

**Impact of Climate on Health: A Specific Focus on Malaria in South Africa's
Limpopo Province**

By

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DEDICATION

I would first like to dedicate this work to God, for life, provision and endurance. Through Him, I can do all things by His strength.

Secondly to my wife: Chebet Kibii who has always endured with all the children in my absence; and my children: Menashe, Chebiwott and Chepng'etich, with Kiplagat's children, my children: Kibet, Chepkemoi, Kipsang and Peter.

To my parents: My late father, Komen Chebii and my mother, Kabon Komen, who have always given me permission and *all* provision to study under *all* difficult and seemingly unlikely circumstances.

To my brothers and sisters: The late Kipkios, Chepkosgei, Cheruto, Kiplagat, Cheptoo, Chemtai, the late Kipkurui, Kandie, Kerui, Chepchirchir and Chelimo.

DECLARATION

I declare that this thesis, which I hereby submit for the PhD degree award at the University of Pretoria, is my own work and has not been previously submitted by me for another degree at this University or any other tertiary institution.

Signed.....

Name: Daniel Kibii Komen

November 2015

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ABSTRACT

Climate change is the defining crisis of our moment and a critical concern for the global economy. One of the big concerns of climate change is its potential impact on health and the health sector in general through the increase in climate-sensitive diseases such as Malaria. The presence of mosquitoes that transmit malaria is influenced by climatic factors: temperature, precipitation, and humidity. Areas in South Africa with optimum conditions for malaria are KwaZulu-Natal, Limpopo, and Mpumalanga Provinces. Limpopo Province (approximately 22–25°S, 27–32°E) is South Africa's northernmost province that shares its international borders with Botswana, Zimbabwe, and Mozambique. Socio-economic factors and other environmental factors also affect the spread of malaria. In the Limpopo Province of South Africa malaria is shifting and is now observed in originally *non-malaria* districts. It is unclear, however, whether climate drives this shift, and if it does, which of the two main climate drivers — rainfall or temperature — are responsible. It is also important to understand which of the two is more significant, when does the malaria season begin, how long does the malaria season last, and what are the policy implications in terms of the timings of malaria interventions for Limpopo Province?

This study attempts to answer these questions. In so doing, it examines the distribution of malaria at district level in the Limpopo Province, determines the direction and strength of the linear relationship and causality between malaria and the meteorological variables (rainfall and temperature), and ascertains their short and long run variations. It identifies the beginning of the malaria season, as well as its duration, and suggests policy directions for the timing of malaria intervention programmes. The spatio-temporal method, correlation analysis, and econometric methods (*Auto-Regressive Distributed Lag (ARDL) model, Multiple Regression Analysis and Impulse Response Function (IRF) in a Vector Moving Average (VMA)*) are applied. Time series monthly meteorological data (1998–2007) are obtained from South Africa Weather Services (SAWS) and clinical malaria data came from the Malaria Control Centre in

Tzaneen (Limpopo Province) and the South African Department of Health. Global data — ERA-Interim, TRMM and TRMMv7 — are obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF).

The study found that malaria changes and pressures vary in different districts with a strong positive correlation between temperature and malaria, $r = 0.5212$, and a weak positive relationship for rainfall, $r = 0.2810$. Strong unidirectional causality runs from rainfall and temperature to malaria cases (but not vice versa): $F(1, 117) = 3.89$, $q = 0.0232$ and $F(1, 117) = 20.08$, $P < 0.001$. A bi-directional causality exists and between rainfall and temperature: $F(1, 117) = 19.80$; $F(1, 117) = 17.14$, $P < 0.001$, respectively. This means that rainfall affects temperature and vice versa. Results show evidence of the strong existence of a long-run relationship between climate variables and malaria, with temperature maintaining a much higher level of significance than rainfall. Temperature, therefore, is more important in influencing the transmission of malaria in Limpopo Province.

Furthermore, the study finds that malaria in Limpopo Province is seasonal with initial cases observed at the end of the third quarter of the year, that is, the end of the winter season in August, and reaching a peak between the fourth quarter of the year (September, October and November) and the first quarter (March, April and May) of the following year. Vector control for anopheles mosquito should therefore begin at the end of July and into mid-August and should be intensified for at least three and a half months for it to be effective. To curb imported malaria there is also a need for collaboration with neighbouring countries. Care should also be taken in terms of the use of DDT as a means of malaria control as it will poison water and destroy vegetation, both of which are absorbed by all living things, and thereby amplify human health challenges beyond climate change impacts.

TABLE OF CONTENTS

DEDICATION	2
DECLARATION	3
ABSTRACT	5
TABLE OF CONTENTS	7
LIST OF FIGURES	10
LIST OF TABLES.....	10
ACRONYMS AND ABBREVIATIONS.....	11
CHAPTER 1: INTRODUCTION AND BACKGROUND.....	12
Introduction	12
1.1. Traditional economy and the emergence of climate change	16
1.2. Climate impacts on human health.....	20
1.3. Climate impacts on malaria	21
1.4. Malaria in South Africa’s Limpopo Province	23
1.5. Context of the study.....	24
1.6. Conceptual framework.....	26
1.7. Problem statement	28
1.8. Goals and objectives	31
1.9. Hypotheses.....	32
1.10. Justification of the study.....	32
1.11. Organisation the thesis.....	33
CHAPTER 2: REVIEW	34
Introduction	34
2.2. Effects of climate change on human health	34
2.3. Africa and vulnerability to climate change impacts.....	39
2.4. Likelihood of climate impacts in Africa.....	42
2.5. Impacts of extreme rainfall, lack of rainfall (drought) and temperature.....	44
2.6. Climate change and vector-borne (communicable) diseases — malaria.....	47

2.7. Climate impact on malaria in South Africa	54
2.8. Chapter Summary	56
CHAPTER 3: METHODOLOGY.....	60
Introduction	60
3.1. Study area	60
3.2. Data and data sources.....	61
3.3. Models.....	63
3.3.1. Spatio-temporal	65
3.3.2. Correlation.....	65
3.3.3. Causality.....	65
3.3.4. Stationarity (unit root) test.....	67
3.3.5. Autoregressive Distributed Lag (ARDL)-Bounds Test Model	68
3.4. Models specification and description.....	69
3.4.1. Vector Auto-regression	73
3.4.2. Multiple Regression model	73
3.4.3. Impulse Response Function (IRF)	75
3.5. Strengths and limitations of methods	75
CHAPTER 4: RESULTS.....	77
Introduction	77
4.1. Results: Objective 1: Spatial analysis	77
4.1.1. Spatio-temporal results	77
4.2. Results Objective 2: Statistical (Econometric) analysis.....	82
4.2.1. Correlation analysis	82
4.2.2. Causal relationships.....	85
4.2.3. Stationarity (unit root)	87
4.2.4. Auto-regressive Distributed Lag Model (ARDL)	88
4.2.5. Cointegration analysis	90
4.3. Results: Objective 3: sensitivity tests	92
4.3.1. Regression analysis.....	92

4.3.2. Impulse response analysis.....	95
4.4. Chapter Summary.....	98
CHAPTER 5: DISCUSSION.....	100
Introduction	100
5.1. Discussion: Literature Review	100
5.2. Objective 1: Discussion – Spatial Analysis	101
5.3. Objective 2: Discussion of the statistical analysis	102
5.4. Objective 4: Discussion of sensitivity analysis	103
CHAPTER 6: SUMMARY, CONCLUSION AND RECOMMENDATIONS.....	106
Introduction	106
6.1. Summary and conclusion	106
6.2. Policy recommendations and future research	111
6.3. Scientific contributions.....	119
REFERENCES	121

LIST OF FIGURES

Figure 1: Malaria-environment nexus.....	27
Figure 2: Limpopo Province.....	61
Figure 3: Ten-year spatial distribution of malaria in Limpopo Province.....	79
Figure 4: Rate of malaria incidence in Limpopo per 10-person population (1998–2007)	81
Figure 5: Correlation of rainfall and temperature with malaria — A graphical outlook	82
Figure 6: Trend-relationship between average rainfall and average temperature in relation to malaria cases	83
Figure 7: Rainfall, temperature and malaria cases plot.....	84
Figure 8: Response of malaria cases to rainfall.....	96
Figure 9: Response of malaria cases to temperature.....	97

LIST OF TABLES

Table 1: Actual and potential impacts of climate change on human health.....	35
Table 2: Causal relationships	85
Table 3: Unit root test results	87
Table 4: Unrestricted Error Correction model	88
Table 5: Cointegration properties	90
Table 6: Long-term relationship: malaria cases with rainfall and temperature	91
Table 7: Short-term relationship: malaria cases with rainfall and temperature.....	91
Table 8: Summary of unit root tests	94

ACRONYMS AND ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARDL	Auto-Regressive Distributed Lag
DDT	Dichlorodiphenyltrichloroethane
ECM	Error Correction Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA	ECMWF re-analysis
IDW	Inverse Distance Weighting
IPCC WG	International Panel on Climate Change
IRF	Impulse Response Function
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
OLS	Ordinary Least Squares
QWeCI	Quantifying Weather and Climate Impacts
SAWS	South Africa Weather Services
SBC	Schwarz Bayesian Criterion
UECM	Unrestricted Error Correction Model
VAR	Vector Auto-regression
VMA	Vector Moving Average

CHAPTER 1: INTRODUCTION AND BACKGROUND

Introduction

This chapter (Chapter 1) discusses the traditional economy and the emergence of climate change. It introduces the general climate impacts on health and discusses climate impacts on malaria transmission with specific focus on malaria in South Africa. This section also provides a conceptual framework, contextualises the study, states the problem, outlines the goals and objectives of the study, and presents the hypothesis to be tested alongside the justification for the study. The last section explains how the thesis is organised.

Climate change is disrupting or otherwise altering a large range of natural ecological and physical systems that are an integral part of Earth's life support system (IPCC 2007). The resulting climate impacts are negative. These negative climate effects are felt in every natural living ecosystem, with humans, wildlife, livestock, crops, forests, and marine life bearing the scourge of climate change effects (Colwell, 1996; Epstein et al, 1993). Ecological changes and economic inequalities strongly influence disease patterns but a warming and unstable climate is playing an ever-increasing role in driving the global re-emergence, resurgence, and redistribution of infectious diseases (Epstein, 2001). This is in combination with traditional factors such as elevation, land use changes, drug resistance, variable disease control efforts, and other socio-

demographic factors (Pascual *et al*, 2006; Patz *et al*, 2002) including immunity of population. Global warming will cause changes in the epidemiology of infectious diseases (Khasnis *et al*, 2005). Some common climate-sensitive epidemics that continue to cause major problems in Africa include fevers (yellow fever, Rift Valley Fever, and Dengue fever), cholera, river blindness, bilharzia, tuberculosis, and malaria.

Malaria is the most prevalent vector-borne killer disease in southern Africa. In South Africa, malaria is endemic in KwaZulu-Natal and Mpumalanga provinces, but over the last few decades there has been a systematic and gradual rise in malaria cases in the Northern Province, Limpopo. *Plasmodium falciparum* accounts for the majority of malaria cases in southern Africa and is the predominant species associated with severe and fatal disease (Gerritsen *et al*, 2008). In a recent study, Komen *et al.* (2015) found that rainfall and temperature drive malaria transmission in Limpopo Province, with temperature being the most important driver.

Malaria is endemic in the low-altitude areas of South Africa on the borders with Mozambique and Zimbabwe. Specifically, transmission is prevalent in three provinces: KwaZulu-Natal, Limpopo, and Mpumalanga provinces (Gerritsen *et al*, 2008; Kondo *et al*, 2002; Ngomane & de Jager, 2012; Sharp *et al.* 1988). Limpopo Province (approximately 22–25°S, 27–32°E) lies in the low altitude area which is pre-disposed to malaria due to warm conditions.

Malaria transmission is distinctly seasonal and limited to the warm and rainy summer months. Case notifications generally increase from November, peak in late March to May, and then decline at the end of June. Craig *et al.* (2004) report that in South Africa, the average seasonal pattern in malaria incidence follows periodicity in rainfall and temperature with a three to four-month lag. Although the study found this lag-time rather long, the response time is not uniform elsewhere. One plausible explanation for this is that the lag-time itself could be temperature sensitive because of the temperature-sensitive development rate of larval mosquitoes and the extrinsic incubation period of the parasite.

The occurrence of malaria cases in the province has been reported to be highly seasonal dependent (Bouma & van der Kaay, 1996). Interventions through the malaria control programme in South Africa rely heavily on the intermittent use of indoor residual spraying in periods shortly after heavy rains when malaria cases tend to rise.

Malaria control programme continues despite there being no empirical evidence that rainfall drives malaria in the province. Therefore, for effective malaria control there is a need to establish the relative importance of rainfall and temperature in malaria transmission. It is important to understand the relative importance, strengths, and direction of causality of climate-malaria drivers, as well as the role of rainfall and temperature as they relate to malaria dynamics in the short and long term. This is

central to enhancing malaria control policy measures and informing the design of malaria early warning systems. Due to the fact that climate change by itself will increase vulnerability (Bohle *et al*, 1994; van Lieshout *et al*, 2004), target planning is necessitated by careful consideration of all factors. Furthermore, the malaria control programme that uses insecticides should also consider the detrimental effects such chemicals have in terms of their effects on water, biodiversity, and the emergence of other diseases, such as cancer, that are associated with their absorption into human tissues.

This study aimed at to establish the link between climate change and health. It specifically examines how rainfall and temperature play a critical role in widening the transmission zones for malaria. It also establishes: (1) that climate has a causal effect on malaria transmission; (2) that the onset of rainfall triggers a malaria season; and (3) proposed key issues in terms of malaria control measures as a policy recommendation. This study contributes to the body of literature on climate change and health as some of the results of this study have been published in international journals. It provides further recommendations for research on the wider implications of malaria control programmes such that the vision of zero malaria in the province can be a reality without further damage to the human life support system — the environment.

1.1. Traditional economy and the emergence of climate change

The progress in economic development that has long been used as a vehicle for economic growth and prosperity, and as a means for dealing with poverty, disease, and hunger, has been found to have an intrinsic market failure or externalities embedded in it such that, in the recent decades, the traditional patterns of development have been highly questioned in terms of delivering the future. The traditional economic allocation of resources has contributed to the manifestation of several concurrent crises: biodiversity, energy, food, water, and more recently, the global financial crisis and climate change (Barbier, 2011; UNEP 2011).

The science of climate change reveals that the climate is now responding to anthropogenic (human) factors. In the past, climate change was not a concern because natural processes ensured a balanced atmosphere with effects that were limited to only 'natural' effects. However, over the last 100 years, the climate has begun to respond to human influences. Climate change is defined as a change in climate that is directly or indirectly attributed to human activities, that alters the composition of the global atmosphere while "climate variability" is attributed to natural causes (UNFCCC, 2007). Climate variability generally refers to the « natural » fluctuations of the climate system. Human activities, for example, the use of fossil-based resources are seen as the main source of Greenhouse gases (GHG) that cause climate change. It is climate change that a determinant to health than climate variability (IPCC 2007).

The main drivers to climate change are past (and present) 'exploitative' economic decisions that do not consider impacts on the environment, high population growth, and extensive conventional energy use patterns. The utilisation of fossil fuels in electricity generation and transport systems is blamed for the emission of greenhouse gases such as carbon dioxide (CO₂), methane, nitrous oxide, water vapour, and volatile hydrocarbons. Human activities also increase the ambient particulate matter, ozone depleting substances, sulphur dioxide, and pollen in the atmosphere. The drive for further social and economic development, together with the unavoidable substantial increase in population size, tend to augment these large scale environmental problems, particularly in less developed countries (McMichael et al, 1998).

The long-term unaccounted social and environmental externalities are now 'biting' deeply into the economies of the world and bringing in additional challenges, especially in 'poor' continents like Africa. The negative environmental consequences from past unsustainable economic practices are revealed in climate change. It is therefore imperative to recognise that climate change is threatening to reverse the gains from the long-term economies of scale that have been enjoyed for decades. Viewed from a different perspective, the supposed long-term 'gains' of economic progress were, indeed, not gains per se but a postponement of 'problems' into the future. These 'problems' are now revealing themselves in the phenomenon of climate change. It is likely that in addressing poverty, disease, and hunger, human actions have interfered significantly with natural systems and, rather than resources being a solution to these

social challenges, the problems have shifted to the environment, which has brought even more, seemingly insurmountable challenges than the original challenge itself.

Some time ago, communities were able to access the ‘free gifts of nature’, such as clean water, clean air, fertile soils, and biodiversity, and ecosystem goods and services with minimal struggle. If utilised optimally, these gifts were, by themselves, the natural regulators of climate: *as per natural dictates*. Today, accessing clean water or clean air, and finding adequate food and nutrition is at a premium. These supposed free natural resources have been somewhat over-utilised, commodified, controlled, and are gradually being sold in the ‘market’.

The consequence of this over-exploitation and commodification is mismanagement that has brought about very high pollution to the extent that nature, rather than being a ‘*provider and protector*’, has become an *adversary*. Human beings are therefore the most threatened of all species in the animal kingdom, yet it is the humans that are the cause and, at the same time, the solution to many of nature’s problems. It is possible that the ‘climate problems’ in this era seems to be greater than the available solutions.

Climate change is therefore putting economies in a dilemma: how to continue utilising available natural resources to address the un-done past challenges of underdevelopment and, at the same time, ‘sustainably’ using these resources to meet

the additional challenges emanating from climate change. One of the greatest challenges in addressing the environmental crisis in the development process is the nature of the environment itself, being collectively shared, and demanding collective effort for its protection. The effects of pollution as a consequence of the emission of greenhouse gases by one economy are borne by all since they are all captured within the atmosphere. But, reaching consensus on collective action to reduce global emissions seems to be almost an impossible dream.

This is mainly because, although economies might agree on the existence of the climate crisis, they seldom agree on the best way to share the responsibility for reversing its negative impacts. There are three key reasons for this, among others. First is the difference in levels of economic progress that has brought about the dichotomy of economies: developing economies versus developed. Second is that the dichotomy follows the historical pathway to development and the subsequent relative contribution or share of environmental damage within the development discourse. Those considered to be developed are perceived to have achieved their development by damaging the environment and therefore they should take the greater share of responsibility for addressing the current climate crisis. Finally, the comparative advantages and economies of scale of the long-term exploitation of natural (fossil-based) resources provide a trade-off that poses a challenge. Traditional economies are heavily reliant on fossil fuels to drive their economies and, due to hundreds of years of perfecting conventional technologies, a shift to alternative and cleaner technologies

might imply huge initial capital costs that are either not readily available or that companies are unwilling to invest.

The consequences of climate change are rising temperatures, sea level rise, the melting of snow and ice, floods, and droughts. These are catastrophic in nature. The changing weather patterns expose human beings to more intense and increasingly frequent extreme events that indirectly result in changes in water, air, food quality and quantity, ecosystems, agriculture, livelihoods, and infrastructure, all of which indirectly influence human health (Working Group II IPCC, 2007). The probability of experiencing an extreme event is very high, such that the key health determinants of good health are being continuously eroded and compromised day by day.

1.2. Climate impacts on human health

Human health is a pre-requisite to productivity and a catalyst to any development process and progress. Through its impact on health, climate change impedes this productivity. The reason that human health is important to climate change is because a healthy human is a productive human, all other things held constant. Basically, health is a panacea for productivity. A healthy person does not require medical attention. Climate change causes injuries and deaths as well as exaggerating the disease burdens within populations. In this respect, governments are forced to allocate more resources, not only to fix damaged infrastructure and to provide emergency response measures,

but also to intensify disease treatment and preventative control measures, either suddenly or gradually.

On a wider scale, further health consequences of climate change include a reduced life span or the impairment of productive populations that, in most cases could be the breadwinners. This compounds the challenges for populations because a loss of productivity (through absence from income generating activity) implies a loss of potential income and, in fact, a further loss of already earned income to compensate for the cost of medication, and greater time resources of care-givers. This can be life threatening for the poor, especially if health facilities are lacking or inadequate, a common characteristic in most developing countries.

The impacts of climate change can be either direct or indirect. The direct health impacts include respiratory and cardiovascular disease, and flood related mortality and morbidity (IWGCCH, 2008). The indirect health impacts include changes in disease transmission, water-related disease, food security and nutrition, and those linked to multiple stresses — population, migration, conflict, and changes in ecosystems (IPCC, 2007).

1.3. Climate impacts on malaria

Of the climate sensitive vector-borne diseases, malaria is by far the most important. Climate change affects health through multiple pathways but rainfall and rising temperatures create ample conditions for the multiplication and spread of vectors and

vector-borne diseases such as malaria. Malaria is the most important parasitic infection affecting humans, accounting for an estimated 300–500 million clinical cases worldwide with 90% of annual cases reported in sub-Saharan Africa (Reiter, 2008). This is five times the amount of the combination of HIV/AIDS, TB, measles, and leprosy cases and is responsible for one in every four childhood deaths, making malaria Africa's biggest killer with regards to disease and infection (SaNTHNet, 2013). Malaria is responsible for the deaths of over one million people in Africa each year (Breman, 2001; Greenwood, 2005; Mishra *et al*, 2003; Snow *et al*, 2005; WHO, 2002).

Although around 3.2 billion people — almost half of the world's population — are reported to have been at risk of malaria between 2000 and 2015, as a result of the relative success of malaria intervention programmes globally, malaria incidence (the rate of new cases) fell by 37%. In the same period, although malaria death rates fell by 60% among all age groups and by 65% among children under five (WHO, 2015), the disease continues to be the main killer in sub-Saharan Africa. In 2015, the African region was home to 89% of malaria cases and 91% of malaria deaths (WHO, 2015).

Malaria is known to be highly climate-sensitive and has remained the main killer in the vulnerable developing world. Human-induced climate change reflects the mounting pressures of human numbers and intensified economic activity (McMichael, 2009).

