average increase in infective bites compared to districts in the bimodal regime. Songea experiences an average increase of +24%, followed by Mbeya at +14% and Dodoma at +2%, further indicating that Dodoma is potentially approaching climatological thresholds for transmission suitability. Mtwara is the only district to demonstrate a reduction in infective bites of -11% (figure 5.18, table 5.13).

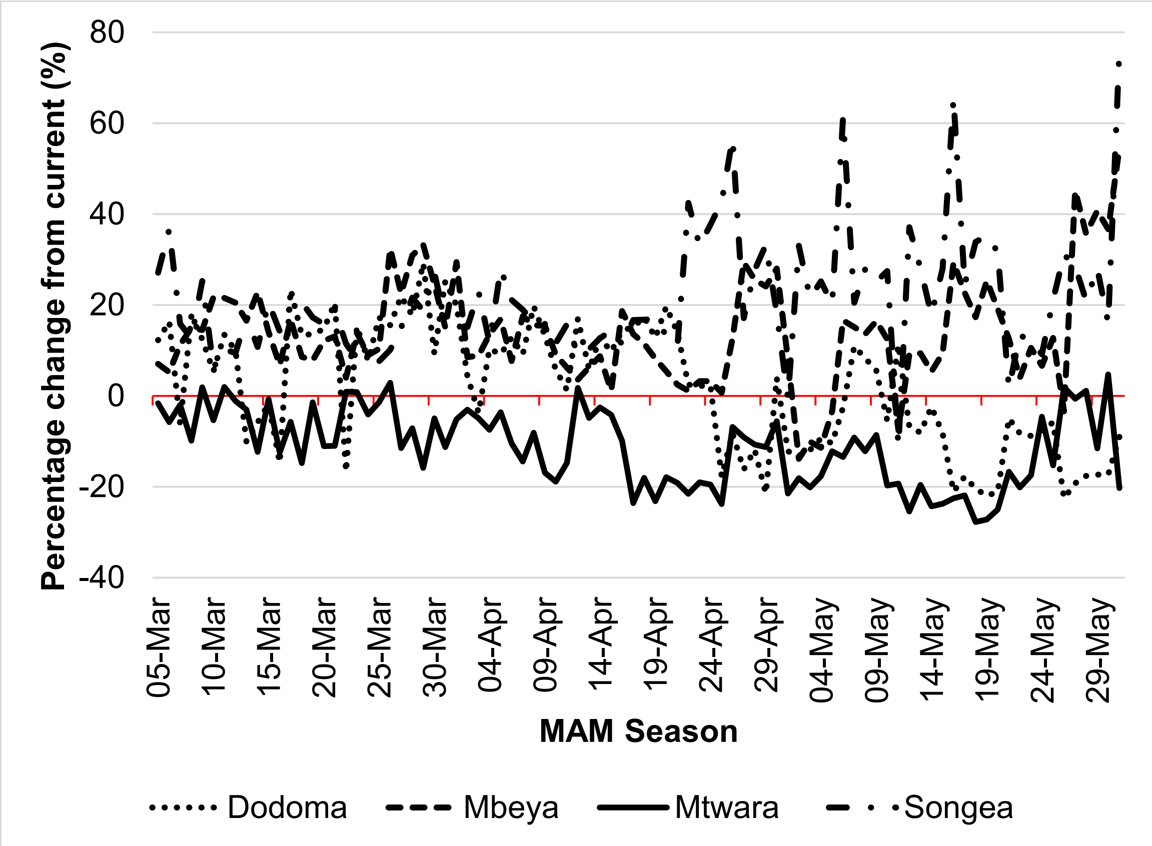


Figure 5.18 - Percentage change in mean entomological inoculation rate from current conditions in unimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.13 - Mean monthly percentage changes in entomological inoculation rates over the MAM season for each unimodal regime district.

	Dodoma	**Mbeya**	**Mtwara**	**Songea**
Average % Change	+2.12	+14.39	-10.98	+24.27

5.5.6 Prevalence

5.5.6.1 Bimodal

Modelled percentage change in prevalence (proportion of the human population which is infectious) indicates that the greatest percentage increase will be observed in Mwanza, increasing by an average of +9% over the MAM season, with the profile suggesting overall prevalence will increase throughout the season. Arusha demonstrates almost no overall change in prevalence at 1% increase with a reduction in the middle of the season (April). Dar es Salaam experiences a reduction in malaria prevalence of -24% (figure 5.19, table 5.14).

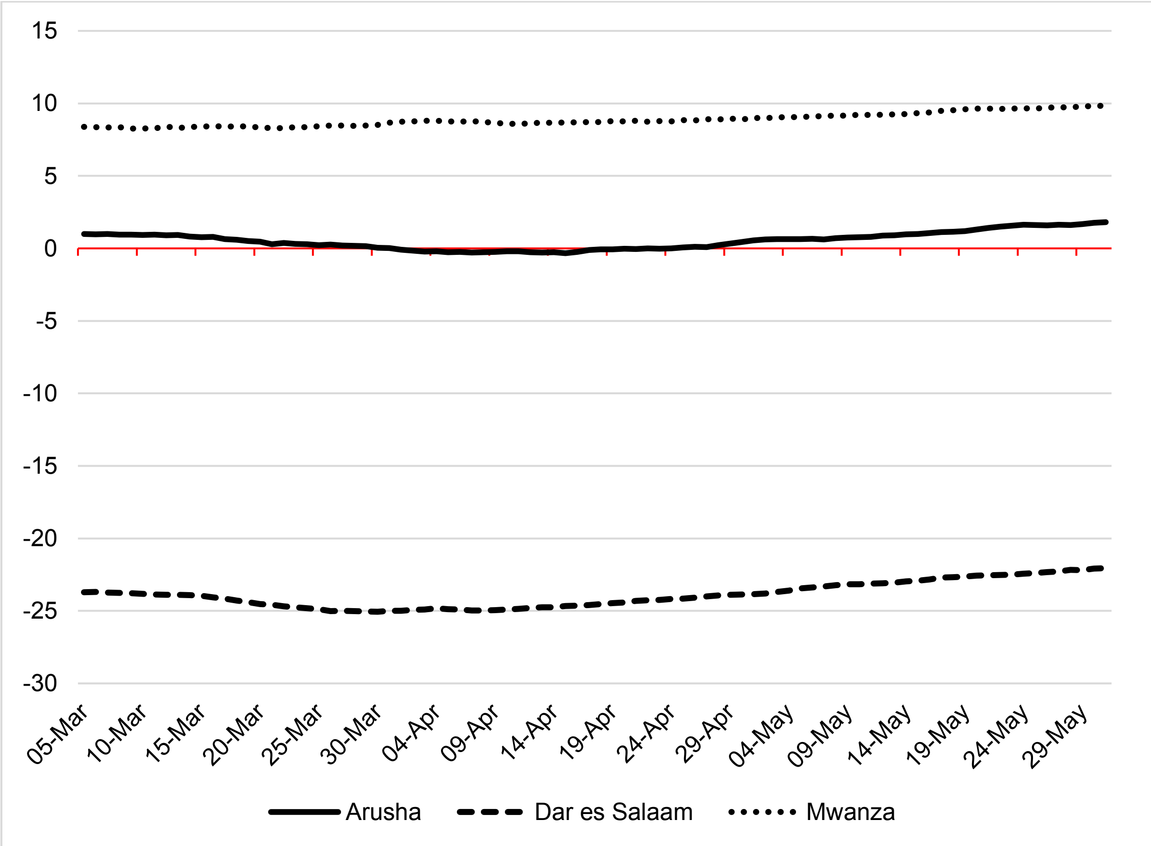


Figure 5.19 - Percentage change in mean prevalence from current conditions in bimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.14 - Mean monthly percentage changes in prevalence over the MAM season for each bimodal regime district.

	Arusha	**Dar es Salaam**	**Mwanza**
Average % Change	+0.58	-23.85	+8.88

5.5.7.2 Unimodal

Prevalence in the unimodal regime by region overall shows a reduction with the exception of Songea which demonstrates an average seasonal increase of +3%, which has an increasing trend throughout the season, starting at approximately current values at the beginning of March. Mtwara demonstrates the greatest decrease in prevalence at -17% which is observed to be consistent throughout the season. Dodoma shows the second greatest reduction of -13% followed by Mbeya with -2% where the profile demonstrates an increase to almost current prevalence levels by the end of the season in May (figure 5.20, table 5.15).

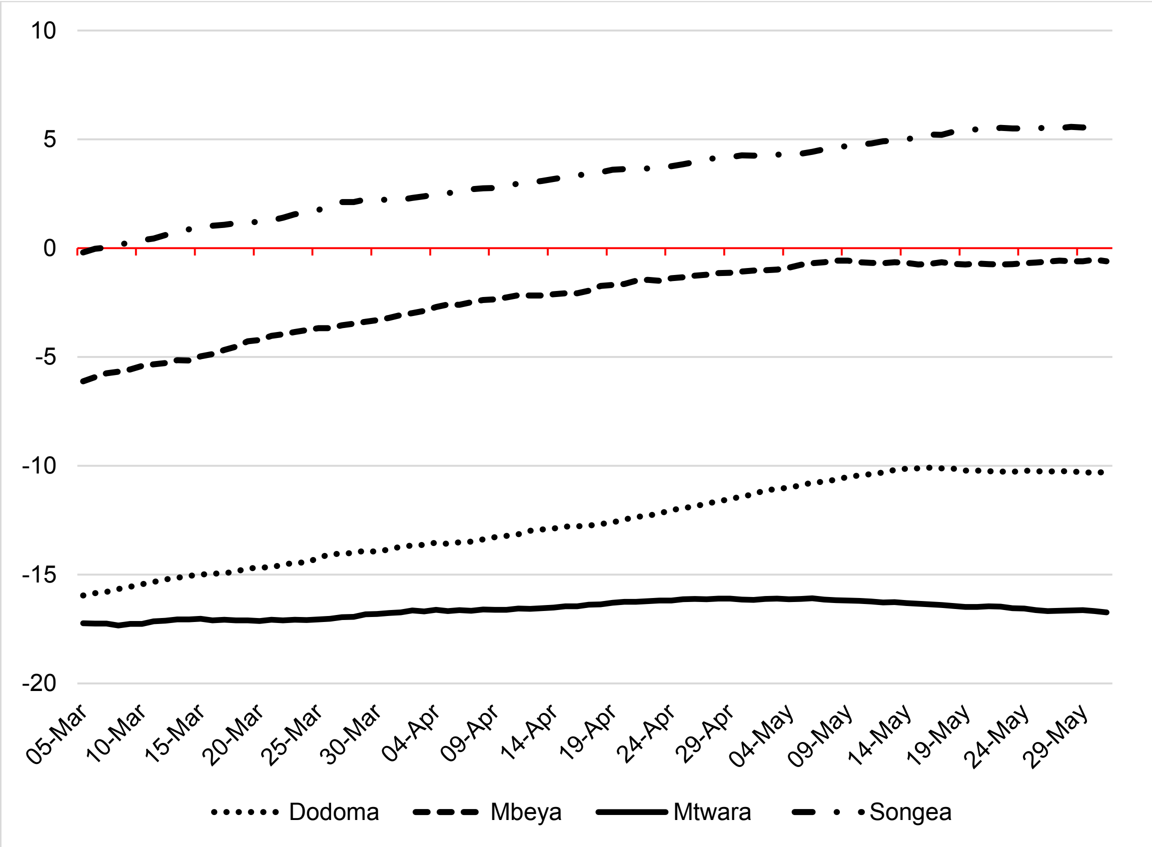


Figure 5.20 - Percentage change in mean prevalence from current conditions in unimodal districts (2006-2016) by 2070 under RCP 8.5.

Table 5.15 - Mean monthly percentage changes in prevalence over the MAM season for each unimodal regime district.

	Dodoma	**Mbeya**	**Mtwara**	**Songea**
Average % Change	-12.59	-2.36	-16.63	3.21

5.5.7 Summary of results

The LMM demonstrates a level of sensitivity to both temperature and precipitation which is accurately reflective of malaria prevalence (section 6.4.1 and 6.4.2). Results indicate greater sensitivity to temperature, based on the thresholds applied. This suggests that temperature is perhaps the greater limiting factor over rainfall in terms of model balance in calculating prevalence. Threshold decreases demonstrate a more arbitrary relationship than threshold increases, which retain seasonal peaks and troughs. Overall, the model demonstrates appropriate sensitivity considering the dataset being used in this analysis. This is discussed further in section 5.6.1.