Variable rainfall patterns and rising temperatures are associated with the spread of malaria. Temperature, precipitation, and humidity are considered risk factors for malaria transmission. Increasing temperature accelerates the rate of mosquito larval development, the frequency of blood feeding by adult female mosquitoes on humans, and reduces the time it takes the malaria parasites to mature in female mosquitoes (Atul & Nettleman, 2005; Kovats & Martens 2000). Increased rainfall creates additional breeding sites for mosquitoes, thus increasing their numbers (WMO, 2015). Moreover, a combination of mutating malaria parasites, resource constraints and weak health systems, alongside drug resistance and land use patterns, imply low adaptive capacity and increases in malaria (Harrus & Baneth, 2005; IOM, 2008; Kovats & Haines, 2005; Pascual et al, 2006; Relman *et al*, 2008).

1.4. Malaria in South Africa's Limpopo Province

Malaria in South Africa could increase with the expansion of habitats suitable for mosquitoes that transmit the disease. *P. Falciparum* is only one of the four malaria diseases but it is by far the most dangerous and most abundant in South Africa and only certain anopheles mosquitoes carry this deadly malarial disease. Once the malaria parasites from this species enter the human body they travel to the liver and into the red blood cells. They then undergo dramatic multiplication and spread rapidly throughout the body, resulting in fatality if untreated. Precautions can be taken before going into a malaria prone area and the disease can be treated and cured. It is estimated that R2 billion goes towards malaria treatment and prevention in Africa.

For many years malaria was endemic in South African's KwaZulu-Natal and Mpumalanga Provinces, but over recent few decades there has been a systematic and gradual rise in malaria cases in the northern Limpopo Province. Despite a reported reduction in malaria trends in South Africa, through a combination of various social, economic, and policy efforts (Blumberg & Frean, 2007), the impact of recent climate change on malaria incidence remains poorly understood. Little has been written about climate impacts on malaria in Limpopo Province. Whereas Shewmake (2008) does not mention malaria in a study of household vulnerability to climate change, Gerritsen *et al.* (2008) provide only an overview of seasonal malaria incidence and mortality, and detect trends over time and places in the province. Although there has been a decrease in the malaria cases reported in Limpopo Province, currently it is the largest contributor to the malaria incidence in South Africa (Maharaj et al. 2012) and have surpassed known endemics in KwaZulu-Natal and Mpumalanga Provinces.

1.5. Context of the study

In Limpopo Province, malaria is now being observed as shifting to originally *non-malaria* districts and it is unclear whether climate change drives this shift. The focus of this study is the climate-sensitive diseases, specifically focusing on malaria, the most common vector-borne disease in the world. It is the objective of this study therefore to examine the distribution of malaria at district level in the province, to determine the direction and strength of the linear relationship and causality between malaria and the

meteorological variables (rainfall and temperature), and to ascertain their short- and long-term variations. The spatio-temporal method, correlation analysis, and econometric methods are applied.

Furthermore, since the onset of the rainfall season always triggers the beginning of a 'malaria season', this should ideally coincide with the timing of malaria control interventions. This study applies economic methods to understand the timing of impact of climate on malaria as well as the length that such impacts last. This is critical in the design of effective malaria control programmes and the proper design of early warning systems. Data on global and local rainfall and temperatures are compared with the local climate for reported malaria cases.

1.6. Conceptual framework

The conceptual framework for this study advances a multiple-factor explanation for malaria, ranging from climate and land use change, to drug resistance, variable disease control efforts, and other socio-demographic factors. Figure 1 below illustrates a simplified, non-detailed interrelationship. This study looks at the climate-malaria inter-relationship.

Malaria is influenced by social, economic and/or environmental factors as depicted in Figure 1 below. The influence of environmental factors in terms of variation in rainfall and temperature is becoming increasingly important in its role in shortening the vector life cycle, thereby increasing its population. Variations in rainfall and temperature influence mosquito populations either positively or negatively (see positive and negative signs in the figure).

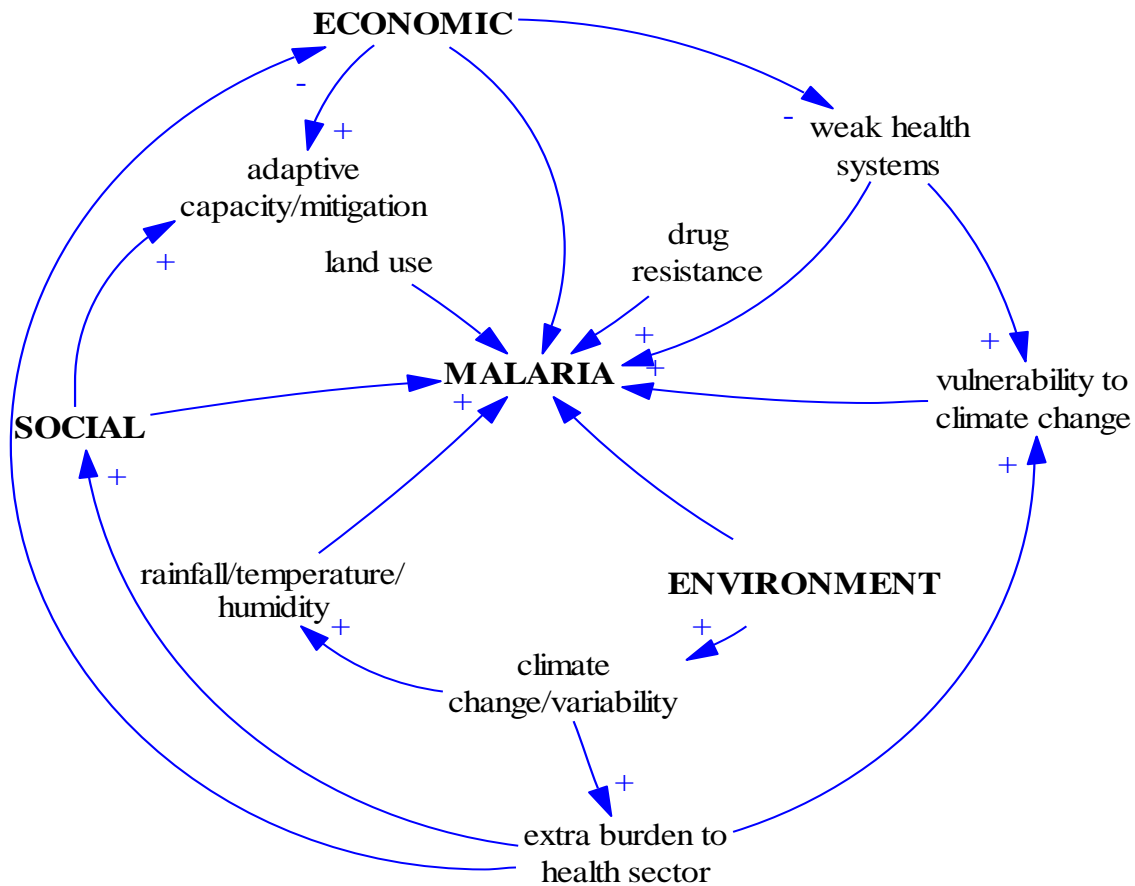


Figure 1: Malaria-environment nexus

Source: This study

High temperature reduces the development time of vector-borne pathogens and, combined with favourable climate conditions, the population of carrier-mosquitoes increases. This in turn increases the likelihood of an infectious bite. Growth of the anopheles vector is accelerated under conditions of increased temperature with optimal larval development at 28°C and optimal adult development between 28°C and 32°C. Very high rainfall and temperatures negatively affect mosquito development, but

a moderate climate will provide a conducive environment for the vectors to grow. Significant warming trends therefore amplify mosquito population dynamics, and thus, alongside drug resistance and land-use patterns, they contribute to the increased incidence of malaria. Empirical studies have reported rainfall and temperature as the main climate factors that influence malaria transmission; however, other studies have included climate variables such as humidity and vegetation.

In both theory and in literature, variations in rainfall and temperature will lead to the increase or decrease in malaria cases observed. Apart from the influence of climate in malaria transmission, socio-economic factors such as population and migration also play significant roles. The rise in malarial disease increases pressure on the health sector. Moreover, a combination of mutating malaria parasites (and subsequent resistance to drugs), resource constraints, and weak health systems, implies low adaptive capacity.

1.7. Problem statement

Increasing rainfall and rising temperature is causing health concerns. It is highly likely and *now certain* and that climate change will impact on health by creating an environment that is conducive to the growth of disease-spreading insects, for example, mosquitoes (IPCC, 2001). Anopheles (female) mosquitoes, for example, are the known vectors responsible for transmitting malaria to the hosts, for example, humans. Over past few decades, there has been a reported case of malaria in various regions of the

world where malaria cases and deaths were previously unheard of. Climate variation may include shifts in the distribution of diseases into areas that were previously disease-free, or may result in a change in severity at a given location (IPCC WG2, 2007). This reality has prompted studies to examine whether variations in temperatures and rainfall could help to demystify the link with malaria. A combination of rainfall and rising temperatures has provided a haven where malaria parasites hatch, multiply, and spread to hosts, thereby increasing the likelihood of observing malaria in regions where previously there were none.

The presence of mosquitoes that transmit malaria is determined by climatic factors: temperature, precipitation, and humidity. Regions in South Africa with optimum conditions are KwaZulu-Natal, Limpopo, and Mpumalanga. The Limpopo Province (approximately 22–25°S, 27–32°E) is South Africa's northernmost province that shares its international borders with Botswana, Zimbabwe, and Mozambique. Socio-economic factors and other environmental factors also affect its spread.

The indirect impacts of climate change on malaria transmission, especially the role that rainfall and temperature play, remain very poorly understood, particularly in South Africa. In order to put effective control measures in place it is important to ascertain the influence of recent climate changes on malaria prevalence and to understand the current factors that exacerbate the prevalence of malaria. The central focus of this study is to review the impacts of climate change on general health with a specific focus on the

impact of climate change on malaria transmission in Africa and in particular, in South Africa.

In the Limpopo Province of South Africa malaria is shifting and is now observed in originally *non-malaria* districts. It is unclear, however, whether climate drives this shift and, if it does, which of the two main climate drivers, rainfall or temperature, is responsible. Of greater importance, are the following questions: when is the onset of the malaria season; what is the duration of the malaria season; and what are the policy implications in terms of the timings of malaria interventions for Limpopo Province? The malaria period follows the onset of the rainfall season and has been found to be different for different countries. For example, in the East African Highlands, Zhou *et al.* (2004) found a one-to-two and two-to-five-month lag for minimum and maximum temperature respectively, whereas Briet (2008) and Hashizume *et al.* (2009) report a rainfall lag time of zero to three months and two to three months for Sri Lanka and Kenya, respectively.

The aim of this study is to establish the link between variations in rainfall and temperature in relation to the observed malaria cases in Limpopo Province. The purpose is to understand whether wet or dry, and cold or hot environments increase the likelihood of malaria cases in the districts within the scope of this study. This is undertaken in order to inform policy on the development of early warning systems at the times and seasons during which malaria is likely to be observed.

This study attempts to answer these questions by examining the distribution of malaria at district level in Limpopo Province, determining the direction and strength of the linear relationship and causality between malaria and the meteorological variables (rainfall and temperature), and ascertaining its short- and long-term variations. It seeks to establish the onset of the malaria season, as well as its duration, and suggests policy direction for the timing of malaria intervention programmes.

1.8. Goals and objectives

The study seeks to empirically assess how climate change is associated with increasing malaria transmission in South Africa, focusing on Limpopo Province, South Africa.

To achieve this goal, the following research objectives were identified:

- i. Using spatial, ascertain the malaria distribution in Limpopo Province, South Africa both provincial and district levels.
- ii. Using statistical methods, run models to ascertain the relationship between meteorological variables (rainfall and temperature) on malaria transmission in Limpopo Province, South Africa and determine relative influence.
- iii. Test the sensitivity of malaria with regard to the onset of rainfall (and temperature) and the duration of climate impacts using more 'sensitive' statistical tools in Limpopo Province.
- iv. Provide a policy framework for malaria prevention in South Africa under climate change.

1.9. Hypotheses

The following hypotheses will be tested in the study:

- Rainfall is an important driver for malaria transmission in Limpopo Province.
- Temperature is an important driver for malaria transmission in Limpopo Province.
- Malaria is sensitive to the onset of rainfall season in Limpopo Province.

1.10. Justification of the study

The association between climate and disease is of primary importance, especially in the case of malarial disease because it is a major threat in the developing countries. The health implications of malaria are colossal and the ways of managing it — from treatment to prevention — are costing already-struggling economies huge amounts annually in terms of health bills, *let alone* the multiplier effects of non-valued costs when a household loses its bread-winner. Information on the proper timing of malaria interventions programmes, based on the onset of malaria season, are demonstrated by the study (e.g., indoor residual spraying will assist in reducing or optimising the cost of the programme).

1.11. Organisation the thesis

This thesis is organised into six chapters. Chapter 1 is the introduction and background section. This section contextualises the challenges and failures of the traditional economy and introduces general climate impacts on health. The chapter proceeds by examining the way in which climate change impacts on malaria transmission, both generally and in South Africa. The chapter concludes by presenting the conceptual framework, the problem statement, the objective of the study, the hypotheses, and the justification of the study. Chapter 2 is a review of the empirical literature on climate change and health. It examines the effects of climate change; Africa's vulnerability to climate change impacts in general; the likelihood of the impacts; the impacts of rainfall and temperatures, climate change and communicable diseases; climate change and malaria in South Africa; and provides a summary of the literature of climate impacts on health.

Chapter 3 outlines the study area; data and data sources; and methodology and models used in the study, as well as the strengths and limitations of the methods. Chapter 4 contains the presentation of the results. The main findings are divided into three sections according to the objectives of the study. Chapter 5 is dedicated to a discussion of the results and is also divided as per the objectives of the study. A summary of the study is presented in Chapter 6, together with its scientific contribution and policy recommendations.

CHAPTER 2: REVIEW

Introduction

This chapter presents a review of the impacts of climate or global change on human health. In so doing it considers climate variability, vulnerability to climate change, climate impacts on health with a specific focus on how climate influences disease transmission and spread (the link between climate and vector-borne diseases).

The chapter also examines Africa's vulnerability to climate change; the methodologies used in analysing the association between climate and disease, and climate and malaria in Limpopo Province. The chapter concludes with a summary of the results.

2.2. Effects of climate change on human health

Over the last few decades, the direct and indirect consequences of climate on population health have been enormous. The IPCC's Fourth Assessment Report (2007) concludes that human health, already compromised by a range of factors, could be negatively impacted further by climate change and climate variability.

Several empirical studies in various regions under diverse climatic conditions reveal that climate variations have significant influence on the transmission of some vector-borne diseases. Climate-induced effects are consistent with the observed changes and are linked to increasing vector-borne diseases, such as malaria, in some regions of Africa and South America (Caminade et al, 2014). The IPCC (2001) concludes that the climate is changing; humans are contributing to this change; weather patterns have

become more extreme; and biological systems on all continents are responding to warming. In essence, the aggregate human impact on the environment has exceeded the limits of natural absorption or regeneration, resulting in an altered atmospheric composition, widespread land degradation, and depletion of fisheries, freshwater shortages, and biodiversity losses (McMichael *et al.* 1998).

Climate change, because of the scale, magnitude and breadth of its multiplier effects, poses a challenge to already-struggling economies. Warmer temperatures and ample rainfall, positively and significantly provide the necessary conditions for the multiplication and spread of vector-borne pathogens that are responsible for transmitting diseases such as malaria and Rift Valley Fever. This further burdens the health sector, especially in developing and middle-income countries. Climate change directly increases the pathogen population by shortening its life cycle. Details about how these changes are affecting the health of human populations are spelled out by the IPCC (2007) and summarised in Table 1 below.

Table 1: Actual and potential impacts of climate change on human health

	Climatic trend	IPCC assessment of health impacts*	Likely sector impacts	Likelihood*
Temperature	Warmer temperatures	<i>High confidence</i> (about 8 out of 10 chance) – Fewer cold days and nights, warmer and more frequent hot days and nights – Alteration in seasonal distribution of some allergenic pollen species		Virtually certain (> 99% probability)

	Warm spells/heat waves	<p><i>Very high confidence</i> (at least 9 out of 10 chance)</p> <ul style="list-style-type: none"> – Frequency increases over most land areas – Mixed effects on malaria; geographical range contracting or expanding; and/or changes in transmission season 	Health, Agriculture, forestry & ecosystems,	Very likely (> 90% probability)
Rainfall/precipitation	Heavy precipitation events	<p>frequency increases over most areas</p> <p><i>High confidence</i> (about 8 out of 10 chance)</p>	Water, Society & settlements	Very likely (> 90% probability)
	Drought	<ul style="list-style-type: none"> – Areas affected increase – Increase in cardio-respiratory morbidity and mortality associated with ground-level ozone; – Continued alteration in distribution of some infectious disease vectors; – Increase in number of people suffering death, disease, and injury from heat waves, floods, storms, fires, and drought; – Some benefits to health, including fewer deaths from cold (but expected to be outweighed by the negative effects of rising temperatures, especially in developing countries; <p><i>Medium confidence</i> (about 5 out of 10 chance)</p> <ul style="list-style-type: none"> – Increased burden of diarrhoeal diseases; – Increase in heat wave-related deaths; – Increase in malnutrition and consequences (e.g. child growth and development); <p><i>Low confidence</i> (about 2 out of 10 chance)</p> <ul style="list-style-type: none"> – Increase in number of people at risk of dengue. 		Likely (> 66% probability)
Other climate impacts include intense tropical cyclones and extreme high sea levels with a likelihood of greater than 66% probability.				

Source: IPCC 2007, Synthesis Report.

Based on the assigned confidence levels, climate change is already affecting human health, directly or indirectly, from the resultant extreme events such as heat waves, cyclones, floods, storms, and wildfires. It is changing the patterns of infectious disease, affecting food yields and availability, and the quality of freshwater supplies. It is damaging the proper functioning of ecosystems, for example, wetlands as water filters, and is displacing vulnerable populations — especially those living in low lying islands and coastal areas — and is causing a general loss of livelihoods. It is certain from the IPCC and empirical evidence that climate impacts are most likely and extensive and will threaten the health of millions of people, vulnerable and non-vulnerable alike.

According to the IPCC report, the principal sectors affected by climate change are the health sector, agriculture, forestry and ecosystems, water, and society and human settlements. The IPCC provides a summary of the impacts of temperature and rainfall as depicted in Table 1 above. These clusters and categories are directly or indirectly linked to climate change and are acute and/or long-term in nature.

The health effects that can be attributed to climate change are: heat-related morbidity and mortality; asthma, respiratory allergies, and airway diseases; vector-borne and zoonotic diseases; cardiovascular disease and stroke; weather-related morbidity and mortality; food-borne diseases and nutrition; water-borne diseases; human developmental effects; mental health and stress-related disorders; neurological diseases and disorders; and cancer (IWGCCH, 2008).

Climate change is therefore disrupting or otherwise altering a large range of natural ecological and physical systems that are an integral part of Earth's life support system. The resultant climate impacts are both positive and negative but predominantly negative (WHO, 2003), whether direct or indirect. The overall balance of effects on health is likely to be negative (Haines et al, 2006), and populations in low-income countries are likely to be particularly vulnerable to the adverse effects.

The direct impacts include very cold, moderate to extreme high temperatures, and very low and very heavy rainfall (McMichael, 2008). The direct impacts are felt immediately as a result of the mortality and morbidity associated with extreme weather events such as heat-waves, floods, and drought. The collapse of infrastructure and sudden death or injury provides some of the evidence and, depending on the magnitude and the number of people exposed, the impact can range from minimal to catastrophic.

The indirect effects of climate change are negative impacts on agriculture and livelihoods, the quantity and quality of food available, disruption of ecosystems, vector ecology, disease transmission, and the destruction of infrastructure. Although some of these effects might not necessarily be felt immediately, the impact can be massive, affecting a large number of people and, in the long-term, the indirect impact of climate change will, in all likelihood, exceed the direct negative impacts of climate change.

Aside from droughts and extreme precipitation which results in flooding, Patz, *et al.* (2002) argue that climate warming and changes in rainfall patterns may have significant and wide-ranging impacts on health, including changes in thermal stress and in the distribution and seasonality of vector-borne (Kovats *et al.* 1999) and other infectious diseases (Haines *et al.* 2006).

2.3. Africa and vulnerability to climate change impacts

Africa is a continent plagued with multiple stresses. The pressures of poverty, disease, hunger, and illiteracy are seemingly never-ending. Even the demise of colonisation across the continent over 50 years ago and rapid economic advancement has achieved little to improve the livelihoods of the African people. In Sub-Saharan Africa, poverty, disease, and hunger statistics are still among the highest in the world. In addition to the gruesome effects of persistent poverty and income inequalities that have rendered Africa porous and vulnerable, the already-struggling continent must again bear an additional unavoidable burden, that of climate change.

There is a general consensus that developing countries, specifically Africa, are vulnerable to change in climate. Climate change will disproportionately affect the resource-poor and geographically vulnerable populations in many tropical countries (Campbell-Lendrum, 2007; McMichael *et al.*, 1998). The greatest risks are to the poorest populations, those who have contributed least to greenhouse gas emissions (Campbell-Lendrum, 2007).

Risk factors contributing to vulnerability in Africa are low-income and geographical location. The primary reason why poor countries are vulnerable to climate change, argue Mendelsohn *et al.* (2006), is because they lie in the low latitudes and therefore experience very high temperatures, such that further warming pushes them even further away from optimal temperatures. The rapid economic development and urbanisation of poorer countries mean that Africa will be vulnerable to health hazards, and it is already vulnerable to a number of climate-sensitive diseases (Africa Partnership Forum, 2007).