Six biological indicators were examined for malaria during the MAM rainfall season under RCP 8.5 (2070). Results indicate that malaria EIR and prevalence demonstrate varied percentage change by location, and in cases opposing direction of change. EIR indicates the largest percentage increase in malaria will occur at Songea, with the largest percentage decrease being at Dar es Salaam. Prevalence indicates the largest percentage increase will occur at Mwanza with the largest percentage reduction occurring at Dar es Salaam. When compared to results from chapter four, the EIR results closely match the results from the developed malaria risk model. This is discussed further in section 5.6.2.

The largest contributing factors to changes in prevalence and EIR are unanimous percentage decreases in the time required to complete the sporogonic and gonotrophic cycles (table 6.16). The largest decreases occur for the sporogonic cycle, peaking at a 36.78% reduction in time for Mwanza and also Arusha. Peak reduction in gonotrophic cycle length also occurs in Mwanza, with a 15.42% of time taken. These results indicate increasingly optimum climate conditions for both gonotrophic and sporogonic process across Tanzania.

R_0 results indicate that the largest increases in new cases arising from a single case in a non-immune host population will occur in Songea (86.50%), Mwanza (81.86%) and Arusha (61.74%). Dodoma will experience a marginal increase (1.33%) where Dar es Salaam and Mtwara will experience reductions of -32.30% and -27.43% respectively. Survival probability reduces across all locations, with the greatest reduction observed in Dar es Salaam (-4.91%). This is likely due to temperature and rainfall conditions reducing in suitability for vector survival and transmission.

All percentage change results obtained for each epidemiological factor over the 3-month rainy season (MAM) are summarised in table 5.16. Malaria risk for each district highlighted in chapter four is also included and discussed in section 5.6. However, it is important to consider that the model operates on differing spatial scales to the ERA grids used here.

Table 5.16 - Summary of total percentage change (%) values and malaria risk obtained for chapter four over the MAM season for each district and factor by 2070 (RCP 8.5).

	Arusha	**Dar es Salaam**	**Dodoma**	**Mbeya**	**Mwanza**	**Mtwara**	**Songea**
Gonotrophic Cycle Length	-14.95	-13.75	-13.97	-14.46	-15.42	-13.68	-15.12
Sporogonic Cycle Length	-36.77	-29.22	-30.52	-32.14	-36.78	-29.11	-35.56
Basic Reproduction Rate	61.74	-32.30	1.33	49.67	81.86	-27.43	86.50
Survival Probability	-2.65	-4.91	-4.80	-2.79	-1.46	-4.57	-1.54
Entomological Inoculation Rate	9.56	-13.89	2.12	14.39	-4.93	-10.98	24.27
Prevalence	0.58	-23.85	-12.59	-2.36	8.88	-16.63	3.21
Chapter 4 environmental model: malaria risk	High Increase	High decrease	Medium increase	High increase	No change	High decrease	High increase

5.6 Discussion

Results presented in sections 5.4 and 5.5 are discussed within the wider body of literature and further work suggested.

5.6.1 Environmental predictors in epidemiological modelling

Model sensitivity to temperature and precipitation and the subsequent impacts on prevalence demonstrate realistic results when considered within the wider literature. It is well established that malaria presence and transmission is dependent on appropriate climatic conditions, where temperature plays a key role in development and survival stages (Mordecai et al., 2013; Drake and Beier, 2014). Sporogonic, gonotrophic and survival probability all possess varying temperature niches within which optimum development and vector survival takes place, factors of which are presented in table 5.4 and chapter two (Teklehaimanot et al., 2004; Emami et al., 2017). Studies have found a complex and non-linear relationship between rainfall and malaria, which is arguably reflected in the LMM sensitivity results (Jones et al., 2007).

Whilst the sensitivity of the model to temperature performs well, an interesting contrast in the profile between percentage increase and percentage decrease is observed. Increases in temperature appear to demonstrate a more reactive and emphasised response to peaks and troughs in the profiles, as mathematically expected. Although in areas, peaks and troughs in data are unusually matched and at the 75% decreased threshold an almost uniform sine wave is observed with almost none of the annual variability characteristics observed in the increased profile present. There is no obvious cause of this within the data, and as a result, it is speculated that perhaps there is a process within the LMM which means temperatures below malaria thresholds are treated in a default manner for such sine waves to form. This would require further investigation outside the scope of this study.

The LMM treats rainfall as an accumulation of the last ten days, as this is more important in relation to puddling and mosquito habitat provision (Hoshen and Morse, 2004). Sensitivity profiles shown in figure 5.8 suggest consistency with current knowledge with regards to rainfall, where percentage increase exhibits a maximum of 10% increase in prevalence, and reductions peaking at 25% reduction in prevalence. This is reflective of malaria transmission where an accumulated 10 day minimum of 10mm is able to sustain transmission in contrast to the previously applied 80mm (Tanser et al., 2003; Zhou et al., 2005; Usher, 2010). In comparison, there is no identified maximum threshold, although extremely heavy rainfall could impact larvae growth through washing away eggs, supporting limited observed improvement (Ermert et al., 2011, 2013).

5.6.2 Examining transmission potential and intensity

When examining overall changes in transmission intensity (EIR and prevalence) by 2070 (RCP 8.5), differing and inconsistent conclusions per district are drawn from the results obtained in this study, correlating with inconsistent conclusions from a malaria study conducted in West Africa which also examined EIR and prevalence changes (Yamana and Eltahir, 2013). It is important to consider that EIR is broadly considered a more direct measure of transmission intensity than the more traditionally adopted use of prevalence, although prevalence is more routinely used due to standardisation of procedure and reporting (Onori and Grab, 1980; Kelly-Hope and McKenzie, 2009). Furthermore, it is important to note that both of these factors and model do not account for changes in social policy, response and human behaviour and as such these results are purely based on environmental changes and are capable of reflecting future changes in malaria (Koella and Antia, 2003; Ermert et al., 2011).

Considering the above, EIR results for Tanzania suggest that Arusha will see a respective increase in transmission (10%) in EIR, whereas Mwanza will experience decrease in transmission (-4%) in EIR for 2070 (RCP 8.5) within the bimodal rainfall regime districts. Prevalence results, which also indicates transmission, demonstrate that for the same areas, Arusha shows little change (1%) whereas Mwanza will increase (9%). Both indicate Dar es Salaam will decrease by differing percentages. Similar instances of contrast can be seen in the unimodal regime districts where EIR for Dodoma, Mbeya and Songea increase by 2%, 14% and 24% respectively, compared to prevalence transmission changes of -13%, -2% and 3% respectively. Both indicate Mtwara will decrease by differing percentages. Interestingly, both prevalence and EIR indicate reductions in transmission for Dar es Salaam and Mtwara which are low elevation, coastal settlements in differing climate zones.

Prevalence and EIR results from the LMM provide the clearest indications that for low-lying, currently optimal locations, particularly for urban locations such as Dar es Salaam and Mtwara, transmission will reduce overall due to unfavourable environmental conditions (Caldas de Castro et al., 2004; Kabaria et al., 2016). Similarly, both anticipate a rise in transmission for the elevated district of Songea. Both support conclusions drawn for those areas from the risk model developed in chapter four (table 5.16). Dodoma, Mbeya and Mwanza demonstrate contrasting results due to the way in which each parameter evaluates transmission potential. EIR includes the vectoral capacity, which may be the key factor causing differing results in simulated transmission intensity. This is an aspect which could benefit from increased uniformity in EIR measures, as this conflicting information between two widely applied measures would not be beneficial for policy makers.

5.6.2.1. Contributory factors to changing transmission

The results presented in section 5.5 highlight the importance of monitoring multiple epidemiological variables enabling further consideration of changes in malaria transmission, where transmission indicators such as prevalence and EIR remain inconclusive or contradictory. Results for R_0, Sporogonic cycle length, Gonotrophic cycle length and survival probability are presented in table 5.16.

The greatest contributing factors to increasing malaria transmission are identified as the basic reproduction rate (R_0) and the sporogonic cycle length, both of which are observed to increase for all stations over the MAM season. High increases in sporogonic cycle rate are likely results of increasingly suitable temperature conditions where temperature thresholds for sporogony development are crossed by 2070 for RCP 8.5 (table 5.4), indicating faster parasite development (Teklehaimanot et al., 2004). This is associated with increasing R_0 where the number of secondary cases generated per infected human introduced to an otherwise susceptible population (Smith et al., 2007; Parham and Michael, 2010). Sporogony and R_0 are intrinsically related (figure 5.21), thus increases in both are likely to be related. Reductions observed for R_0 are more likely to be correlated with unsuitable temperature conditions for malaria vectors (Mordecai et al., 2013; Ryan et al., 2015).

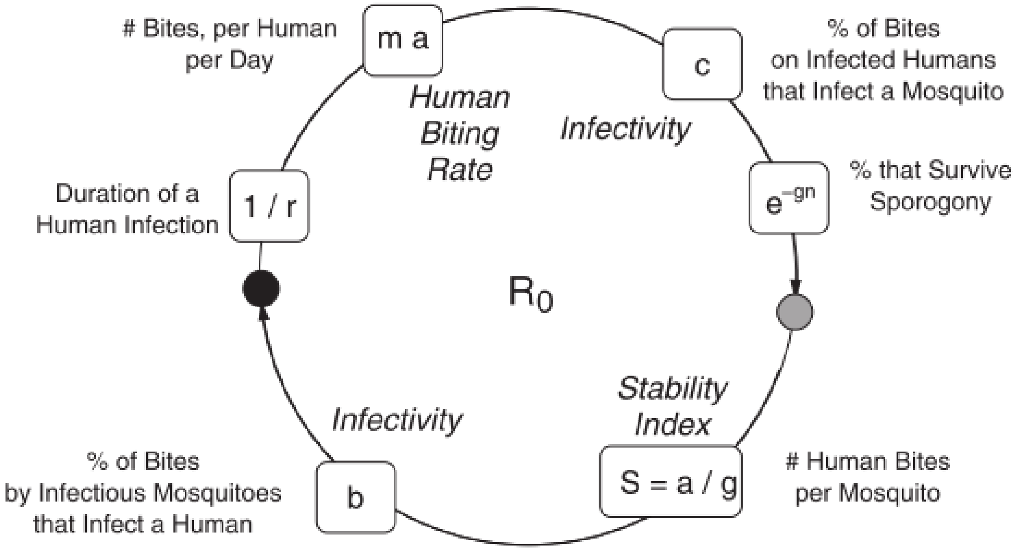


Figure 5.21 - The life cycle model and R_0. For further information see Smith et al. (2007).

Gonotrophic cycle length demonstrates unanimous percentage reductions, ranging from -13% to -16%. Causes of reduction are linked to those for sporogony, where temperatures are increasingly suitable for rapid development of mosquito eggs (Lardeux et al., 2008; Mordecai et al., 2013; Christiansen-Jucht et al., 2014). Precipitation plays an increasingly important role in the gonotrophic cycle compared to the sporogonic cycle, due to ovipositions (egg-laying) requiring bodies of water of approximately 0.5mm in depth (City Medical Office of Health (CMOH), 2005). Gonotrophic results indicate that water provision from rainfall is likely to be the limiting factor in gonotrophic percentage change, due to the profiles presented in figure 5.10 reducing towards the end of the MAM season, which is increasingly notable in the unimodal regime districts (WHO 2013c; Petrić et al., 2014).

Survival probability is modelled to unanimously reduce across all districts by 2070 (RCP 8.5) (table 5.16, figures 5.15 and 5.16). Malaria transmission is sensitive to changes in mosquito survival probability due to the requirement of the vector to survive long enough to complete both sporogonic and gonotrophic cycles in order for transmission to take place (Scott, 2002; Christiansen-Jucht et al., 2014). The observed results indicate that increased temperatures are likely to shorten survivability of mosquitoes (Patz et al., 1998; Kolivras, 2006). Despite survival probability reducing, the percentage reductions are comparatively minor when put into context with the observed reduction in both sporogonic and gonotrophic cycle length, which is further highlighted by increases in R_0 (Glass et al., 2000; Smith et al., 2007).

5.6.3 Future work

The RCP 8.5 pathway was highlighted for Tanzania as the most crucial to examine (section 5.3), and thus was investigated in this chapter. It would be beneficial for future research to examine the biological response to malaria factors under all RCP pathways to determine the degree of difference in impact between each RCP. Furthermore, this evidence could be used to support development of appropriate long term strategies to minimise the impact of malaria before potential modelled conditions for 2070 are observed. In addition, a more comprehensive comparison of these models compared to static risk models and seasonal forecasting models could prove beneficial in understanding the most crucial elements required for malaria simulation and modelling.

In addition to the recommendations above, it would be beneficial to further tailor and validate the LMM settings to better represent Tanzanian rainfall distribution and topography, with a view to examining key driving differences between East Africa and West Africa. Tailoring the LMM in this way would provide invaluable insight into the degree of difference (if any) in the way malaria operates in West Africa and East Africa, allowing for more accurate simulations and informing the development of other mathematical-biological models such as the VECTRI model and in turn more accurate simulations for East African countries (Tompkins and Ermert, 2013; Tompkins et al., 2015).

5.8 Conclusions

There is a clear case for continued use and improvement of mathematical-biological epidemiology models, where improvements in monitoring on the ground and recording of malaria epidemiological parameters for validation in countries such as Tanzania is paramount in developing models to be more reflective for East Africa. It is recognised that uniformity in standardisation of methods such as EIR could go a long way to improving the interpretation and use of epidemiological factors for decision making. Alongside this, there are a number of social, political and intervening factors impacting upon the development and accuracy of mathematical-biological models which are not currently incorporated (Koella and Antia, 2003). Despite these factors, the LMM arguably performs well in Tanzania.

Research conducted in this chapter has demonstrated using the LMM that malaria transmission during the MAM rainfall season in 2070 (RCP 8.5) for Tanzania is simulated to increase predominantly in elevated regions such as Arusha, Mwanza and Songea whilst coastal communities (Dar es Salaam, Mtwara) will see a reduction. Although results vary by epidemiological output used. Results further demonstrate that this reduction occurs at various stages in the malaria transmission cycle, where sporogonic and gonotrophic cycles contribute considerably to this notable reduction in time, further supporting R_0 (secondary transmission) leading to increased malaria transmission. Overall, rises in temperature would benefit malaria transmission in Tanzania, wth some offset occurring due to increased rates of mosquito desiccation in relation to temperature (2070, RCP 8.5).

Chapter 6 : Experimental Conclusions

This section concludes the main empirical findings, before presenting the wider implications for environmental disease modelling and considerations for policy inclusion discussed in chapter seven.

6.1 Addressing the overarching aims and objectives

This thesis set out to research the overarching aim which was: to develop a validated framework for the integration of environmental and biophysical information, to support health and disease decision making and risk-modelling, resulting from short and long-term climate change. This encompassed five research objectives:

1. Identify key climatic characteristics and features of Tanzania, including assessing sensitivity to El Niño events.
2. Develop an environmental malaria risk model to model current and future malaria risk in Tanzania.
3. Establish the performance and predictions of a climatologically driven, dynamic mathematical-model for Tanzania.
4. Assess the validity, accuracy and usefulness for prediction of change in disease distribution and transmission for Tanzania.
5. Discuss the potential impact of socioeconomic, cultural behaviours and malaria policies on environmental model predictions.

Table 6.1 illustrates the chapters within which each of these research objectives were met.

Table 6.1 – Chapters in the thesis where the research objectives were met.

Research Objective	**Chapters**
Identify key climatic characteristics and features of Tanzania, including assessing sensitivity to El Niño events.	2, 3
Develop an environmental malaria risk model to model current and future malaria risk in Tanzania.	2, 4
Establish the performance and predictions of a climatologically driven, dynamic mathematical-model for Tanzania.	2, 4, 5
Assess the validity, accuracy and usefulness for prediction of change in disease distribution and transmission for Tanzania.	4, 5, 7
Discuss the potential impact of socioeconomic, cultural behaviours and malaria policies on environmental model predictions.	2, 7
Chapter two: Literature Review Chapter three: Examining baseline climatological conditions and the effect on El Niño events on climate conditions in Tanzania. Chapter four: Current and projected environmental risk mapping of malaria. Chapter five: Examining changing malaria epidemiology by 2070s under the worst-case climate scenario (RCP 8.5) for Tanzania. Chapter six: Provide an overview of conclusions drawn from empirical research presented in chapters three, four and five. Chapter seven: Identifying social, economic and ecosystem components for improved health and disease management in Tanzania.	

6.2 Overarching summary and contribution to knowledge

Through addressing the research objectives presented in chapter one and recapped in section 6.1, this thesis has addressed gaps in knowledge which are highlighted in the systematic literature review presented in chapter two. Understanding in multidisciplinary theory across epidemiological modelling; climate and environmental relationships, disease dynamics and socioeconomic factors is contributed throughout. Contributions to epidemiological practice are made through the development of a uniquely weighted GIS based malaria risk model. Advances to malaria modelling are made through the inclusion of environmental variables not previously assessed in an epidemiological model. This further highlights the lack of knowledge surrounding the role of some environmental variables and climate dynamics, particularly for Tanzania, factors which have not been explicitly assessed before.

Research conducted in chapter three concludes that El Niño events cause statistically significant changes to local temperature, rainfall and absolute humidity throughout Tanzania. Changes vary across the country and by season and event. Results depict conditions suitable to alter malaria and vector based dynamics and seasonality during El Niño events, supporting conclusions from the literature identified in chapter two. Further to exploration of changes, an examination of current absolute humidity indicates that areas of south Tanzania (e.g. Mbeya) are theoretically suitable to sustain the transmission of bacterial meningitis from June through to October. Bacterial meningitis has only been recorded in the north of Tanzania to date. Suggested further research based on these results are presented in section 6.4. These results address research objective one.

Chapter four presents the development of a GIS weighted sum environmental risk malaria model for May, addressing research objectives two and four. The development of the model presents nine environmental variables which contribute to malaria risk. A hierarchy of the importance of environmental variables is presented; where vegetation, rainfall and temperature are identified as the most contributing factors with the remaining variables contributing to model accuracy. A hierarchy of environmental variable importance remains under debate within the literature. The developed model is accurately capable of simulating malaria prevalence throughout Tanzania for May ($r=0.8401$, $p<0.05$; $r^2=0.706$, $p<0.01$). Analysis of changing risk under climate scenarios concludes that overall, malaria risk will increase throughout Tanzania under most RCP scenarios with the exception of RCP 8.5 for 2050 and RCP 2.6 for 2070. The total population living in high risk areas also increases under all scenarios.

Chapter five examines changes in key biological components of malaria transmission under RCP 8.5 for 2070 using the LMM. This addresses research objectives three and four. Results conclude that for study locations used throughout Tanzania the greatest contributing factor to changing malaria dynamics are decreases in the time required to complete the sporogonic and gonotrophic cycles as a result of increasing temperatures. This does not equate to unanimous increases in malaria EIR and prevalence, and in places the two malaria indicators infer opposing change. EIR is still debated in the literature as the most reliable malaria transmission indicator and is a variable which the results from chapter four match the closest with regards to changes in malaria risk.

Chapter seven addresses research objective five through critically assessing the key impacts of socioeconomic, cultural and policy factors upon the epidemiological triangle. Results conclude that a number of socioeconomic and cultural factors in Tanzania at present contribute to the persisted prevalence of malaria. These factors are not captured in spatial epidemiological methods at present, largely due to an absence of data and difficulties with quantification of some parameters with regards to impact. Whilst policy support tools, e.g. MDAST have been developed for Tanzania, they lack the inclusion of environmental parameters and thus, faces a number of operational barriers. A considerable barrier to the development and widespread use of developed tools is the lack of a communication framework to translate scientific results into information to support policy and practice. The methodological inclusion of socioeconomic, cultural and policy data within a spatially explicit model is considered and further commented upon in section 6.4.

The results and theoretical considerations presented here were conducted with a view to addressing the overarching research aim: To develop a validated framework for the integration of environmental and biophysical information to support health and disease decision-making and risk modelling resulting from short and long-term climate change. This has been achieved through a combination of validated methods in analytical research, systematic research and environmental prediction modelling and has overall addressed gaps in the literature highlighted in chapter two. Addressing these gaps has provided new information upon which decision makers are able to further develop and apply prevention and risk management policy.

6.3 Limitations of the research

The use of climate and environmental modelling, statistical methods, GIS based techniques and use of geospatial data introduce inherent limitations. Data quality, where quality is defined as the degree of excellence, is a key aspect in modelling, whereby the quality of the data used in a model can have a profound impact on the output (Khormi and Kumar, 2015). This was addressed to some extent by sourcing data from reputable sources (e.g. Met Office, ECMWF) which use standardised methods and techniques of data collection and quality control. However, there are still some limitations in the quality of these datasets. With regards to meteorological data from the MIDAS project, removal of data outside of statistical bounds (4 x standard deviation) was applied to further ensure good quality data (Met Office, 2016a). In addition, data availability limited the inclusion of what is a standardised baseline climatology (30 years) which resulted in the use of a 10-year period to represent the baseline climate of Tanzania.

Assessing data at different spatial resolutions also introduces errors, for example comparing maps with finer detail to that of coarser detail can lead to invalid results (Dungan et al., 2002). This aspect influences chapter four, where spatial scales were different. This was addressed using a GIS method of nearest neighbour resampling to ensure the same spatial scale was attained for each dataset included in the study. The nearest neighbour method does have its own associated limitations but is a recognised method of resampling (Levine and Domany, 2000; Prashanth et al., 2009). Results should therefore be interpreted with awareness of the limitations of the processes involved. However, the value of the outputs out-weigh the limitations presented.

Mathematical assumptions and linear representation of non-linear processes introduce further limitations. Prediction of NDVI was based on a linear increase based upon NDVI change over a period of time, as presented in chapter four. This may be a simplistic and overestimated representation of potential NDVI change from current conditions to 2050 and 2070. Whilst there is no standardised method of representing NDVI change in association with climate change, this is being researched (Zhu et al., 2012; Clinton et al., 2014). However, the application of these methods would have required further work outside the scope of this research. Thus, to predict future risk using NDVI, the simplified method was applied.

6.4 Recommendations for further research

This section presents key recommendations for further research drawn from both empirical and systematic conclusions. Overall, it is recommended that interdisciplinary research in environment and health continues to be supported, particularly within the overarching relationships addressed within this thesis. Successful application of climate and environmental based epidemiological models in health policy requires an understanding of climate change, environment, disease biology and socio-economic interactions. A key aspect of this is to improve communication of information between the sectors, something which this thesis strongly recommends.

6.4.1 Recommendations for environmental epidemiological modelling

Tanzania's baseline climate variables such as rainfall, temperature and humidity is comparatively poorly examined within the scientific literature and requires further examination with regards to driving features and the impacts this has on local climates and environments. In addition, the impacts of El Niño on the global climate could also benefit from further analysis. Particularly considering that results presented in chapter three and section 6.2 demonstrate statistically significant changes as a result of El Niño events. However, no discernible relationship has yet been identified to aid policy makers. This is of increasing importance considering the role of extreme events in altering disease dynamics, particularly with regards to changing spatial distributions which results suggest could also impact bacterial meningitis and thus, should be explored.

It is highly recommended that analysis of climate and environmental variables beyond temperature and rainfall continue to be explored. Considering results presented in this thesis, variables such as NDVI, humidity and soil drainage remain poorly understood and underrepresented in epidemiological modelling despite demonstrable influence on the dynamics of malaria transmission. NDVI is increasingly influential as this aids in providing habitats and regulation for transmission vectors, which is further underpinned by soil drainage which controls the pooling of water for reproductive habitats. Humidity impacts on mosquito flight, however the relationship is not currently clear. Thus, these factors require further exploration despite the contributions made in this thesis.

Contributions to the advancement in understanding the role of environmental variables can be achieved through extending the scope and operation of the weighted GIS model developed in chapter four. Extending the model to annual operation and through extreme event years (e.g. El Niño) would contribute further understanding of the role and relationship of environmental variables in malaria risk and how this may change under climate change scenarios.

A key factor in the limitations of research (identified in 6.3) is the availability of data. It is recommended that improvements in the recording of clinical malaria data is a focus of collective bodies throughout developing countries. This data could provide valuable verification information for dynamic mathematical-biological models such as the LMM. Furthermore, it is recommended that this model be applied to a wider range of RCP scenarios to provide further indication of biological changes under differing climate scenarios.

6.4.2 Recommendations for socioeconomic, cultural and policy consideration

Initiatives to improve the quality and systematic collection of social data in developing countries are strongly recommended. The consistent and coherent collection of social and health data could lead to this information being included in spatially explicit epidemiological model as discussed in section 7.2.6. This incorporation of social and health data would allow for a more in depth analysis of relationships between environmental disease dynamics and social elements of disease dynamics which are introduced in section 7.2. An analysis of this nature would further benefit vulnerable populations through increased efficiency and reduction of costs with increasingly targeted campaigns based on model outputs.

The development of a global communications framework between policymakers, health professionals and researchers is also strongly recommended. Whilst frameworks currently exist as introduced in section 1.2.3 these do not appear to be implemented in all cases. Based on examination of the MDAST project (section 7.2.5), stakeholders play a considerable role in the development of policy and decision making tools, with concern that they are overly influential in the policy development process. Developing a framework to allow for a more moderated evidence to stakeholder ratio in policy development would benefit developed models, their implementation and subsequent decisions.