Vulnerability to climate change is a function of exposure, sensitivity, and the adaptive capacity of the population. Populations that have been singled out as being at risk¹ are women, children, the elderly, and the chronically ill, as well as the poor. The level of exposure to climate change is based on (a) the projections of changes in mean temperature and precipitation, extreme events, and climate variability, and (b) people's account of how the climate has changed over time. Sensitivity is defined in regard to (a)

¹ People living in small island developing states and other coastal regions, megacities, and mountainous and polar regions are particularly vulnerable. Children – in particular, children living in poor countries – are among the most vulnerable to the resulting health risks and will be exposed longer to the health consequences. The health effects are also expected to be more severe for elderly people and people with infirmities or pre-existing medical conditions. Areas with weak health infrastructure – mostly in developing countries – will be the least able to cope without assistance to prepare and respond. WHO (2014)

the relative risks and effects — biophysical effects and hazards, and (b) who will be affected by climate change impacts, who are the vulnerable groups, and where do they live? Adaptive capacity is discussed in terms of (a) adaptation constraints — social and physical, and (b) the current capacities in the identified hotspots in general that could facilitate adaptation to climate change.

Exposure and sensitivity to climate impacts affect populations across the divide. The most hard-hit groups are those who dwell in informal settlements, the majority of who live in remote and rural areas, as well as coastal dwellers and peri-urban and urban areas. Informal settlements and rural areas have characteristics of high and dense populations per square kilometre, have poor shelter and, due to lack of proper planning, exist in vulnerable zones such as flood lines. These populations have weak adaptive capacity due to their reliance of natural resources and low income.

Vulnerability within populations varies because of their differences in geographical location, social and technical resources, and concurrent health status (McMichael et al, 1998). The range of factors contributing to vulnerability in Africa include high levels of poverty and illiteracy, a lack of skills, weak institutions, limited infrastructure, a lack of the application of appropriate technology and information, poor health care, poor access to resources, low management capabilities, and armed conflicts (UNFCCC, 2007).

The sudden impact of natural hazards such as floods, cyclones, and mudslides results in loss of crops and livestock which has a direct impact on family food security; low onset hazards (drought, desertification, deforestation, land degradation); and less access to early warnings and lower ability to respond. Water supply problems compound the problems of poor sanitation, hygiene, and poverty. A high proportion of the continent's population die from climate or water-related disease and many more are chronically ill with the debilitating effects of such diseases (Hulme et al, 1995).

The climate in Africa thus encourages the endemicity of vector-borne disease and the greatest burden for malaria is borne by the African continent, and remains unacceptably high (Warsame et al, 1995). Malaria epidemics have long been reported as occurring among vulnerable populations where immunity is often non-existent or poorly developed. It is estimated that epidemic malaria causes between 12% and 25% of the estimated annual malaria deaths worldwide, including up to 50% mortality in people under the age of 15 (Thomson *et al*, 2005).

2.4. Likelihood of climate impacts in Africa

There is a great volume of literature on the impact of climate on health. The confidence levels assigned by the IPCC (2007), based on the uncertainty of the occurrence of climate impacts, suggest *very high confidence* of certainty of malaria contraction and expansion as well as changes in the transmission season. A contraction of malaria is a

positive aspect of climate change, although of a smaller magnitude. The negative aspect is the expansion of malaria. In some regions malaria transmission will expand, whereas in other regions it will contract. This is because in some locations the climate conditions will no longer be conducive for malaria, whereas in other regions the climate will create very favourable conditions.

There is also *high confidence* in the increase in malnutrition; the number of deaths, diseases, and injuries from extreme weather events; the increase in frequency of cardiovascular and respiratory diseases caused by changes in air quality; changes in the range of infectious disease vectors; and a reduction in cold-related deaths. Of *medium confidence* is the increase in the burden of diarrhoeal diseases (IPCC, 2007).

Climate change may affect health through a range of pathways of variable complexity, scale, and directness, and with different timing impacts varying geographically as a function of both environment and topography and the vulnerability of the local population (WHO, 2003). The changes to natural climate systems cause extreme weather events. These changes increase the frequency and intensity of heat waves, lead to a reduction in cold-related deaths, increased floods and droughts, alter the distribution of vector-borne diseases, and affect the risk of disasters and malnutrition. These assigned probabilities are reasonably accurate in the context of Limpopo Province in South Africa.

2.5. Impacts of extreme rainfall, lack of rainfall (drought) and temperature

Climate change is affecting the natural rainfall patterns across the world and with that, human beings, either directly or indirectly. With climate change there is no real certainty in terms of rainfall and temperature patterns. Either very high (torrential) rainfall is observed or no rainfall at all (drought). This goes hand in hand with temperature patterns where there are either many conspicuous, extremely long hot days or very cold days and nights.

Average rainfall is not harmful to population health but extreme rainfall, in combination with temperature can be catastrophic through flooding and associated diseases. The resultant indirect impacts of warmer temperatures include changing patterns of infection; increased risk for populations with little or no immunity to new infections; the extension of transmission zones of malaria increase or change; the widening of transmission zones for dengue fever; and increases or changes in the distribution of other infections (e.g., schistosomiasis, lyme disease, and tick-borne encephalitis).

Heavy rainfall and drought are becoming common occurrences globally. It is reported that, on average, rainfall increased by 7% in the United States of America between 1970 and 1990, with two, four, and six inches per day, an increase of 14, 20 and 27 per cent respectively (Groisman et al, 2004; Groisman & Knight, 2008). Outbreaks of water-borne diseases are highly correlated with heavy rains and flooding (Curreiro et al, 2001).

Drought engenders some life-threatening health consequences by causing conditions that produce intensified wildfires, leading to injuries, burns, respiratory illness, the loss of the vegetation that support life, and loss of life itself. Inadequate water is a favourable condition for outbreaks of infectious diseases such as meningitis. Crop losses have increased by 133% and caused higher economic losses in Africa than in other world regions due to a combination of drought (brought about by inadequate rainfall and high temperatures), plant diseases, and the subsequent lower use of pest control technologies (Pimentel et al, 1992, as cited by McTegart & Sheldon, 1992).

South Africa has a warm climate and much of the country experiences average annual temperatures of above 17°C (DST, 2010). The spring begins August and ends in Mid-October. Summer season lasts from mid-October to mid-February. Autumn begins in Mid-February and ends in April while the winter season lasts from May to July. In Limpopo Province, average annual temperature is around 22°C, with the highest temperatures around 25°C recorded between December and January, while the lowest temperatures are experienced in July, about 15°C (Tshiala et al, 2011).

The likelihood of warmer temperatures is virtually certain. Warmer temperatures will impact on health, agriculture, and human settlements. These will see fewer cold days and nights as well as more frequent hot days and nights in most land areas. The implication of this warming trend is reflected in respect of reduced mortality from

decreased cold exposure in temperate climates, positive effects in agricultural production, forestry, and ecosystems through increased yields in cold environments, decreased yields in warm areas, and an increased number of vectors that transmit vector-borne diseases.

The effects of heat wave and other extreme events, such as cyclones, floods, storms and wildfires, significantly affect human health (McMichael, Nyong & Corvalan, 2008). There is very high probability that this will alter the seasonal distribution of allergenic pollen species.

Heat waves caused by high temperatures are also highly likely. Heat waves results in heat-related mortality, cardiovascular, and respiratory diseases. This will also affect water supply and water quality and will cause desertification, thereby reducing crop yields and predisposing communities to wildfires. A combination of warm spells and heavy rainfall will increase malaria transmission, cardio-respiratory morbidity, mortality linked to ground-level ozone, a continued alteration in the distribution of some infectious disease vectors; increase the number of deaths, diseases, and injuries from heat waves, floods, storms, fires, and drought. There will be some benefits to health, including fewer deaths from the cold but these are expected to be outweighed by the negative effects of rising temperatures, especially in developing countries.

2.6. Climate change and vector-borne (communicable) diseases — malaria

In respect of communicable diseases, land-use changes, species extinctions, migration, wars, and widening socio-economic inequalities are associated with emerging infectious diseases (IOM, 1992; Jones *et al.* 2008; McMichael *et al.* 1996, 2003; Patz *et al.* 1996; WHO, 1996). There are also indirect effects of climate change on malaria transmission emanating from population movements (migration), people fleeing due to economic challenges, and extreme events such as droughts. Such population movement may be from non-infested to infested areas, or it could result in transferring the parasite to a population with no immunity. The disruption of the climate system is also linked to the emergence and spread of climate-sensitive vector-borne diseases.

Ecological changes and economic inequalities strongly influence disease patterns but a warming and unstable climate is playing an ever-increasing role in driving the global re-emergence, resurgence, and redistribution of infectious diseases (Epstein, 2001). This is in combination with traditional factors such as elevation, land use changes, drug resistance, variable disease control efforts, and other socio-demographic factors (Pascual *et al.*, 2006; Patz *et al.*, 2002), including population immunity. Global warming will result in changes in the epidemiology of infectious diseases (Khasnis *et al.*, 2005). Some common climate-sensitive epidemics that have continued to be a major problem in Africa include fevers (yellow fever, Rift Valley Fever and dengue fever), cholera, river blindness, bilharzia, tuberculosis, and malaria.

The occurrence of Dengue fever, yellow fever, Rift Valley fever, Chikukunya fever, and malaria were once limited to 1000m above sea level but are now reported in elevations of above 1500 to over 2000m above sea level. Dengue fever has been reported at an elevation of about 1700m in Mexico, Latin America (Koopman et al, 1991), with vectors for Dengue fever, yellow fever, Rift Valley fever, and Chikukunya fever occurring at 2200 meters in the Andes (Suarez & Nelson, 1981), and malaria in the highlands of Rwanda, Uganda, Ethiopia, Kenya, and Zimbabwe (Ebi, 2005; Githeko & Ndegwa, 2001; Koenraadt *et al*, 2006; Lindblade *et al*, 1999; Loevinsohn, 1994).

Malaria is an extremely climate-sensitive disease (Patz & Olson, 2006; Rogers & Randolph, 2000) that is common in the tropics (Patz & Olson, 2006) but is also reported in mild-to-cold climates (Hulden, 2009). Climate change will result in shifting, expanding, or contracting known mosquito boundaries, and thus lead to changes in malaria transmission by widening malaria transmission zones. Large epidemics of malaria elsewhere have been associated with climate and temperature anomalies, such as in Colombia, the Indian subcontinent, and Uganda, and it has been shown that in Botswana, indices of El Niño-related climate variability can serve as the basis of malaria risk prediction and early warning (Bouma & van der Kaay, 1996; Lindblade *et al*, 1999; Poveda *et al*, 2001; Thomson *et al*, 2005, as cited by Patz *et al*, 2002).

The main climatic factors that influence malaria transmission are rainfall and temperature, as well as humidity. Rainfall provides conducive conditions for mosquito

breeding, while humidity and temperature together affect mosquito survival (Poveda *et al*, 2001). Warmer temperatures shorten the mosquito life cycle, thereby increasing its population (Patz & Olson, 2006; Patz *et al*, 2005). High temperatures shorten the development time of vector-borne pathogens; accelerate vector life cycles and decrease the incubation period of the parasite; and, combined with favourable climatic conditions, the population of carrier mosquitoes increases (Huang *et al*, 2011; Naqvi, 2009).

Malaria is also influenced by social, economic, and/or environmental factors (Haines *et al*, 2000). Climatic determinants are considered to be particularly important since both the disease agent (*Plasmodium*) and vector (Anopheles mosquitoes) are strongly affected by climate. Temperature, rainfall, and humidity have been associated with the dynamics of malaria vector populations and, therefore, with the spread of the disease (Alemu *et al*, 2011). Alongside vegetation cover, temperature determines parasite and vector development; rainfall provides conducive site conditions for mosquito breeding; and humidity, temperature, and vegetation together affect mosquito survival (Haque *et al*, 2010; Poveda *et al*, 2001).

Variations in rainfall and temperature influence the mosquito population. By shortening its life cycle its population is increased (Patz & Olson, 2006; Patz *et al*, 2005). With changes in vegetation cover and breeding sites, mosquito development is quickened, feeding frequency increased, and life-span enhanced, which in turn

multiplies their numbers (Atul & Nettleman, 2005; Hulme *et al*, 1995; Naqvi, 2009; Patz & Olson, 2006; Patz *et al*, 2005), thereby increasing the probability of infectious bites among susceptible populations. The impact of rainfall and temperature is linked to malaria transmission (Craig *et al*, 2004a; Craig *et al*, 2004b; Githeko & Ndegwa, 2001; Kleinschmidt *et al*, 2001; Kleinschmidt *et al*, 2002; Zhou *et al*, 2004). Studies by Connor *et al*. (1999), Ngomane and de Jager (2012), Nkomo *et al*. (2006), Paaijmans (2010), Pascual *et al*. (2006) and; Thomson *et al*. (2005) have confirmed that rainfall anomalies and warmer temperatures are the main climatic drivers of the inter-annual variability of malaria incidence.

A recent resurgence of malaria in the East African highlands involves multiple factors ranging from climate and land use change to drug resistance, changes in immunity, variable disease control efforts, and other socio-demographic factors (Harrus & Baneth, 2005; IOM, 2008; Pascual *et al*, 2006; Patz *et al*, 2002; Relman *et al*, 2008).

Whereas rainfall anomalies are widely considered to be a major driver of the inter-annual variability of malaria incidence in the semi-arid areas of Africa (Connor *et al*, 1999; Thomson *et al*, 2005), recently recorded warming trend in the East African highlands have corresponded with concomitant increases in malaria incidences (Pascual *et al*, 2006; Patz *et al*, 2002). The same studies have also reported that the biological response of mosquito populations to warming is more than the order of magnitude larger than the measured change in temperature. This finding thus shows

the importance of the nonlinear and threshold responses of malaria (a biological system) to the effect of regional temperature change.

In Kenya, meteorological factors have been associated with malaria incidence, with temperature having the largest effect (Yé, 2007). A study of the population dynamics of mosquitoes in relation to warming in sites in the East African highlands found that mosquito abundance was amplified with warming, with more than a ten-fold increase with every unit increase (0.1°C) in temperature (Pascual *et al*, 2006). This finding suggests that temperature increases will increase malaria cases. However, others have cautioned against attributing malaria dynamics to climate change and point to the uncertainties of predicting malaria epidemics nationally and locally (Reiter *et al*, 2007). Rainfall is an important limiting factor in disease transmission. Malaria has decreased in association with long-term decreases in annual rainfall in Senegal and Niger (Julvez *et al*, 1997; Mouchet *et al*, 1996, as cited by IPCC, 2007).

Other factors, for example, social and economic factors — population and migration — also play a significant role (Haines *et al*, 2000; van Lieshout *et al*, 2004). Moreover, a combination of mutating malaria parasites, resource constraints, and weak health systems, alongside drug resistance and land use patterns, implies low adaptive capacity and increases in malaria (Harrus & Baneth, 2005; IOM 2008; Kovats & Haines, 2005; Pascual *et al*, 2006; Relman *et al*, 2008).

Very high rainfall and temperatures negatively affect mosquito development, but a moderate climate will provide a conducive environment for the vectors to grow. Significant warming trends therefore amplify mosquito population dynamics, contributing alongside drug resistance and land-use patterns to the increased incidence of malaria (Harrus & Baneth, 2005; IOM, 2008; Pascual *et al*, 2006; Relman *et al*, 2008). Apart from the influence of climate on malaria transmission, socio-economic factors such as population and migration also play significant roles (van Lieshout *et al*, 2004). A rise in malaria disease increases pressure on the health sector.

High temperature shortens the development time of vector-borne pathogens and, combined with favourable climate conditions, the population of carrier-mosquitoes increases. A mere 0.5°C increase in temperature trends can translate into a 30–100% increase in mosquito abundance, thus indicating a ‘biological amplification’ of temperature effects (Pascual *et al*, 2006). In both theory and in literature, variations in rainfall and temperature will lead to the increase or decrease in malaria cases observed. The growth of the anopheles vector is accelerated under conditions of increased temperatures with optimal larval development at 28°C and optimal adult development between 28°C and 32°C (Atul & Nettleman, 2005; Naqvi, 2009).

Mordecai *et al*. (2013) conclude that as temperatures increase due to climate change, vector control will likely become more important, more difficult, and more expensive in temperate areas but in some, areas temperatures may simply become too hot to

support malaria. Projections also suggest that some regions will experience a longer season of transmission. Although an increase in months per year of transmission does not directly translate into an increase in malaria burden, it would have important implications for vector control. By comparing climate suitability maps for malaria in Zimbabwe, a country that is topographically diverse, Ebi *et al.* (2005) found that the projected warming from global climate models would make the country's entire highland area climatologically more favourable to malaria by the year 2050.

One positive aspect of heavy rainfall and very high temperatures is a low malaria transmission rate. This is because a trade-off exists between fast parasite development and high mosquito mortality at temperatures and rainfall ranges above or below optimum, such that high temperatures do not always increase transmission. Although the temperature shortens the mosquito life cycle with optimal transmission occurring at 25°C (Lunde *et al.*, 2013; Mordecai *et al.*, 2013), at very high temperatures, above 28°C, or low temperatures, below 16°C, the cycle cannot occur or becomes incomplete and transmission declines dramatically (Mordecai *et al.*, 2013; Williams *et al.*, 1999; Zucker, 1996).

Changes in temperature and precipitation will have a variety of effects, for example, increased flooding will facilitate the breeding of malaria carriers in formerly arid areas (Warsame *et al.*, 1995). Climate change will boost the population of disease-carrying mosquitoes and result in increased malaria epidemics (Kulindwa, 2006) and probably

the resurgence of indigenous malaria (Chin & Welsby, 2004) in new or old malaria transmission zones. In South Africa, there have been reports of significant reductions in malaria trends over recent years (Blumberg & Frean, 2007), not as a result of extreme weather events but as a result of increased DDT spraying. It seems that there are changes in mosquito habitats in the province and that the effects of climate change are spreading into new malaria transmission zones, new districts.

2.7. Climate impact on malaria in South Africa

In South Africa, malaria is endemic in KwaZulu-Natal and Mpumalanga provinces but over recent decades there has been a systematic and gradual rise in malaria cases in the Northern Province of Limpopo. *Plasmodium falciparum* accounts for the majority of malaria cases in southern Africa and is the predominant species associated with severe and fatal disease (Gerritsen et al, 2008).

Despite reported reductions in malaria trends in South Africa through a combination of various social, economic, and policy efforts (Blumberg & Frean, 2007), the impact of recent climate change on malaria incidence remains poorly understood. Little is written about climate impacts on malaria in Limpopo Province. Whereas Shewmake (2008) does not mention malaria in a study of household vulnerability to climate change, Gerritsen *et al.* (2008) provide only an overview of seasonal malaria incidence and mortality and detect trends over time and places in the province.

In South Africa, although the prevalence and incidence of malaria transmission has been established, there is still limited information regarding the actual influence of rainfall and temperature on malaria epidemics in Limpopo Province. Statistical methods have been applied to study malaria incidence within South Africa with a specific focus on either Limpopo Province, or in a specific district within the Province, using local malaria and meteorological variables. These studies have used basic retrospective descriptive analysis, for example, Khosa et al (2013), Geritzen *et al.* (2013), to detect malaria incidence rates, case fatality rates (CFR), and indoor residual spraying (IRS) coverage rates and incidences, as well as tracking the effectiveness of malaria control interventions implemented across the seasons.

Few studies that have considered the role climate change in malaria distribution have followed similar approach. Ngomane and de Jager (2012), used Autoregressive Integrated Moving Average to study the changes in malaria morbidity and mortality in Mpumalanga Province and to assess the association between climate and malaria, whereas Thompson (2012) used regression analysis to study how climate change affects children's general health in Limpopo.

By using both passive and active surveillance, the case reporting system aims to capture every infection rather than clinical cases only (Sharp et al, 1988). Malaria transmission is found to be distinctly seasonal, with transmission limited to the warm and rainy summer months (Craig et al, 2004). Historically, and without intensive control

programmes, case notifications generally increase from November onwards, peak in late-summer to autumn (March–May), and decline by the end of June. As a result, the average seasonal pattern in malaria incidence follows the periodicity in rainfall and temperature with a 3–4-month lag (Craig et al, 2004).

Kulindwa (2006) provides a worrying trend for malaria transmission under climate change in South Africa — that the area suitable for malaria will double and that there is a 5–7% potential increase (mainly altitudinal) in malaria distribution with 7.8 million people potentially at risk by 2100 with little increase in the latitudinal extent of the disease.

2.8. Chapter Summary

The health effects that can be associated with climate change are: heat-related morbidity and mortality; asthma, respiratory allergies, and airway diseases; vector-borne diseases such as malaria; cardiovascular disease and stroke; weather-related morbidity and mortality; food-borne diseases and nutrition; waterborne diseases; human developmental effects; mental health and stress-related disorders; neurological diseases and disorders; and cancer (IWGCCH, 2008). These clusters and categories are directly or indirectly linked to climate change and are acute and/or long-term in nature.

All published models have limited parameters for some of the key factors that influence the geographical range and intensity of malaria transmission. There is a 5–7%

projected estimate of the potential increase (mainly altitudinal) in malaria distribution by the year 2100, with surprisingly little increase in the latitudinal extents of the disease (Tanser et al, 2003).

Although descriptive analyses reveal trends in incidence and basic relationships between variables, they do not show when the actual impact occurred, as well as how far the impact is sustained. The time of impact and also the duration of such impacts are important in malaria control programmes and critical to the design of effective early warning systems. This paper uses the regression method to analyse the relationship between metrological variables and malaria cases and it applies Impulse Response Functions (IRF) in a Vector Moving Average (VMA) to achieve these aims. Elsewhere, IRF has been used to study the effects of meteorological factors on the incidence of Dengue haemorrhagic Goto *et al.* (2013). Impulse response is an essential tool in causal analysis and policy effectiveness. Global data sets are eventually validated against local time series observation in Limpopo Province, South Africa.