Chapter 7 : Identifying social, economic and ecosystem components for improved health and disease management in Tanzania.

7.1 Introduction

Malaria remains a major public health concern for Tanzania, where 100% of the population (50,400,000) live in what is classified by the WHO as high malaria transmission areas, although malaria prevalence varies by region and district (NBS, 2011; MoHSW, 2015; WHO, 2015c). A total of 678,207 malaria *Plasmodium falciparum* cases were reported in 2015, resulting in 5368 deaths, placing Tanzania as one of the top countries accounting for the global malaria burden (figure 7.1) (WHO, 2015c). When 2015 health statistics are placed in the context of recent survey trends (2000-2014, figure 7.2) the complexities of tackling and quantifying malaria in Tanzania become increasingly apparent. In particular, the misreporting of data and changes in health service accessibility and diagnostic testing have impacted upon official recordings, disrupting signals from socioeconomic variables and implemented policy changes (NBS, 2011; WHO, 2015c).

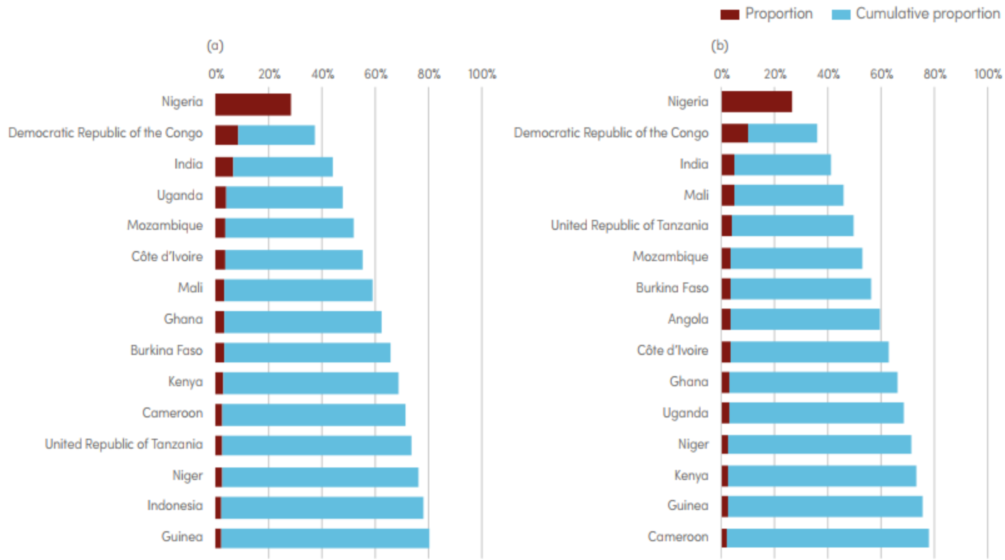


Figure 7.1 - Estimated proportion, and cumulative proportion of the global number of (a) malaria cases and (b) malaria deaths in 2015 for countries accounting for the highest share of the malaria disease burden *(WHO, 2015c)*.

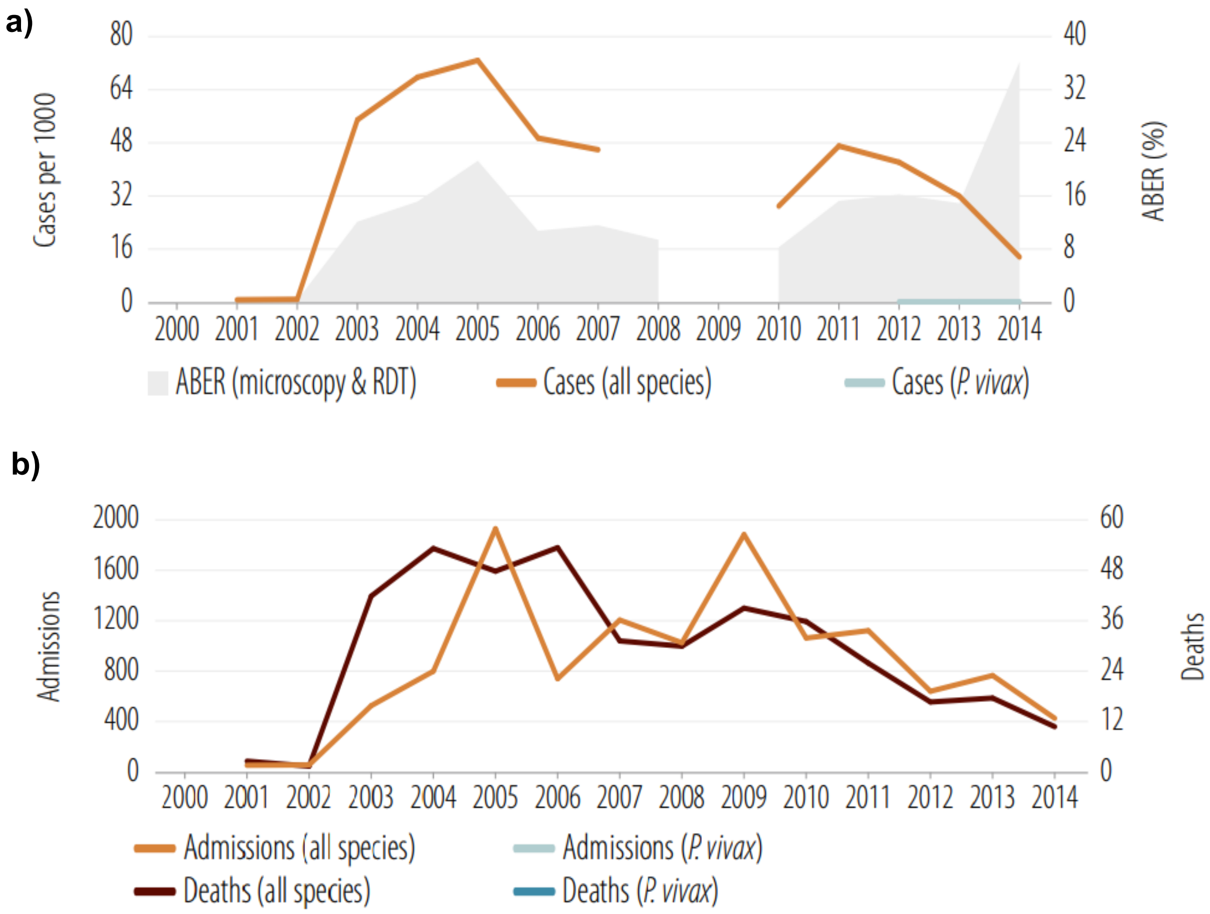


Figure 7.2 - a) Confirmed malaria cases per 1000 and ABER (treatment) since 2000 for United Republic of Tanzania (Mainland b) malaria admissions and deaths (per 1,000,0000) *(WHO, 2015c)*.

Inconsistencies in reporting throughout Tanzania can be attributed to complex socioeconomic, political and major policy changes since 2000. This includes modernising national guidelines for malaria diagnosis and treatment, changes in distributed malaria drugs as a result of malaria resistance, distribution of insecticide treated nets (ITNs) from 2004 onwards, as well as targeted voucher schemes for long-lasting insecticidal nets (LLINs) (MoHSW, 2006; Kramer et al., 2017). This initiative was launched in 2009, the impacts of which could be the cause of a reduction in malaria admissions from 2010 onwards (figure 7.2b). Furthermore, these policies have faced, and continue to face challenges from largely unpredictable countrywide socioeconomic and sociocultural conditions (Oberlander and Elverdan, 2000; Mtenga et al., 2016; Suk, 2016). Whilst the implemented changes have overall led to an apparent decline in malaria, it continues to undermine local health and the socio-economic development, particularly in rural communities, highlighting the need to strengthen intervention, data collection, surveillance and malaria prediction efforts going forward (Mutero et al., 2014; Mlozi et al., 2015; Shayo et al., 2015).

7.1.1 Aims and objectives

This chapter addresses research objectives four and five. Firstly, the role of non-physical socioeconomic and population determinants of disease, presented in chapter two, will be discussed in the context of how these individual behaviours and circumstances further modify the relationships observed within the epidemiological triangle, introduced in chapter one. Secondly, planned changes in using socioeconomic data to further guide policy development and considerations surrounding the non-physical elements of epidemiology, alongside projected social and demographic changes will be discussed. This will be reinforced using a case study, the Malaria Decision Analysis Support Tool (MDAST). Finally, conclusions drawn from this chapter will be presented. Overall contributions to knowledge and recommendations are presented in sections 6.2 and 6.4.

7.2 The impact of socio-economic, demographic and policy determinants impacting epidemiology

Current socio-economic, demographic and policy determinants impacting malaria prevalence were presented in chapter two. The impact of each of these determinants has a complex relationship with the epidemiological triangle, and thus environmental models, a key focus of this thesis, introduced in chapter one. Considering the complex relationships between socioeconomic, policy and environment presented in chapter two, a diagram has been created and presented in figures 7.3 and figure 7.4 to frame the interrelationships between these variables and epidemiology. This outlines whether a policy or social conditions has a positive, negative or dependent (circumstantial) impact on key variables within the epidemiological triangle. Changes within these individual impacts and the influence on interpreting environmental model results will be presented here, and discussed within the context of this diagram, where changes in circumstance or policy approach could yield positive or negative impacts.

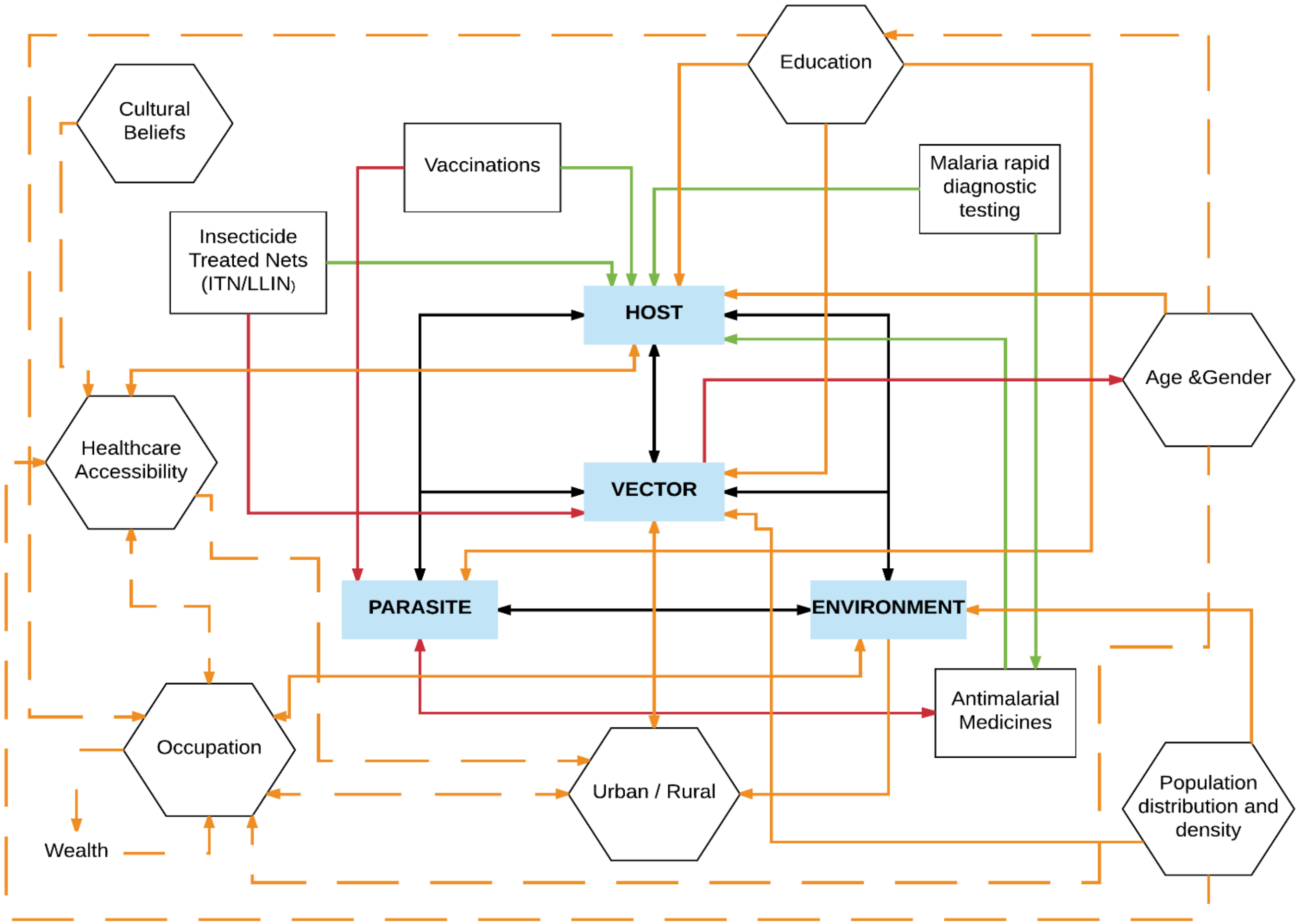


Figure 7.3 - Interactions between socioeconomic, cultural, policy and malaria prevention variables and the epidemiological triangle.

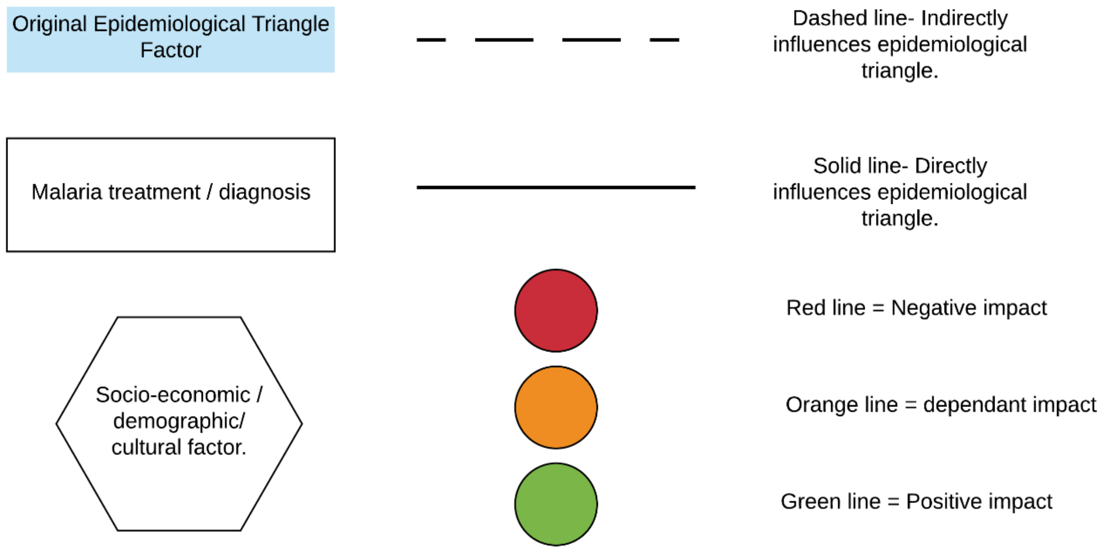


Figure 7.4 - Legend for figure 7.3.

7.2.1 Projected changes in social, economic and population factors

This section will discuss the likely direction of change and impact upon the epidemiological triangle from the socio-economic, demographic and cultural factors, coupled with malaria treatment and diagnosis outlined in figure 7.3, providing an indication of whether changes will have positive or negative impacts. Not all potential scenarios are discussed, however, the most significant will be addressed.

7.2.1.1 Population growth and distribution

Population location and density play an important role in malaria dynamics and funding decisions for malaria treatment and prevention (Hagenlocher and Castro, 2015). The Tanzanian population has grown considerably since initial censuses were carried out in 1967, recording a population of 12.3 million at the time (NBS, 2011). As of 2015, population is estimated to be 48.8 million by the NBS, although UNDEP estimates are slightly higher at 53.8 million (UNDEP, 2017). Population projections estimate that by 2050, Tanzania is predicted to be the 14th largest population globally with 137 million people, and 6th largest by 2100 with 299 million people (Melorose et al., 2015).

This level of population growth will be accompanied by considerable urban growth alongside increasing population density in key townships. Dar es Salaam was once a small township, but went through a period of rapid expansion due to economic growth, becoming the most densely populated region in Tanzania to date (3,133 people per sq. km) (Barke and Sowden, 1992; Briggs, 1993; NBS, 2013b). Other localities within Tanzania have also begun to follow this same route such as Arusha, Mtwara and Mwanza, where change is driven by a number of factors including local resources, connectivity and economic growth (Linard et al., 2012).

Areas of high population density are associated with dense urban structures which have been demonstrated to reduce habitat suitability for malaria transmission vectors through reduction of breeding sites (Caldas de Castro et al., 2004; Kabaria et al., 2016). This is further supported through experimental work conducted in chapter four. Thus, based on current knowledge township expansion would grow in accordance with projected population growth, resulting in a change in land use which is unsuitable for supporting the mosquito lifecycle, overall reducing the likelihood of malaria transmission, and having a positive impact on the health of the human host (Gwitira et al., 2015; Wilson et al., 2015).

In contrast, if population growth occurred via an expansion of peri-urban areas rather than through the growth of dense urban areas, then malaria transmission is likely to persist, as peri-urban areas are defined as transitional zones between urban and rural, with heightened transmission compared to dense urban areas (Caldas de Castro et al., 2004). This is supported by model results presented in chapter four, as well as Kabaria et al., (2016) and Wilson et al., (2015). This is something town planners and health officials must consider in accordance with population growth, although increasing research is needed on neighbourhood scales and urban to peri-urban transitions (Wilson et al., 2015).

At present, health facility distribution is calculated based upon population density and locality. How this will alter with future population growth will be addressed in section 7.2.1.3 where access to healthcare is discussed.

Key impacts on the epidemiological triangle from population growth and distribution include:

- Expansion of dense urban area with population growth would aid in reducing transmission (negative impact on vector).
- Expansion of peri-urban area would support continued malaria transmission (positive impact on epidemiological triangle: environment)
- Population growth would support continued malaria transmission through increased provision of host (positive impact on epidemiological triangle: host)
- Growth of rural villages into townships would see sustained malaria transmission until their density is high enough to have a negative impact upon malaria transmission.

7.2.1.2 Economic growth and occupation

Economics play a key role in shaping population distribution, occupation and family/individual wealth, which further impacts on access to healthcare (discussed in section 7.2.1.3) and plays a role in impacting epidemiology as indicated in figure 7.3. Economic growth is largely responsible for the expansion of Dar es Salaam, attracting many who once lived in rural communities, becoming the present day international hub for Tanzania and connecting towns (Paavola, 2008).

Current indicators of poverty (food poverty line and basic needs poverty line, shown in table 7.1) indicate that conditions improved between 2007 and 2012 in Tanzania, although a high percentage of residents remain below the basic needs poverty line, predominantly in rural areas (NBS, 2016). Based on current rates of reduction, it would take approximately 23 years to reduce the total percentage of population below the basic needs poverty line down to zero percent at a sustained pace.

Table 7.1 - Changes in poverty indicators between 2007 and 2011/12 (NBS, 2016).

Year	**Region**	**% of Population below Food Poverty line.**	**% of Population below Basic Needs Poverty line**	**% of Female Headed Households**
2007	Dar es Salaam	3.2	14.1	24.4
	Other Urban	8.9	22.7	30.1
	Rural	13.5	39.4	23.0
	Total	**11.8**	**34.4**	**24.5**
2011/12	Dar es Salaam	1.0	4.1	22.5
	Other Urban	8.7	21.7	27.6
	Rural	11.3	33.3	24.3
	Total	**9.7**	**28.2**	**24.7**

Tanzania is appearing to enter a phase of industrial and economic development whereby tertiary activities (e.g. trade, information, communication and others) have overtaken primary activities (agriculture and mining) as the largest contributor to GDP (figure 7.5) (NBS, 2016). However, the largest employer within the country is the agriculture and industrialisation sectors, employing 65% of people (Agwanda and Amani, 2014; Deloitte, 2017). This sector has one of the lowest minimum wages of non-government minimum wages in Tanzania (100,000 TZS), manufacturing wages are not reported (NBS, 2016). The industrialisation of Tanzania is centred on processing of agricultural foods, where by 2050, Tanzania aims to have at least 40% of the GDP contributed by the manufacturing sector, which is already being seen in recent surveys (Ministry of Energy and Minerals, 2009; Deloitte, 2017).

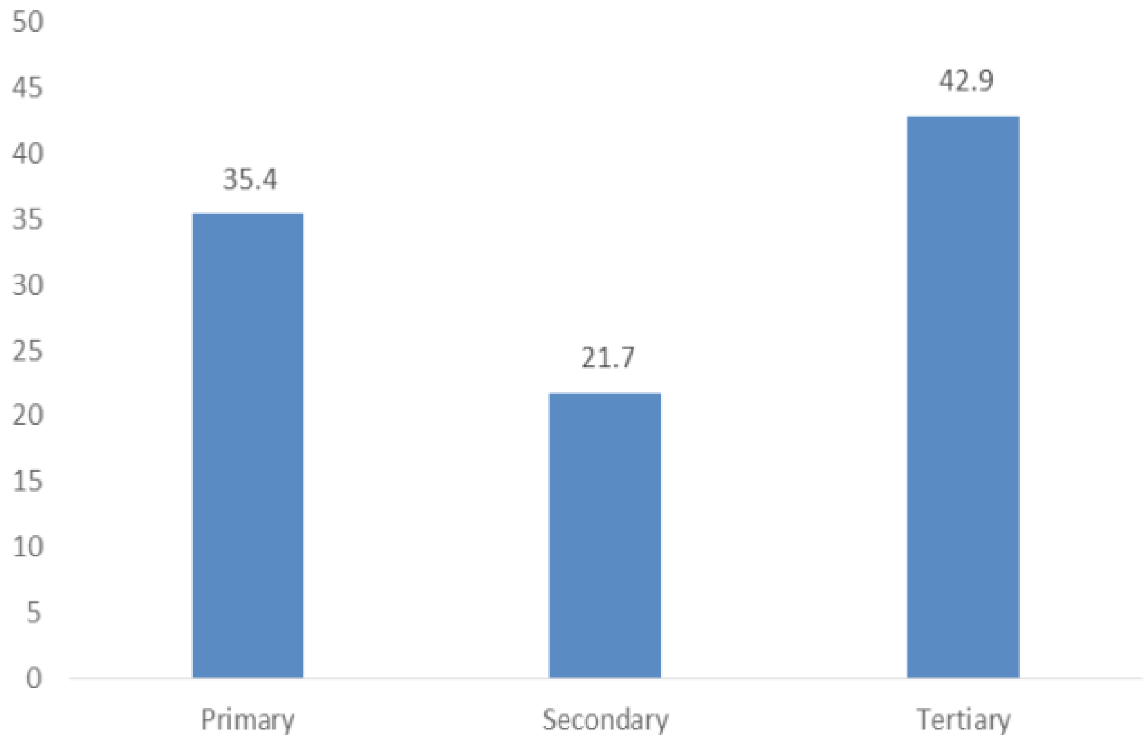


Figure 7.5 - Percentage share of GDP at current prices for Tanzania Mainland, 2015. Primary activity involves Agriculture and Mining. Secondary activity involves manufacturing, electricity, gas and water. Tertiary activity includes services like wholesale trade, retail trade, information, communication and others.

Considering the information presented within this section and projected population growth; manufacturing and the agricultural sector will retain importance for the foreseeable future, prompting populations to stay in agriculture and thus, high transmission rural locations. This will sustain presence of the working-poor, which is common amongst farming communities, contributing to the continued spread of malaria through surrounding habitat, occupation and inaccessibility to healthcare which was outlined in chapter two (Mboera et al., 2010; Mayala et al., 2015). Further instability to farming communities is predicted through the impacts of climate change on crop growth, leading to poor harvests across areas of sub-Saharan Africa. This will add further instability to farming communities and exacerbate the spread of diseases, with increasing influence on the epidemiological triangle and persons in high risk demographics (Putterman and Island, 2000; Ahmed et al., 2011; Shayo et al., 2015).

Models centred around examining the impact of climate change on agriculture do not currently reach a consensus on the future of Tanzania. Some models suggest improvements in rural conditions, reducing poverty; where some extreme scenarios indicate that as many as 90,000 more people could enter into economic poverty (Ahmed et al., 2011; Agwanda and Amani, 2014). In contrast, economic migrants who move to peri-urban and urban locations for higher paying tertiary roles are likely to experience an overall reduction in malaria risk, which is to some extent offset by healthcare affordability and less impacted by climate change than agricultural sectors. This is largely dependent on the improvements of malaria control and habitat provision in peri-urban areas and the occupations of residents.

In addition, Tanzania is heavily reliant on support from external countries (Deloitte, 2017). Should this support cease, with Tanzania having no way to replace these funds, there may be an overall negative impact on health and malaria transmission.