Like many rural communities, Limpopo is predominantly rural with agriculture being the most practiced economic activity. There is lower degree of ownership of land and other productive assets that implies less control over production and markets, and a lower ability to adapt to ecological changes, resulting in crop failures as well as loss of income (UNISDR, UNDP & IUCN, 2009). Lower income and access to resources implies greater vulnerability in the face of shocks such as food shortages, crop failure, climate disasters, and also a reduced ability to recover. These resources would otherwise lessen

the impacts of climate change on vulnerable populations (UNISDR, UNDP & IUCN, 2009).

There is also a lower degree of access to assets (physical, financial, human, social, and natural capital) that largely determine how populations will respond to a given hazard. The more assets people have, the less vulnerable they are likely to become (Moser & Satterthwaite, 2008), whereas the greater the erosion of people's assets, the greater their insecurity.

Limpopo Province has three distinct climatic regions: the Lowveld region, the Middle and Highveld, and the Escarpment. The Lowveld is characterised by semi-arid climatic conditions, the Middle and Highveld are considered semi-arid, and the Escarpment experiences a sub-humid climate (Limpopo Department of Agriculture, 2008). In terms of temperature, the province can become very hot in summer, between October and March, with average temperatures rising to 27°C in summer and 20°C in winter. The bulk of precipitation occurs in summer and annual rainfall totals range from about 400–600 mm over most of the province (Anon, 2007).

Of the nine provinces in South Africa, Limpopo Province remains among the poorest, with the majority of the population living in rural areas. Overall, approximately 57% of individuals in South Africa were living below the poverty income line in 2001. This figure has remained unchanged since 1996. Limpopo and the Eastern Cape had the highest proportion of poor with 77% and 72% of their populations, respectively, living

below the poverty income line. The Western Cape had the lowest proportion of people in poverty (32%), followed by Gauteng (42%) (HRSC, 2004). This level of poverty predisposes the province to climate impacts such that the populations' ability to bounce back in the wake of a climate impact, especially in respect of health, becomes a challenge. The coping mechanisms that are suggested as significant include access and control of productive assets, such as land, and access to information through early warning systems ahead of a potential climate hazard.

CHAPTER 3: METHODOLOGY

Introduction

This Chapter presents the study area, data and data sources and describes the methodology applied in the study in detail. This study uses spatio-temporal, correlation, and econometric approaches (unit root tests and causality tests). The spatial method examines the distribution of malaria at the district level within the province, while Pearson Correlation determines the direction and strength of the linear relationship between malaria and the meteorological variables. The econometric approach is applied to (1) validate and examine the intrinsic characteristics (stationarity) of malaria cases, rainfall, and temperature; (2) test the direction and relative strength of causation; and (3) ascertain the short-term and long-term equilibrium relationship of the variables. The strength of econometric methods lies in their ability to distinctively separate the effects of correlation from those that are related to causality, thereby eliminating the common fallacy that correlation implies causation. Causality is tested using the standard Granger Causality Test.

3.1. Study area

The Limpopo Province (approximately 22–25°S, 27–32°E) is South Africa's northernmost province that shares its international borders with Botswana, Zimbabwe, and Mozambique.

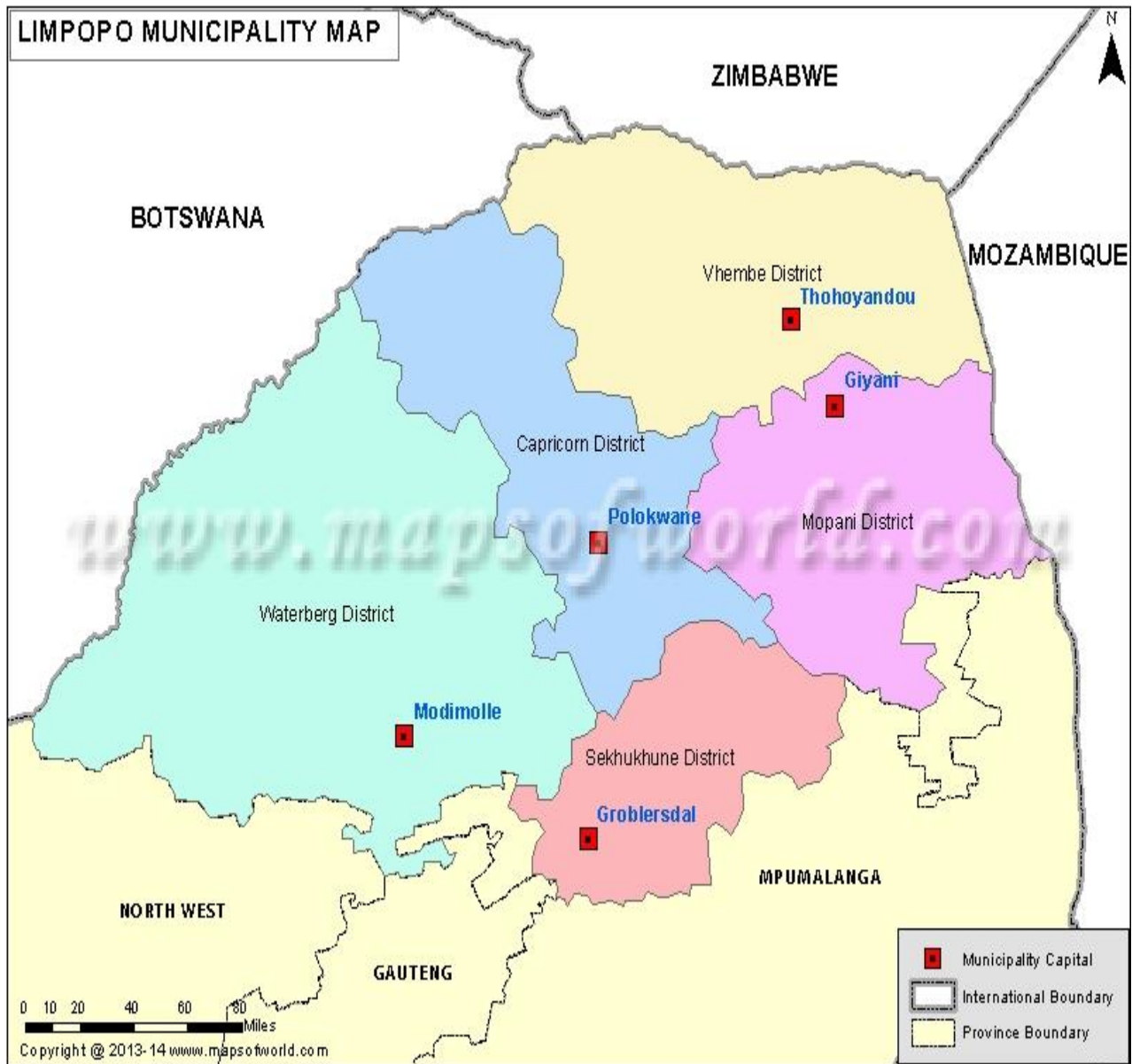


Figure 2: Limpopo Province

3.2. Data and data sources

Time series monthly meteorological data (1998–2007) (average rainfall and temperature) have been obtained from South Africa Weather Services (SAWS). Clinical malaria data were sourced from the Malaria Control Centre in Tzaneen (Limpopo

Province) and the South African Department of Health. Malaria data were captured through passive and active surveillance systems. Details of the methods on how these data were collected can be obtained from Gerritsen *et al.* (2008). Global data were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). The study uses the ERA-40 and ERAINTERIM data collected by the European Centre for Medium-Range Weather Forecasts (ECMWF). The European Centre for Medium-Range Weather Forecasts (ECMWF) is an independent inter-governmental organisation supported by 18 European Member States and 15 Co-operating States.

Daily station data of precipitation and temperature (minimum and maximum) from 1998 to 2008 were used to construct climate disease envelopes at municipal and district levels. Daily malaria cases were converted into monthly data. Malaria data contains different variables including confirmed malaria cases captured through passive and active surveillance systems. Different demographic, geographic, and social-economic data were also captured. These data include: the date the blood sample was taken, sex, age, and other geographical variables such as the current and original district, the health facility, and the local municipality and district. The data also contain information on whether or not the person died. Details of the methods on how these data were collected can be obtained from Gerritsen *et al.* (2008).

3.3. Models

In the study of malaria in South Africa, focus has been mainly on malaria control and elimination (Maharaj *et al.* 2013; Maharaj *et al.* 2012); and prevalence (Okanga *et al.* 2013). In terms of methods applied, basic retrospective descriptive analysis have been used by Khosa *et al.* (2013) and Geritzen *et al.* (2013), to detect malaria incidence rates, case fatality rates (CFR), and indoor residual spraying (IRS) coverage rates and incidences, as well as tracking the effectiveness of malaria control interventions implemented across the seasons while Okanga *et al.* (2013) utilizes remote sensing method to analyse environmental factors pertinent to mosquito ecology such as rainfall, season, temperature and water quality. There is no study that has used combination of spatial and econometric approaches. This study goes beyond the descriptive analysis and uses a combination of approaches: spatio-temporal, correlation, and econometric approaches (unit root tests and causality tests); to show how climate variables are related with malaria cases, when the actual impact occurred as well as how far the impact is sustained. The time of impact and also the duration of such impacts will be important in malaria control programmes and critical to the design of effective early warning systems.

The spatial method examines the distribution of malaria at the district level within the province, while Pearson Correlation determines the direction and strength of the linear relationship between malaria and the meteorological variables. The econometric approach is applied (1) to validate and examine the intrinsic characteristics

(stationarity) of malaria cases, rainfall, and temperature; (2) to test the direction and relative strength of causation; and (3) to ascertain the short- and long-term equilibrium relationship of the variables. Stationarity is a process in which the parameters of the process do not change with time, that is, the mean, variance, and autocorrelations are constant in time, whereas a non-stationary variable is otherwise.

The study applies the spatio-temporal method, correlation analysis, econometric methods (Auto-Regressive Distributed Lag (ARDL), multiple regression analysis, and Impulse Response Function (IRF) in a Vector Moving Average (VMA). As a requirement for time series analysis, this study first analyses the univariate characteristics (stationarity) of rainfall, temperature and malaria cases. Stationarity tests are important in order to avoid spurious results. The study then applies multiple regression analysis and Impulse Response Function (IRF) in a Vector Moving Average (VMA) process. The VMA representation of a stationary VAR system is used to derive the IRF of the model. VAR is one of the most flexible models for analyses of multivariate time series. The main advantage of VAR is that multivariate variables are both explained and explanatory variables. IRF is used to identify shock reactions to the maximum temperature and total rainfall. IRF tracks the impact of all the climate variables on malaria cases in the system. All analyses are performed using Eviews Version 6 (IHS Global Inc.)

3.3.1. Spatio-temporal

The spatial distribution of malaria at municipality and district levels were mapped using inverse distance weighting (IDW) interpolation routine in ArcGIS. The IDW routine assumes that each measured point has a local influence that diminishes with distance (Baltas, 2007). It gives greater weights to points closest to the prediction location and the weights diminish as a function of distance. Malaria records for the various municipalities were spatially weighted and aggregated at the district level. The weighted points at the centroid of each district were then interpolated using the IDW following Hanafi-Bojd *et al.* (2012), Jorgensen *et al.* (2010) and Messina *et al.* (2011).

3.3.2. Correlation

Given seasonalised climate variables, a linear relationship between temperature, rainfall, and malaria cases was derived from the Pearson Correlation coefficients as reported by Wilks (1995). The linear relationship between temperature and rainfall with malaria cases are determined as a partial correlation following Mardia *et al.*, 1979; Panofsky & Brier, 1968).

3.3.3. Causality

A causality test is a test of ‘what *causes what*’, that is, whether rainfall or temperature, or both, cause or can explain malaria transmission in Limpopo Province. In order to determine causality, Granger (1969) proposed a time series data-based approach. Intuitively, the standard Granger-causality test examines whether past changes in one variable, *y*, help to explain current changes in another variable, *x*, over and above the information provided by the lagged values of *x*. If not, then one concludes that ‘*y* does

not Granger-cause x' . To determine whether causality runs in the opposite direction, from x to y , one basically repeats the experiment but with the variables interchanged. The null hypothesis that y does not Granger-cause x is rejected if the coefficients in the equation are jointly significant based on the standard F-test.

There are three different types of situations in which a Granger-causality test can be applied and four possible feasible outcomes. The situations are: (i) a simple Granger-causality test with two variables and their lags; (ii) a multivariate Granger-causality test with more than two variables; and (iii) Granger-causality in a VAR framework. For the purposes of this study the focus on the second situation (multivariate Granger-causality) since three variables are considered: malaria cases, rainfall, and temperature. The four feasible outcomes are: (1) *independence* — here, neither malaria cases, rainfall, nor temperature, *Granger-cause* each other; (2) *unidirectional Granger-causality* where rainfall *or* temperature independently *Granger-causes* malaria cases, but not the other way round; (3) *unidirectional Granger-causality* where malaria cases cause rainfall or temperature independently, but not vice versa; and (4) *bi-directional (or feedback) causality* where malaria cases, rainfall, and temperature *Granger-cause* each other. Theoretically, it is expected that rainfall and temperature influence malaria cases. A bi-directional causality is expected between rainfall and temperature. There is no expectation of malaria cases to cause rainfall or temperature.

3.3.4. Stationarity (unit root) test

Stationarity tests are performed using the standard Augmented Dickey-Fuller (ADF) (Dickey & Fuller 1981) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests (Kwiatkowski et al, 1992). Variables are tested using this standard methodology and where variables are found to be non-stationary, they are transformed to be stationary. A non-stationary variable can be transformed into a stationary process by either adjusting for trends or including a time index as an independent variable in the regression. Sometimes de-trending and the inclusion of time index may not be sufficient to make the series stationary due to the possibility that the statistics for changes in the series between periods and seasons are constant, in which case the data is differenced. Differencing implies transforming the variables into a series of period-to-period and/or season-to-season differences. A stationary series is denoted as $I(0)$, but when the series is differenced once it is said to be integrated to order one, that is, $I(1)$ and a twice difference is $I(2)$.

In econometrics, testing for stationarity is an indispensable requirement for two main reasons. Firstly, without stationarity tests it is not possible to obtain any meaningful sample statistics such as means, variances, and correlations with other variables. Secondly, stationarity tests provide important clues in the search for appropriate methodology and forecasting models.

Although it is known from the literature that combining stationary variables with non-stationary variables in a regression model yields spurious (nonsensical) results and, therefore, an unreliable outcome (Gupta & Komen, 2009; Komen & Kapunda, 2006), models now exist that regress both stationary and non-stationary data. The recourse lies in the recently developed Autoregressive Distributed Lag (ARDL)-Wald (Bounds) test framework developed by Pesaran and Shin (1995, 1999; Pesaran, 1997; Pesaran et al, 1996).

3.3.5. Autoregressive Distributed Lag (ARDL)-Bounds Test Model

The ARDL methodology is applicable in testing causation and long-term relationship in cases where not all variables are integrated to the same order. Cointegration (long-term relationship) is a situation where two or more series are non-stationary but a linear combination of them is stationary. The advantage of using the ARDL-Bounds test in testing cointegration is that whereas the conventional cointegration method estimates the long-term relationships within the context of a system of equations, the ARDL method employs only a single reduced form equation (Pesaran & Shin, 1995). Most importantly, the ARDL framework avoids the larger number of specifications to be made in the standard cointegration test, such as decisions regarding the number of endogenous and exogenous variables to be included, the treatment of deterministic elements, as well as the optimal number of lags to be specified (Duasa, 2007). The procedure can be applied irrespective of whether the regressors are stationary, non-stationary, or mutually cointegrated (Pesaran *et al*, 2001).

3.4. Models specification and description

The ARDL specification takes the following form:

$$\Delta \ln mala_t = \gamma + \sum_{i=0}^{\eta} \alpha_i \Delta \ln rain_{t-i} + \sum_{i=0}^{\eta} \delta_i \Delta \ln temp_{t-i} + \sum_{i=1}^{\eta} \varpi_i \Delta \ln mala_{t-i} + \beta_1 \ln rain_{t-1} + \beta_2 \ln temp_{t-1} + \beta_3 \ln mala_{t-1} + \varepsilon_{t-1} \quad (1)$$

Where

$\ln mala$ is the natural logarithm of malaria cases

$\ln rain$ is the natural logarithm

$\ln temp$ is the natural logarithm

Δ denotes first difference operator

η is the optimal lag length

$\beta_1, \beta_2,$ and β_3 are the long-term coefficients

α_i, δ_i and ϖ_i represents the short-term dynamics

ε is the random disturbance term

The F-test is performed on null hypothesis (H_0) of no long-term relationship among variables (estimation of equation (1)) is tested against an alternative hypothesis (H_1), as presented below.

$$H_0 = \beta_1 = \beta_2 = \beta_3 = 0$$

$$H_1 = \beta_1 \neq \beta_2 \neq \beta_3 \neq 0$$

The *absence* of a long-term equilibrium relationship between the variables coincides with zero coefficients for $\ln \text{rain}_{t-1}$, $\ln \text{temp}_{t-1}$ and $\ln \text{mala}_{t-1}$. A *rejection* of H_0 implies that there is a long-term relationship.

The ARDL estimation proceeds in two steps. First is the estimation of equation (1) by Ordinary Least Squares (OLS) in order to establish the existence of a long-term linear relationship. Once cointegration is confirmed the second step is to estimate the long-term coefficients (equation 2).

$$\ln \text{mala}_t = \gamma_1 + \sum_{i=0}^{\eta} \alpha_{1i} \ln \text{rain}_{t-i} + \sum_{i=0}^{\eta} \delta_{1i} \ln \text{temp}_{t-i} + \sum_{i=0}^{\eta} \varpi_{1i} \ln \text{mala}_{t-i} + \varepsilon_{t-1} \quad (2)$$

The investigation of the long-term relationship using the ARDL approach involves the estimation of equation 2 through an Unrestricted Error Correction Model (UECM). Since specification assumes that the disturbances are serially uncorrelated, the choice of appropriate lag order is important (Sultan, 2010). The appropriate lag length in the ARDL model is selected by either Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC). The lag length that minimises SBC is selected. To achieve orthogonality, the unrestricted model is then estimated and progressively reduced,

eliminating the statistically insignificant coefficients and reformulating the lag structure where appropriate. The unrestricted ECM minimises the possibility of estimating spurious relations while retaining the long-term information which is suitable for economic interpretation (Greenidge *et al*, 2001). A battery of diagnostic tests can then be used to check the performance of the UECM (Akinboade *et al*, 2008; Hendry *et al*, 1984, as cited by Sultan, 2010).

The short-term dynamics is derived from the ARDL specification, equation (3), by constructing an Error Correction model (ECM), equation (4).

$$\Delta \ln mala_t = \gamma_2 + \sum_{i=1}^{\eta} \alpha_{2i} \Delta \ln rain_{t-i} + \sum_{i=0}^{\eta} \delta_{2i} \Delta \ln temp_{t-i} + \sum_{i=1}^{\eta} \varpi_{2i} \Delta \ln mala_{t-i} + \sigma ECM_{t-1} + \varepsilon_{t-1} \quad (3)$$

Where ECM is the error correction term, defined as:

$$ECM_t = \ln mala_t - \gamma_1 - \sum_{i=0}^{\eta} \alpha_{1i} \ln rain_{t-i} - \sum_{i=0}^{\eta} \delta_{1i} \ln temp_{t-i} - \sum_{i=0}^{\eta} \varpi_{1i} \ln mala_{t-i} \quad (4)$$

All coefficients of the short-term equation are coefficients relating to the short-term dynamics of the model's convergence to equilibrium, and σ represent the speed of adjustment.

The F test is used to test the existence of long-run relationship.

The asymptotic distribution of the obtained *F-statistic* is nonstandard regardless of the degree of integration of the variables. This, however, depends on (1) whether the variables included in the ARDL model are I (0) or I (1); (2) the number of regressors; (3) whether the model contains an intercept and/or a trend; and (4) the sample size. Two sets of critical *F-values*, representing the lower bound and the upper bound, have been provided by Pesaran and Shin (1999) for large samples. Narayan (2004) presents the critical *F-values* for sample sizes ranging from 30–80. If the computed *F-statistic* for a chosen level of significance lie outside the critical bounds, a conclusive decision can be made regarding the cointegration of the regressors. If the statistic is higher than the upper bound, the null hypothesis of no cointegration can be rejected and the next step is to estimate the ARDL ECM where the short-term and long-term elasticity may be determined (Narayan, 2004; Pesaran & Shin, 1999 as cited by Sultan, 2010).

Computed and critical bounds of the *F-Statistic* are provided by Pesaran *et al.* (2001). The *F-statistics* should lie outside the bounds for a long-term relationship to exist, but for a short-term, the coefficient of the error correction model (ECM) should be negative and statistically significant.

3.4.1. Vector Auto-regression

As a requirement for time series analysis, this paper first examines the univariate characteristics (stationarity) of rainfall, temperature, and malaria cases in this study. Vector Auto-regression (VAR) is an econometric model used to capture the linear interdependencies among multiple time series. VAR models generalise the univariate auto-regressive model (AR model) by allowing for more than one evolving variable. It then applies multiple regression analysis and Impulse Response Function (IRF) in a Vector Moving Average (VMA) process. The VMA representation of a stationary VAR system is used to derive the IRF of the model. VAR is one of the most flexible models for analyses of multivariate time series. The main advantage of VAR is that multivariate variables are both explained and explanatory variables. IRF is used to identify shock reactions to the maximum temperature and total rainfall. IRF tracks the impact of all the climate variables on malaria cases in the system. All analysis was performed using Eviews Version 6 (IHS Global Inc.).

3.4.2. Multiple Regression model

Available data on malaria cases are used to calculate malaria incidence by adjusting the population for Limpopo Province. The standard way of indicating the proportion of people affected by the disease is to divide the number of cases by the total population. The incidence is often multiplied by 1,000 to indicate how many people in a typical sample of 1,000 people are infected with malaria. The multiple regression model, equation 1, is estimated with malaria incidence as the dependent variable with five independent variables: rainfall, lag of rainfall, temperature, and the exponent of rainfall

and temperature (rainfall and temperature squared). Since malaria incidence is also heavily determined by the past level of rainfall, inclusion of the lag of rainfall is therefore a prerequisite of the model. Independent research results indicate the existence of a quadratic relationship between rainfall and malaria incidence.

Model specification

$$\ln Incidence = \beta_0 + \beta_1 \ln rain + \beta_2 \ln rain(-1) + \beta_3 \ln rain^2 + \beta_4 \ln temp + \beta_5 \ln temp^2 + \varepsilon$$

Equation 5

Where

β_s Are the coefficients of the regression

ε : is the Error term. This accounts for all other independent variables that may explain malaria incidence that are not included in the model.

An increase in the mosquito population, and hence the epidemic risk, with an increase in rainfall will only occur up to a certain point; if there is too much rainfall the risk of an epidemic may decline. Excess rainfall and temperature directly impact negatively on mosquito populations through the destruction of breeding sites. To consider these possible effects, two additional variables, rainfall squared and temperature squared, are included.

Variables are log-transformed to eliminate the positive skewness common in time series monthly and annual data. This regression model is adjusted for trends for each

of the data sets ERA, TRMM, TRMMv7 and Station data, and the results tabulated in terms of coefficients, coefficient of adjustment, t-statistics, and F-statistics.

3.4.3. Impulse Response Function (IRF)

Typically, an impulse response describes the reaction of a dynamic system in response to some external change as a function of time, or possibly as a function of some other independent variable that parameterises the dynamic behaviour of the system. The Vector Moving Average (VMA) description of a stationary VAR system can be used to derive the Impulse Response Functions (IRF) of a model, using the VMA representation of a stationary VAR model.

3.5. Strengths and limitations of methods

The strength of econometric methods lies in their ability to distinctively separate the effects of correlation from those that are related to causality; thereby eliminating the common fallacy that correlation implies causation. Causality is tested using the standard Granger Causality Test. Although the time series data is short in annual terms, using monthly data allowed for inference. In statistical analysis, inference can be deduced even with old data provided that the time series data are more than 21 observations but in this case there are 107 observations, meaning a good inference can be deduced.

The study had the following limitations.

- On limitation of this study is in terms of lack of current malaria data. The available data spanned the period from 1998 to 2007.
- The limitations of this study relate to the fact that temperatures in the study area are limited to a range on the curve where it is linear. The study did not look at the non-linearity.
- A further limitation is that the study did not show whether year to year changes in malaria cases were driven by year to year change in temperature/rainfall.

CHAPTER 4: RESULTS

Introduction

In this chapter, results are presented following the format of the objectives that are investigated: encompassing the spatial analysis of disease distribution within the province at district level, correlation results between climate variables and malaria cases and the results of causality tests.

4.1. Results: Objective 1: Spatial analysis²

Spatial analysis is first presented then followed by statistical analysis and finally sensitivity tests. The results reported here determine the long-run relative importance of rainfall and temperature as the main drivers for malaria transmission in Limpopo Province, South Africa using econometric approaches³.

4.1.1. Spatio-temporal results

² ²These results are published in **EcoHealth** Journal (Springer): The International Association for Ecology and Health, ISSN 1612-9202. March 2015, Volume 12, [Issue 1](#), pp. 131-143. DOI 10.1007/s10393-014-0992-1

(Approximately

22–25°S,

27–32°E)

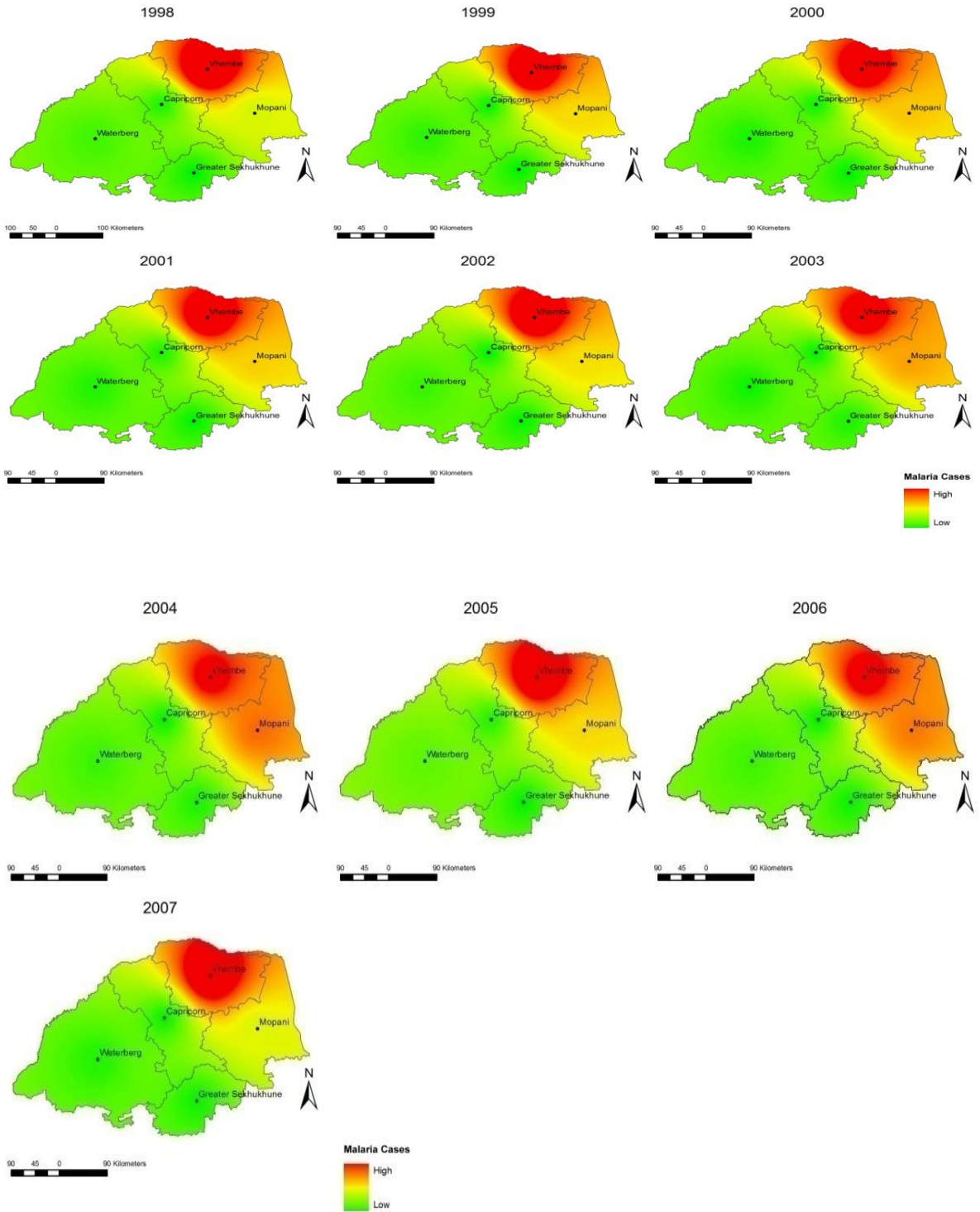
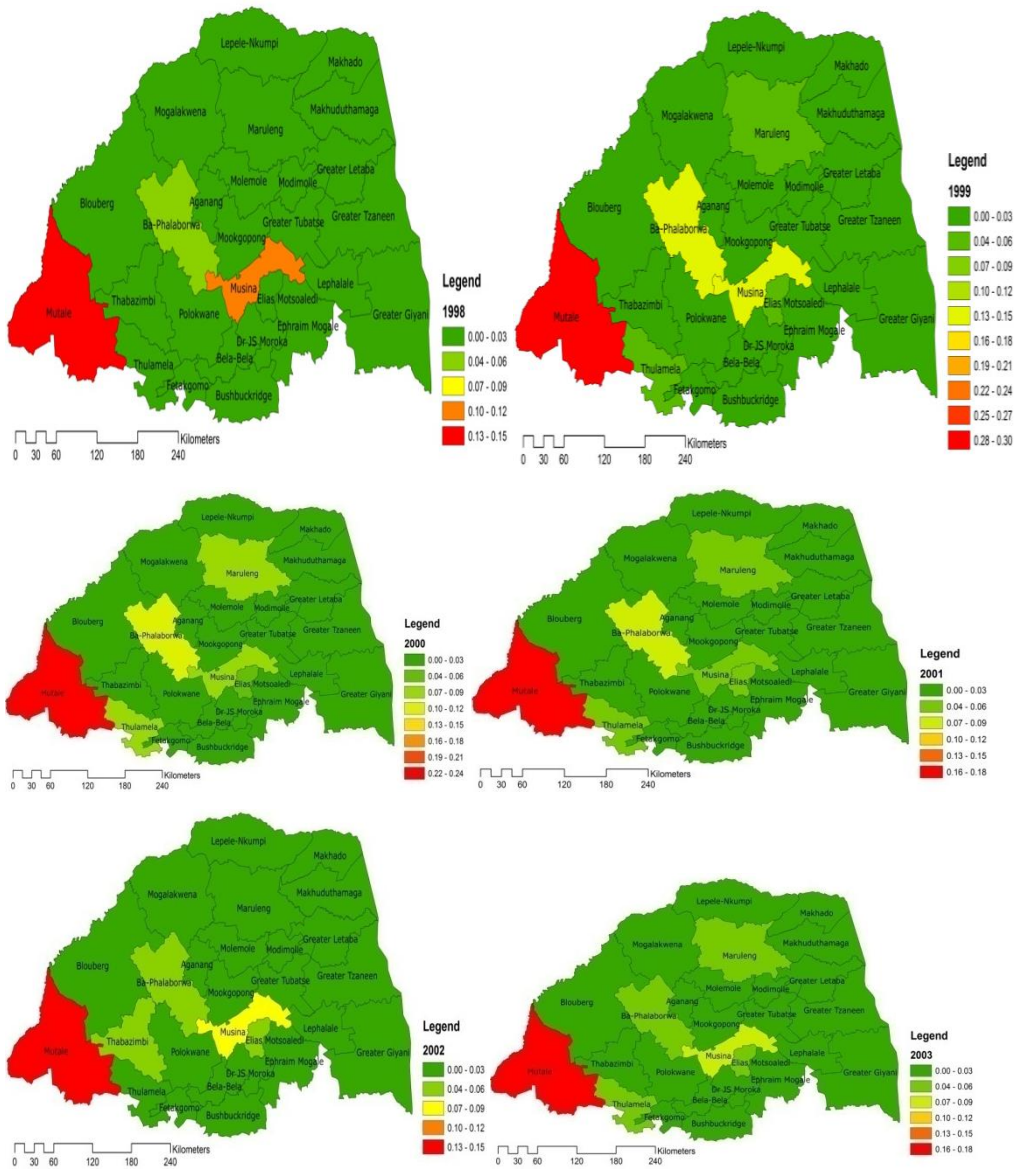


Figure 3: Ten-year spatial distribution of malaria in Limpopo Province

The study reports the GIS results of five districts (Capricorn, Greater Sekhukhune, Mopani, Waterberg, and Vhembe) in Limpopo Province (Figure 3 and 4). Vhembe district consistently shows more malaria cases, while very few cases are observed in Capricorn, Waterberg, and Greater Sekhukhune throughout the period of analysis. . On the other hand, in the Mopani district malaria cases appear to be erratic, as shown on the maps. The overall trend shows that, whereas there were fewer cases in 1998, this was followed by a slight increase from 1999 to 2006.



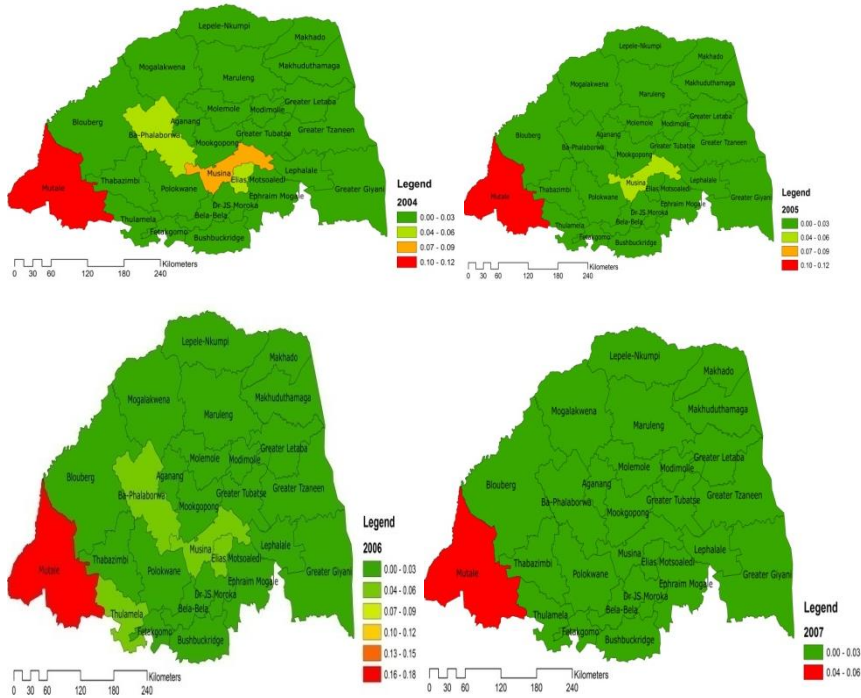


Figure 4: Rate of malaria incidence in Limpopo per 10-person population (1998–2007)

First, this study plots five monthly data sets (four from global datasets and one station observation) on rainfall and temperature against malaria cases (see the summary in Figure 1). Second, the study reports the univariate characteristics of each of the datasets and then run four regression models with five independent variables. The study finally reports the results of Impulse Response Function. The results are reported for each quarter of the year with each quarter having a three-month duration coinciding with South African seasons — summer (December, January and February); autumn (March, April and May); winter (June, July and August); and spring (September, October and November). Figure I present the summary results.

4.2. Results Objective 2: Statistical (Econometric) analysis

4.2.1. Correlation analysis

Malaria vs rainfall

Malaria vs temperature

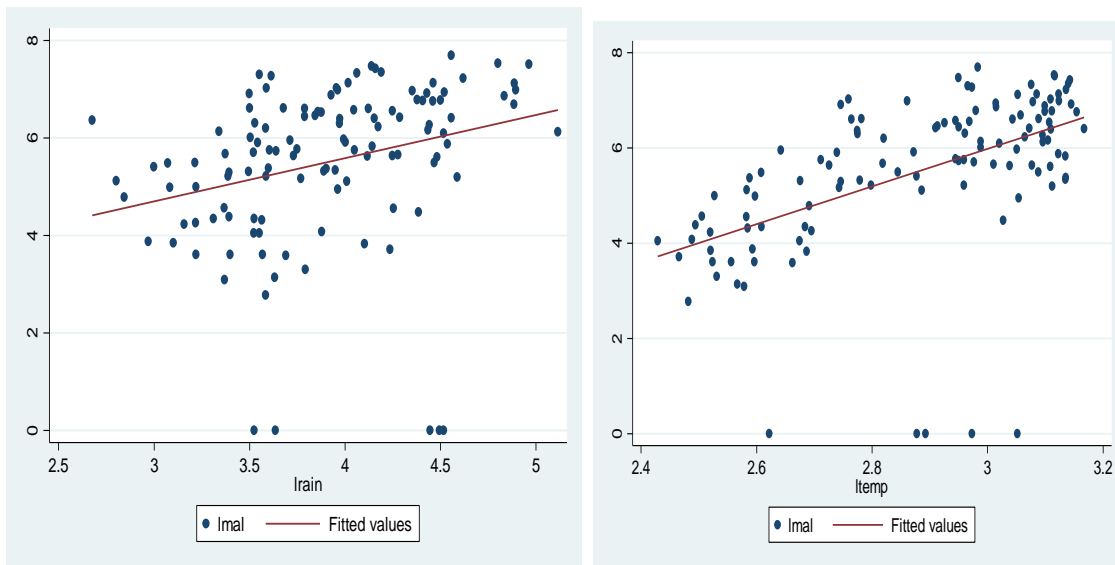


Figure 5: Correlation of rainfall and temperature with malaria — A graphical outlook

Figure 5 shows a scatter plot for rainfall and temperature with malaria cases. More observations are scattered away from the fitted line in the first panel (rainfall) than in the second panel (temperature). This indicates a higher positive correlation with temperature than with rainfall with an R-squared of 57.8%.

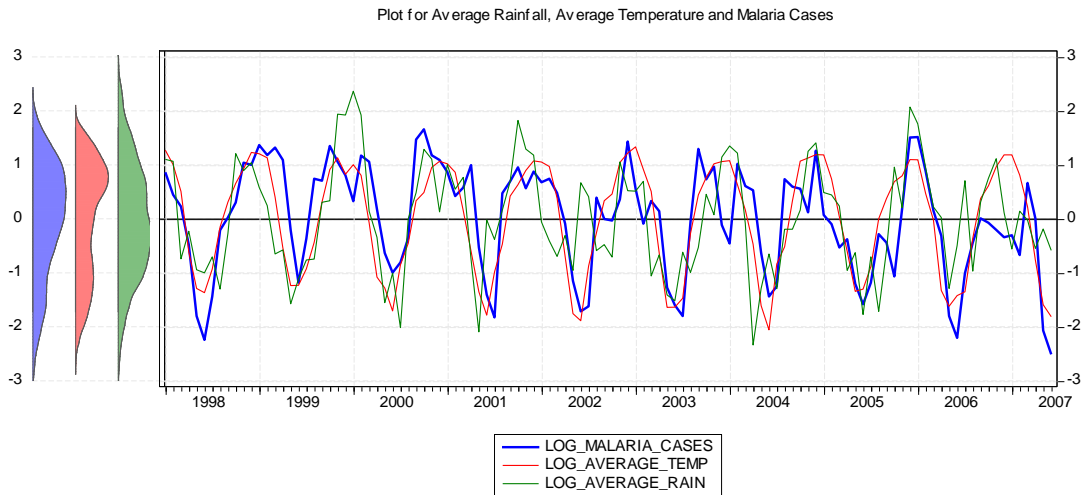


Figure 6: Trend-relationship between average rainfall and average temperature in relation to malaria cases

This reveals a very strong positive correlation between rainfall and temperature with malaria cases, although higher rainfall does not increase malaria cases significantly (e.g., 1999, 2001 and 2005). An increase in temperature is, however, consistent with an increase in malaria cases. The actual influence is further validated by statistics using the cross correlation method. This study finds a strong positive correlation of climate variables with malaria cases, with temperature exhibiting a stronger influence as compared to rainfall. The coefficient for temperature and rainfall is found to be 0.5212 and 0.2810 respectively.

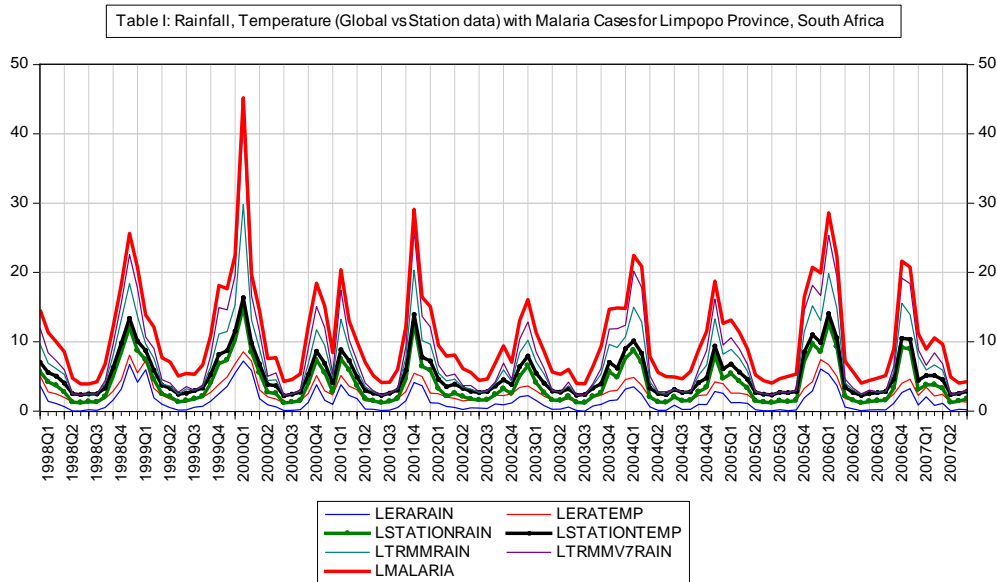


Figure 7: Rainfall, temperature and malaria cases plot

Figure 7 above summarises the performance of each of the global datasets against local observation and malaria cases in Limpopo Province. The season is split into four quarters with each quarter consisting of three months. Quarter 1 (Q1): January February, March; Quarter 2 (Q2): April, May, June; Quarter 3 (Q3): July, August September; and Quarter 4(Q4): October, November and December. Overall, climate data flow with malaria cases in all seasons. The highest malaria cases are observed between 1999 (Q4) and 2000 (Q1), and the lowest among the seasonal highest is found in 2002–2003. A sudden and dramatic fall in malaria cases is observed between the year 2000 (Q4) and 2001 (Q1). Typically, here, malaria cases consistently rise at the end of Q3, reach their highest in Q4 and Q1 of the following year, then fall to their lowest in Q2.

The global data matches local malaria observations in most of the seasons. At local level, station data rainfall (LSTATIONRAIN) and LIMPRAIN have the highest level of influence on malaria. At global scale, although LTRMMRAIN portrays a positive relationship, it does not pick very high and very low malaria cases as compared to the other two data sets, ERARAIN and TRMMv7. In essence, there is very high correlation between malaria cases with global data. Local data correlate highly followed by Provincial Average data and then TRMMv7.

4.2.2. Causal relationships

Table 2 presents Granger causality test results.