Key impacts on the epidemiological triangle from economy and occupation:

- Increased wealth from tertiary sectors would have a negative impact on the epidemiological triangle. Thus, reducing malaria through increasing affordability of healthcare.
- Sustained mass agricultural work would have a positive impact on the epidemiological triangle, where host provision would remain high in high transmission locations.
- Economic migrants will have a dependant response, based on the location where residents seek work (see section 7.2.1.1) and occupation.

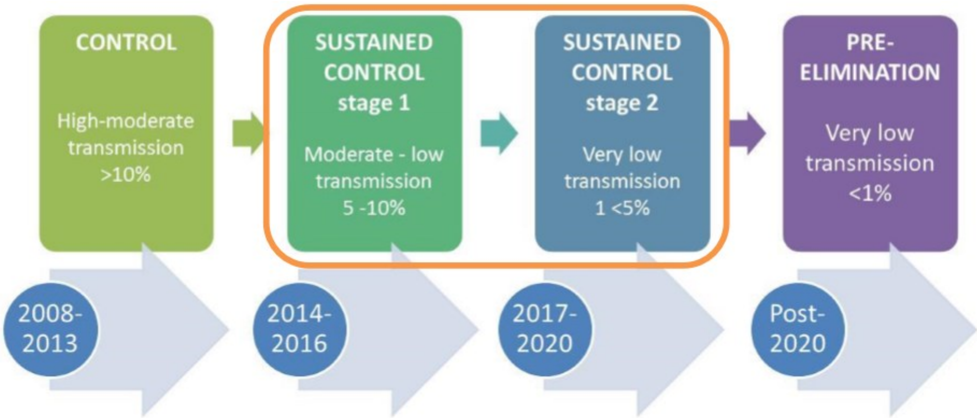
7.2.1.3 Access to healthcare, and malaria prevention and treatment

Whilst there have been significant improvements in tackling malaria, it remains the leading cause of morbidity and mortality in women and children under five in Tanzania, highlighting the need for continued efforts (MoHSW, 2013b). The MoHSW recognises Tanzania needs to move away from only implementing malaria control and into a pre-elimination phase, placing increased emphasis on improving malaria surveillance (MoHSW, 2013b). The aim for the current national malaria five year strategic plan (2014-2020) is to reduce malaria prevalence to 1% by 2020 (MoHSW, 2013b). This is to be achieved by building upon previous multi-stakeholder successes, focusing on strategic malaria control phases and strategies (figure 7.6a and b) and over-arching strategic objectives listed below (MoHSW, 2013b):

- Scaling up and maintaining efficient vector control.
- Promote universal access to appropriate early diagnosis and prompt treatment.

- Create an enabling environment where individuals and household members are empowered to minimize their own malaria risk and seek treatment if and when needed.
- Provide timely and relevant information to assess progress towards the set global and national targets.
- Ensure effective programmatic and financial management of malaria control interventions at all levels.

a)



b)

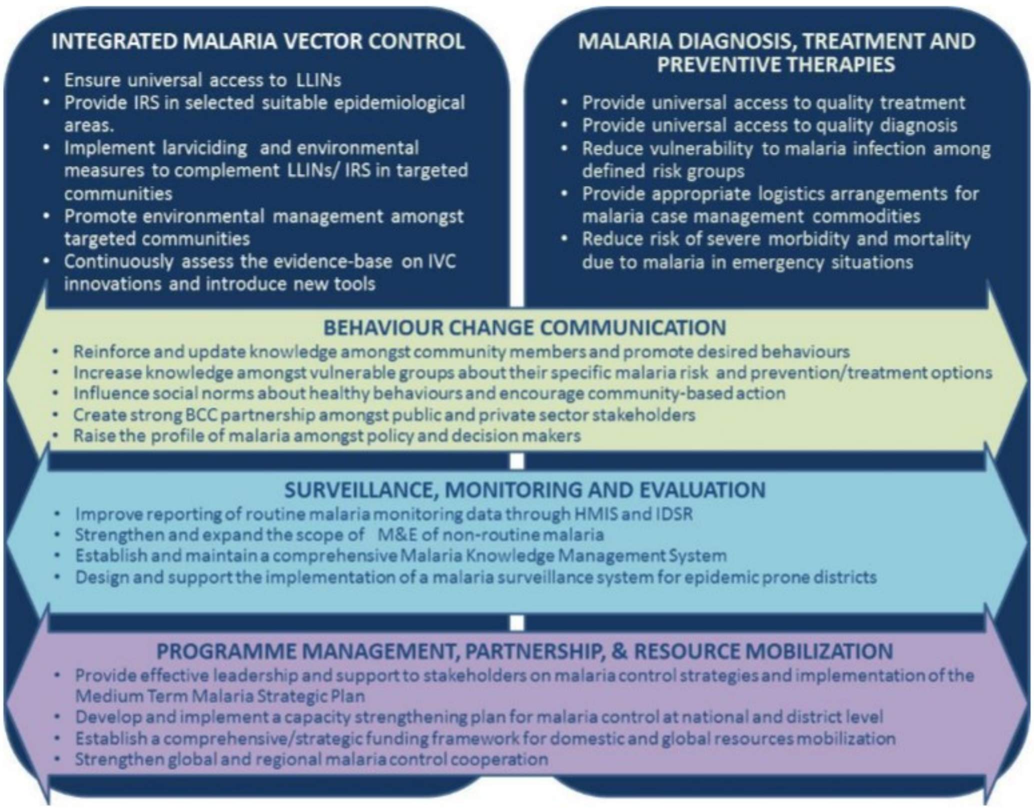


Figure 7.6 - a) malaria control phases and timelines in Tanzania b) Overview of malaria strategies (MoHSW, 2013b).

Assuming the Tanzanian malaria programme achieves its aims and objectives, this would result in an overall negative effect on the epidemiological triangle through health interventions, as shown in figure 7.3, by reducing the ability for the vector to transmit the parasite to the host (human), resulting in a positive impact on the host. However, population growth and expansion will need to be accounted for. At present, healthcare facility distribution is based predominantly on population density and distribution, as presented in chapter two. As populations grow Tanzania must allocate enough resources to continue to fund growing surveillance and prevention programmes alongside providing healthcare facilities to administer malaria treatment. If this is not managed properly, there will be spatial gaps in treatment coverage which will have a positive effect on the epidemiological triangle and will continue to support malaria transmission. Should this occur, gaps are likely to be in rural regions, where malaria risk is high and health facility coverage is low.

The requirement for increased health facilities could lead to an increase in private clinics to meet healthcare facility needs where government spending cannot afford cover. Should increases in private clinics locate in expanding rural districts due to population growth, this could lead to an imbalance of high-cost treatments in low-wage locations, which would reduce access to healthcare for high risk patients and support malaria spread, having an overall positive effect on the epidemiological triangle. This strongly links to economic and population growth, covered in sections 7.2.1.1 and 7.2.1.2, which further highlights the complexities of socio-economic interactions.

Key impacts on the epidemiological triangle from population growth and distribution include:

- Increases in private clinics in rural locations will have a positive effect on the epidemiological triangle, increasing malaria prevalence.

- Increases in current policy coverage (and introduction of new policy, e.g. vaccines) will have a negative effect on the epidemiological triangle, reducing malaria prevalence.
- Increases in surveillance methods would have a negative effect on the epidemiological triangle, reducing malaria prevalence.

7.2.1.4 Education, Age and Gender issues

Chapter two highlighted the biological vulnerability of women and children to mosquitoes and the subsequent malaria parasite. It is important to emphasise that this factor will remain constant for the foreseeable future, unless genetically modified mosquitoes are developed with a view to reducing this biological behaviour. This presents a danger in impacting ecological balances which is not discussed further here (Beisel and Boete, 2013; Alphey, 2014). Overall, this has a positive effect on the epidemiological triangle.

Low education attainment has been linked to lower levels of malaria knowledge, contributing to heightened risk of contracting malaria (Hagenlocher and Castro, 2015). Initiatives being implemented at present aim to increase access to education for both male and females, alongside increasing malaria awareness initiatives (Williams and Jones, 2004; NBS, 2011). Increases in education surrounding malaria dynamics coupled with education on prevention methods and guidance to access treatment, will have an overall negative impact on the epidemiological triangle through increased awareness and thus preventative measures being taken to avoid being bitten by transmission vectors.

Women currently face major disadvantages stemming from historic culture in Tanzania. Gender equality is becoming increasingly supported within Tanzania as presented in chapter two. As gender equality grows, this in theory, should eliminate some of the barriers faced by women in terms of access to healthcare and malaria prevention methods and treatments, particularly when pregnant. As these barriers are reduced, and healthcare and education accessibility increased, this will have a negative impact on the epidemiological triangle and reduce malaria transmission through increased protection and knowledge of the factors contributing to malaria transmission.

Key impacts on the epidemiological triangle from population growth and distribution include:

- Increased education for both males and females would have a negative impact on the epidemiological triangle, reducing malaria prevalence.
- Women and children would remain biologically vulnerable to malaria, sustaining malaria prevalence.
- Increases in gender equality would have a negative impact on the epidemiological triangle, reducing malaria prevalence.

7.2.3 Developments in malaria treatment: Vaccinations

New methods for treatment of malaria will play a role in the changing shape of malaria distribution in future. Vaccination for malaria treatment and prevention has been researched for the past 50 years, although the complexity of *Plasmodium falciparum* has provided an unprecedented challenge in vaccine development (Halloran et al., 1989, 1991; Lyke, 2017). A variety of stages within the malaria lifecycle have been targeted by vaccination developers outlined in table 7.2 and figure 7.7. The most successful vaccination to date, reaching phase 3 of medical trials, is the RTS,S/AS01E vaccination. Trials indicate initial success in offering malaria protection, however results were offset by rebound in areas with higher than average exposure to malaria parasites, a factor which was identified in early 1990's vaccine models, to which solutions are being actively explored (Halloran et al., 1989; Olotu et al., 2016; Penny et al., 2016).

Increased likelihood for a pre-erythrocytic malaria vaccine within the next decade has prompted examination of introducing RTS,S/AS01E into Tanzanian policy, alongside further modelling of the demographic impact and cost-effectiveness of RTS,S/AS01E (Penny et al., 2016; Romore et al., 2016; Lyke, 2017). Modelled impacts indicate a significant public health impact and high cost effectiveness of the RTS,S/AS01 vaccine across a range of prevalence settings, provided that appropriate policy can be delivered and crucially, that finance and the capacity within the health system to deliver the vaccine is available (Halloran et al., 1991; Penny et al., 2016). Malaria policy adoption in Tanzania often takes years, Romore et al. (2016) has developed a potential policy framework, reducing the time needed to introduce vaccination into Tanzanian policy. Further limitations include the necessity of consistent, low temperature storage to keep vaccines active and useable (Hunter, 1989). Rural Tanzania has mixed access to electricity which may cause problems for rural dispensaries although electricity provision is improving with the introduction of electricity co-operatives (Ilskog et al., 2005).