Table 2: Causal relationships

Pairwise Granger Causality Tests Date: 06/23/13 Time: 23:50 Sample: 1998M01 2007M12 Lags: 2				
	Null Hypothesis:	Obs	F-Statistic	Prob.
a)	RAINFALL does not Granger Cause MALARIA	117	3.89071	0.0232
	MALARIA does not Granger Cause RAINFALL		1.44730	0.2396
b)	TEMPERATURE does not Granger Cause MALARIA	117	20.0805	4.E-08
	MALARIA does not Granger Cause TEMPERATURE		0.07211	0.9305
c)	TEMPERATURE does not Granger Cause RAINFALL	117	19.7996	4.E-08
	RAINFALL does not Granger Cause TEMPERATURE		17.1410	3.E-07

a. Rainfall versus malaria cases

The study finds a *unidirectional* causality from rainfall to malaria cases. For 117 observations, at a 5% significance level, the computed F-statistic is equal to 3.89071 with $p=0.0232$, implying that the null hypothesis that rainfall does not *Granger-cause* malaria is rejected. Rainfall, therefore, influences malaria but the reverse is not true. The null hypothesis cannot be rejected that malaria *Granger-causes* rainfall since the F-statistic is equal to 1.44730 with $p=0.2396$.

b. Temperature versus malaria cases

The study also finds a *unidirectional* causality from temperature to malaria cases. The computed F-statistic is 20.0805 with $p<0.001$, implying rejection of the null hypothesis that temperature does not *Granger-cause* malaria cases, whereas from malaria cases to temperature, the F-statistic is 0.07211 with $p=0.9305$, implying that malaria cases do not *Granger-cause* temperature.

4. Temperature versus rainfall

This study finds a *bi-directional causality* between temperature and rainfall at a 1% level of significance. The F-statistic for the causation from temperature to rainfall and from rainfall to temperature is 19.80 and 17.14 respectively, with $p<0.001$, in both cases meaning that rainfall influences temperature and vice versa.

4.2.3. Stationarity (unit root)

Table 3 is a summary of the stationarity test.

Table 3: Unit root test results

Test	Log of Malaria		Log of Rainfall		Log of Temperature	
	Levels	First difference	Levels	First difference	Levels	First difference
ADF_μ			-7.926***		-2.252	-11.029***
ADF_τ	-4.283***					
KPSS_μ	0.620		0.033***		0.021***	
KPSS_τ						
Conclusion	Stationary at levels: I(0)		Stationary at levels: I(0)		Non-Stationary	Stationary at First Difference: I(1)
<p>Note: *, ** and *** means significance at 10%, 5% and 1% respectively. <i>Source:</i> Computed</p> <p>ADF is the Augmented Dickey-Fuller (Dickey & Fuller 1981) and (KPSS) is the Kwiatkowski, Phillips, Schmidt and Shin tests (Kwiatkowski et al, 1992).</p>						

The results indicate that malaria and rainfall follow an auto-regressive process with a unit root and the null hypothesis is rejected for these variables, whereas for temperature, the null hypothesis for the existence of a unit root could not be rejected, implying that rainfall and malaria cases are stationary, whereas temperature is non-stationary.

4.2.4. Auto-regressive Distributed Lag Model (ARDL)

Short-term and long-term results

These are the results of estimating equation (1). This stationarity test result pointed to ARDL-Bounds Test as the appropriate methodology for the analysis of the short-term (in this case, variation within months) and long-term (variation in years) dynamics of rainfall and temperature as they relate to malaria. UECM results are summarised in Table 4 below, following similar procedures used by Hendry *et al.* (1984) and Akinboade *et al.* (2008).

Table 4: Unrestricted Error Correction model

<i>Variables</i>	<i>Coefficient</i>	<i>Standard Error</i>
Constant	-3.158603	2.156372
D(LMALA (-2))	-0.473095	0.123357***
D(LRAIN (-1))	0.745233	0.248330***
D(LTEMP (-1))	4.343676	1.129335***
LMALA (-1)	0.249101	0.104620**
LRAIN (-1)	-0.499685	0.300813*
<p>Note:</p> <p>*, ** and *** means significance at 10%, 5% and 1% respectively.</p> <p>Source: Computed</p> <p>LMALA is logarithm of Malaria</p>		

LRAIN is Logarithm of Rainfall

LTEMP is Logarithm of Temperature

(-1 and -2 indicate lags)

Diagnostic tests

Rampsey RESET = 2.271595 (0.1350):

Null hypothesis that model has no omitted variable is not rejected, implying no omitted variables in the model.

White's test = 1.2668 (0.3869)

Null hypothesis of homoscedasticity is not rejected, implying that variance of the variables in the model are homogeneous.

Breusch-Godfrey LM test = 0.868 (0.423)

Null hypothesis of no serial correlation is not rejected, implying that the model does not suffer from serial correlation.

The model passes all basic time series tests. There is no autocorrelation or serial correlation and no omitted variables; variance is homogeneous and residuals are normally distributed as confirmed by Durbin Watson statistic, Ramsey RESET test, Breusch-Godfrey LM, White's test, and Jarque-Bera test. The R-Squared for the UECM is 50%, which indicates a relatively good and satisfactory fit in this case. The appropriate

lag-length automatically selected by SBC is 3. Empirical studies report a non-uniform lag time for malarial response to climatic variation. There seems to be an average malaria response within three months from the onset of the rainy season. Briet (2008) reports a rainfall lag time of zero to three months, whereas Hashizume *et al.* (2009) report two to three months. With regard to temperature, Zhou *et al.* (2004) find a minimum and a maximum temperature lag time to be between one to two months and two to five months, respectively.

4.2.5. Cointegration analysis

Bounds test (cointegration) results are presented in Table 5.

Table 5: Cointegration properties

Critical bounds (5%)			
Dependent variable	F-stat	Bottom	Top
d(lmala)	8.29	3.23	4.35
k=3			
Source: Computed, critical bounds are obtained from Narayan (2004) d(lmala) is the first difference of logarithm malaria			

The *F-statistic* is outside the critical bounds (8.29 lies outside 4.35_{top} and 3.23_{bottom}). Therefore, null hypothesis is rejected that there is no cointegration at a 5% significance level, and conclude that a long-term relationship (cointegration) exists between malaria and the climatic variables.

The long-term relationship is reported in Table 6, while the short-term results are reported in Table 7.

Table 6: Long-term relationship: malaria cases with rainfall and temperature

Variable	Coefficient	Standard Error
C	-6.155823	0.0006***
LRAIN	-0.373873	0.2648
LTEMP	4.557185	0.0000***
Note: *** means significance at 1% respectively. LRAIN is the logarithm of Rainfall LTEMP is the logarithm of Temperature		

Table 7: Short-term relationship: malaria cases with rainfall and temperature

Variable	Coefficient	Standard Error
C	-0.080311	0.2668
D(LMALA (-2))	-0.231066	0.0047***
D(LMALA (-3))	-0.205359	0.0120**
D(LRAIN)	-0.263281	0.1509
D(LTEMP(-1))	4.784184	0.0000***
Ecm_{t-1}	0.005002	0.9783
Note: ** and *** means significance at 5% and 1% respectively. LMALA is logarithm of Malaria LRAIN is Logarithm of Rainfall LTEMP is Logarithm of Temperature (-1 and -2 indicate lags)		

In both short- and long-run instances, temperature maintains a very high level of significance: 4.784184 (0.0000) and 4.557185 (0.0000); whereas rainfall is low in both: 0.263281 (0.1509) and 0.373873 (0.2648).

4.3. Results: Objective 3: sensitivity tests⁴

4.3.1. Regression analysis

The stationarity test and regression results are summarised in Table 8. Rainfall (for all the data sets: global (ERA, TRMM and TRMMv7) and local observations (Station data) and malaria cases are stationary at levels. On the other hand, temperature is non-stationary for both global and local observations. The Table also displays the results of the four regression models, with five independent variables, malaria cases being the dependent variable (see Equation 2). The signs of the coefficients are as expected, positive for rainfall and temperature and negative for their exponents for all the models.

Similarly, the partial t -statistics for the regression parameters are well above 2.0 for at least three variables, indicating that the five variables explain a significant proportion of the total variance at a 95% level of confidence. For the three models (model 1 to 3), three out of five independent variables —the lag of rainfall, temperature and the square of temperature — consistently maintain a very high statistical level of significance (at 1 per cent), and therefore map exactly the station observations that are also highly significant (model 4). The coefficients for rainfall and rainfall squared, on the other hand, are insignificant only for ERA data, similar to station observations (although the parameter is positive for rainfall: 0.23, 0.00 and negative for rainfall squared: -0.02,

⁴These results have been submitted for publication in *EcoHealth: The International Association for Ecology and Health*.

0.00, as expected). TRMM and TRMMv7 miss this prediction of rainfall effect on malaria incidence as the coefficients are highly insignificant.

The coefficients for the five climate variables describe an inverted *u*-shape for all the four models because the parameter for the exponents of rainfall (-0.02, -0.01, -0.02, -0.00), and temperature (-46.61, -47.46, -48.14, -36.04) are both negative, confirming that excess rainfall results in a decrease in malaria incidence. Throughout, temperature consistently maintains much high significance with malaria incidence than as it does with rainfall. It is, in fact, significant for all models. Partial *t*-statistics are above 2.0 for at least three variables with positive regression coefficients, implying that rainfall and temperature explain malaria at a 95% confidence level.

Table 8: Summary of unit root tests

		Intercept	Rain	Rain (-1)	Rain ²	Temp	Temp ²
1. ERA	ADF- Levels		-6.23*** S I(1)			-1.89 NS	
	ADF-1 st Difference					-3.63*** I(1)	
	Coefficient	-80.39	0.23	0.44	-0.02	122.24	-46.61
	t-statistic	-4.92***	1.56	5.75***	-0.92	4.65***	-4.41***
	R²=73%, DW=2.01, F-Statistic = 35.47***						
2. TRMM	ADF- Levels		-6.16*** S I(0)				
	ADF-1 st Difference						
	Coefficient	-81.93	0.17	0.45	-0.01	124.66	-47.46
	t-statistic	-5.00***	2.00***	6.06***	-1.93***	4.69***	-4.44***
	R²=73%, DW=2.01, F-Statistic = 35.47***						
3. TRMMv7	ADF- Levels		-5.82*** S I(0)				
	ADF-1 st Difference						
	Coefficient	-82.80	0.20	0.45	-0.02	126.15	-48.14
	t-statistic	-5.04***	2.44**	5.85***	-2.25*	4.77***	-4.54***
	R²=73%, DW=1.98, F-Statistic = 31.08***						
4. Station Data	ADF- Levels	-6.60*** S				-1.26 NS	
	ADF-1 st Difference					-11.75*** I(1)	
	Coefficient	-62.38	0.00	0.50	-0.00	94.96	-36.04
	t-statistic	-4.63***	0.00	7.80***	-0.01	4.29***	-4.00***
	R²=69%, DW=1.96, F-Statistic = 48.54***						
Malaria Cases	ADF- Levels	-6.22*** S I(0)					
Note: 1. Variables are log to base <i>e</i> 2. S- means the variable is Stationary; NS – means Non-Stationary; I(0) is stationarity at Levels; I(1) is stationarity at First Difference 3. *(**) [***] indicates statistical significance at 10(5) [1] per cent level. 4. All roots lie within the unit cycle.							

The F-statistic of joint significance of variables included in the model is all positive and highly statistically significant at $p < 0.05$, implying that both rainfall and temperature jointly affect malaria. There is no autocorrelation in the entire model as depicted by the

high Durbin Watson statistic (all >2.0). The coefficient of determination, R^2 , that provides a measure of how well observed outcomes are replicated by the model (as the proportion of total variation of outcomes explained by the model), are all above 69 per cent. This implies that over 69% of the variation in malaria incidence is explained by climatic conditions. ERA Interim, TRMM and TRMMv7 predict very high R^2 (73%), whereas the station data was the lowest at 69%. In this regard, non-climatic factors, such as ecological and environmental factors, and socio-economic factors (such as changes in health care infrastructure) only account for 31% of the station data and 27% for global data.

4.3.2. Impulse response analysis

The study uses the Choleski decomposition on a VAR model to analyse malaria sensitivity to variation in rainfall and temperature. Monthly climate data from Limpopo Province from January 1998 to July 2007 is used. Climate data are obtained from ERA Interim, TRMM, and TRMMv7 and this is validated using Limpopo station data. The purpose here is to first examine whether malaria incidence and malaria cases are sensitive to changes in rainfall. The second purpose is to ascertain which of the global data sets best simulates the observations at station level. Impulse response also detects the length over which the effect of the onset of rainfall is sustained in terms of the effect on malaria. The rainy season in South Africa is shortly after winter and it is always sudden, especially given that it emerges immediately following a dry season. Here, impulse response outputs with data ordering (1) ERA, (2) TRMMv7, (3) TRMM,

and (4) Station. Figure 8 shows the results of the analysis of how malaria cases respond to rainfall.

The results of the response of malaria to rainfall and temperature are reported in Figure 8 and Figure 9 respectively.

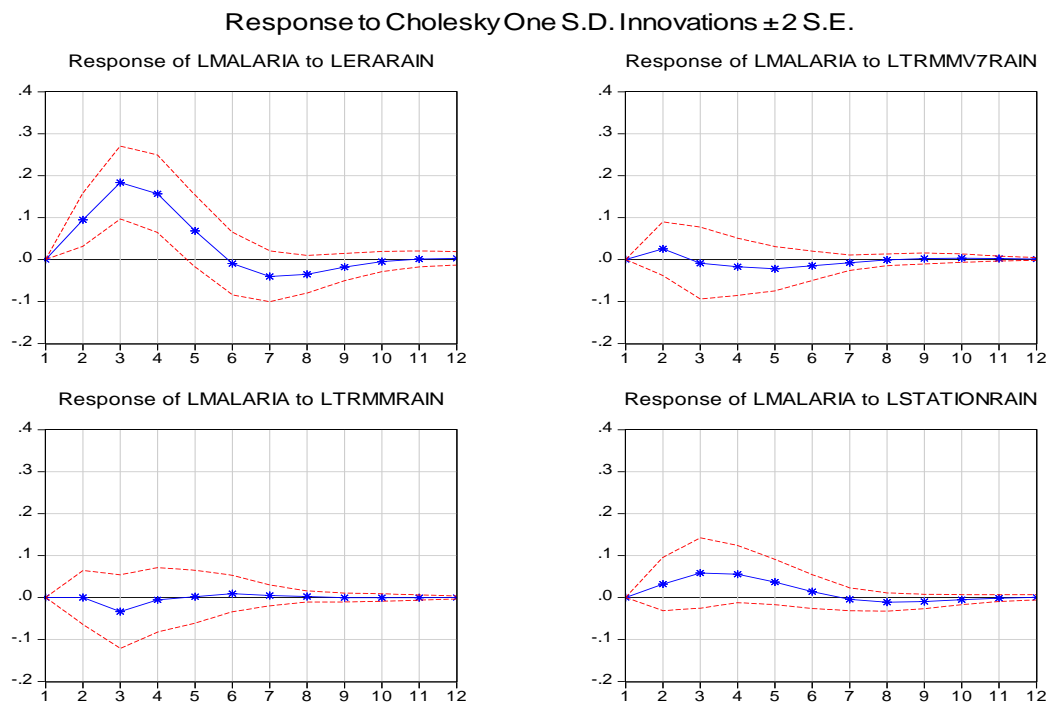


Figure 8: Response of malaria cases to rainfall

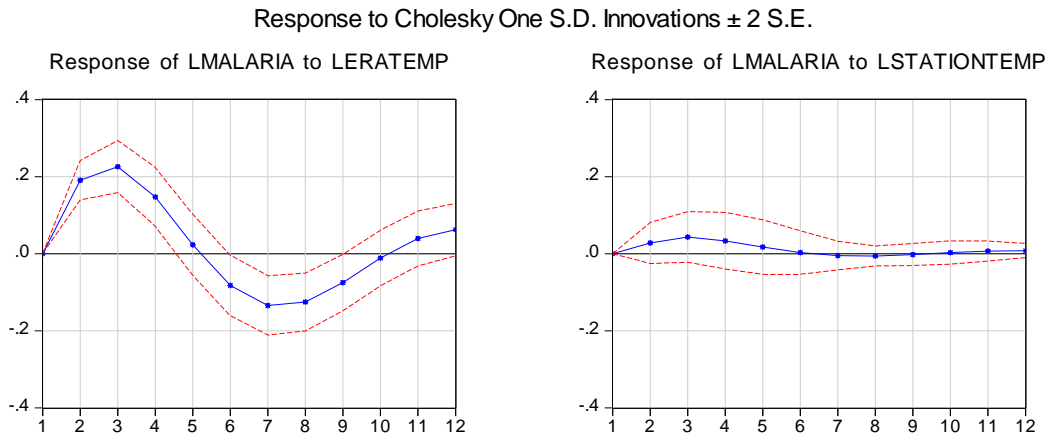


Figure 9: Response of malaria cases to temperature

Panel 4 (Response of LMALARIA to LSTATIONRAIN) reports results for station data. A one standard deviation rise in rainfall (rainfall onset following winter) increases malaria cases and the effects become statistically significant for over three months, after which they begin to fall. Malaria cases revert to their previous value after month six. The effects of a one deviation shock to LERARAIN and LTRMMV7RAIN, Panel 1 and Panel 2, is similar to the effect in the station data, but not identical. LTRMMV7RAIN is very close to the station observation as it indicates rising malaria cases at rainfall onset but the effect is statistically significant only for three and a half months, falling below the zero line and then reverting to the previous value after eight months. LERARAIN depicts a very high rise that is sustained at the beginning of month six; falls further below the zero line then station and ERA and then reverts back after month ten. LTRMMRAIN fails to replicate station observations completely. There are no effects in the first two months, this falls far below the zero line at the end of the second month and reverts in month seven.

For temperature, Figure 4 shows that a 1 standard deviation rise in temperature increases malaria cases and the effect is sustained for the first three months for both the global data and the local temperature observations. The magnitude is higher for the global data than for local observations. For both datasets, mean reversion occurs at the tenth and sixth month respectively.

4.4. Chapter Summary

The study aimed at establishing how climate impact on malaria transmission in Limpopo Province, test the existence of long-term relationships between rainfall and temperature and determine at what time during a cycle of one year does the intensity of malaria transmission occurs, as well as the length that malaria intensity is sustained. Results in this section relate to the analysis of how the onset of rainfall and changes in temperature trigger a 'malaria season' and how long this is sustained in terms of 'malaria months' before malaria incidence declines.

Spatial results indicate that Vhembe district is a malaria hotspot since very few cases are observed in Capricorn, Waterberg, and Greater Sekhukhune. The statistical results indicate a correlation between rainfall and temperature with malaria cases with a higher positive correlation of malaria cases with temperature than with rainfall with an R-squared of 57.8%. The highest malaria cases are observed between 1999 (Q4) and 2000 (Q1), and the lowest among the seasonal highest is found in 2002–2003. A sudden

and dramatic fall in malaria cases is observed between the year 2000 (Q4) and 2001 (Q1). The study finds a *unidirectional* causality from rainfall and temperature to malaria cases. This study finds a *bi-directional causality* between temperature and rainfall at a 1% level of significance. The results indicate that malaria and rainfall follow an autoregressive process implying that rainfall and malaria cases are stationary, whereas temperature is non-stationary. The coefficients for the five climate variables describe an inverted *u*-shape. Partial *t*-statistics are above 2.0 for at least three variables with positive regression coefficients, implying that rainfall and temperature explain malaria at a 95% confidence level. The study found that a 1 standard deviation rise in temperature increases malaria cases and the effect is sustained for the first three months.

CHAPTER 5: DISCUSSION

Introduction

This section presents the discussion of the results of the study as per outlined objectives. It first discusses the results of the review followed by spatial analysis and finally statistical results.

5.1. Discussion: Literature Review

The literature review finds some key issues: that malaria is spreading to traditionally non-malaria districts. This is consistent from other empirical studies on the climate impacts on health that show that in some countries, for example, the neighbouring Zimbabwe, the entire highland will be conducive to malaria under climate change.

Also imported malaria from the neighbouring countries of Zimbabwe and Mozambique will exaggerate the disease burden since Limpopo Province is the gateway to many migrants from these neighbouring counties and they bring disease to the non-immune population. Malaria control in Limpopo Province relies heavily on DDT in indoor residual spraying (Moonasar *et al.* 2012). This in itself is an environmental concern in that in the drive to protect the population it may be destroying the environment and further exposing the population to greater environmental dangers. With climate change expanding the spread of disease, there is a need to reformulate the malaria control intervention programme to follow climate patterns and, in particular, to follow the onset of the rainfall season in the district.

As a result of its impacts on health, climate change impedes productivity. The combination of weak health systems and low adaptive capacity to climate change is escalating health problems in Africa. The combination of vector (mosquito) mutation, malarial drug resistance (Maharaj *et al.* 2013), lack of, or, poor immunity of the population (especially among those who are infected as a result of migration), weak health systems, and climate change are principle factors driving the expansion of malarial disease (Maharaj, 2013). The cost of treatment and prevention of malaria will significantly increase in the future. Cross-country public-private research and joint collaboration (RBM 2015) to track, prevent, and treat malaria and to address the health challenges posed by the association between climate and disease is vital in developing countries.

5.2. Objective 1: Discussion – Spatial Analysis

Although malaria is reported to have decreased, to about 49.2 %, through Malaria Control programme, malaria in Limpopo Province remains above elimination threshold (Maharaj *et al.* 2012) and the results of this study validates this assertion. This study found that Vhembe district consistently shows more malaria cases, while very few cases were reported in Capricorn, Waterberg, and Greater Sekhukhune throughout the period of analysis. This makes Vhembe district a malaria hotspot in Limpopo Province followed by Mopani district where malaria cases appear to be erratic. Several reasons could explain the spatial differences that range from: socio-economic reasons; to migration; malaria control programmes; and even climate change. Understanding the

differences in spatial distribution and areas burdened is crucial for targeted control measures.