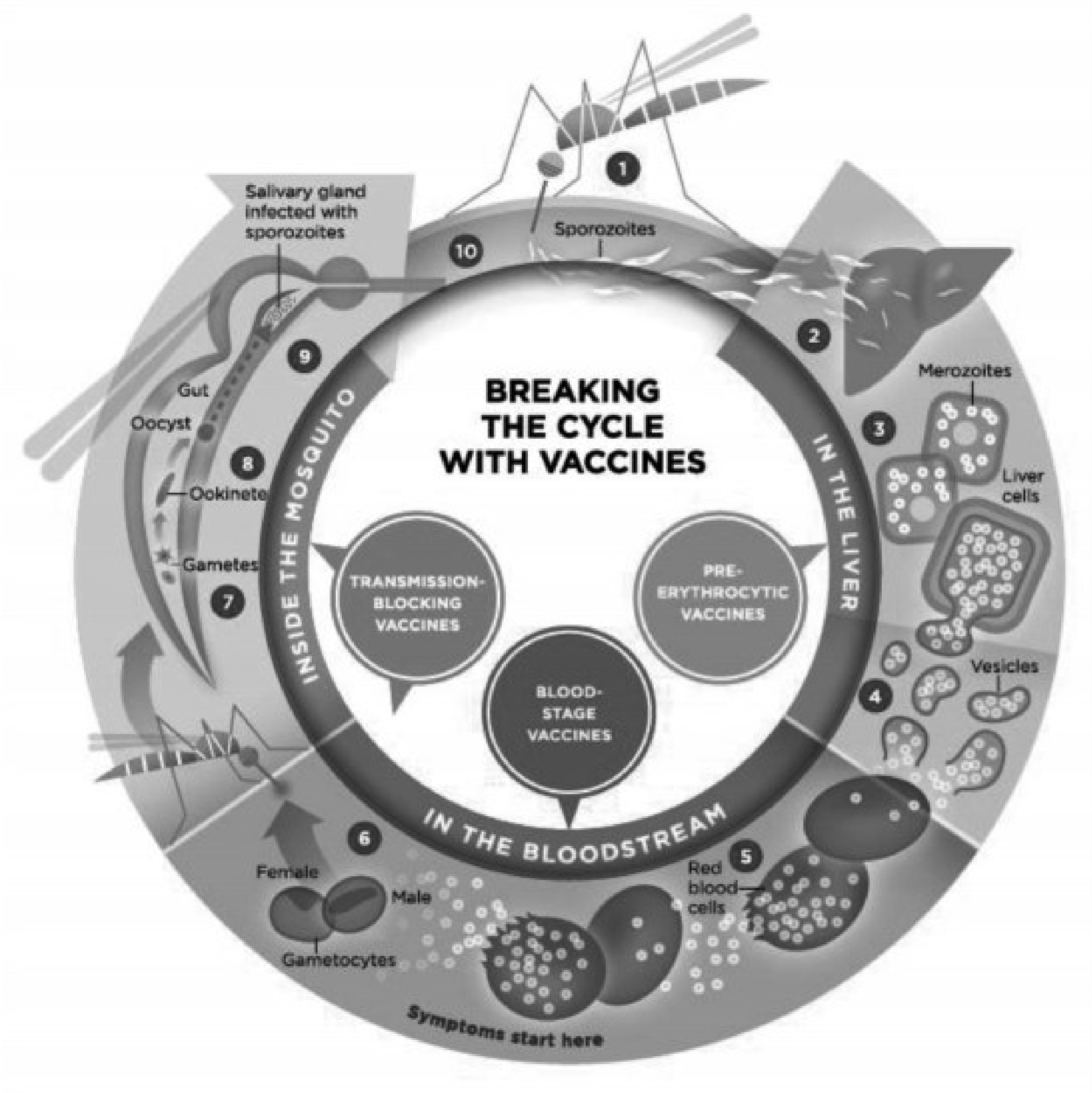


Figure 7.7 - The malaria life cycle broken down by potential vaccine stages (Lyke, 2017).

Table 7.2 - Clinical stage candidate malaria vaccines broken down by stages (Lyke, 2017)

Candidate vaccine	Phase achieved	Sponsor
Preerythrocytic vaccines		
RTS,S/AS01E	Phase 3	GlaxoSmithKline, Belgium
RTS,S/AS01E delayed fractional third dose	Phase 2a	GlaxoSmithKline, Belgium
ChAd63 / MVA ME-TRAP	Phase 2b	University of Oxford (UK)
ChAd63 / MVA ME-TRAP / Matrix M	Phase 1a	University of Oxford (UK)
PfSPZ vaccine	Phase 2b	Sanaria Inc.
PfCelTOS FMP013	Phase 1a	Office of the Surgeon General, Department of the Army USAMRMC
CSVAC	Phase 1a	University of Oxford (UK)
R21 / AS01B	Phase 1a	University of Oxford (UK)
R21 / Matrix-M1	Phase 1b	University of Oxford (UK)
Adjuv R21 (RTS,S-biosimilar) + ChAd/MVA ME-TRAP	Phase 1a	University of Oxford (UK)
Blood-stage vaccines		
GMZ2 (GLURP+MSP3) / Alhydrogel	Phase 2b	European Vaccine Initiative, AMANET, Statens Serum Institute
PfAMA1-DiCo/GLA-SE or Alhydrogel	Phase 1b	Inserm (France)
P27A/GLA-SE or Alhydrogel	Phase 1b	Centre Hospitalier Universitaire Vaudois (CHUV)
MSP3/Alhydrogel	Phase 2b	Europena Vaccine Initiative, AMANET
SE36/AIOH	Phase 1b	Research Foundation for Microbial Diseases of Osaka University, Japan
PfPEBS/AIOH	Phase 1b	Vac4All
ChAd63 RH5 +/- MVA RH5	Phase 1a	University of Oxford (UK)

PRIMVAC/GLA-SE or Alhydrogel	Phase 1b	Inserm (France)
PAMVAC/GLA-SE, GLA-LSQ or Alhydrogel	Phase 1b	University Hospital Tuebeingen (Germany)
Sexual stage		
Pfs25 VLP/Alhydrogel	Phase 1a	Fraunhofer USA
Pfs25-EPA/Alhydrogel	Phase 1a	NIAID/NIH (USA)
Pfs230D1N-EPA / Alhydrogel and/or Pfs25-EPA/Alhydrogel	Phase 1a	NIAID/NIH (USA)
Pfs230D1N-EPA / Alhydrogel and/or Pfs25-EPA/AS01	Phase 1b	NIAID/NIH (USA)
ChAd63 Pfs25-IMX313/MVA Pfs25-IMX313	Phase 1a	University of Oxford (UK)
P. vivax vaccines		
ChAd63/MVA PvDBP	Phase 1a	University of Oxford (UK)

7.2.3.1 The potential impact of vaccinations on malaria distribution

Vaccines have been successfully implemented to treat numerous global diseases which have had positive influences on reducing and eliminating disease. A large-scale vaccination programme was applied in several countries in Africa following the introduction of a meningococcal conjugate (bacterial meningitis) vaccine (Moore, 1992; Jodar et al., 2003; Djingarey et al., 2012). The challenges faced during the rollout of the meningococcal conjugate vaccine are likely to be similar to those faced during the introduction of a malaria vaccine in Tanzania, for which advisories and a framework for the poorest countries can be drawn (Jodar et al., 2003; Sow et al., 2011; Trotter et al., 2017). This summary will assume that vaccine safety has already been assessed (Sow et al., 2011; Amarasinghe et al., 2013).

For an immunisation programme to be successful, vaccines need to be stored continually in conditions at low temperatures, specific temperatures of which vary by vaccination (Hunter, 1989). This must be persisted when moving vaccines from one location to another, thus requiring cold storage transport facilities alongside cold-room storage (Djingarey et al., 2012). Tanzanian dispensaries are unlikely to have this facility and fitting them would be costly, immediately putting rural residents at a disadvantage when vaccination treatments become available (MoHSW, 2013a). Thus, the introduction of a malaria vaccine is more likely to be available in larger urban and peri-urban facilities (clinics and hospitals) which are more likely to have suitable vaccine storage facilities. This will have little impact on overall malaria risk due to urban locations already being at lower risk than rural residents (Kabaria et al., 2016).

Alongside storage, vaccination programmes produce hazardous waste which requires incineration disposal. It is important to handle waste in a safe manner in order to prevent disease spread from vaccination waste (Djingarey et al., 2012). With similar logistical problems to storage, waste would have further to travel from rural locations which would require safe and effective transport, alongside prompting further costs for disposal transport and facilities. This was documented as a factor which was not appropriately addressed in the case study of Burkina Faso and the meningitis vaccine (Djingarey et al., 2012).

Vaccination programmes are expensive to implement and maintain (table 7.3), which often sees low to middle income governments opt out of supporting vaccination programmes despite being a proven cost-effective health intervention (Glassman et al., 2013; Ozawa et al., 2016). This is due to high costs associated with various stages and requirements of vaccination, particularly in cases where external funding is unavailable or not enough to cover a substantial amount of vaccination costs (Amarasinghe et al., 2013; Glassman et al., 2013). Table 7.4 provides an example breakdown of costs associated with the meningitis vaccination programme implemented in Burkina Faso (Djingarey et al., 2012). Malaria is a Gavi (vaccine alliance) supported vaccine, which will attempt to ensure equal access to new drugs for children living in the poorest countries (Ozawa et al., 2016).

Table 7.3 – Financial components to be addressed within a vaccine programme.

Components	**Vaccines with Gavi support (Financed by Gavi, government & other development partners.**	**Vaccines without Gavi support (Financed by government & other development partners)**
Routine Vaccine ● Vaccine incl. freight ● Injection equipment and safety boxes Supply chain ● Immunization-specific transportation ● Storage ● Labour Service delivery ● Immunisation-specific personnel ● Shared personnel ● Non-personnel incl. raining, surveillance, program management, social mobilization	DTP-HepB-Hib, HPV, IPV, JE, Malaria, Measles 2nd, MR, MenA, PCV, Rotavirus, Typhoid, YF	BCG, DTP, HepB, Measles 1st, MMR, OPV
SIA Vaccine ● Vaccine incl. freight ● Injection equipment and safety boxes	JE, Malaria, Measles, MR, MenA, Typhoid, YF	MMR, OPV

Operational support ● Personnel ● Other operational costs including training, transportation, and social mobilization		

Table 7.4 – Funding for the Burkina Faso meningococcal vaccine campaign (Djingarey et al., 2012).

Costs and donors	**Amount (US$)**	**Activities**
Campaign budget		
Vaccine, syringes, needles, safety boxes	10,295,059	Purchase of vaccine, needles, syringes and safety boxes
Operational costs	3,338,019	Vaccine, needles, syringes, and safety boxes
Total cost	13,633,078	Material (cold chain support, waste disposal, and vaccination cards); and operational costs
Donor resources		
GAVI contribution through UNICEF Supply Division	4,089,442	Communication and operational costs
Dell Foundation through WHO	2,558,208	Operational costs
Dell Foundation through WHO and PATH	3,908,676	Operational costs
		Operational costs
GAVI through UNICEF Program Division	865,179	
Burkina Faso national budget	703,898	
West African Health Organisation (WAHO)	106,382	
Lions Club (Italy)	77,767	
Total resources mobilised	12,309,556	
Financial gap on December 6th 2010	1,323,522	

A further consideration of cost, is the price of vaccination for Tanzanian residents. The Developing Countries Vaccine Manufacturers Network (DCVMN) is a model of international alliance which aims to reduce the cost of vaccines, to allow universal access to treatment (Amarasinghe et al., 2013; Pagliusi et al., 2013). Despite this, private-for-profit clinics, are likely to inflate pricing for profit as is the case in other localities (Glazner et al., 2004). These clinics make up the majority of health facilities in Dar es Salaam, hence this factor should be monitored with regards to access to healthcare (MoHSW, 2013a).

7.2.4 Impacts of socioeconomics, culture and policies on the use of epidemiological models in decision making

Section 7.2.3 has demonstrated the role that social and policy variables play in influencing malaria (and wider disease) epidemiology in the context of the epidemiological triangle, further highlighting the complexities and cross-variable interactions summarised in table 7.5. These variables and key relationships are all unquantifiable and unincorporated within the context of environmental models at present, despite knowledge of their influence on malaria transmission. Furthermore, the combination and degree of negative and positive impacts are poorly understood. Although many of the discussed factors are directly unquantifiable, there are certain indirect numerical aspects of social data (*e.g.* household income, population distribution) which could contribute to epidemiological modelling as discussed in section 7.2.6.

Whilst there are significant complexities in assessing the relationships and impacts of these relationships discussed thus far in this chapter, the WHO has attempted, in collaboration with stakeholders from Kenya, Uganda and Tanzania, to create a decision analysis support tool built upon the foundation of social data presented in section 7.2.5. It is important to note that this tool is not spatially explicit, a factor which will be discussed further in section 7.2.5.

Table 7.5 – Summary of key socioeconomic, demographic and policy interactions with the epidemiological triangle. (Table continues on next page)

Factor	Key interactions with environmental epidemiology
Population growth and distribution.	• Expansion of dense urban area with population growth would aid in reducing transmission (negative impact on vector). • Expansion of peri-urban area would support continued malaria transmission (positive impact on epidemiological triangle: environment) • Population growth would support continued malaria transmission through increased provision of host (positive impact on epidemiological triangle: host) • Growth of rural villages into townships would see sustained malaria transmission in these locations until a density great enough to have a negative impact upon malaria transmission is reached.
Economic growth and occupation development.	• Increased wealth from tertiary sectors would have a negative impact on the epidemiological triangle. Thus, reducing malaria through increasing affordability of healthcare. • Sustained mass agricultural work would have a positive impact on the epidemiological triangle, where host provision would remain high in high transmission locations. • Economic migrants will have a dependant response, based on the location where residents seek work (see section 7.2.1.1) and occupation.

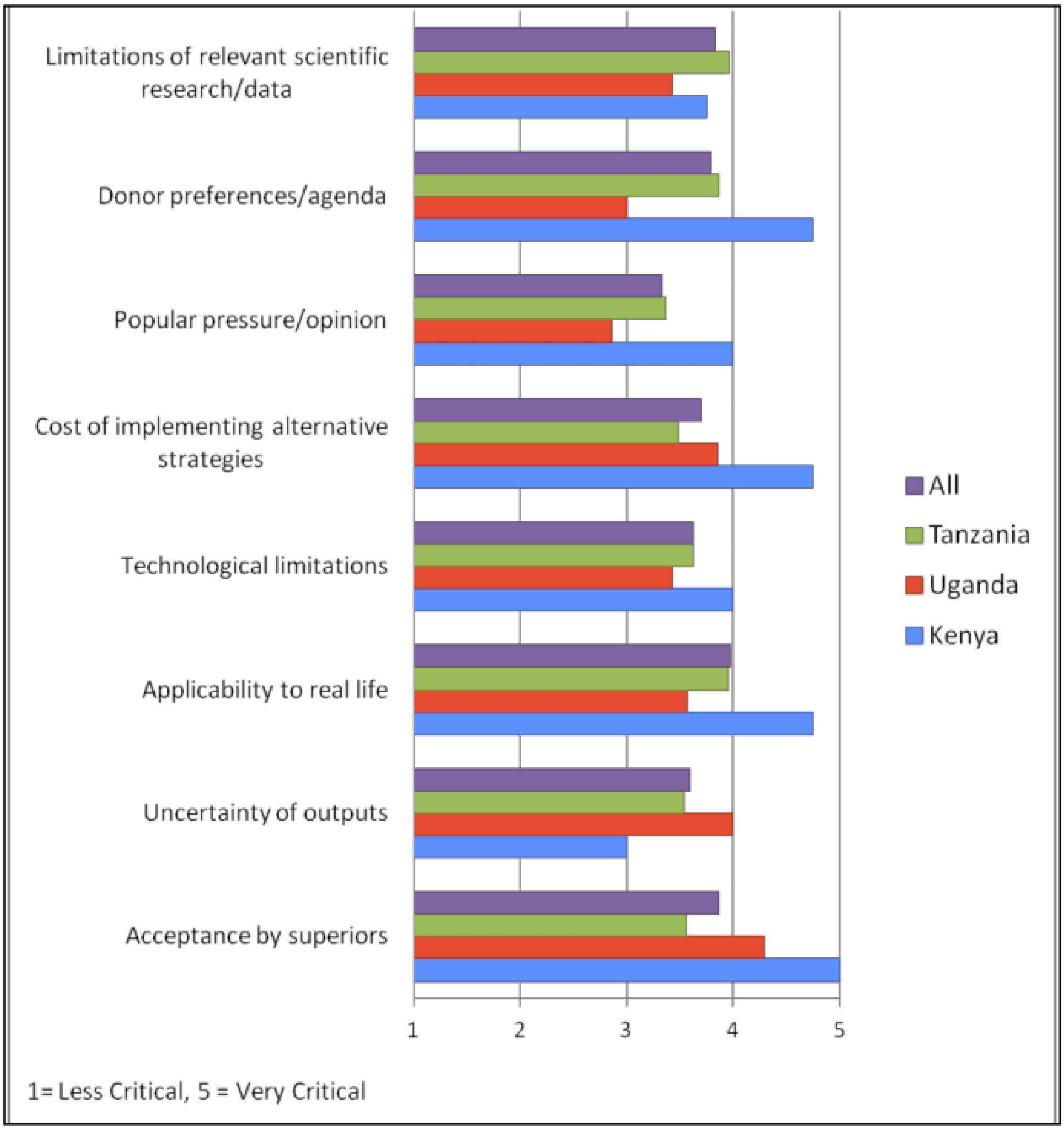
Access to healthcare, malaria prevention and treatment (including vaccination).	• Increases in private clinics in rural locations will have a positive effect on the epidemiological triangle. Increasing malaria prevalence. • Increases in current policy coverage (and introduction of new policy, e.g. vaccines) will have a negative effect on the epidemiological triangle. Reducing malaria prevalence. • Increase in surveillance methods would have a negative effect on the epidemiological triangle. Reducing malaria prevalence.
Education, Age and Gender.	• Increased education for both males and females would have a negative impact on the epidemiological triangle. Reducing malaria prevalence. • Women and children would remain biologically vulnerable to malaria. Sustaining malaria prevalence. • Increases in gender equality would have a negative impact on the epidemiological triangle. Reducing malaria prevalence.

7.2.5 Challenges of using social data in malaria modelling: The Malaria Decision Analysis Support Tool (MDAST)

Surveillance is highlighted as being of increasing importance in upcoming malaria intervention in Tanzania (figure 7.5a and b), requiring the underpinnings of malaria models such as those presented in chapters four and five. Current environmental malaria surveillance and prediction models do not incorporate health or social data and rely solely on environmental predictions. MDAST, a malaria decision analysis support tool, is currently being developed and improved for Kenya, Tanzania and Uganda by UNEP and GEF with a view to jointly incorporating health, social and environmental priorities for malaria control (WHO, 2013a; USAID, 2015). It aims to form an intersectoral approach to allow policy makers to weigh the health, environmental and economic trade-offs of different combinations of malaria intervention strategies using evidence based methods (Brown et al., 2012; Mboera et al., 2013).

MDAST has been developed based upon stakeholder identification of the key risks which contribute to determining the effectiveness of different policies, and have not been previously combined in a flexible tool (Brown et al., 2012). Features ranged from contextual factors, such as malaria prevalence, to environmental conditions, for example rainfall. However, there are limitations introduced by the aim of the project to be user friendly and as such, only simple environmental relationships are included, centred on rainfall and temperature only (Brown et al., 2012; WHO et al., 2013). During the development of MDAST, multiple issues arose in the challenges to better incorporate environmental modelling, health, and social data into malaria decision making. In particular, it was discovered that donor preferences and agendas are exerting too much influence on malaria policies in the countries at present (Mutero et al., 2014).

The MDAST project was completed in 2013, however there has been no report on its use and progress of malaria surveillance in Tanzania thus far. This could potentially be related to numerous factors raised by Tanzanian officials presented in figure 7.8, the greatest concerns of which for Tanzania are limitations of relevant scientific research and data, alongside the application to real life scenarios (WHO et al., 2013). The MoHSW identify that malaria surveillance for the 2014-2020 period will use operational findings for regular assessment and evaluation of the intervention and the evidence generated will be used to further help policy makers to make appropriate, informed decisions (MoHSW, 2013b). It remains unclear whether this will be using the specifically developed MDAST system which the MoHSW has actively contributed to.



7.8 - Expert consultation responses to the question "please indicate how critical each of the following barriers is to full implementation (or dissemination) of the tool for decision-making?" *(WHO et al., 2013)*.

7.2.5.1 Conclusions drawn from MDAST

Overall, the lack of uptake and reporting on use of MDAST in Tanzania is likely to be associated with barriers highlighted in figure 7.8, where Tanzania highlighted all factors presented as moderately critical to highly critical in implementing the MDAST tool. These barriers are arguably reflective of the overall difficulty in implementing decision support models within a policy framework. This thesis does contribute to some of the barriers presented, particularly the limitations of relevant scientific research and further highlights areas of weakness for Tanzania.

Overall, MDAST appears to be a supported framework in theory, although key environmental variables are notably lacking, an aspect which stakeholders voiced concerns over (WHO et al., 2013). Furthermore, the results presented in this thesis further highlight the importance of environmental data within malaria assessment. Considering this, approaches which could incorporate both social data and environmental data are discussed in section 7.2.6.

7.2.6 The future of socioeconomic data in epidemiological modelling

Section 7.2 discussed the key socioeconomic, cultural and policy impacts on the epidemiological triangle. An example of addressing social data in a non-spatial malaria decision analysis support tool has also been presented, demonstrating the desire and need for inclusion of socioeconomic data for the purposes of policy development. This section will highlight how socioeconomic data could potentially be included within a spatially explicit framework to support environmental epidemiological modelling, such as that developed and presented within chapter four of this thesis.

Geographically weighted models allow for components to be added and reweighted as new or updated data sources become available (Khormi and Kumar, 2015). As census data increases in quality and resolution for Tanzania; multiple numerically derived social variables could be incorporated into GIS based environmental epidemiological models to both assess the spatial relationship with disease (on a district level), and then incorporate this within a GIS based epidemiological model to examine risk (Khormi and Kumar, 2011; Houngbedji et al., 2016).

A way of refining epidemiological modelling could be built upon the methodology presented by Khormi and Kumar (2011) who examined dengue fever risk based on socioeconomic parameters using predominantly age groups, housing and population density. This could be further modified to include district level records of percentage of residents below the basic needs poverty line (introduced in section 7.2.1.2). This would represent the level of district poverty, and provide an indication of the percentage of the district which could feasibly afford malaria prevention tools and treatment. This factor could also be coupled with distance to a health-care facility within the district. For example, if the nearest health care facility is located in the next district, this would impact malaria treatment seeking behaviour due to distance, which could be assigned a weighting within a GIS.

7.3.6.2 Recommendations drawn from socioeconomic and cultural determinants

A general recommendation is for the improvement of a communication framework between researchers and policy developers. Whilst outlines currently exist, in practice this is not always met and results do not necessarily get translated into policy as effectively as they could be. Improving communication between science and policy would benefit vulnerable populations and further help through related variables such as reduced cost and increased efficiency with targeted campaigns based on model results.

Initiatives to improve the quality and systematic collection of social data in Tanzania is recommended. Following this, it is recommended that this improved social data is used within an epidemiological modelling system as presented in section 7.2.6. Numerically recorded social data on a district level could be incorporated into a GIS epidemiological model to allow inclusion and examination of socioeconomic data with respect to disease risk, which would further build upon current models.

7.3 Concluding remarks

The main aim of this thesis was to develop a framework for the integration of environmental and biophysical information, to support health and disease decision-making and risk modelling, resulting from short and long-term climate change.

Understanding the extent and likely development of disease dynamics with climate change aids policymakers to implement prevention methods and strategies to mitigate against disease outbreaks as a result of change. Whilst models provide invaluable support with this, they currently cannot capture the complexity of socioeconomic interactions which further modify disease distribution and behaviour. The multi-method approach adopted in this thesis coupled with systematic literature examination has contributed to the evidence that Tanzania is at risk of changing disease distribution as a result of climate and environmental change, where its population and socioeconomic status at present, serves to exacerbate this.

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Appendix: Code Developed for PhD by Author

Bespoke R script was coded to achieve the following functions:

- Data sorting
- Statistical analysis
- Extraction of data
- Data merging
- Conversion of “hours since 01-01-1990” to Gregorian calendar date
- Re-arrangement of data from Matrix to stack
- Reading of NetCDF files.

Appendix: Author Output during Ph.D

Papers:

Reynolds, R., Cavan, G. and Cresswell, M. (2017) 'The local response of El Niño events and changing disease distribution in Tanzania.' *Weather*, 72(7) pp. 206–215.

(Available at: https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/wea.3022)

Public speaking:

31st January 2017: Manchester Metropolitan University, Environment and Geographical Sciences Seminar. Invited to co-present a presentation with Dr. M.P Cresswell, entitled *"Current and potential future environmental risk mapping of malaria".*

15th September 2016: Manchester Metropolitan University, 2016 Science and Engineering Research Symposium. Invited to deliver a presentation entitled: *"Examining the sensitivity and response of disease environments to climate change within Tanzania".*

06th July 2016: University of Manchester, The Royal Meteorological Society Student Conference. Invited to deliver a presentation entitled *"Examining the sensitivity and response of disease environments to climate change within Tanzania".* This work was subsequently published as a paper: see papers.

29th March 2016: Online: Invited by UniGIS to present a webinar entitled *"Examining the impact of climate change in Tanzania"*. This presentation can be viewed online at: https://unigis.net/news/webinar-29-march-examining-the-impact-of-climate-change-in-tanzania/

16th February 2016: Manchester Metropolitan University, School of Science and the Environment Public Seminar Series in E34. Invited to present a seminar introducing my work entitled *“Examining the impact of climate change upon disease ecosystems in Tanzania”.*

Posters:

Reynolds, R., Cresswell, M.P, Cavan, G (2017). Current and projected environmental risk mapping of malaria. *Impact of Environmental Changes on Infectious Diseases Conference.* International Centre for Theoretical Physics, Trieste, Italy. May 2017.

Reynolds, R., Cresswell, M.P, (2016). The Potential of GIS and Earth Observation for Disease Modelling. *UNIGIS: A celebration of 25-year milestone for the distance learning programme.* Salford Media City, UK. June 2016.

Reynolds, R., Cresswell, M.P, Cavan, G (2015). The effect of climate conditions on disease risk in Tanzania. *2015 Science and Engineering Research Symposium,* Manchester Metropolitan University, UK. September 2015.