5.3. Objective 2: Discussion of the statistical analysis

In this study, rainfall and temperature are positively correlated with malaria, whereas temperature shows a stronger influence when compared to rainfall. The study finds the correlation coefficient of temperature and rainfall to be 0.5212 and 0.2810 respectively. A positive correlation between malaria and climate variables has been reported elsewhere. For studies of rainfall: Huang *et al.* (2011); for Tibet: Briët *et al.* (2008), for Sri Lanka, rainfall and temperature: Craig *et al.* (2004); for studies on the Kenyan Highlands in Eastern Africa: Githeko and Ndegwa (2001); for rainfall, temperature, humidity, and vegetation cover in Bangladesh: Haque *et al.* (2010). In Ghana, a positive correlation was found to exist between malaria and climate elements (Nkomo *et al.*, 2006). The strength of the effect seems to flow from humidity to temperature and rainfall. This result is consistent with Huang *et al.* (2011) who found the correlation coefficient for Tibet to be 0.518 and 0.348 for temperature and rainfall respectively, concluding that temperature had a greater influence on malaria.

Regardless of the greater influence of temperature, warming and rainfall will create the conditions for malaria vectors to thrive (Epstein *et al.*, 1997), boost the population of disease-carrying mosquitos, and result in increased malaria epidemics (Lindsay & Martens, 1998; Nkomo *et al.*, 2006). Increases in temperature generally accelerate

vector life cycles and also decrease the incubation period of the parasite (Huang et al, 2011; Kovats & Martens, 2000). However, at a very high temperature the mosquito life cycle cannot be completed and transmission cannot occur (Williams *et al*, 1999; Zucker, 1996). It is interesting to observe the strong influence of temperature on malaria transmission in Limpopo. Ngomane and de Jager (2012), however, have reported rainfall as the main driver in the neighbouring Mpumalanga province.

5.4. Objective 4: Discussion of sensitivity analysis

Ideally, understanding the onset of the malaria season informs the timing of malaria control interventions. Impulse response is an essential tool in sensitivity analysis and used for policy effectiveness. The finding of very high correlation between malaria cases with rainfall and temperature implies that the onset of the rainfall season triggers the beginning of a 'malaria' season in Limpopo Province. Rainfall and temperatures influence malaria significantly, but at extreme temperatures and with excessive rainfall, malaria incidence is affected negatively. This is concomitant with studies by Williams *et al.* (1999) and Zucker (1996) who conclude that at very high or very low temperatures, usually above 33°C or below 16°C, the cycle cannot be completed and transmission cannot occur.

The study finds that malaria in Limpopo Province is seasonal with initial cases noticed at the end of the third quarter of the year, that is, the end of the winter season in August,

reaching its peak between the fourth (September, October and November) and the first quarter (March, April and May) of the next year, which corroborates the findings of Craig *et al.* (2004) who found malaria transmission to be distinctly seasonal and limited to warm and rainy summer months with case notifications increasing from November, peaking in late March to May, and then declining by the end of June. Typically, malaria cases consistently rise at the end of Q3, reaching a peak in Q4 and Q1 of the following year, and then falling to their lowest in Q2. The highest number of malaria cases were observed between 1999 (Q4) and 2000 (Q1), and the lowest among the seasonal highest is 2002-2003. A sudden and dramatic fall in malaria cases is observed between the year 2000 (Q4) and 2001 (Q1).

A one standard deviation rise in rainfall for station data results in an increase malaria cases observed, with effects lasting for over three months then beginning to fall after month four and reverting to its previous value after month six. LERARAIN and LTRMMV7RAIN replicate this result but not identically. LTRMMV7RAIN is very close but the effects last longer, three and half months, falling below the zero line then reverting to the previous value after eight months. LERARAIN depicts a very high rise that is sustained up to the beginning of month six, falls further below the zero line and then reverts back after month ten. LTRMMRAIN fails to replicate station observations completely. There are no effects in the first two months, falling far below the zero line at the end of the second month and reverting at month seven. Vector control for

anopheles mosquito should begin between the end of July and the middle of August and should be intensified for at least three and a half months for it to be effective. This will ensure that mosquito breeding is curtailed, mosquito development is reversed, feeding frequency is reduced, and life-span is shortened, which, in turn, significantly reduces their numbers and hampers their infection rates. This result is crucial for malaria control programmes, disease preparedness, and policy interventions, the effectiveness of which rely on timing.

CHAPTER 6: SUMMARY, CONCLUSION AND RECOMMENDATIONS

Introduction

This is the section that summarises and concludes the results of the whole study and provides general recommendations in terms of climate-disease impacts as well as policy recommendations. This section provides an insight into the policy frameworks that are in place to combat malaria in Limpopo Province. It analyses what exists, identifies some gaps, and provides policy recommendation to the policy-makers for future interventions in the war against malaria in an era of climate change.

6.1. Summary and conclusion

Social, economic and environmental factors affect the incidence of malaria. This study has only considered the environmental aspect, namely, climate change. Empirical studies have reported rainfall and temperature as the main climate factors that influence malaria transmission; however, other studies have included climate variables such as humidity and vegetation. This study has examined how variation in rainfall and temperature impacts on malaria cases. Literature review has revealed that high temperature reduces shortens the development time of vector-borne pathogens; and, combined with favourable climate conditions, the population of carrier-mosquitoes increases. This in turn increases the likelihood of an infectious bite. Growth of the anopheles vector is accelerated under conditions of increased temperature with optimal larval development at 28°C and optimal adult development between 28°C and 32°C. Very high rainfall and temperatures negatively affect mosquito development, but

a moderate climate will provide a conducive environment for the vectors to grow. Significant warming trends therefore amplify mosquito population and thus, contribute alongside drug resistance, and land-use patterns, they contribute to the increased incidence of malaria.

The strain that climate change places on the health sector is evident in Africa. The multiplier effect felt in the health sector is not necessarily a unique problem, it is merely an exaggeration of the existing health problems. The majority of developing countries are characterised by extremely weak health systems such that any additional burden translates into a multiplier effect in all the sectors of the economy. The reality is that there is a likelihood that natural systems have been tampered with to such an extent that no human effort can sufficiently return them to their original status.

It is imperative to understand that climate change is threatening to reverse the gains from the long-term economies of scale that have been enjoyed for decades. Viewed differently, the supposed long-term 'gains' of economic progress by economies were, indeed, not gains per se but a postponement of 'problems' into the future -the-now-future. These problems are now being revealed in climate impacts. It is plausible that in addressing poverty, disease, and hunger, human actions have significantly tampered with the natural systems such that instead of optimal utilisation of resources being a solution to address these social challenges, it has caused a climate crisis that appears to be becoming an even more un-surmountable challenge than the original challenge itself.

Whether social and economic challenges warranted the rate and intensity at which humans interacted with the environment, or whether it is a reflection of other factors that go beyond need, pointing towards ‘wants’ and insatiable appetites (greed), is reflected in climate change.

In particular, climate change is a form of externality because the markets failed to account of the true costs of economic activity. When the market price of a good or service is lower than its actual social and environmental costs, then it qualifies as an externality. Such difference is primarily borne by the environment and by people other than the buyer and seller. Over the last few decades, environment has suffered dearly because the market for ecosystem services was non-existent or ignored and economic policies and market incentives were detrimental to the environment and society, and there were few checks. Investment in sustainable options, for example, renewable energy, sustainable agriculture, ecosystems and biodiversity protection, and land and water conservation, was totally ignored in the development discourse.

The IPCC has ‘very high confidence’ of the mixed effects on malaria: in some places the geographical range will contract, elsewhere the geographical range will expand and the transmission season may be changed. The causal links between climate and malaria transmission dynamics are known, but there is still much uncertainty about the potential impact of climate change of malaria at local and global levels.

The climate impacts on health are real and threaten the health of millions of people, vulnerable and non-vulnerable alike. Accessing clean water or clean air, adequate food and nutrition is now a challenge. The probability of experiencing an extreme event is very high, such that the key health determinants of good health are becoming compromised day by day. Either way, humans are the most threatened of all species in the animal kingdom, yet it is the human species that are a cause and, at the same time, the solution to many of nature's problems. Curbing climate change therefore also requires addressing the underlying factors that cause vulnerability.

Whether social and economic challenges warranted the rate and intensity at which humans interacted with the environment, or whether it is a reflection of other factors that go beyond need to reflect wants and insatiable appetite, climate change can be observed. The reality is that it is possible that the natural systems have been tampered to such an extent that, worryingly, no human effort will be able to reverse the natural systems to their original status, that is, no human effort can sufficiently reverse the impacts of climate change. Mitigation and adaptation costs for climate impacts in the health sector are likely to be large.

Although malaria prevalence and the incidence of malaria transmission have been established in South Africa, there is still limited information regarding the actual influence of rainfall and temperature on malaria epidemics in Limpopo Province. This study has applied spatial and statistical methods examine relationship between malaria

with climate variables within South Africa with a specific focus on either Limpopo Province, at particular district level within the Province.

Other studies have used basic retrospective descriptive analysis (see, for example, Geritzen et al, 2013; Khosa et al, 2013) to detect malaria incidence rates, case fatality rates (CFR), and IRS coverage rates incidences as well as tracking the effectiveness of malaria control interventions implemented across the seasons. From the literature the study finds that very few studies that have considered the role of climate change in malaria distribution and, where found, a similar basic retrospective approach is used. For example, Ngomane and de Jager (2012), uses Auto-regressive Integrated Moving Average to study the changes in malaria morbidity and mortality in Mpumalanga Province and to assess the association between climate and malaria, and Thompson (2012) used regression analysis to study how climate change affects children's general health in Limpopo. Furthermore, descriptive analyses reveal trends in incidence and in the basic relationship between variables.

This study has utilised spatial, correlation methods as well as a bound testing approach to cointegration developed within an auto-regressive distributed lag framework to test spatial malaria distribution at district levels, the strength of correlation, and to determine the existence of a long-term equilibrium relationship between climatic variables and malaria. There is strong evidence that climate influences malaria

significantly both in the short and long run. The study found that malaria pressure varies in different districts.

This study confirms that climate change directly increases the mosquito population by shortening its life cycle and widening the transmission zones, thereby increasing malaria cases. With the combination of socio-economic and environmental factors, changes in immunity, land-use patterns, drug resistance, migration, and poverty, complicate the quest for a 'malaria free world'.

6.2. Policy recommendations and future research

Curbing the scourge of climate impacts on health requires resources and deliberate and proper planning. Two key options are under global discussion and these relates to adaptation and mitigation. Adaptation is the acceptance that climate change and the impacts of climate change are here to stay and, therefore, the population need to finds ways and means of coping with the changing climate.

Adaptation is a key response strategy for minimising the potential impacts of climate change. Examples of adaptation options include planting climate resistant crops, changing the planting seasons depending on changing rainfall patterns, and sustainable land management practices. A primary objective of adaptation is to minimise any adverse effects on health and society (WHO, 2000) through the reduction, with the least

cost, of disease, death, disability, and human suffering. Adaptation strategies in Africa require public-health strategies and improved surveillance (Haines et al, 2006) and must address both short-term disaster prevention and long-term investment in infrastructure (Ramin & McMichael, 2009) since the ability to adapt to climate change and, specifically, the impacts on health, will depend on many factors including existing infrastructure, resources, technology, information, and the level of equity in different countries and regions (WHO, 2000).

Mitigation involves cutting greenhouse gas emissions through policies related to transport systems, urban planning, building regulations, and household energy supply. The great debate in mitigation is around the use of conventional energy, namely, fossil fuel use in the production process. Proponents of renewable energy are in favour of mitigation, whereas those who are against mitigation argue on the basis of the cost effectiveness of long-term investment in fossil-fuel technology and the comparative advantage. In order to improve health in the short term, by reducing exposure to air pollution, Haines *et al.* (2006) support the idea of the mitigation of climate change through the reduction in the use of fossil fuels and increasing the use of a number of renewable energy technologies.

Technology plays a critical role in the 'management' of climate impacts on health through the measurement of carbon dioxide and other greenhouse gas emissions, but the cost, together with the dynamics of the transfer of these essential technologies from

the developed to the developing countries, has always been a mission. New technologies for adapting to the direct effects of carbon dioxide, pests and pathogens, already exist but how these technologies will be transferred to Africa and then implemented, laments Hulme *et al.* (1995), remains a key issue.

Early warning systems plays a major role in easing the effects of climate change on health as populations living in climate-risk areas can be relocated before the occurrence of an extreme event. However, few countries have studies this particular indicator of vulnerability to climate change. Assessments of vulnerability and carbon footprint becomes essential means of mapping hotspots and estimating and projecting the potential damage that can be associated with a climate event and effective planning based on the population settlements, infrastructure, and health consequences of such an occurrence. A combination of monitoring health indicators and long-term surveillance of diseases that are sensitive to climate have to be considered in suspected hotspots to minimize potential health risks emerging from climate change. These strategies need to be developed to detect and enhance practices for the detection and prevention of disease and to respond to the impacts of climate change on human health (Kovats *et al.*, 1999; Patz, Jonathan, Kovats & Sari, 2002). Relevant variables should include building codes, warning systems, disaster policies, evacuation plans, and relief efforts (Greenough *et al.*, 2001).

In order to achieve efficiency and effectiveness in adaptation and mitigation, there is a great deal of capacity vacuum. In addition to funding the infrastructure for adaptation and mitigation, an enormous amount of resources need to be earmarked and ring-fenced for capacity building through education, training, and raising awareness. Where there is a legislation gap and a lack of institutional frameworks, deliberate efforts are essential for creating these enablers. The knowledge of consequences ensures that populations make well-informed decisions for the long-term benefit of society.

Inter-sectoral and cross-sectoral collaboration between key health sectors that drive the health sector require enhancement. This is because the health sector alone, or in limited collaboration with a few other sectors, cannot deal with the necessary primary adaptation (WHO, 2000). Coordination within and across relevant sectors is wanting in many developing countries. In some cases, policies occasionally contradict each other and efforts are frequently duplicated, thus opening up avenues for wasteful expenditure.

Weather services that are responsible for metrological monitoring and surveillance need to work closely together with the departments of health as well as the health sector both at sub-national and national levels of government. Sensitive indicators of climate-health impacts cannot be ignored to monitor possible changes at regional and national levels. Campbell-Lendrum (2007) suggests that there is a need for a more active input from the health sector to ensure that development and health policies

contribute to a preventive approach to local and global environmental sustainability, urban population health, and health equity.

The study recommends the development of a malaria early warning system and that malaria control programmes should be intensified within the first three months following the onset of rainfall. Collaboration, joint programming and financing with the neighbouring countries of Zimbabwe and Mozambique, should also be enhanced to reduce imported malaria.

The complex interplay between physical, ecological, and social stressors suggests that any analysis of climate change, as well as any solutions, must be multi-sectoral and encompass broad-based socio-economic development (Ramin & McMichael, 2009). Frumkin (2008) emphasises that a public health approach to climate change should be based on the essential public health services that extend to both clinical and population health services, on the coordination of government agencies (federal, state, and local), on academia, the private sector, and non-governmental organisations. WHO (2000) assert that cross-sectoral policies that promote ecologically sustainable development and address the underlying driving forces will be essential in managing health impacts and adaptation measures.

In this regard, research should also be enhanced. In many developing countries there is either inadequate data or the available data are variegated such that the true inference

of the impact of climate on health cannot be correctly inferred. There is a need for proper records for each phenomenon, for example, malaria case notifications within clinics and all other climate related diseases. This would allow for the correct linking of climate to health and the development of preventative measures. A lack of accurate data means that global health effects are poorly identified, data that could otherwise inform policy-makers of the climate impacts on health 'beyond normal thresholds'. This also leads to the poor application of quantitative risk assessment methods. Kovats *et al.* (2005) find that all health risk assessments are biased toward conservative best-estimates of measured health effects and that global, regional, and national risk assessments take no account of irreversibility, or of plausible low-probability events with potentially very high burdens on human health.

In order to improve public health preparedness, Greenough *et al.* (2001) propose that future research on the health impacts of extreme weather events should focus on improving climate models to project any trends in regional extreme events. They also argue for research on epidemiologic studies of health effects beyond the direct impacts of disasters as this will provide a more accurate measure of the full health impacts and will assist in planning and resource allocation.

In coordinating efforts to minimise the impacts of climate change on health, the WHO (2004) provide three key recommendations for research and suggest the specific assignments of responsibilities to key sectors viz-a-viz:

- i. *Local authority social services departments and national census departments* are to provide better information on the vulnerable groups (these are the elderly; those with prior-event health problems; the poor; and those with dependants, especially children) that are likely to suffer health impacts from floods, so that they can be located and targeted for assistance.
- ii. *Meteorological and water/basin agencies; local authorities; and emergency services (police, fire services)* are to provide better warnings of floods before the events occur and better arrangements for responses to these flood warnings. This includes longer warning lead times; more accurate warnings; more advisory warning messages (not just facts, but advice as to what to do); and better warnings for agencies
- iii. *Medical authorities; local authority social services departments; insurance and related organisations* are responsible for the provision of better post-event social care for those who have been affected, even those who appear at first sight to be unaffected. This includes visits to identify problems; assistance with recovery work phases; financial assistance and advice; and medical/social advice.

Furthermore, despite excellent strategies and massive increases in investment to eradicate malaria, the struggle for 'malaria free South and Southern Africa' seems far from over. One worrying trend is not only the global increase in climate-sensitive vector-borne diseases such as malaria, especially in the developing countries, worse

still, is the methods applied to combat the menace. There are potential looming health consequences of malaria control programmes, which could prove to be a greater danger. South Africa relies solely on the annual use of dichlorodiphenyltrichloroethane (DDT) and pyrethroids in its indoor residual spraying programme for malaria control. Although a reduction in the number of malaria cases has been observed, a great concern among wildlife biologists is the potential indirect damage since DDT is quickly absorbed into all living things, and is rapidly absorbed by living tissue. DDT that is sprayed in an estuary is taken up by first-level producers, which are then consumed by humans. As these producers are consumed by creatures higher up the food chain, the dosage multiplies geometrically.

Carson (1962) produced an important, controversial account of the way in which man's use of poisons for controlling insect pests and unwanted vegetation is changing the balance of nature. Apart from the biological effects of DDT that cause indirect effects on health, DDT pre-disposes children under the age of five, who are most vulnerable malaria, to other deadly diseases such as cancer. Indoor residual spraying using DDT may affect the child's health in his or her later years of development by predisposing them to breast cancer. Exposure to DDT early in life, assert Cohn *et al.* (2007) may increase breast cancer risk.

The fight against malaria is intensifying in South Africa's Limpopo Province. There is a reported reduction in malaria due to the intensification of indoor residual spraying

(Maharaj *et al.* 2013; Maharaj *et al.* 2012). Despite climate impacts that are exaggerating the transmission and redistribution of malaria in the province, malaria control efforts should be examined in terms of potential and actual impacts on the environment. This is because in trying to solve the economic challenges of poverty and hunger, economies have ignored the environment which is now *biting* human population through widening disease transmission. In the same way, in further studies of the health effects of climate change it is important to ascertain the impacts of the use of poisons to control pests and insects as this will further poison water and destroy vegetation — absorbed by all living things — thereby extending challenges from *climate-disease control* to *disease control-climate*.

Climate is exaggerating malaria, and malaria control efforts further negatively impact on human health. Human health appears to be in jeopardy in all respects. It is therefore a recommendation of this study that the DDT impacts on environment should not be ignored in malaria intervention programmes. The effects on vegetation and biodiversity loss, water poisoning, and subsequent effects on aquatic life that supports life and livelihoods are already known, and the absorption of poisons in human tissues causes cancerous cells that are lethal.

6.3. Scientific contributions

This study has established the link between climate change and health. It has specifically examined how rainfall and temperature play a critical role in widening the

transmission zones for malaria. It has also established: (1) that climate has a causal effect on malaria transmission; (2) that the onset of rainfall triggers a malaria season; and (3) has proposed key issues in terms of malaria control measures as a policy recommendation. This study has contributed to the body of literature on climate change and health as some of the results of this study have been published in international journals. It has also provided further recommendations for research on the wider implications of malaria control programmes such that the vision of zero malaria in the province can be a reality without further damage to the human life support system — the environment.

REFERENCES

1. Adenomon, M. O., Ojehomon, V. E. T. & Oyejola, B. A. (2013) Modelling the dynamic relationship between rainfall and temperature time series data in Niger State, Nigeria. *Mathematical Theory and Modeling*, 3 (4), 2013. ISSN 2224-5804 (Paper) ISSN 2225-0522.
2. Africa Partnership Forum. (2007) Climate Change and Africa. 8th Meeting of the Africa Partnership Forum Berlin, Germany 22-23 May 2007.
3. Akinboade, O. A., Ziramba, E. & Kumo, W. L. (2008) The demand for gasoline in South Africa: an empirical analysis using co-integration techniques. *Energy Economics*, 30: 3222–3229.
4. Alemu, A., Abebe, G., Tsegaye, W. & Golassa, Lemu. (2011) Climatic variables and malaria transmission dynamics in Jimma town, South West Ethiopia. *Parasites & Vectors*, 4:30.
5. Atul, K. & Nettleman, M. (2005) Global warming and infectious disease. *Archives of Medical Research*, 36: 689-696.
6. Baltas, E. (2007) Spatial distribution of climatic indices in northern Greece. *Meteorological Applications*, 14: 69-78.
7. Barbier, E. (2011) The policy challenges for green economy and sustainable economic development. *Natural Resources Forum*, 35 (3), 233–245.
8. Blumberg, L. & Frean, J. (2007) Malaria control in South-Africa – challenges and successes. *South African Med. Journal*, 97, 1193-1197.
9. Bohle, H. G., Downing, T. E. & Watts, M. J. (1994) Climate change and social vulnerability: toward a sociology and geography of food insecurity. *Global Environmental Change*, 4 (1): 37–48.
10. Bouma, M. J. & van der Kaay, H. J. (1996) The El Niño/Southern Oscillation and the historic malaria epidemics on the Indian subcontinent and Sri Lanka: an early warning system for future epidemics? *Trop. Med. Int. Health*, 1, 86–96.

11. Breman, J. G. (2001) The ears of the hippopotamus: manifestations, determinants, and estimates of the malaria burden. *Am J Trop Med Hyg*, 2001, 64 (1-2 Suppl), 1-11.
12. Briet, J., Vounatsou, P., Gunawardena, D., Galappaththy, N. & Amerasinghe, P. (2008) Temporal correlation between malaria and rainfall in Sri Lanka. *Malaria Journal*, 7, 77.
13. Caminade, C., Kovats, S., Rocklov, J., Tompkins, A. M., Morse, A. P., Colón-González, F. J., Stenlund, H., Martens, Pim. & Lloyd S. J. (2014) Impact of climate change on global malaria distribution. *PNAS*, 111 (9), 3286–3291.
14. Campbell-Lendrum, D. H., Corvalán, C. F. & Prüss-Ustün, A. (2003) How much disease could climate change cause? In: McMichael, A. J. et al (eds.) *Climate change and human health: risks and responses*. WHO.
15. Carson, R., Darling, L. & Darling, L. (1962) *Silent spring*. Boston, Houghton Mifflin; Cambridge, Mass., Riverside Press.
16. Chin, T. & Welsby, P. (2004) Malaria in the UK: past, present, and future. *Postgrad Med J*, 80, 663–666. doi: 10.1136/pgmj.2004.021857
17. Cohn, B. A., Wolff, [M. S.](#), Cirillo, P. M. & Sholtz, R. I. (2007) DDT and breast cancer in young women: new data on the significance of age at exposure. *Environ Health Perspect*, 115 (10): 1406–1414. Published online 24th July 2007. doi: [10.1289/ehp.10260](https://doi.org/10.1289/ehp.10260)
18. Colwell, R. R. (1996) Global climate and infectious disease: the cholera paradigm, *Science*, 274 (5295), pp. 2025-2031.
19. Connor, S., Thomson, M. & Molyneux, D. (1999) Forecasting and prevention of epidemic malaria: new perspectives on an old problem. *Parassitologia*, 41, 439–448.
20. Craig, M. H., Kleinschmidt, I., Nawn, J. B., Sueur, D. & Sharp, B. L. (2004) Exploring 30 years of malaria case data in KwaZulu-Natal, South Africa : Part I. The impact of climatic factors. *Tropical Medicine and International Health*, 9 (12), 1247–1257.

21. Dickey, D. A. & Fuller, W. A. (1981) Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49, 1057–1072.
doi: 10.1186/1475-2875-12-370
22. Duasa, J. (2007) Determinants of Malaysian trade balance: an ARDL Bound Testing approach. *Journal of Economic Cooperation*, 28 (3), 21-40.
23. Ebi, K. L., Hartman, J., Chan, N., McConnell, K. J., Schlesinger, M. & Weyant, J. (2005) Climate suitability for stable malaria transmission in Zimbabwe under different climate change scenarios. *Climate Change*, 73, 375–393.
24. Epstein, P. R., Diaz, H. F., Elias, S. A., Grabherr, G., Graham, N. E., Martens, W. J. M., Mosley-Thompson, E. & Susskind, J. (1997) Biological and physical signs of climate change: focus on mosquito-borne diseases. *Bulletin of the American Meteorological Society*, 78, 409-417.
25. Gerritsen, A. A. M., Kruger, P., Schim van der Loeff, M. F. & Grobusch, M. P (2008) Malaria incidence in Limpopo Province, South Africa, 1998–2007. *Malaria Journal*, 7 (162), doi:10.1186/1475-2875-7-162
26. Githeko, A. K. & Ndegwa, W. (2001) Predicting malaria epidemics in the Kenyan Highlands using climate data: a tool for decision makers. *Global Change & Human Health* 2 (1), 54-63, DOI: 10.1023/A:1011943131643
27. Goto, K., Kumarendran, B., Mettananda, S., Gunasekara, D., Fujii, Y., et al. (2013) Analysis of effects of meteorological factors on Dengue incidence in Sri Lanka using time series data. *PLoS ONE*, 8 (5), e63717. doi: 10.1371/journal.pone.0063717
28. Granger, C. J. (1969) Investigating causal relationships by econometrics models and cross spectral methods. *Econometrica*, 37, 425-435.
29. Greenidge, K., Holder, C. & Mayers, S. (2009) Estimating the size of the informal economy in Barbados. *Business, Finance and Emerging Economies*, 4 (1).
30. Gupta, R. & Komen, K. (2009) Time aggregation and the contradictions with causal relationships: can economic theory come to the rescue? *Studies in Economics and Econometrics*. 33: 13–24 ISSN: 03796205.

31. Haines, A., McMichael, A. J. & Epstein, P. R. (2000) Environment and health: 2. Global climate change and health. *Canadian Med. Association Journal*. 163 (6).
32. Hanafi-Bojd, A. A., Vatandoost, H., Oshaghi, M. A., Charrahy, Z., Haghdoost, A. A., Zamani, G., Abedi, F., Sedaghat, M. M., Soltani, M., Shahi, M. & Raeisi, A. (2012) Spatial analysis and mapping of malaria risk in an endemic area, south of Iran: a GIS based decision making for planning of control. *Acta Tropical*, 122 (1), 132-137.
33. Haque, U., Hashizume, M., Glass, G. E., Dewan, A. M., Overgaard, H. J. & Yamamoto, T. (2010) The role of climate variability in the spread of malaria in Bangladeshi Highlands. *PLoS ONE*, 5 (12), e14341. doi: 10.1371/journal.pone.0014341
34. Harrus, S. & Baneth, G. (2005) Drivers for the emergence and re-emergence of vector-borne protozoa and bacterial diseases. *International Journal of Parasitology*, 35 (11-12), 1309-1318.
35. Hashizume, M., Terao, T. & Minakawa, N. (2009) The Indian Ocean Dipole and malaria risk in the highlands of western Kenya. *Proc Natl Acad Sci USA*, 106, 1857-1862.
36. Hendry, D. F., Pagan, A. & Sargan, J. D. (1984) Dynamic specification. In: Griliches, Z. & Intriligator, M. (Eds.), *Handbook of Econometrics*. vol. 2. North Holland, Amsterdam.
http://www.wmo.int/pages/themes/climate/applications_health.php.
37. Huang, F., Zhou, S., Zhang, S., Wang, H. & Tang, L. (2011) Temporal correlation analysis between malaria and meteorological factors in Motuo County, Tibet. *Malaria Journal*. 10, 54; doi:10.1186/1475-2875-10-54
38. Hulden, L. (2009) The decline of malaria in Finland – the impact of the vector and social variables. *Malaria Journal*. 8, 94 doi:10.1186/1475-2875-8-94
39. Hulme, M. (1996) Climate change and Southern Africa: an exploration of some potential impacts and implications for the SADC region. *Report Commissioned by WWF*. Climate Research Unit, University of East Anglia, Norwich.

40. IOM. (2008) Vector-borne diseases: understanding the environmental, human health and ecological connections. Washington, DC, The National Academies Press.
41. IPCC. (2007) Climate Change 2007, Impacts, Adaptation and Vulnerability: Contribution of Working Group II to the Fourth Assessment Report of the IPCC. Cambridge, UK, Cambridge University Press.
42. IWGCCH. (2008) Interagency Working Group on Climate Change and Health. A Human Health Perspective on Climate Change. USA: Environmental Health Perspectives and the National Institute of Environmental Health Sciences.
43. Jorgensen, P., Nambanya, S., Gopinath, D., Hongvanthong, B., Luangphengsouk, K., Bell, D., Phompida, S. & Phetsouvanh, R. (2010) High heterogeneity in Plasmodium falciparum risk illustrates the need for detailed mapping to guide resource allocation: a new malaria risk map of the Lao People's Democratic Republic. *Malaria Journal*, 9 (59); doi: 10.1186/1475-2875-9-59.
44. Khasnis, A. & Nettleman, D. (2005) Global warming and infectious disease. *Archives of Medical Research* 36, 689–696. Published by Elsevier Inc.
45. Khosa, E., Kuonza, L. R., Kruger, P. & Maimela, E. (2013) Towards the elimination of malaria in South Africa: a review of surveillance data in Mutale Municipality, Limpopo Province, 2005 to 2010. *Malaria Journal*. 12, 7, doi:10.1186/1475-2875-12-7
46. Komen K., Olwoch, J., Rautenbach, H., Botai, J. & Adetunji, A. (2015) Long-run relative importance of temperature as the main driver to malaria transmission in Limpopo Province, South Africa. The International Association for Ecology and Health, ISSN 1612-9202. *EcoHealth*, 12, (1), 131-143. DOI 10.1007/s10393-014-0992-1.
47. Komen, D. K. & Kapunda, S. M. (2006) Macroeconomic determinants of poverty reduction in the era of globalisation in Kenya: policy implications. *African Journal of Economic Policy*. 13 (2). ISSN 1116-4875.

48. Kondo, H., Seo, N., Yasuda, T., Hasizume, M., Koido, Y., Ninomiya, N. & Yamamoto, Y. (2002) Post-flood infectious diseases in Mozambique. *PrehospDisast Med*,17 (3), 126–133.
49. Kovats, R. S. & Haines, A. (2005) Global climate change and health: recent findings and future steps. *Canadian Medical Association Journal*, 172 (4), 501–502.
50. Kovats, R. S. & Martens, P. (2000) Human health. In Parry, M.L. (Ed.): *Assessment of Potential Effects and Adaptations for Climate Change in Europe: The Europe ACACIA Project.*, Norwich, United Kingdom, Jackson Environment Institute, University of East Anglia, pp. 227-242.
51. Kwiatkowski, D., Phillips, P. C. B., Schmidt, P. & Shin Y. (1992) Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54, 159–178.
52. Lindblade, K. A., Walker, E. D., Onapa, A. W., Katungu, J. & Wilson, M. L. (1999) Highland malaria in Uganda: prospective analysis of an epidemic associated with El Nino. *Trans. R. Soc. Trop. Med. Hyg*, 93, 480–487.
53. Lindsay, S. W. & Martens, W. J. M. (1998) Malaria in the African highlands: past, present and future. *Bulletin of the World Health Organization*, 76, 33-45.
54. Lunde, T. M., Bayoh, M. N. & Lindtjørn, B. (2013) How malaria models relate temperature to malaria transmission. *Parasites & Vectors*, 6, 20.
55. Maharaj, R., Morris, N., Seocharan, I., Kruger, P., Moonasar, D., Mabuza, A., Raswiswi, E., & Raman, J. (2012) The feasibility of malaria elimination in South Africa. *Biomedical Journal*, 11:423. DOI: 10.1186/1475-2875-11-423.
56. Maharaj, R., Raman, J., Morris, N., Moonasar, D., Durrheim, D N., Seocharan, I., Kruger, P., Shandukani, B., & Kleinschmidt, I. (2013) Epidemiology of malaria in South Africa: From control to elimination. *South African Medical Journal*, 103: 10.
57. Mardia, K., Kent, J. & Bibby, J. (1979) *Multivariate analysis*. London, Academic Press. .

58. McMichael, A. J. (2003) Global climate change: will it affect vector-borne infectious diseases? *Intern. Med. J.* 33, 554–555, 10.1111/j.1445-5994.2003.00492.x
59. McMichael, A. J. (2009) Climate change and human health. , 11-20. ISBN978-0-85092-872-3. Record Number 20103153805.
60. McMichael, A. J. et al (2004) Global Climate Change. In: Ezzati, M., Lopez, A., Rodgers, A., & Murray, C., (Eds.) *Comparative Quantification of Health Risks: Global and Regional Burden of Disease due to Selected Major Risk Factors*, pp. 1543–1649.
61. McMichael, A. J., Campbell-Lendrum, D., Corvalan, C. F., Ebi, K. L, Githeko, A., Scheraga, J. D. & Woodward, A. (2003) Climate change and human health: risks and responses. WHO/WMO/UNEP.
62. McMichael, A. J., Patz, J. & Kovats, R. S. (1998) Impacts of global environmental change on future health and health care in tropical countries. *British Medical Bulletin*, 54 (2), 475-488.
63. Mendelsohn, R., Dinar, A. & Williams, L. (2006) The distributional impact of climate change on rich and poor countries. *Environment and Development Economics*, 11, 159–178 doi:10.1017/S1355770X05002755
64. Messina, J. P., Taylor, S. M., Meshnick, S. R., Linke, A. M., Tshefu, A. K., Atua, B., Mwandagalirwa, K. & Emch, M. (2011) Population, behavioural and environmental drivers of malaria prevalence in the Democratic Republic of Congo. *Malaria Journal*, 10 (161); doi: 10.1186/1475-2875-10-161.
65. Mishra, S. K, Mohapatra, S. & Mohanty, S. (2003) Jaundice in Falciparum Malaria. *JACM*, 4, 12-13.
66. Moonasar D., Nuthulaganti T., Kruger PS., Mabuza A., Rasiswi, ES., Benson, FG., & Maharaj, R. (2012) Malaria control in South Africa 2000-2010: beyond MDG6. *Malaria Journal*, 11:294. doi: 10.1186/1475-2875-11-294.
67. Mordecai, E. A., Paaijmans, K. P., Johnson, L. R., Balzer, C., Ben-Horin, T., Moor, E., McNally, A., Pawar, S., Ryan, S. J., Smith, T. C. & Lafferty. (2013) Optimal

- temperature for malaria transmission is dramatically lower than previously predicted. *Ecology Letters*, 16, 22–30, doi: 10.1111/ele.12015
68. Mouchet et al. (1996) Julvez et al., 1997, cited in IPCC 2007.
 69. Naqvi, Z. R. (2009) Using remote sensing to assess potential impacts of hurricanes on mosquito habitat formation: investigating the mechanisms for interrelationship between climate and the incidence of vector-borne diseases. Theses/Dissertations-Environmental Studies. Submitted to the Graduate Faculty of Baylor University.
 70. Narayan, P. K. (2004) Reformulating critical values for the bounds F-statistics approach to cointegration: an application to the tourism demand model for Fiji. Department of Economics 2004 Discussion Papers no.02/04. Monash University, Melbourne, Australia.
 71. Ngomane, L. & de Jager, C. (2012) Changes in malaria morbidity and mortality in Mpumalanga Province, South Africa (2001- 2009): a retrospective study. *Malaria Journal*, 11, 19.
 72. Nkomo, J. C., Nyong, A. O. & Kulindwa, K. (2006) The Impacts of Climate Change on Africa. Final Draft Submitted to: The Stern Review on the Economics of Climate Change.
 73. Okanga, S., Cumming G S., & Hockey, PAR. (2013) Avian malaria prevalence and mosquito abundance in the Western Cape, South Africa. *Malaria Journal*: 2013, 12:370
 74. Paaijmans, K. P., Blanford, S., Bell, A. S., Blanford, J. I., Read, A. F. & Thomas, M. B. (2010) Influence of climate on malaria transmission depends on daily temperature variation. *PNAS*, 107 (34), 15135–15139.
 75. Panofsky, H. A. & Brier, G. W. (1968) Some applications of statistics to Meteorology. The Pennsylvania State University, University Park, Pennsylvania 224.

76. Pascual, M., Ahumada, J. A., Chaves, L. F., Rodo, X. & Bouma, M. (2006) Malaria resurgence in the East African highlands: temperature trends revisited. *Proc. Natl. Acad. Sci. U.S.A.* 103, 5829–5834, 10.1073/pnas.0508929103
77. Patz, J. A. & Olson, S. H. (2006) Malaria risk and temperature: influences from global climate change and local land use practices. *Ann Trop Med Parasitol*, 100 (5-6), 535-549.
78. Patz, J. A., Campbell-Lendrum, D., Holloway, T. & Foley, J. A. (2005) Impact of regional climate change on human health. *Nature*, 438, 310-317, doi: 10.1038/nature04188
79. Patz, J. A., Hulme, M., Rosenzweig, C., Mitchell, T. D., Goldberg, R. A., Githeko, A. K., Lele, S., McMichael, A. J. & Le Sueur, D. (2002) Climate change: regional warming and malaria resurgence. *Nature*, 420, 627–628, doi: 628. 10.1038/420627a
80. Pesaran, M. H. & Shin, Y. (1999) An autoregressive distributed lag modelling approach to cointegration analysis. In: Strøm S, (Ed.) *Econometrics and economic theory in the twentieth century: the Ragnar Frisch Centennial Symposium*. Cambridge, Cambridge University Press.
81. Pesaran, M. H., Shin, Y. & Smith, R. J. (2001) Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16, 289-326.
82. Poveda, G., Rojas, W., Quinones, M. L., Velez, I. D., Mantilla, R. I., Ruiz, D., Zuuaga, J. S. & Rua, G. L. (2001) Coupling between annual and ENSO timescales in the malaria-climate association in Colombia. *Environ. Health Perspect*, 109, 489–493.
83. Reiter, P. (2008) Global warming and malaria: knowing the horse before hitching the cart. *Malaria Journal*, 7 (Suppl 1), S3, doi:10.1186/1475-2875-7-S1-S3
84. Reiter, P. et al. (2004) Global warming and malaria: a call for accuracy. *Lancet Infect Dis*, 4, 323–324. cited in IPCC 2007.

85. Relman, D. A., Hamburg, M. A., Choffnes, E. R. & Mack, A. (2008) Global Climate Change and Extreme Weather Events: Understanding the Contributions to Infectious Disease Emergence: Workshop Summary. ISBN: 0-309-12403-4, 304 pages, 6 x 9.
86. Rogers, D. J. & Randolph, S. E. (2000) The global spread of malaria in a future, warmer world. *Science*, 289, 1763–1766.
87. Roll Back Malaria, RBM (2015). Lessons learned from fifteen years of responding to malaria globally: A prototype for sustainable development. *Briefing Paper*.
88. SaNTHNet. (2013) The South African National Travel Health Network, <http://www.santhnet.co.za/index.php/malaria-advice-for-travellers/item/312-what-is-malaria.html>
89. Sharp, B. L., Ngxongo, S., Botha, M. J., Ridl, F. C. & Le Sueur, D. (1998) An analysis of 10 years of retrospective malaria data from the KwaZulu areas of Natal. *South African Journal of Science*, 84,102–106.
90. Shewmake, S. (2008) Vulnerability and the Impact of Climate Change in South Africa's Limpopo River Basin. IFPRI Discussion Paper 00804.
91. Snow, R. W., Guerra, C. A., Noor, A. M., Myint, H. Y. & Hay, S. I. (2005) The global distribution of clinical episodes of Plasmodium falciparum malaria. *Nature*, 434, 214-217.
92. Sultan, R. (2010) Short-run and long-run elasticities of gasoline demand in Mauritius: an ARDL bounds test approach. *Journal of Emerging Trends in Economics and Management Sciences*, 1 (2), 90-95.
93. Tanser, F. C., Sharp, B. & le Sueur, D. (2003) Potential effect of climate change on malaria transmission in Africa. *Lancet*, 362, 1792–1798.
94. Thompson, A. A., Matamale, L. & Kharidza, S. D. (2012) Impact of climate change on children's health in Limpopo Province, South Africa. *Int J Environ Res Public Health*, 9 (3), 831-854. doi: 10.3390/ijerph9030831.

95. Thomson, M. C., Mason, S. J., Phindela, T. & Connor, S.J. (2005) Use of rainfall and sea surface temperature monitoring for malaria early warning in Botswana. *Am. J. Trop. Med. Hyg.* 73 (1), 214–221.
96. Tshiala, M. F., Olwoch, J. M. & Alwyn, E. F. (2011) Analysis of temperature trends over Limpopo Province, South Africa. *Journal of Geography and Geology*, 3 (1).
97. UNEP. (2011) United Nations Environment Programme. Adaptation to Climate Change in Africa Plan of Action for the Health Sector. 2012-2016.
98. UNFCCC. (2007) United Nations Framework Convention on Climate Change. Climate Change: Impacts, Vulnerabilities and Adaptation in Developing Countries.
99. van Lieshout, M., Kovats, R. S., Livermore, M. T. J. & Martens, P. (2004) Climate change and malaria: analysis of the SRES climate and socio-economic scenarios. *Global Environmental Change*, 14 (1), 87-99.
100. WHO. (2000) World Health Organization. Climate Change and Human Health: Impact and adaptation. Edited by Kovats, R. S., Menne, B., McMichael, A. J., Corvalan, C., Bertollini, R.
101. WHO. (2002) World Health Organization, 2002. The World Health Report 2002: Reducing risks, promoting healthy life.
102. WHO. (2003) Africa Malaria Report 2003. Geneva: World Health Organization.
103. Wilks, D. S. (1995) Statistical methods in the atmospheric sciences. *International Geophysics Series*, 59, 469.
104. Williams, H. A., Roberts, J., Kachur, S. P., et al. (1999) Malaria surveillance—United States, 1995. *Morbidity and Mortality Weekly Report*, 48 (1), 1–23.
105. WMO. (2015) World Meteorological Organization.
106. Yé, Y., Louis, V. R., Simboro, S. & Sauerborn, R. (2007) Effect of meteorological factors on clinical malaria risk among children : an assessment using village-based meteorological stations and community-based parasitological survey. *BMC Public Health*, 7, 101.

107. Zhou, G., Minakawa, N., Andrew, K. & Guiyun, Y. (2004) Association between climate variability and malaria epidemics in the east African highlands. *Proc Natl Acad Sci USA*. 101, 2375–2380.
108. Zucker, J. R. (1996) Changing patterns of autochthonous malaria transmission in the United States: a review of recent outbreaks. *Emerging Infectious Diseases*, 2 (1), 37–43.